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The gender gap in carbon footprints: determinants and implications

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The Gender Gap in Carbon Footprints: Determinants and Implications

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Abstract

Climate change mitigation requires understanding differences in individual carbon footprints. We document that women emit 26 percent less than men from food and transport, using detailed consumption data from France. After accounting for socioeconomic characteristics and differences in the scale of consumption, an 8 percent gap remains. Red meat and car use—high-emission goods associated with masculine identity—drive most of the residual gap, suggesting that gender differences in carbon footprints are partly driven by gender stereotypes. As a result, climate policies may affect men and women differently, and their political acceptability could become polarized across gender lines.

Keywords: Gender, Carbon Footprints, Climate Policy
JEL codes: J16, Q54, Q57

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1 Introduction

Mitigating climate change requires drastic reductions in carbon emissions and major shifts in consumption behavior (Creutzig et al., 2022), especially in high-emission sectors such as food and transport (IPCC, 2023). A growing literature documents heterogeneity in carbon footprints across income groups and locations, with important implications for climate policy targeting and equity. Much less is known about systematic gender differences, even though men and women display distinct consumption and mobility patterns that may translate into differences in emissions. Any gender gap in carbon footprints could reflect differences in socioeconomic factors, climate preferences, as well as social norms and identity-related consumption.[1] Understanding the extent of the gap and its underlying mechanisms is key for policy design and acceptability. If at least part of it arises from differing climate concerns or identity-related consumption choices, climate policies may have gendered implications beyond economic constraints. For instance, men who are more strongly attached to high-emission goods because these goods carry symbolic or identity value may resist such policies more than would be explained by their level of income or location alone.

This paper documents a significant gender gap in carbon footprints from food and transport, drawing on detailed consumption data from France. Carbon footprints are defined as the total greenhouse gas emissions (GHG) directly or indirectly caused by individual consumption, measured in tons of CO2 equivalent (tCO2e). We link nationally representative individual-level survey data to granular emissions intensity measures for over 2,000 food products and car models.[2] Methodologically, we draw on decomposition approaches developed in the gender wage gap literature (Blau and Kahn, 2000). After documenting the unadjusted gap, defined as the percentage difference in the average carbon footprints of women relative to men, we apply sequential regressions and Gelbach (2016) decompositions to assess the contribution of socioeconomic characteristics, differences in the scale of consumption (calories and distances), as well as the unexplained residual.[3]

We find that women's carbon footprints from food and transport are, on average, 26 percent lower than men's—a difference comparable to the gap between individuals in households with below-median and above-median income. The gaps are of similar magnitude across both sectors. Socioeconomic characteristics explain only part of these differences. After adjusting for education, age, household income, size of urban unit, and occupation, the gap remains around 20 percent. We refer to this gap as the *characteristics-adjusted gap*. We then show that the gap is not solely driven by a scale effect, whereby men simply eat more (including due to biological differences) or travel longer distances (e.g., due to longer commutes).[4] For food, the difference is 7 percent once calories are controlled, leaving 24 percent

[1]Evidence of identity-driven consumption includes Atkin et al. (2021).

[2]Our transport data cover any trip, whether the respondent is the driver or a passenger.

[3]In the survey, respondents declare their sex; in the absence of data on gender, we assign to each survey respondent the gender corresponding to the sex variable.

[4]The French public health guidelines (ANSES, 2016) recommend daily calorie intakes of 2,600 kcal for adult men and 2,100 kcal for adult women.

of the unadjusted gap unexplained. We call this difference the *scale-adjusted gap*. For transport, the gap narrows to 9 percent after controlling for distances, leaving 35 percent of the original transport gap unexplained.

The residual gender gap is driven by two goods: red meat and cars. Their respective contributions to the residual difference per sector (86 percent for red meat and 100 percent for cars), are far greater than their respective shares in the average individual footprints (14 percent for red meat in food and 82 percent for cars in transport). Both goods are highly carbon-intensive and closely associated with masculine identity (see e.g., Rothgerber (2013); Love and Sulikowski (2018) for meat and Willer et al. (2013) for cars). Men's greater consumption of these goods may reflect lower climate concern or stronger preferences for their non-climate attributes. Although we cannot directly identify the underlying motivation, we find no gender gap in air-travel emissions—another high-emission good that is less strongly linked to masculine identity. The prominence of identity-associated goods in the residual gap, but not of all carbon-intensive goods, highlights the role of preferences beyond climate concern.

Finally, we compare individuals living in couples to those living alone and show that household arrangements and intra-household dynamics shape the gendered distribution of carbon footprints. The gender gap in transport footprints is observed only within couples—especially those with children—suggesting patterns of intra-household specialization. The food gap is smaller among couples than among singles, though the difference is not statistically significant, consistent with convergence through shared meals and joint decisions. Focusing on singles also provides further suggestive evidence on the role of identity-related goods in driving the gap: although imprecise, we find a gender gap in red meat emissions three times larger for singles than couples without kids. Single women also own cars that are 0.4 SD less carbon-intensive than those owned by single men, yet they do not fly less.

To understand the broader relevance of our findings, we translate the gender gap into potential implications for climate goals. We quantify by how much France's emissions in food and transport would decrease if all adult men adopted the average carbon intensity of women as observed in our sample, while keeping men's calorie requirements and transport distances unchanged. In this scenario, men's carbon footprints would be 3.8 percent lower than they currently are for food, and 16 percent for transport. Each quantity represents about three times the annual emission reductions expected from the agriculture and transport sectors, respectively, to comply with France's climate targets by 2030 (Haut Conseil pour le Climat, 2024).[5]

To illustrate the policy incidence of the gap we measure, we conduct a back-of-the-envelope calculation. A uniform €100/tCO_2e carbon tax on food and transport would translate into gender-differentiated net burdens once revenues are recycled: about €530 for men and €390 for women annually (2.5% and 1.9% of median disposable income in 2017), assuming that both are tax-inelastic.[6] Assuming equal per-capita recycling, the average net burden would be around +€72 for men and –€68 for women. Although this

[5] France's reduction targets cover domestic emissions, whereas our consumption-based approach includes imports.

[6] We are not aware of studies estimating differential carbon tax elasticities by gender.

exercise abstracts from behavioral responses, it highlights that even a uniform carbon tax can generate gender-differentiated outcomes given the large differences in baseline emissions.

Our analysis of food and transport covers 52% of individual carbon footprints (CGDD, 2022).[7] We believe that the gender gap in carbon footprints is unlikely to disappear when considering the remaining sectors for which we lack individual data. Indeed, for housing and public goods and services, which account for 31% of individual carbon footprints (Baude, 2022), the literature suggests only a null to small gender gap. Given this and our results for food and transport, we estimate that reversing the gap would require emissions from all other goods and services (e.g., furniture, appliances, clothing) to be at least 71% higher for women than for men.

Our paper contributes to several strands of the literature. First, we add to the limited body of research linking gender and carbon footprints (Räty and Carlsson-Kanyama, 2010; Rippin et al., 2021; Carlsson Kanyama et al., 2021; Osorio et al., 2024; Arduini and Le Henaff, 2025). We move beyond measuring the gap by examining the mechanisms underlying it and highlighting possible policy implications. Moreover, most of these studies rely on samples of single individuals in household budget surveys. We show that such estimates may be biased, given the large differences in carbon footprints observed across household arrangements.

More broadly, we contribute to the literature examining heterogeneity in carbon footprints along various dimensions, primarily income (Chancel, 2022; Sager, 2019) and more recently location (Lyubich, 2025). Most of this literature relies on household budget surveys (Ivanova and Wood, 2020; Cronin et al., 2019), where most households typically include both genders, precluding a systematic analysis of the gender dimension. Using individual-level data, we show that gender is a significant source of heterogeneity in carbon footprints. In addition, unlike most of these studies, which rely on household expenditure data, our volume-based measures capture physical quantities consumed, thereby avoiding biases from price or quality differences.[8]

Second, we add to the literature on gender differences in economic outcomes (Blau and Kahn, 2017). To our knowledge, we are the first to apply decomposition methods from the gender wage gap literature to environmental outcome gaps. A related literature documents gender differences in food consumption (e.g., Rothgerber, 2013; Love and Sulikowski, 2018; Rosenfeld, 2020; Hopwood et al., 2024) and transport behavior (e.g., Scheiner and Holz-Rau, 2012; Motte-Baumvol et al., 2017; Le Barbanchon et al., 2021). We contribute by quantifying the environmental consequences of these gendered consumption patterns.

Third, our study contributes to the literature on the political economy of environmental policies. Prior research shows that women in high-income countries are more concerned about climate change than men (McCright, 2010; Bush and Clayton, 2023), and that female politicians have stronger climate

[7] Magnitudes are similar for the US: Song et al. (2019).

[8] Two products of the same volume can have very different prices yet similar carbon intensity—for example, a 100g premium chocolate and a 100g standard one with similar production processes. Measuring carbon intensity per euro instead of per kilogram, as is common with expenditure data, overestimates the premium chocolate's footprint.

leadership (Mavisakalyan and Tarverdi, 2019; Bandyopadhyay et al., 2023). Yet there is little evidence on whether men and women face different individual costs of climate mitigation, which could help explain these gender gaps (Bush and Clayton, 2023). Another strand of the literature emphasizes that such costs as key determinants of climate policy support (Dechezleprêtre et al., 2025). While our data do not allow us to estimate elasticities, they reveal large and previously understudied differences in the baseline distribution of emissions across population groups—a crucial step toward designing equitable climate policies.

2 Data and methods

We leverage two surveys, one on food and the other on transport, that we analyze separately. They each record consumption quantities for a representative sample of the French population. The method for estimating carbon footprints is similar across surveys and consists in multiplying quantities of consumed foods in kilograms (respectively traveled distances in kilometers) by emission intensity at the food product (respectively transport mode or car model) level. Our emission intensity measures reflect the life-cycle greenhouse gas emissions embedded in each final product consumed.

2.1 Building food and transport carbon footprints

2.1.1 Food

We use data from the INCA3 survey, produced by the French National Health Safety Agency (ANSES). It was conducted in 2014-2015 and includes individual food consumption patterns for a representative sample of the French adult population (N=2,121). The data producer estimates daily quantities consumed for each individual for around 2,800 food products based on a consumption diary filled for three representative days, including food consumed at home and out of home. Estimated daily caloric intake associated with this consumption is also reported.

We matched this data with product-level emission intensities from the 2017 (3.0) version of the Agribalyse database produced by the French Energy Agency (ADEME). This dataset includes the environmental impact of 2,480 distinct products consumed in France, from 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 each product takes into account GHG emissions embodied in farming practices, the transport of raw inputs, their transformation, distribution through retail and cooking.

Given different product classifications in each dataset, we matched them using a mixed method involving string matching, Natural Language Processing (NLP), and, for 14% of the products, manual corrections. The full procedure is detailed in Appendix A. Appendix Figure D.1 shows the large heterogeneity in emission intensity across individual food products, including within a broad food category (e.g., meats).

Appendix Figure D.2 shows average emission intensity by food category. Animal meats have the highest emission intensities, Consistent with previous research (Poore and Nemecek, 2018; Clark et al., 2022). Red meat, defined as ruminant meat (excluding veal), is the highest-emission category, with an estimated footprint approximately three times greater than the subsequent category, 'other meat' (comprising cold cuts and mixed meats).

