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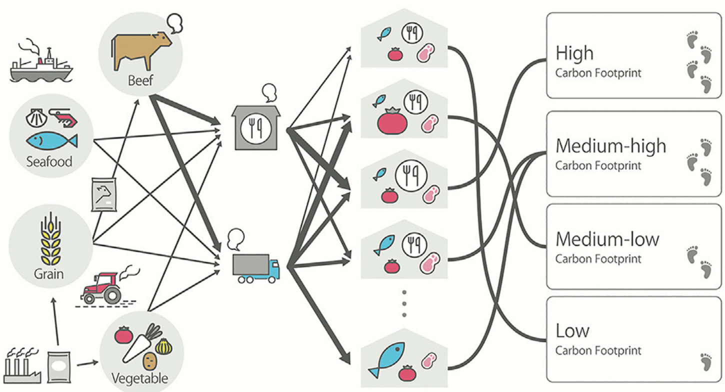
Meat Consumption Does Not Explain Differences in Household Food Carbon Footprints in Japan

Graphical Abstract



Highlights

- We investigated potential drivers of household food carbon footprint
- Demography, geography, income, and saving are not strong explanatory factors
- Meat consumption only weakly explains household carbon footprint difference
- Household food carbon footprints are driven by eating out, confectionary, alcohol, and others

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In Brief

Undoubtedly, the dietary shift to eat less red meat and more vegetable-based diets is one of the most effective ways to reduce household carbon footprints, but Kanemoto et al. show that excess consumption of restaurant food, confectionary, and alcohol also contribute to climate change—by using a 60,000 Japanese household-level microconsumption dataset. As current Japanese dietary patterns are in line with other national dietary guidelines, this study can provide insights for the possible directions of future diets globally.

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Meat Consumption Does Not Explain Differences in Household Food Carbon Footprints in Japan

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SCIENCE FOR SOCIETY Food is a large part of the household carbon footprint (CF). Previous literature focuses on Western dietary patterns and recommending reducing red meat consumption as important for a more a sustainable mean diet. Here, we explore factors differentiating household food CF in Japan: a country with lower red meat consumption and a unique gastronomy. We find that consumption of specific food categories is key to understanding household CF. Consumption of meat and dairy is fairly homogeneous across households, but consumption of vegetables, fish, confectionary alcohol, and restaurant food are important drivers that differentiate high versus low carbon footprint households. We surmise that in Japan, the CF from food cannot be reduced by changing the attitude of a small number of meat-loving households.

SUMMARY

Many studies, including the EAT-Lancet Commission report, have argued that changing diets—in particular, shifting away from beef in favor of white meat and vegetables—can substantially reduce household carbon footprints (CFs). This argument implies that households with high CFs consume more meat than low-CF households. An observation of diet and CF across 60,000 households in Japan, a nation whose diet and demographics are in many ways globally indicative, does not support this. Meat consumption only weakly explains the difference between high- and low-CF households and is not localized to any particularly easily targeted group. We find that while nearly all households can reduce their CF by eating less meat, higher-CF households are not distinguished by excessive meat consumption relative to other households but rather have higher household CF intensity because of elevated consumption in other areas including restaurants, confectionery, and alcohol.

INTRODUCTION

The question of how to feed a growing global population without transgressing planetary limits is one of the most overarching environmental challenges today.[1–3] An emerging consensus is that meat, especially beef, is problematic.[4,5] Animals, together with their feed, have large land, water, and greenhouse gas (GHG) emissions footprints. Meat demand is expected to continue to grow.[6–16]

Many studies confirm that meat is an environmentally intensive food, yet it remains challenging to recommend how policy should or can respond to this. Broadly, income determines the level and composition of diet. The so-called Engel curve shows that food demand, even for luxury foods, levels off after a certain level of income. However, aside from income, it is not clear which other household characteristics are associated with higher demand for meat. It is easier to form policy responses when specific intervention points can be identified. Thus, the ubiquitous demand for meat presents a challenge in many countries. It is often implicitly assumed that some policy can specifically target high-meat-consuming households, but it remains a major challenge to substitute meat with a more fish-, vegetable-, or chicken-based diet.