2.1.2 Transport

We use data from the 2019 wave of the French National Transport Survey (EMP), which documents the travel patterns for a representative sample of French adults (N=12,510). Individuals report all trips below 80km made on a representative day of the past week—accounting for their daily mobility—, and all trips above 80km made over the past six weeks—accounting for long-distance mobility, including both leisure and business trips.[9] All trips in a personal vehicle are recorded, whether or not the respondent is the driver. For employed individuals recording a trip from home to work on the representative day, the commuting distance by road is provided.

Trip-level GHG emissions have been estimated by the data provider by multiplying travel distances with mode-specific emission intensities per kilometer, as reported by official sources. For trips using a personal vehicle owned by the household, the emission intensity is vehicle-specific, based on information in vehicle registration records. We adjust these emission estimates to account for upstream manufacturing emissions and walking time, as detailed in Appendix A. For trips by car and two-wheeler, we adjust for occupancy by dividing emissions by the number of passengers. Consequently, emissions from trips involving children are only partly attributed to the accompanying adults: for instance, a 10 km car journey driving two children to a leisure activity counts as one-third of the emissions of a 10 km solo trip. We replicate our main results on transport assigning all emissions from car trips to the respondent irrespective of occupancy rate in Appendix Figure D.11.

Compared to the existing literature, our trip-level emission intensities are much more granular, especially for cars. This is valuable to study differences in the type of car men and women use. Appendix Figure D.3 illustrates this heterogeneity by showing unique values of CO_2 emission intensity by car model, expressed in grams of CO_2 equivalent per kilometer (gCO_2e/km). Emission intensities range from under 100gCO_2e/km, usually for electric or hybrid cars, to above 300gCO_2e/km for the highest-emitting cars.

Appendix Figure D.4 presents the average emission intensity by mode accounting for occupancy

[9]The data was collected in six waves of two months over one year. We include wave fixed effects in our regressions to account for the seasonality of travel demand, especially for long-distance trips.

rate, distinguishing short-distance and long-distance travel. Car is the top emitting mode for short distances with an average intensity of 168 gCO_2e per km.passenger, 45% more than the second highest-emitting mode, two-wheelers. Plane is the top emitting mode for long distance, with 174 gCO_2e per km.passenger.[10]

2.1.3 Estimation sample

We harmonize individual-level food and transport data to reflect annual carbon footprints per capita for the same population groups.[11] The carbon footprints that we obtain are consistent with per capita carbon footprints estimated with top-down approaches combining data on sectoral GHG emissions, trade and input-output tables. Our average individual has an annual food carbon footprint of 1.9tCO_2e and an annual transport carbon footprint of 2.7tCO_2e. A top-down approach in Baude (2022) gives estimates of respectively 2.1tCO_2e and 2.8tCO_2e for 2017. After data harmonization, average sociodemographic characteristics are similar across the food and transport surveys once we apply survey weights (see Appendix Table D.2).

2.2 Quantifying the gender gap in carbon footprints

Our first quantification of the gender gap in carbon footprints is the percentage difference in the average carbon footprints of women relative to men. To understand the role of other characteristics, we then estimate the gap after adjusting for several groups of covariates, running sequential 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. X_i is a vector of socioeconomic, demographic and location controls observed at the individual or household level. μ_i is the error term. β_1 is our coefficient of interest reflecting the association between being female and the outcome. This coefficient reflects the portion of the gender gap that remains after adjusting for observable factors in X_i such as occupational type or income, even though these variables may also be influenced by gender.[12] We apply survey weights to obtain results representative at the national level, and use robust standard errors.

[10] The low per passenger emission intensity for long-distance trips by car is due to the higher occupancy rate for long vs short-distance car trips. We neglect boat which has a very low modal share.

[11] We drop individuals aged 80 and more in the transport data since the food survey only interviews individuals until 79. Daily and six-week carbon footprints are scaled to annual values for food and transport, respectively.

[12] We take as main outcome the absolute carbon footprints, so β_1 reflects the average difference in levels. We prefer a specification in levels to one in logs because a significant share of individuals (10%) have a zero transport carbon footprint. This is mostly due to them traveling a positive distance using a zero-emission mode (80% of them), which complicates a specification in logs (Chen and Roth, 2024). Compared with the relative gaps derived from Figure 2a, estimating equation 1 with the log-transformed value of emissions yields similar results for the food gap (where all carbon footprints are strictly positive) and a larger magnitude for the transport gap.

We define the *unadjusted gap* as the estimate controlling only for survey wave, which closely matches the raw difference in averages. Control variables in X_i are harmonized across datasets (categories detailed in Appendix B). Beyond survey wave, we sequentially add controls for age, education, and household size ("+sociodemographics" regression), for urban unit size ("+location" regression), for categories of household income ("+household income" regression),[13] and employment status/professional category ("+employment status and professional category" regression).[14] The gap from this last specification is the *characteristics-adjusted gap*. To examine the role of scale (Section 3.3), we add calories in the food regression and distances traveled in the transport regression, yielding the *scale-adjusted gap*. Although our regressions yield estimates of the absolute gap, we report our findings as relative gaps by dividing the point estimate on the dummy "female" by the average carbon footprint of men.

We perform a Gelbach decomposition to quantify the impact of each set of covariates on the gender gap, invariant to the order in which they are introduced (Gelbach, 2016).[15]As discussed in Cook et al. (2021), this method allows for a consistent interpretation of the difference in the estimated gap with and without a given control, even when controls are correlated. For example, because household income is strongly associated with sociodemographic characteristics such as education, the change in the gap when adding education may also reflect income differences. The Gelbach decomposition adjusts for these correlations, isolating each control's net contribution.

3 Results

3.1 Unadjusted gender gap in carbon footprints

Figure 1 shows the average carbon footprints by gender and consumption category. The annual carbon footprints associated with women's food and transport consumption is 26% lower than men's on average. The gender gap is driven by differences in both food (28% gap) and transport (25% gap). Despite the right-skewed distributions of carbon footprints (see Appendix Figures D.5, D.6, D.7), the gender gaps are not driven by outliers. After excluding the top and bottom 5% of the distribution within each gender, the gender gap in carbon footprints decreases from 28% to 25% for food. It is unchanged for transport (see Appendix Table D.1).

Appendix Figures D.8 and D.9 decomposes food and transport footprints into two categories: at home versus out-of-home food, and work-related (including both commuting and other business-related travel) 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

[13]Individual income is not recorded in our data.

[14]A LASSO selection confirmed all controls as relevant, except survey wave in the food survey.

[15]The Gelbach decomposition is increasingly used in labor economics (Cook et al., 2021; Bachan and Bryson, 2022) and nests the Oaxaca–Blinder decomposition as a special case.

(25%). For transport, 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.

To put our result on the unadjusted gender gap in perspective, we compare it to the unadjusted income gap in carbon footprints for the same sectors. Splitting the sample into two equal-sized income groups, we obtain an unadjusted gap of 27%, similar in magnitude to the gender gap and driven by transport. Comparing the extremes of the distribution—top and bottom income quintiles, excluding the middle 60%—yields a gap of 48%, only 1.8 times larger than the gender difference.

Would the gender gap disappear or even reverse if we could observe individual footprints for all consumption categories? The remaining 48% includes housing (23%), tangible goods (10%), the reallocation of emissions from final government consumption (8%), and other services (8%) (Baude, 2022). Based on our estimates and those from the literature, we find that women's carbon footprints for all tangible good and services would need to be at least 71% larger than men's to fully cancel out the gap in food and transport, which is unlikely (see Appendix C for detailed calculations).[16]

3.2 Does the gap persist conditional on socioeconomic characteristics?

A vast literature documents gender differences in economic conditions, labor market integration, domestic labor, and leisure activities (see Blau and Kahn, 2017, for review of the gender wage gap). Figure 2a shows the results of sequential regressions obtained in the specifications described in section 2.2. The average gap across the two categories decreases from 26% to 20% after controlling for the full set of household and individual characteristics. Since the 95% confidence intervals of the unadjusted and characteristics-adjusted estimates overlap, we cannot reject that the two are equal. For food, the gap decreases only slightly, from 28% to 24%. A Gelbach decomposition highlights that, for food, 87% of the gender gap remains unexplained (top panel of Appendix Table D.3) . The largest contribution to the difference between the unadjusted and characteristics-adjusted gap comes from employment status and socio-professional category.

For transport, the gender gap narrows from 25% to 18% after adding all the controls.[17] The Gelbach decomposition in Appendix Table D.4 shows that location, income, and employment status all play a role

[16]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 consumption. Sources: European Environment Agency, 2020 figures https://www.eea.europa.eu/publications/textiles-and-the-environment-the/textiles-and-the-environment-the.

[17]The transport survey provides additional controls not available in the food survey, such as detailed occupation, driving license, and the number of cars per household. Appendix Figure D.11 shows that including these factors reduces the gap to 14% but does not eliminate it. The figure also shows that the gap persists when we do not account for car occupancy rate and assign all emissions from car trips to the respondent: the unadjusted gap for transport decreases from 25% to 18% and the characteristics-adjusted gap decreases from 18% to 12%.

in explaining the gender gap in transport carbon footprints, with employment status having the strongest influence. 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. Still, 70% of the unadjusted gender gap remains unexplained.

Given the differences in employment rates between men and women in France, we examine employment status in more detail.[18] The unadjusted gender gap in carbon footprints is of similar magnitude among the employed as in the general population: 28% for food and 25% for transport ("Controls: survey wave", Appendix Figure D.10). When we re-estimate sequential regressions for this subsample, adding a control variable specific to employed individuals night shift work, the gap narrows only slightly to 26% for food and 23% for transport ("Controls: + employment charact." in Appendix Figure D.10).

3.3 The role of scale: biological differences and travel demand

Given that individual carbon footprints are the product of quantities consumed (in kilograms of food or kilometers traveled) and the emission intensity of that consumption, any gender difference in the scale of consumption will mechanically translate into differences in carbon footprints. For food, this difference in scale could be due to gender differences in dietary requirements, while for transport, it could arise due to e.g., more constrained trips related to work among men than women. In this section we investigate the role of scale separately for each sector.

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

The French Health Agency (ANSES, 2016) recommend that women consume on average about 20% fewer calories than men. In our data, however, the difference in caloric intake is 10% larger than these recommendations. This excess gap is primarily due to men's higher alcohol consumption, which is not included in dietary guidelines. Thus, part of the food gender gap reflects differences in total consumption beyond biological needs.

Because recommended intake differs from actual consumption—and excludes alcohol—we adjust for scale by controlling for observed caloric intake in our regressions.[19] Controlling for recommended intake would better capture biological needs, but since it is determined entirely by gender and age, it is collinear with our sociodemographic controls.

Figure 2b shows how the characteristics-adjusted gap changes when we additionally control for individual caloric intake. Accounting for caloric intake substantially reduces the gender gap in food carbon

[18] In 2016, 62.2% of women aged 15–64 in France were employed compared to 67.7% of men (INSEE).

[19] Caloric content is not directly linked with carbon footprint; for example, raw sugar is high in calories but low in carbon intensity.

footprints. The corresponding scale-adjusted gender gap in carbon footprints is 6.7%.[20] This unexplained residual component, accounting for 23% of the unadjusted gap (see Appendix Table D.3), reflects systematic differences between men and women in the carbon intensity of the good consumed.

3.3.2 Gender differences in distances traveled

The labor and transport literature highlights a gender gap in willingness to accept jobs with long commutes (Le Barbanchon et al., 2021; Frändberg and Vilhelmson, 2011). This suggests that, as with food, women's scale of consumption in transport is lower than men's. A key difference is that while food intake has a biologically determined upper limit, travel demand is constrained only by time, with faster—and more carbon-intensive—modes often enabling longer distances.[21] This implies a positive correlation between distances traveled and the emission intensity of the transport modes used. Therefore, controlling for the scale of consumption using distances traveled will partial out both the mechanical effect of distances on carbon emissions, and the effect of distance on the transport mode chosen and its intensity.

We first examine how much the gap among the employed changes when controlling for commuting distances. The characteristics-adjusted gap decreases only from 23% to 19% (see left panel of Appendix Figure D.12). Part of the gap must, therefore, also be driven by gender differences in the carbon intensity of commuting, or in the scale and carbon intensity of other trips.[22]

To disentangle the role of scale from emission intensity, we control for total distance traveled in the main regression on the full sample. Compared to the characteristics-adjusted gap of 15%, the scale-adjusted gap is of 8.8% (right panel of Figure 2b). The Gelbach decomposition in the lower panel of Appendix Table D.4 indicates that distance is the most important factor in explaining the difference between the raw gap and the scale-adjusted gap, accounting for almost half of the overall reduction. Nevertheless, the residual gap of 8.8% still represents 35% of the unadjusted gap. Therefore, for a given distance traveled, women's trips are less carbon-intensive than men's, likely due to differences in mode choice or vehicle characteristics. We return to these explanations in the next section.

3.4 Contributions of red meat and cars to the gender gap

The social science literature emphasizes the association of masculine identity with red meat consumption (Rothgerber, 2013) and with cars (Scheiner and Holz-Rau, 2012).[23] We study the specific contribution of

[20] 9.7% if we exclude the calories from alcohol.

[21] This holds given the low penetration of electric vehicles in France, EVs made up just 2.2% of registered cars in 2024 (Ministry for the Environment, 2024), and the lack of low-carbon alternatives to long-distance flights.

[22] It is unclear whether work-related trips beyond commuting should be included in consumption-based carbon footprints, given their intrinsic link to production activities. The right panel of Appendix Figure D.12 shows that the gender gap in transport carbon footprints persists among the employed even when these trips are excluded.

[23] For instance, (Cuevas et al., 2025)identify many car-related items among the 500 Most Masculine Interests based on Facebook data; random feedback suggesting that men are feminine increases their interest in buying an SUV (Willer et al.,

these two goods to the gender gap in carbon footprints, as they are also the most carbon-intensive (along with air travel).

We isolate the role of red meat and car use in the gender gap by re-estimating equation 1, using as outcomes the annual carbon footprints associated with these goods. Figure 3 shows their key contributions to the gender gap. Carbon footprints from red meat consumption are 0.38 SD lower for women with only simple controls (unadjusted), 0.34 SD lower when adjusting for all socioeconomic characteristics (characteristics-adjusted), and 0.24 SD lower when additionally adjusting for total caloric intake (scale-adjusted). The corresponding gaps for cars are -0.23 SD, -0.17 SD, and -0.10 SD. The persistent scale-adjusted gap shows that the gap is not only driven by higher calorie requirements and the need to travel longer distances. For plane, the other major emission source, we do not find a significant gender gap (Appendix Figure D.15).

Another way to illustrate the role of red meat and cars is to compare their share in the average carbon footprint with their share in the footprint gap. On average, red meat accounts for 14% of food emissions, while cars account for 82% of transport emissions. We measure their contribution to the gender gap by dividing the coefficient on the gender dummy in regressions where the outcome is red meat (or car)-related carbon footprints by the coefficient in regressions of food (or transport) carbon footprints, using the three specifications presented in Figure 3. Appendix Figure D.13 shows that red meat accounts for 35% of the unadjusted gender gap and 86% of the scale-adjusted gap, a disproportionate share compared to its 14% in average food emissions. By contrast, while car causes most of transport carbon footprints, gender differences in car use explain essentially 100% of the scale-adjusted gap (Appendix Figure D.14).

What explains the gap in car emissions? Unlike red meat, which women consume in smaller quantities relative to men as a share of total food volume, we do not find that women use cars significantly less as a share of total distances traveled, once socioeconomic factors are controlled for (see Appendix Figure D.16). Instead, the gap reflects both shorter travel distances and lower emission intensity of women's car trips (see Appendix Figure D.17). The latter has two components: women more often travel with additional passengers, consistent with the fact that they are more likely to accompany children (Motte-Baumvol et al., 2017), and they drive less carbon-intensive vehicles. In couples with two cars, men are more likely to drive the higher-emission vehicle, while among singles, women's cars are substantially less carbon-intensive than men's (-0.4 SD).

3.5 Heterogeneity by household type: couples vs singles

We open the black box of household dynamics, often obscured in household-level data, and compare the gender gap in footprints across household structures. Appendix Figure D.18 reports the unadjusted

2013); and men are more likely than women to believe that eating meat is natural and necessary for humans (Rothgerber, 2013) gender gap separately for singles, couples without children, and couples with children.[24] On average, single men and single women have lower carbon footprints than individuals in dual-adult households. The differences are especially pronounced for transport, with individuals in households with children having the highest carbon footprint, likely reflecting greater travel demand when children are present.

Figure 4 shows the characteristics-adjusted gap for each household type. The gender gap in food carbon footprints is smaller for couples than for singles, though the differences are not statistically significant. The narrower gap observed among couples may be explained by their smaller gap in red meat emissions compared to singles; however, the confidence intervals still overlap (see Appendix Figure D.19). After controlling for observable characteristics, the predicted average food carbon footprint is 0.2 tCO2e higher for women in couples without children than for singles, while that of men remains unchanged. This asymmetrical pattern suggestive of convergence among couples is in line with the food studies literature, which finds that women are more likely to align their eating habits to those of their male partners (Brown and Miller, 2002; Sobal, 2005; Gregson and Piazza, 2023).

In contrast, the results for transport are suggestive of specialization within the household. The characteristics-adjusted gap is much larger for couples than for singles, for whom we cannot rule out a zero gap. It is twice as large for couples with than without children. This result is consistent with the labor literature, which shows that couples with children trade off commuting time and childcare responsibilities (Blundell et al., 2018). Le Barbanchon et al. (2021) find that the gender gap in willingness to commute is strongest for married women with children and lowest for single women without children. Among singles, the absence of gap can be explained by the fact that single women travel the same distances as single men. Although their trips remain less carbon-intensive than men's—with a higher occupancy rate in car trips and ownership of less polluting cars, see Appendix Figure D.17—, this is not enough to generate a statistically significant gap in total carbon footprints.

4 Conclusion

In this paper we uncover a significant gender gap in carbon footprints from food and transport in France. Even after adjusting for a rich set of covariates and for differences in the scale of consumption, a large portion of the gap remains unexplained. The residual differences we document are driven by the disproportionate contribution of red meat and car in men's carbon footprints.

Our findings have several implications for climate policy. Our back-of-envelope calculation suggests that men may have a larger carbon tax burden than women in food and transport. Estimating more precise gender-specific carbon tax incidence, while accounting for behavioral responses, is a promising avenue for future research. In addition, since the perceived individual cost of climate policy strongly shapes support (Dechezleprêtre et al., 2025), women's lower carbon footprints may translate into greater

[24] Single parents are excluded due to the small number of men (N = 16).

support for mitigation measures. If the gap partly reflects gendered preferences for carbon-intensive goods, climate policy could become polarized along gender lines.

Our results suggest that the gender gap cannot be explained solely by differences in climate concerns. The prominence of high-emission goods associated with masculine identity, such as red meat and cars, but not of gender-neutral polluting goods like air travel, indicates that identity-related preferences predating climate concerns play an important role. Variation in the magnitude of the gap across household structures highlights that conformity with traditional gender roles and intra-household dynamics contribute to it.

Given these mechanisms, the gap we uncover could be affected by measures outside traditional climate policy instruments. Information policies that challenge the association between masculine identity and the consumption of certain goods—particularly those linked to "dominance masculinity" (De Haas et al., 2024)—could indirectly lower household carbon footprints by reducing demand for these goods. Likewise, countering stereotypes that frame green consumption or vegetarianism as feminine (Brough et al., 2016; MacInnis and Hodson, 2015; Rosenfeld, 2020) could encourage pro-environmental behaviors among men. By contrast, cultural trends promoting raw or all-meat diets risk reinforcing traditional masculine norms and worsening environmental outcomes.[25]

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

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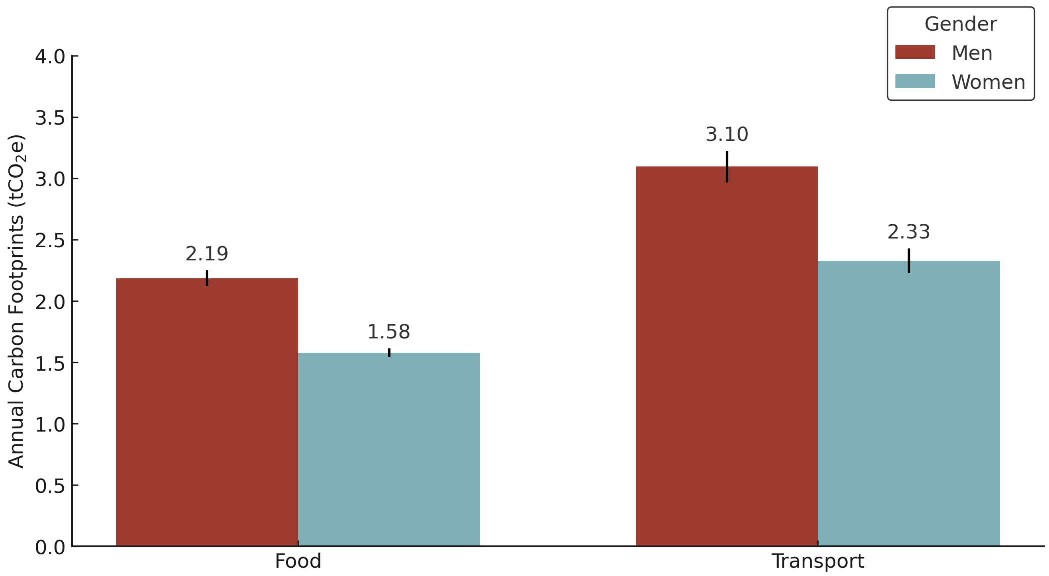
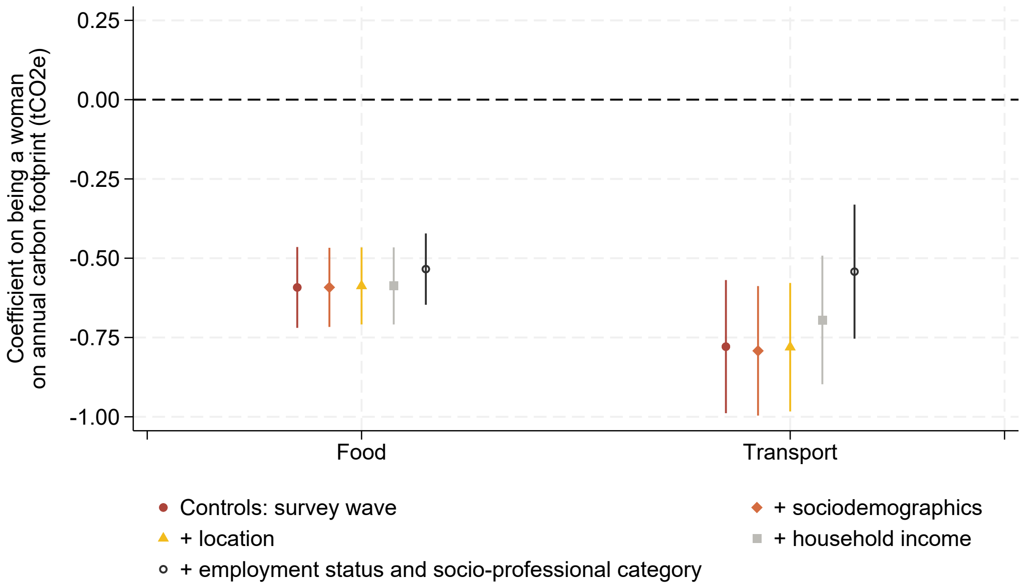
5 Figures