In this study we assembled a detailed picture of diet carbon footprint (CF) across households in Japan to search for characteristics associated with meat demand. We identified several noteworthy results, including that meat consumption is not localized to any particularly easily targeted group.

Household CFs from food are determined by the volume and composition of food consumed and the environmental intensity of that food. These factors can be further decomposed and compared with household income, geography, and other variables in order to identify factors that best differentiate higher-CF and lower-CF households. To do this, we combined microdata on 60,000 households with diet, income, and demographic data for each household. We used a subnational input-output model documenting subnational production and trade across 47 prefectures in Japan. Input-output models are a family of supply-chain databases that follow the life-cycle of all products produced in one or multiple countries through trade and transformation steps to final consumption, in flows expressed in monetary or physical units or units of embodied environmental impacts, e.g., embodied GHG emissions (for examples and to learn more about these models see Minx et al.,[17] Moran and Kanemoto,[18] and Bruckner et al.[19]). We then investigated potential drivers of household food CF, including geography, income, and diet.

Our results are based on the 47-prefecture Japanese MRIO model and consider only carbon dioxide (CO_2) emissions for almost all of the analysis (with the exception of Figure 4). In Figures S1–S3 (Note S1), we did the same analysis using national input-output table and including methane (CH_4) and nitrous oxide (N_2O) in addition to CO_2 for some part of the main analysis. While it is important to consider non-CO_2 GHGs because these gases are often a high share of the total GHG footprint of food, focusing on CO_2 is advantageous—often, it is already 60%–90% of total global GHG emissions (see https://edgar.jrc.ec.europa.eu/) and is more accurately measured than other emissions.

In the remainder of the paper, we will discuss why subnational detail is important when studying household diets, discuss the degree to which the findings from Japan may be globally representative, present five main results from our attempt to distinguish households with high diet footprints and discuss the results in total, and detail the data and methods used in this study.

RESULTS

Subnational Detail Is Important

The environmental profile of diets can be evaluated by combining information about the environmental intensity of foods with data on consumption patterns. To account for the various environmental pressures exerted at different points along food production chains, most studies, including ours, adopt a footprint or "farm-to-plate" approach to understand the total environmental impact of food consumption.

A number of studies have evaluated the environmental profile of foods and diets, accounting for globalized supply chains of feed and food.[20–25] While these studies are useful, most global-scale models have an important shortcoming; they do not consider subnational variations in food production and consumption. This lack of subnational detail is significant because subnational detail could be more important than global coverage and may show the opportunity to promote and use different subnational policy. 70%–80% of food is still produced and consumed domestically, and within one country, farming and husbandry practices can vary widely.[26–31] Estimates of the CF of diet are sensitive to the subnational structure of production and consumption. Furthermore, most diet CF results based on national-level models treat consumption in aggregate and do not distinguish how diets vary across households. Though limited, some literature around the environmental impacts of dietary choices between households have recently been published. Studies on Australia,[32] the Netherlands,[33] and the UK[34] show that differences in household income (and socio-economic status) lead to different consumption choices, and though the changes needed to shift to sustainable healthy diets were broadly similar across all groups (i.e., lowering the trophic index of the household diet), the specific foods that had the highest impact differentiated for different income groups. None of these studies examined how geographic or regional population effects alter dietary CF. Preliminary results from these studies indicate that tailoring policies to income and other subdemographic groups will be more effective than applying blanket national advice and policies.

Results based on nation-level models may indicate policy recommendations that are substantially different than what would be recommended once variations in subnational production and consumption are taken into account.

Japan as a Representative Country

For this study, we constructed a detailed case-study model using data from Japan. We examined diet profiles from 60,000 Japanese households and estimated the CF of those diets using a subnational input-output model detailing production and trade across 47 Japanese prefectures, including imported food and feed. Japan provides highly detailed household consumption statistics and is one of the few nations where a subnational input-output model documenting regional variation in production is available. Though the country has a unique cuisine, the composition of the current typical Japanese diet is similar what other national health organizations recommend,[35] i.e., high consumption of soy and isoflavones, fish and n-3 fatty acids, and green tea, and low consumption of red meat and saturated fat.[36] This diet contributes to the fact that Japan has the lowest coronary heart disease mortality and longest life expectancy among developed countries.[37] As these aspects of the current Japanese dietary patterns are in line with the recommendations found in many Western and Asian national dietary guidelines, using Japan as a case study can provide generalizable insights for the possible direction of future diets globally[38–40] (even though these future diets would have to shift from past trajectories onto a more sustainable track, e.g., as recommended by the Eat-Lancet report[5]).

In addition, Japan's demographics and dietary patterns are indicative of likely future demographics of many other Western and Asian nations with an older population, urbanized population, smaller household size, increased consumption of hyper-convenience and ultra-processed foods, and decreased adoption of "traditional" diets.[41–43] Japan's diet and demographics make it a bellwether for other Western and Asian nations that are beginning to encounter these phenomena.

Even if specific results from the Japanese data do not map directly to other countries, if a country-specific model provides results contradictory to a global-scale model, it would indicate that more care should be given before prescribing national policy based on global data.

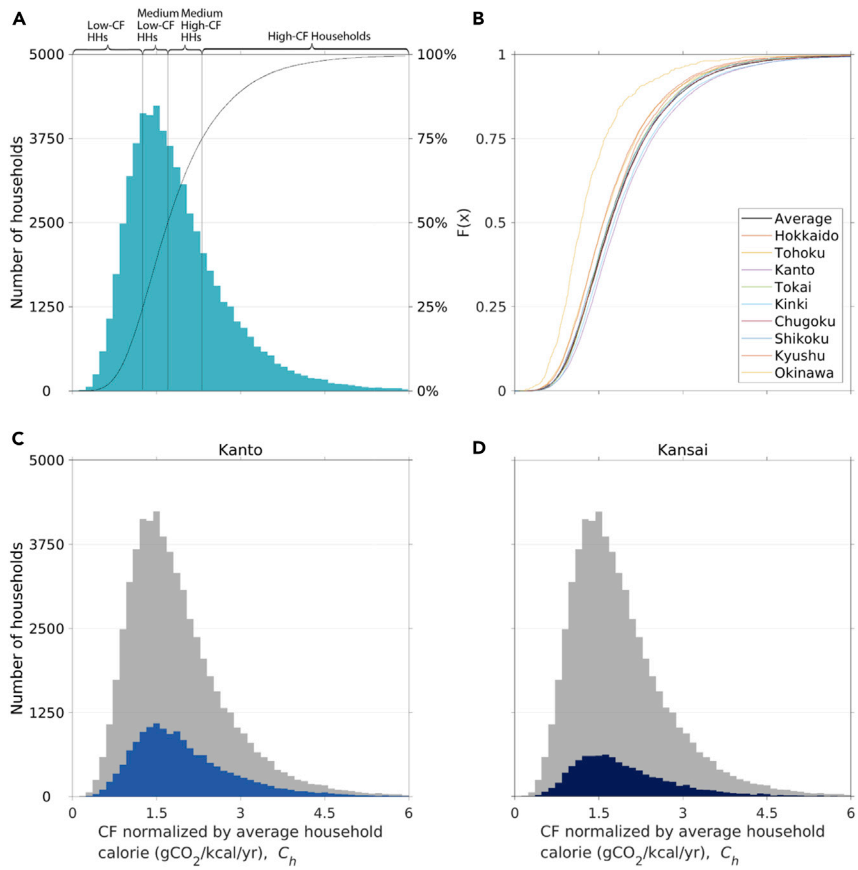

Figure 1. Frequency Distribution of Food-Related Carbon Footprint

(A) Frequency distribution of food-related carbon footprint (CF) of 60,000 households in Japan. Filled curve and left axis show number of households; right axis and line show cumulative relative frequency. Values are food-related CF normalized by average household calorie by regions and national average.

(B) Cumulative distribution by region. Most regions follow a similar distribution as the national average with a slight exception in Okinawa prefecture.

(C) National distribution, in gray, compared with the distribution in Kanto, in blue, which includes the cities of Tokyo, Yokohama, Chiba, and Saitama.

(D) National distribution versus distribution in Kansai, which includes Osaka, Kyoto, and Kobe.

For the histograms in (A), (C), and (D) the bin origin and bin width are 0 and 0.12 gCO_2/kcal/year, respectively.