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

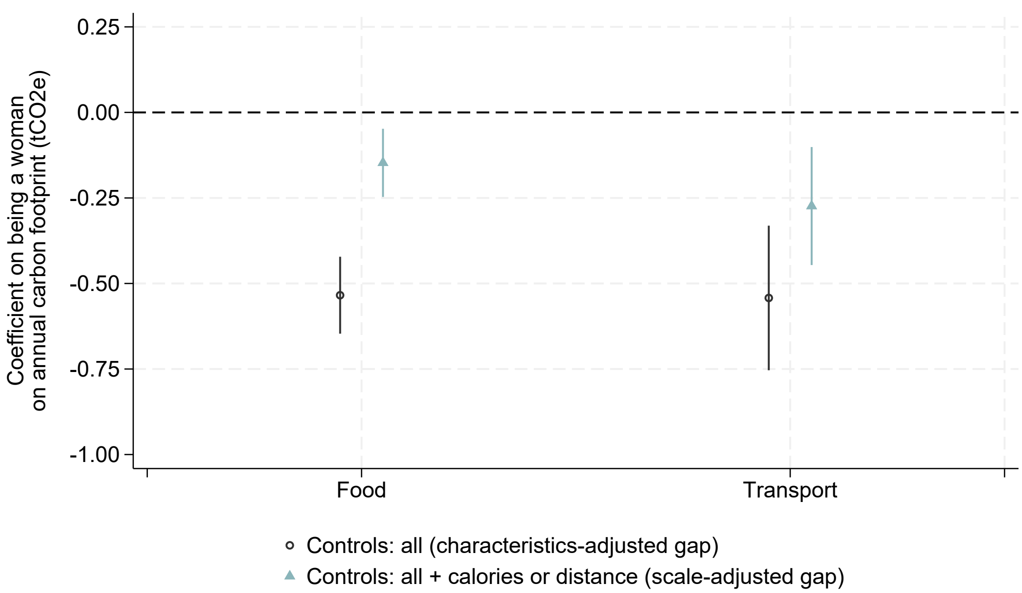


Notes: Sources: Food: INCA3 (N=2,121); transport: EMP (N=11,307). Averages calculated with survey weights. The dark vertical bars indicate 95% confidence intervals.

Figure 2: Gender Gap in Food and Transport Carbon Footprint, the Role of Socio-economic Factors and the Scale of Consumption



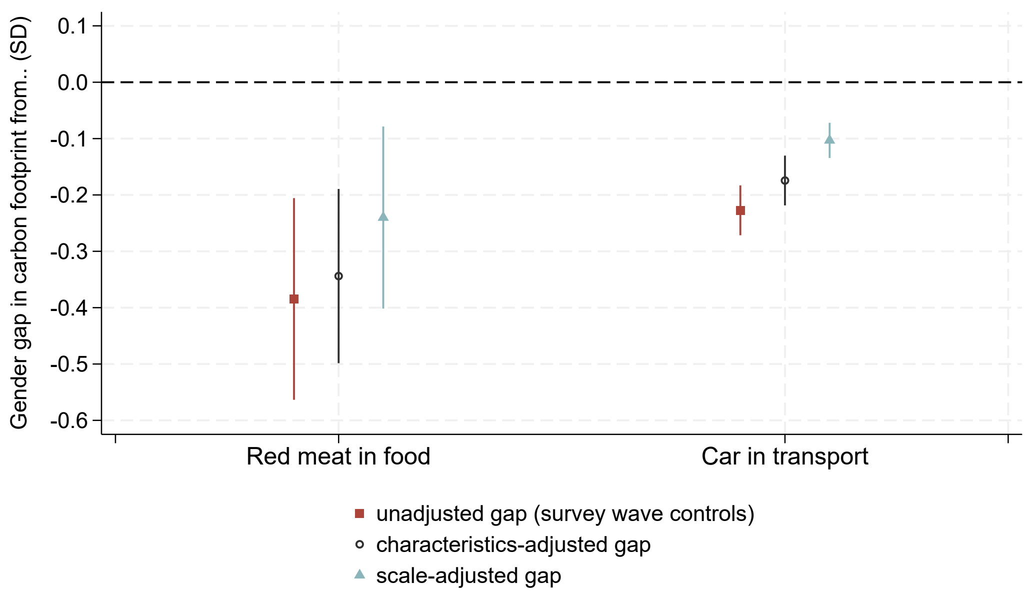
(a) Characteristics-adjusted Gap



(b) Scale-adjusted Gap

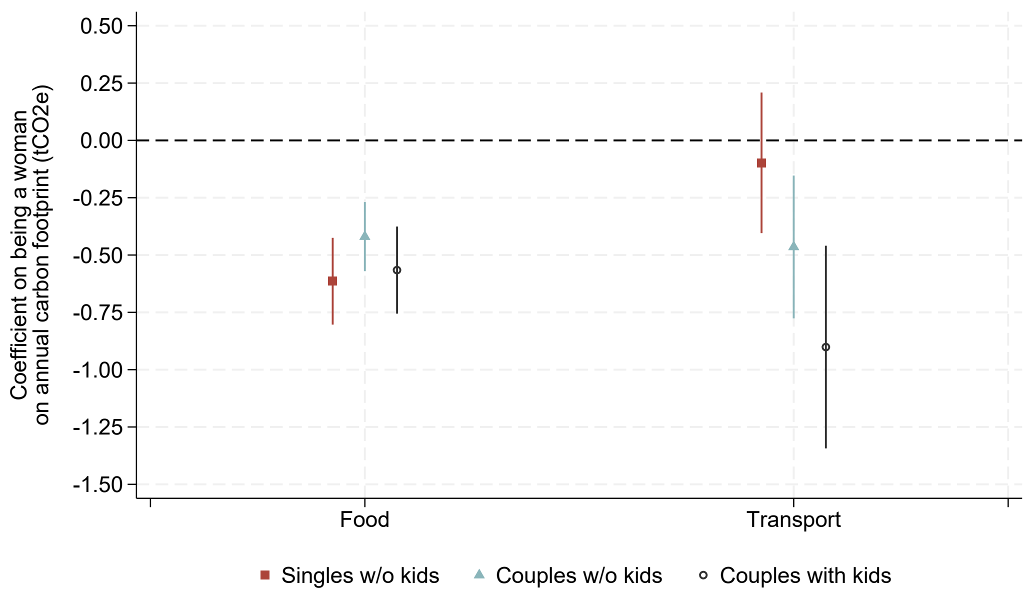
Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each consumption category, with a different set of control variables. In figure (a), "Controls: survey wave" only controls for the time of year when 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. In figure (b), "Controls: all" controls for survey wave, age, education and household size, location, household income, employment status and socio-professional category and coincides with the last point estimate in figure (a); "Controls: all + calories or distance" additionally controls for caloric intake for food and total distances traveled for transport. Source: Food consumption: INCA3 (N=1,957); transport: EMP (N=11,016)

Figure 3: Gender Gap in Carbon Footprints from Red Meat and Car



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". "unadjusted gap (survey wave controls)" only controls for the time of year when the survey is conducted. "characteristics-adjusted gap" additionally controls for age, education, household size, size of the urban unit of residence, household income and employment status and socio-professional category. "scale-adjusted gap" additionally controls for reported daily caloric intake for the regression on food and for reported total distances traveled for the regression on transport. Sources: INCA3 (N=1,957); EMP (N=11,016).

Figure 4: Characteristics-adjusted Gender Gap in Carbon Footprints by Household Type.



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=545; couples without children: N=721; couples with children: N=610); transport: EMP (singles without children: N=3,490; couples without children: N=3,723; couples with children: N=2,943).

Online 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.[26] 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.

[26] 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.

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.[27] 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.

B Control variables used to estimate the adjusted gender gap in carbon footprints

The following control variables are used:

[27] 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.

- “Controls: survey wave” regression: The variables available differ in the food and transport surveys. For the food survey, we use indicators for the four seasons. 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). 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.

- “+sociodemographics” regression: we control for survey wave and additionally for age, education, and household size. 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 ≤ 2 years, and higher education degree > 2 years. Household size is included as a linear control.

- “+location” regression: we control for survey wave, age, education and household size, and additionally for urban unit size with indicators for the size of the residence’s urban area. 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.

- “+household income” regression: we control for survey wave, age, education and household size, size of urban unit, and additionally for household income. We do not have data on individual income or wage. 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. Net income is after transfers and social contributions and before income tax.

- “+employment status and professional category” regression (also referred to as “full set of controls” regression): we control for survey wave, age, education and household size, size of urban unit, household income, and additionally for socio-professional category and employment status. 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. 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 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 for men – and a dummy variable for whether the individual works night shifts.

- For the subsample of individuals in employment, we further include two variables capturing commuting characteristics in the transport regressions : a continuous measure of commuting distance and a dummy variable for whether the individual works night shifts.

C Estimating a bound on the required gap in footprints in other consumption sectors to cancel out the food and transport gap

Let Gap_{w-m} be the gender gap in carbon footprints across all consumption categories expressed in percent, which takes a negative value if women emit less than men and a positive value otherwise. This gap can be rewritten as the average of category-specific gaps, $Gap_{w-m}^{category}$ weighted by each category's share in total average individual footprint, $S_{CO2}^{category}$. Thaking the shares from Baude (2022):

$$\begin{aligned}
Gap_{w-m} &= S_{CO2}^{food} Gap_{w-m}^{food} + S_{CO2}^{transport} Gap_{w-m}^{transport} + S_{CO2}^{housing} Gap_{w-m}^{housing} + S_{CO2}^{gov} Gap_{w-m}^{gov} + S_{CO2}^{other} Gap_{w-m}^{other} \\
&= 0.22 Gap_{w-m}^{food} + 0.3 Gap_{w-m}^{transport} + 0.23 Gap_{w-m}^{housing} + 0.08 Gap_{w-m}^{gov} + 0.18 Gap_{w-m}^{other}
\end{aligned}$$

Where *gov* stands for government consumption, and *other* includes all goods and services other than food, transport, housing and government consumption.

Based on our estimates, $Gap_{w-m}^{food} = -0.28$ and $Gap_{w-m}^{transport} = -0.25$. 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 unadjusted gender gaps in housing energy consumption between -4% (women lower than men) and +4% (women higher than men) 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, or $Gap^{housing} = 0.04$. For government consumption, the dominant approach in the literature is to allocate equal emissions to each individual, so $Gap^{gov} = 0$. We obtain:

$$\begin{aligned}
Gap_{w-m} &= 0.22 \times (-0.28) + 0.3 \times (-0.25) + 0.23 \times (0.04) + 0.08 \times 0 + (0.10 + 0.08) \times Gap_{w-m}^{other} \\
&= 0.18 \times Gap_{w-m}^{other} - 0.1274
\end{aligned}$$

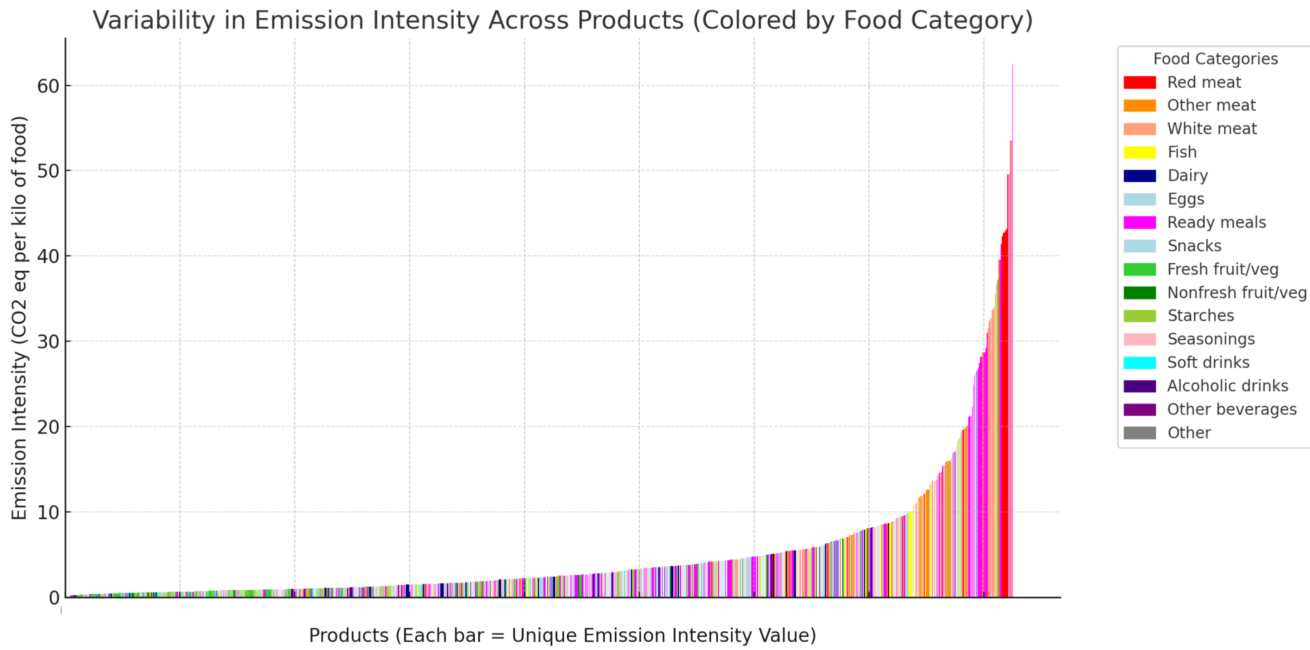
And so we have:

$$Gap_{w-m} > 0 \Leftrightarrow Gap_{w-m}^{other} > \frac{0.1274}{0.18} \Leftrightarrow Gap_{w-m}^{other} > 0.708$$

D Additional Figures and Tables

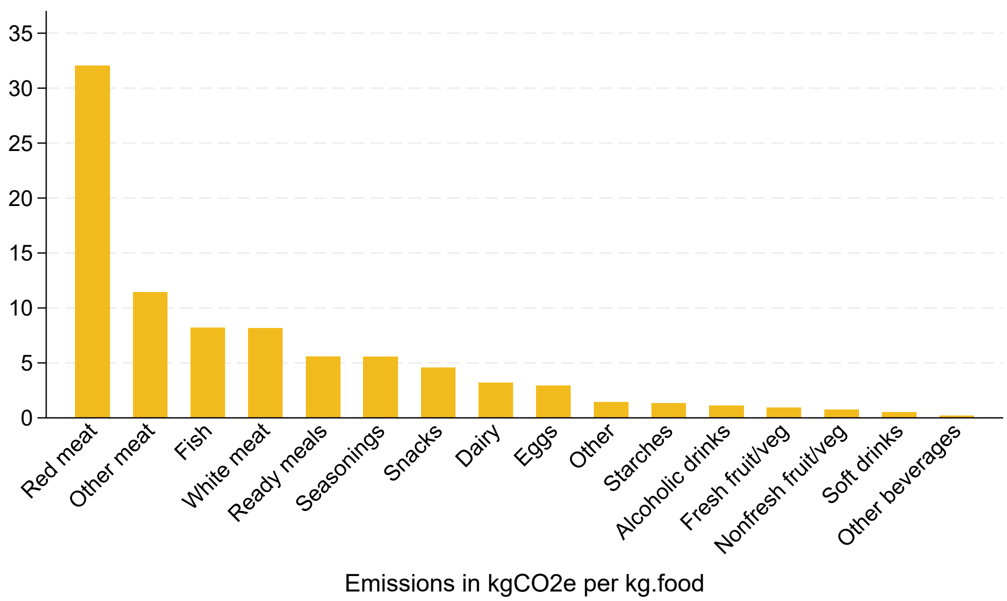
D.1 Figures

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



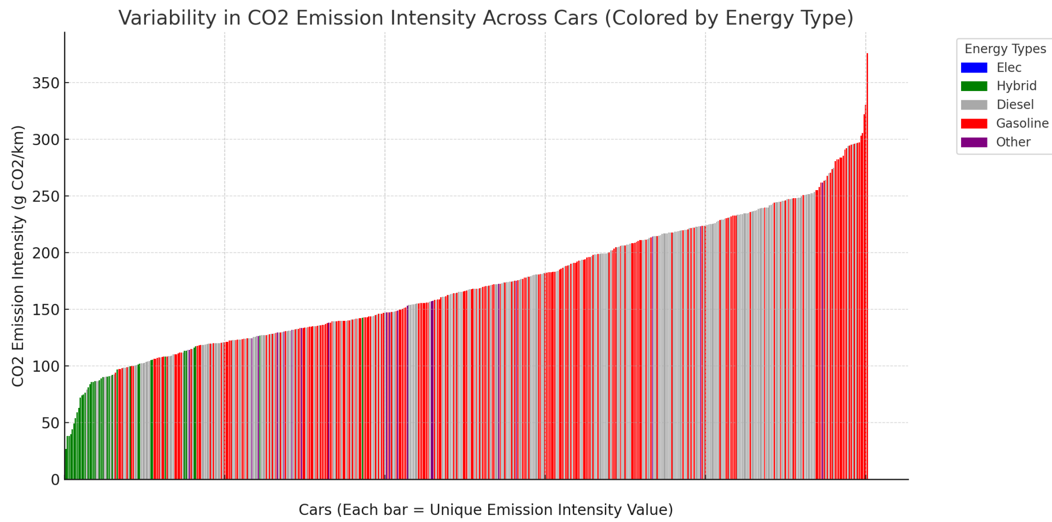
Notes: Distribution of greenhouse gas (GHG) emission intensities (in CO_2e per kilogram of food) across all food products. Each bar represents a *unique value* in the total distribution of emission intensities, sorted from lowest to highest. The visualization highlights the granularity and variability 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, yogurts; *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 flavors, 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, lyophilized 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 D.2: Emission Intensity by Food Category Aggregated in 15 categories.



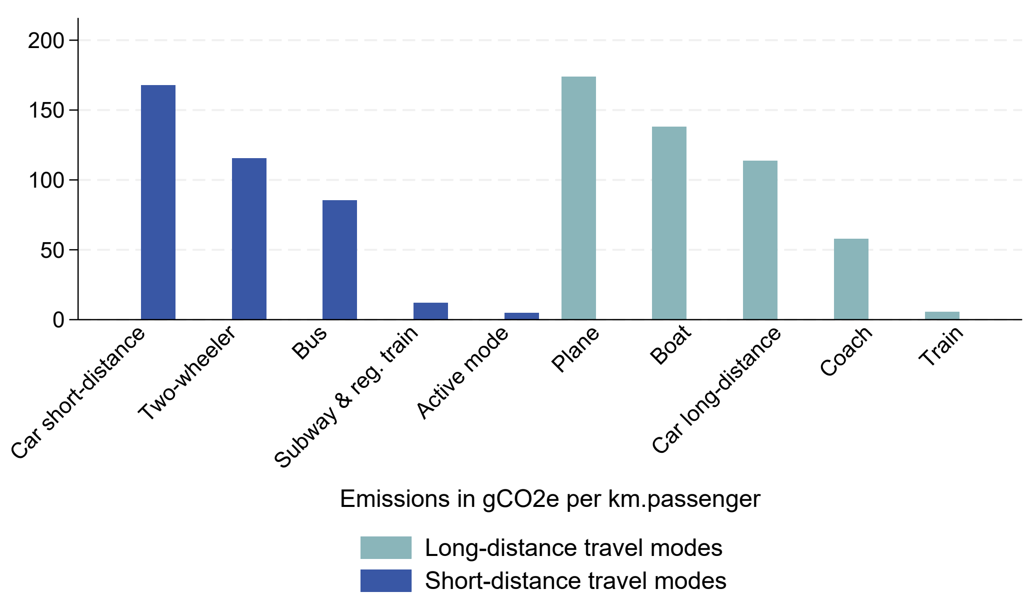
Notes: Volume weighted CO_2e emissions in kilograms expressed in kilogram of the food consumed. Weighted averages across food intakes of the same food category and day, using food quantities as weights. Food categories are defined as follows: *Starchy food*: pasta, bread, semolina, cook-type cereals, 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, yogurts; *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 flavors, 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, lyophilized vegetables, beans, dried vegetables, packaged vegetables; *Other*: baby food, chewing gum, food supplements. Source: INCA3 food intake-by-day data (N=256,301).

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



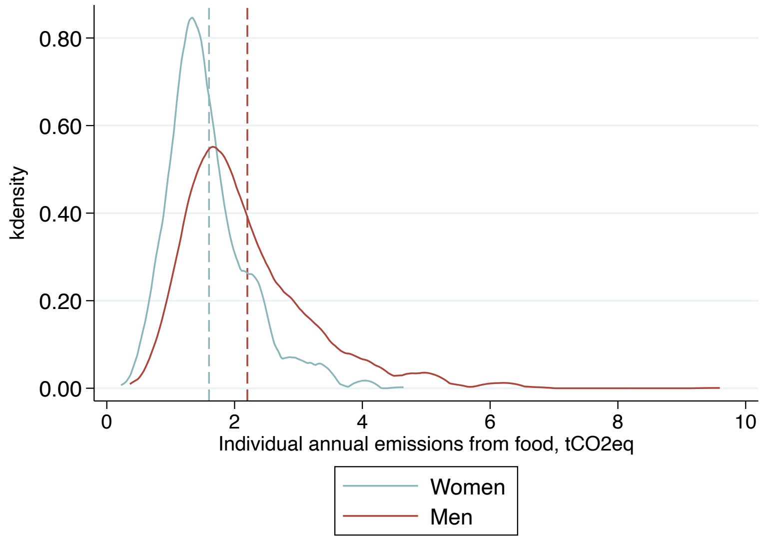
Notes: Distribution of CO_2e emission intensities (in g CO_2e/km) for cars. Each bar corresponds to a *unique value* in the total distribution of cars emissions, sorted from lowest to highest, rather than to an individual vehicle. Bars are colored according to the vehicle's energy type associated with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

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



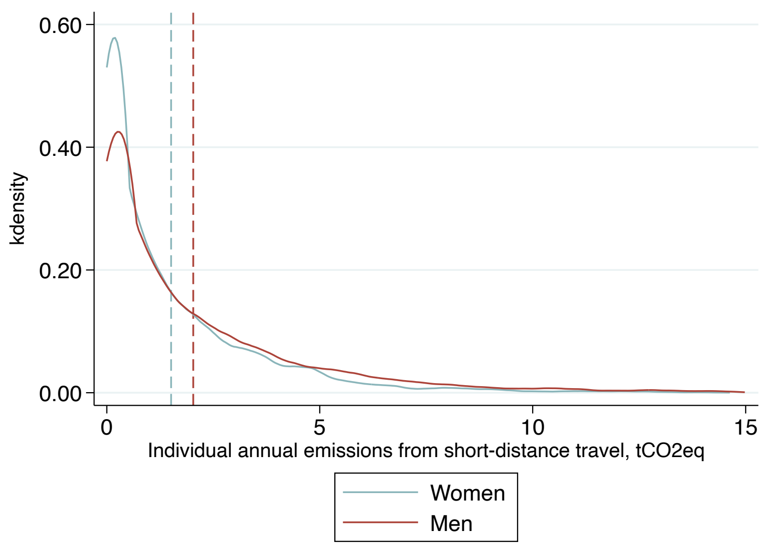
Notes: CO_2e emission intensities (in g CO_2e/km) for different transportation modes. Source: EMP trip-level data (N=44,759 for short-distance trips and N=30,938 for long-distance trips). Weighted averages across trips using the same transport mode category, using distances as weights.

Figure D.5: Distribution of Annual Carbon Footprints: Food.



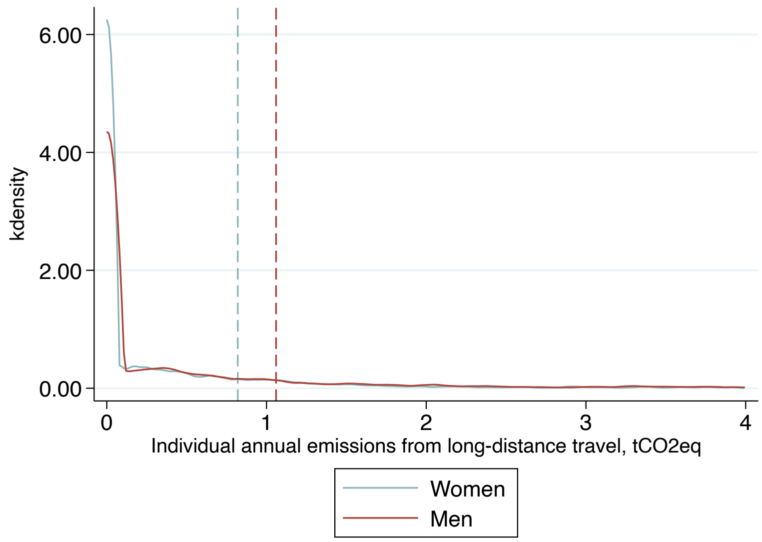
Notes: The blue dashed line indicates the average annual carbon footprints for women and the red dashed line the average annual carbon footprints for men, calculated with survey weights. Source: INCA3 (N=2,121).

Figure D.6: Distribution of Annual Carbon Footprints: Short-Distance Travel.



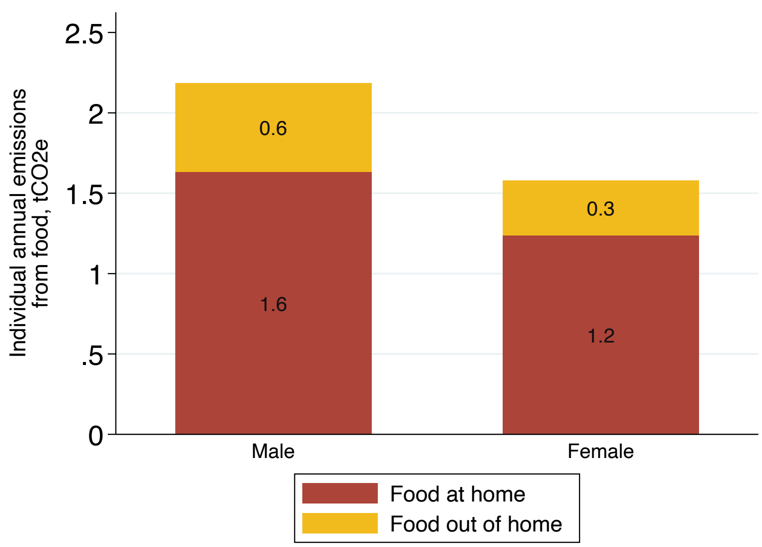
Notes: The blue dashed line indicates the average annual carbon footprints for women, and the red dashed line indicates the average annual carbon footprints for men, calculated with survey weights. Source: EMP (N=11,307).

Figure D.7: Distribution of Annual Carbon Footprints: Long-Distance Travel



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=11,307).

Figure D.8: Decomposition of Food Carbon Footprints Between Food at Home and Out of Home.

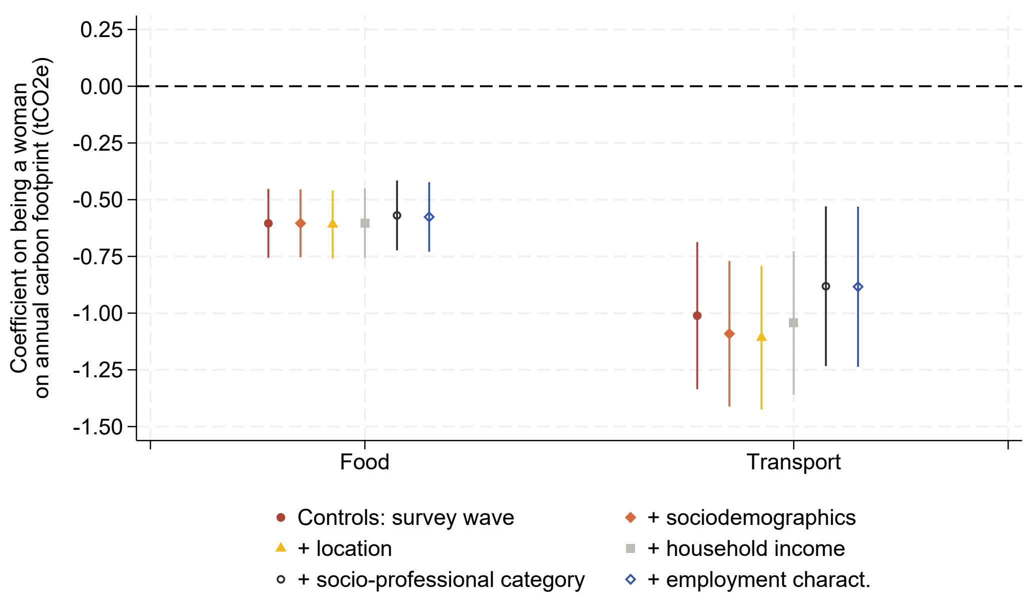


Notes: Food out-of-home includes food taken at friends' or relatives' home, on the workplace or at restaurants and take-aways. Source: INCA3 (N=2,121). Averages calculated with survey weights.

Figure D.9: Decomposition of Transport Carbon Footprints Between Work and Non-Work.

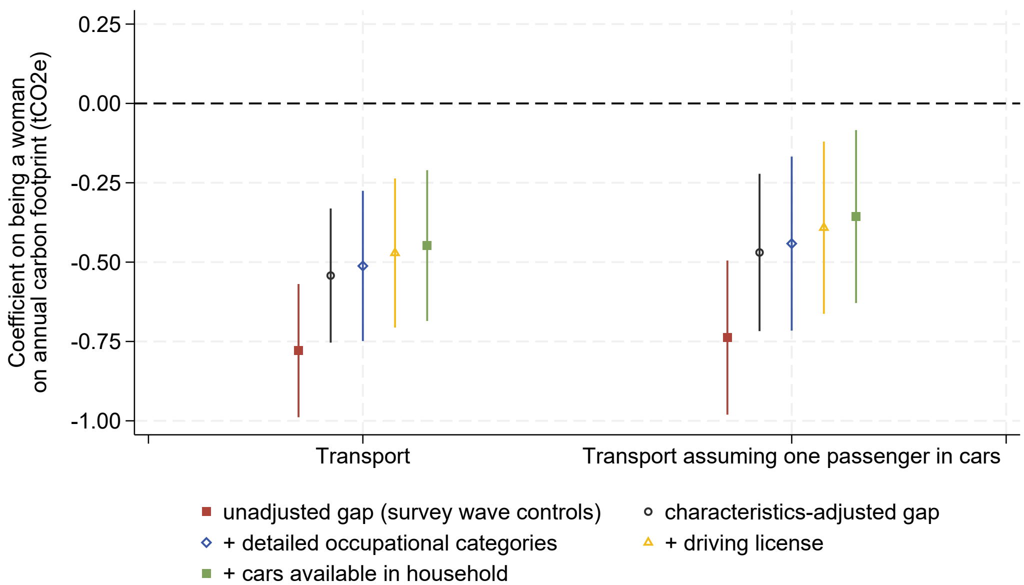
Notes: Work emissions are emissions from trips having a work-related purpose, either commuting or a business trip. Non-work emissions are emissions from trip having as purpose either leisure, shopping or escorting or another purpose. Source: transport: EMP (N=11,307). Averages calculated with survey weights.

Figure D.10: Conditional Gender Gap in Carbon Footprints, Sample of Individuals in Employment.



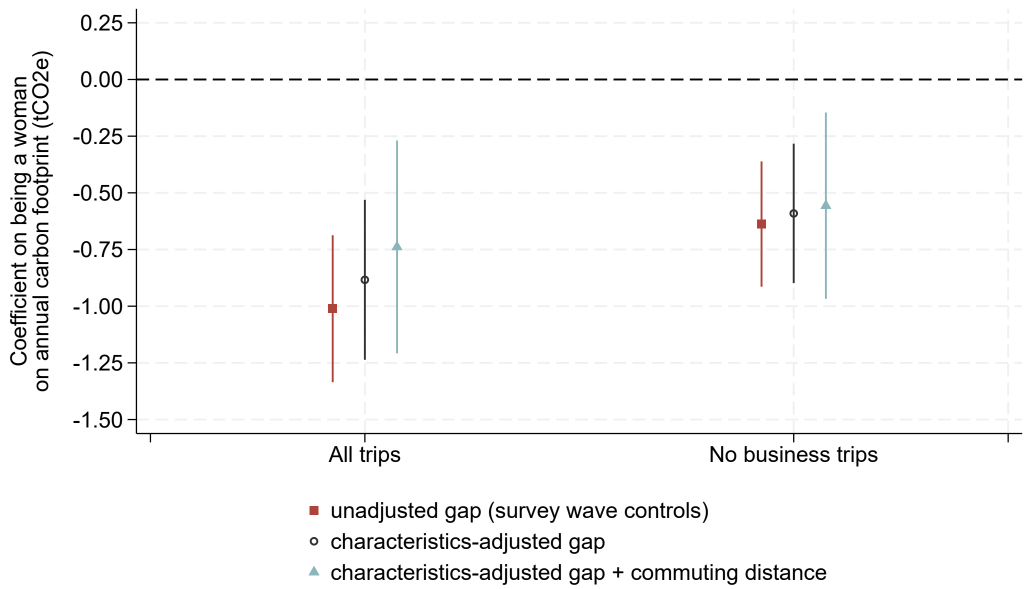
Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each consumption category, including an increasing number of control variables. "Controls: survey wave" only controls for the time of year when the 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 has an atypical working time, defined as going to work or coming back from work between midnight and 5am, or going to work after 3:59pm. Source: Food consumption: INCA3 (N=1,142 for all employed); transport: EMP (N=5,631 for all employed).

Figure D.11: Conditional Gender Gap in Transport Carbon Footprint, additional controls and robustness checks.



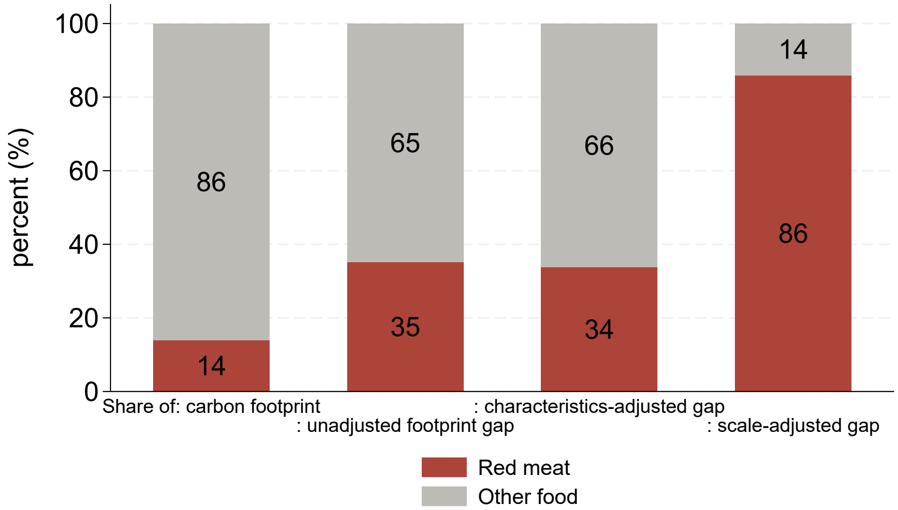
Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each measure of individual carbon footprint from transport, including an increasing number of control variables. "unadjusted gap (survey wave controls)" only controls for the time of year when the survey is conducted. "characteristics-adjusted gap" 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 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. "+ driving license" additionally controls for whether the respondent has a driving license. "+ cars available in household" additionally controls for whether the household owns more than one car. The measure of carbon footprint in "Transport assuming one passenger in cars" does not divide car trips emissions by the number of passengers in the car for that trip. Source: transport: EMP (N=11,016).

Figure D.12: Conditional Gender Gap in Transport Carbon Footprints among the Employed, the role of Commuting and Business Trips.



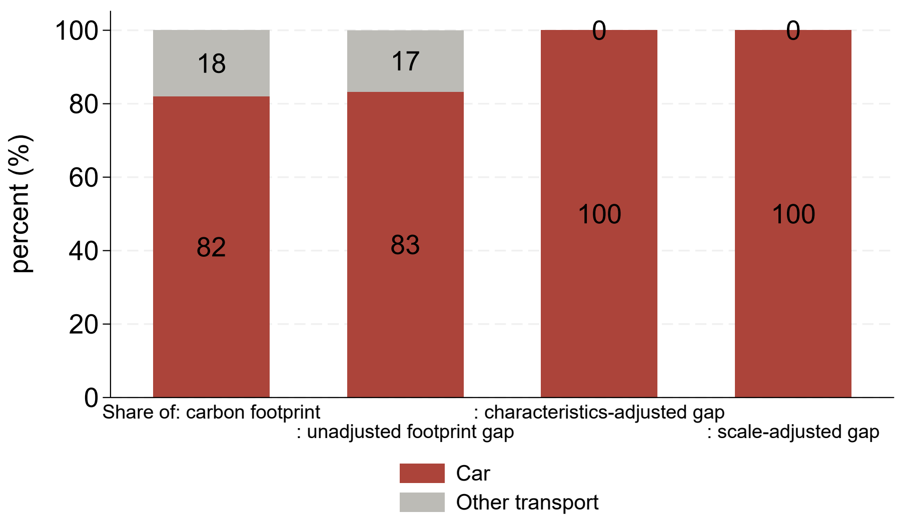
Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each scope of emissions "All emissions" measures individual carbon footprint from all short-distance and long-distance trips, while "No emissions from business trips" exclude work-related trip other than commuting from the calculation of individual footprint. The regressions include an increasing number of control variables. "unadjusted gap (survey wave controls)" only controls for the time of year when the survey is conducted. "characteristics-adjusted gap" additionally controls for age, education and household size, size of the urban unit of residence, household income, employment status, broad socio-professional category, and night shift work. "characteristics-adjusted gap + commuting distance" also controls for commuting distance when available. Source: EMP (N=5,631 and N=2,610 for the regression with commuting distance).

Figure D.13: Contribution of Red Meat to the Food Gap



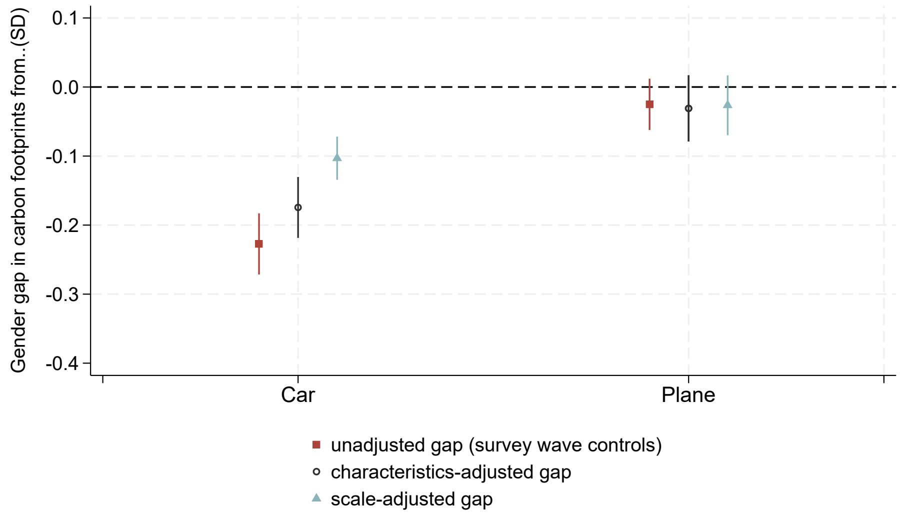
Notes: The first bar shows the relative share of red meat (red) compared to other food (gray) in total carbon equivalent emissions for the average individual. The second to fourth bars shows the share of the conditional gender gap in food carbon footprints that is explained by the gap in red meat emissions. 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=1,957).

Figure D.14: Contribution of Car to the Transport Gap



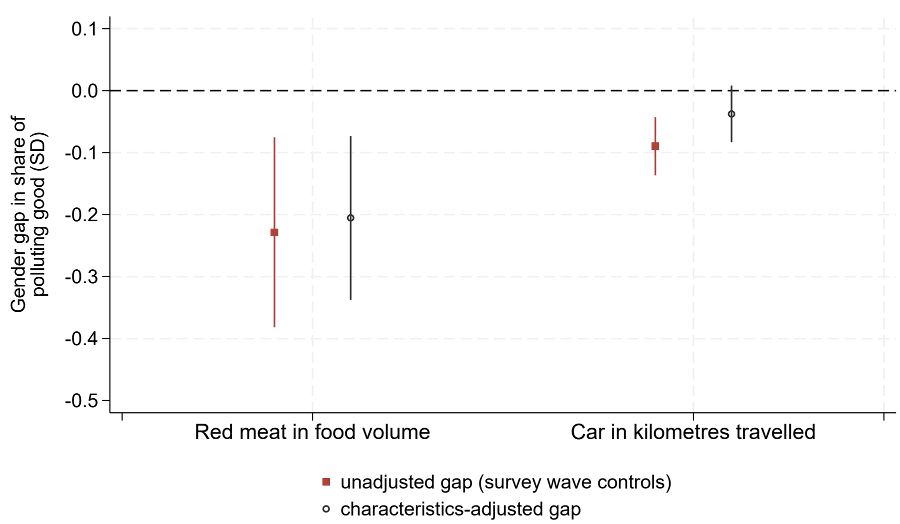
Notes: The first bar shows the relative share of car (red) compared to other transport (gray) in total carbon equivalent emissions for the average individual. The second to fourth bars shows the share of the conditional gender gap in car emissions that is explained by the gap in red meat emissions. This 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=11,016).

Figure D.15: Gender Gap in Car versus Plane Emissions.



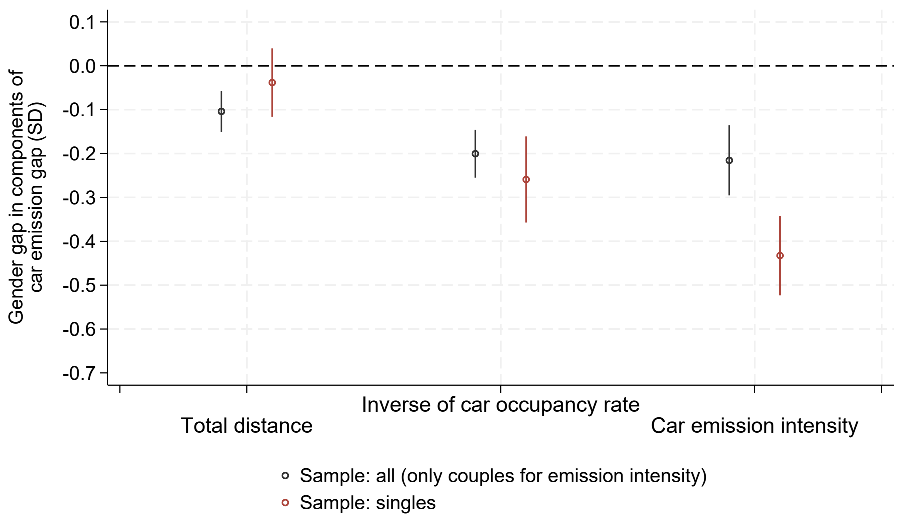
Notes: The point estimates and 95% confidence intervals in blue show the estimated coefficient for the gender dummy "female" from separate OLS regressions of standardized emissions from car trips and plane trips. "unadjusted gap (survey wave controls)" only controls for the time of year when the survey is conducted. "characteristics-adjusted gap" additionally controls for age, education and household size, size of the urban unit of residence, household income, employment status, broad socio-professional category. "scale-adjusted gap" additionally controls for total distances traveled in kilometers. Source: EMP (N=11,016).

Figure D.16: Gender Gap in the Share of Red Meat in Food Volumes and the Share of Car in Total Distances



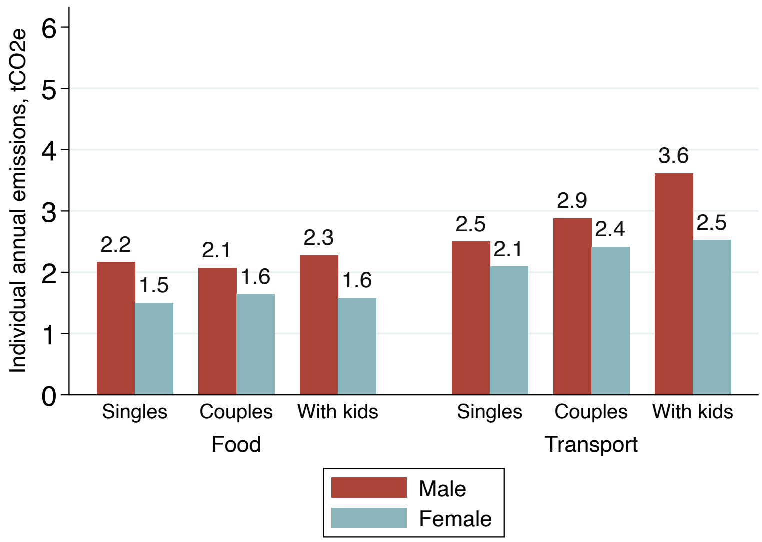
Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions of standardized share of red meat volume in total food volume, and share of kilometers by car in total kilometers traveled."unadjusted gap (survey wave controls)" only controls for the time of year when the survey is conducted. "characteristics-adjusted gap" additionally controls for age, education and household size, size of the urban unit of residence, household income, employment status, broad socio-professional category. Source: INCA3 (N=1,957); EMP (N=10,967).

Figure D.17: Gender Gap in Components of the Car Emission Gap.



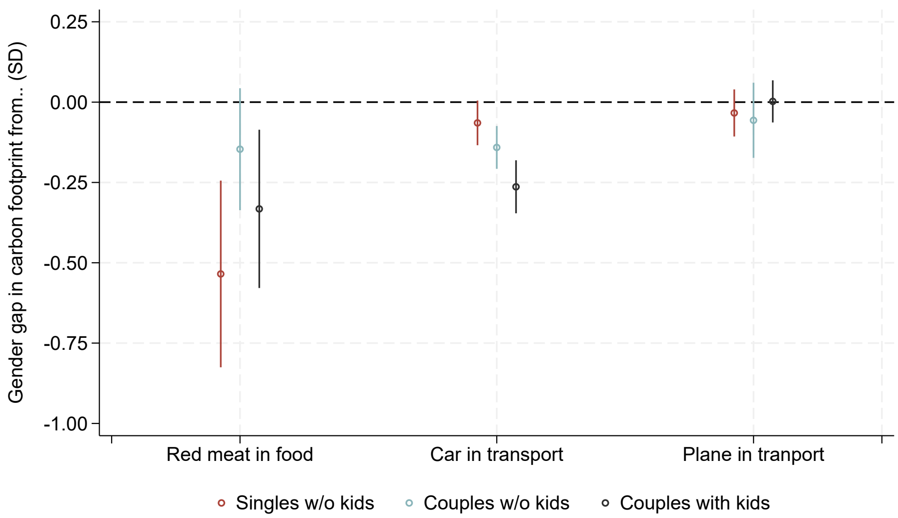
Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from OLS regressions including the full set of control variables, one for each determinant of the gender car emissions gap, for the sample of all individuals (black) and for the subsample of singles (red). The first measure is the standardized total distance traveled with any transport modes, in kilometers; 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 a standardized measure of the emission intensity of the car used for car trips, measured differently for all versus singles. The inverse occupancy rate is defined as one divided by the number of occupants per car. For the sample of all individuals, the emission intensity designates the share of car kilometers driven with the most carbon-intensive car of the household, restricting the analysis to couples owning at least two cars. For singles, it designates the emission intensity of the main car owned by the individual, measured in gCO_2e per kilometer. Source: EMP (all: N=11,016 for distance, N=7,998 for inverse occupancy rate, N=3,751 for emission intensity among couples with two cars; singles: N=3,490 for distance, N=2,230 for inverse occupancy rate, N=2,418 for own car emission intensity.)

Figure D.18: Individual Carbon Footprints from Annual Food Consumption and Transport Use by Gender and Household Composition.



Notes: Source: Food consumption: INCA3 (singles without children: N=545; couples without children: N=721; couples with children: N=610); transport: EMP (singles without children: N=3,490; couples without children: N=3,723; couples with children: N=2,943).

Figure D.19: Characteristics-adjusted Gender Gap in Carbon Footprints from Meat, Car and Plane by Household Type



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, by household arrangement : single individuals without kids, couples without kids, and couples with kids. Control variables include the time of year when the survey is conducted, age, education, household size, size of the urban unit of residence, household income, individual employment status and socio-professional category. Source: Food: INCA3 (singles without children: N=545; couples without children: N=721; couples with children: N=610); transport: EMP (singles without children: N=3,490; couples without children: N=3,723; couples with children: N=2,943).

D.2 Tables

Table D.1: Average Carbon Footprints for Food and Transport, full sample vs trimmed sample excluding top and bottom 5 percent.

	Gender	N	Mean	Std. Dev.	Min	Max	Absolute Gap
Panel A: Food							
Full sample	Men	887	2.19	1.00	0.36	9.60	
	Women	1234	1.58	0.63	0.22	4.65	-0.61
Trimmed	Men	799	2.04	0.64	1.03	3.71	
	Women	1112	1.53	0.45	0.79	2.75	-0.51
Panel B: Transport							
Full sample	Men	5202	3.10	4.72	0.00	55.72	
	Women	6067	2.33	4.00	0.00	75.86	-0.77
Trimmed	Men	4942	2.24	2.33	0.00	10.70	
	Women	5764	1.68	1.79	0.00	8.10	-0.56

Notes: Trimmed indicates that the bottom and top 5 per cent observations for each group separately (i.e. by gender) have been excluded. Units are in metric tons of CO_2 per individual per year. The absolute gap is the difference in mean between women's and men's footprint. The relative gap is the absolute gap divided by men's footprint.

Table D.2: Summary Statistics: Sociodemographics by Sample

		Food		**Transport**	
		Mean	**SD**	**Mean**	**SD**
Household size		2.74	1.39	2.67	1.33
Gender = Female (share)		0.52	0.50	0.52	0.50
Age (shares)					
	18-44	0.45	-	0.44	-
	45-64	0.37	-	0.36	-
	65-79	0.17	-	0.20	-
Work Status (shares)					
	Employed	0.57	-	0.55	-
	Unemployed	0.09	-	0.07	-
	Pupil/Student	0.05	-	0.05	-
	Pensioner or inactive	0.23	-	0.27	-
	Other inactive	0.06	-	0.05	-
Education (shares)					
	Less than secondary or vocational degree	0.51	-	0.46	-
	End of high school diploma	0.15	-	0.21	-
	Higher education degree 3 years† or below	0.17	-	0.13	-
	Higher education degree above 3 years†	0.17	-	0.20	-
Observations		1,957		11,016	

Notes: Summary statistics by sample for the main comparable sociodemographic variables. †:2 years for Transport survey. 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. Sample weights are applied.

Table D.3: Gelbach Decomposition for Food.

	Magnitude in tCO_2 (SE)	Gender gap in %
Unadjusted Gap	-0.615***	27.7
	(0.067)	
Adjusted with controls (Figure 2, left panel)		
Characteristics-adjusted Gap	-0.534***	24.4
	(0.057)	
Total change (Unadjusted - Adjusted)	-0.081**	
	(0.039)	
Of which:		
Survey Wave	-0.013	
	(0.010)	
Sociodemographics	-0.002	
	(0.007)	
Location	-0.004	
	(0.007)	
Household Income	-0.004	
	(0.013)	
Employment Status & socio-professional category	-0.057**	
	(0.028)	
Same controls + calories (Figure 3, left panel)		
Scale-adjusted Gap	-0.147***	6.7
	(0.051)	
Total change (Unadjusted - Adjusted)	-0.468***	
	(0.063)	
Of which:		
Survey Wave	-0.002	
	(0.005)	
Sociodemographics	-0.001	
	(0.008)	
Location	-0.001	
	(0.004)	
Household Income	-0.004	
	(0.012)	
Employment Status & socio-professional category	-0.032	
	(0.022)	
Calories	-0.428***	
	(0.050)	

Notes: Based on regressions with robust estimator. The "Unadjusted Gap" presents the result of the regression in which there are no controls (the only explanatory variable is the indicator for gender). The upper panel presents the decomposition of a model in which five groups of covariates are included. The lower panel presents the decomposition of a model in which six groups of covariates are included, the last control added represents the distance traveled by the individual. The gender gap in percent is calculated by dividing the absolute value of the difference in emissions between men and women by the average carbon footprint of men. The list of control variables is presented in Appendix B.

Table D.4: Gelbach Decomposition for Transport.

	Magnitude in tCO_2 (SE)	Gender gap in %
Unadjusted Gap	-0.769***	24.8
	(0.107)	
Adjusted with controls (Figure 2, right panel)		
Characteristics-adjusted Gap	-0.542***	17.5
	(0.108)	
Total change (Unadjusted - Adjusted)	-0.233***	
	(0.050)	
Of which:		
Survey Wave	0.009	
	(0.010)	
Sociodemographics	-0.011	
	(0.013)	
Location	0.036***	
	(0.011)	
Household Income	-0.094***	
	(0.019)	
Employment Status & socio-professional category	-0.172***	
	(0.039)	
Same controls + distance (Figure 3, right panel)		
Scale-adjusted Gap	-0.274***	8.8
	(0.088)	
Total change (Unadjusted - Adjusted)	-0.501***	
	(0.072)	
Of which:		
Survey Wave	0.006	
	(0.007)	
Socioddemographics	0.001	
	(0.005)	
Location	0.025***	
	(0.009)	
Household Income	-0.049***	
	(0.013)	
Employment Status & socio-professional category	-0.103***	
	(0.031)	
Distance	-0.382***	
	(0.060)	

Notes: Based on regressions with robust estimator. The "Unadjusted Gap" presents the result of the regression in which there are no controls (the only explanatory variable is the indicator for gender). The upper panel presents the decomposition of a model in which five groups of covariates are included. The lower panel presents the decomposition of a model in which six groups of covariates are included, the last control added represents the distance traveled by the individual. The gender gap in percent is calculated by dividing the absolute value of the difference in emissions between men and women by the average carbon footprint of men. The list of control variables is presented in Appendix B.