Trying to Characterize High-CF Households

We identified five key results. First, differences in household demographics (age and sex) do not explain variation in household food CF. Second, regional differences in food-related CF exist, but it is not the main explanatory factor of household differences. Third, household income and savings are weakly correlated with food-related CF. Fourth, there is a 1.9-times-higher difference in food CF between the mean household in the lowest and the highest quartile. Finally, meat consumption is almost identical across the four quartiles, and it is rather the consumption of fish, vegetables, confectionery, alcohol, and restaurants that differentiates high- and low-CF households.

A frequency distribution of food-related household CFs reveals that normalizing by average calorific intake per age and sex does not help explain variation across household CFs (Figure 1A; see Experimental Procedures for the normalization procedure). The bottom quartile of households has a CF of less than 1.26 grams of CO_2 (gCO_2)/kcal/year while the top quartile emits more than 2.31 gCO_2/kcal/year.

First, we tested the null hypothesis that there is no regional variation in consumption. Although diets vary between countries,[10] there could be substantial differences in household food CF between regions within a country. Even in Japan, there are noticeable regional differences in food culture. Figure 1 shows the distribution of household CF for food consumption nationally and for each of the 9 regions. The distribution is similar across all regions and the nation as a whole; therefore, we can say that regional food culture is not a large factor driving differences among household CFs. While a two-sample Kolmogorov-Smirnov test reveals statistically significant differences for almost all combinations (see Note S2 for detail) as we observe in Figure 1B, the regional differences are not large, though the Okinawa prefecture as well as Chugoku do stand out as showing a different distribution of household CFs.

Income has been considered a primary explanatory variable for household CFs.[44–46] Food consumption does vary with income, with purchases rising initially at higher levels of income (this is the so-called Engel curve).[47] We analyzed whether there is correlation between income or savings and household food CF. The results indicate there is a positive, albeit weak, correlation between the two. Household diet CF is essentially inelastic to income for households earning <8 million (m) Japanese yen (JPY)/year (c. €67,000) but does slowly increase with incomes beyond this (Figure 2A). Household wealth can also be measured by savings instead of income. Diet CFs grow positively with net worth up to a point but decouple once household net assets exceed ≈30 m JPY (€0.25 m) (Figure 2B). Further regression analysis results are available in Note S3.

To investigate the relationship between household diet CF and meat consumption, we analyzed to determine whether there is a relationship between household CF and meat consumption or not. We divided the 60,000 households into quartile groups according to household diet CF normalized by mean caloric consumption per household (see Figure 1A for the grouping) and compared expenditure patterns across the four groups. We observe that high diet CF households do not consume more meat compared with low-CF households (Figure 3).

Meat and dairy provide the largest share of household CF (≈30% of household food CF, excluding restaurant; see Note S7 for details), but the data indicate that meat and dairy consumption is fairly homogeneous across households. On the

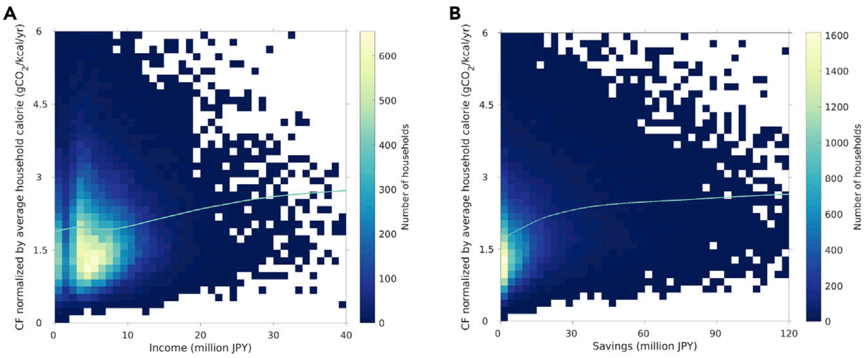

Figure 2. Relationship between Food-Related CF and Income and Saving

No clear correlation is observed between household diet CF and income or savings. Density scatterplot of income (A) and savings (B) versus household CF normalized by average household caloric consumption (brighter pixels contain more observations than darker pixels). Lines show a nonparametric regression curve. Note that Japanese households have a high average income and relatively small variation in household food CF; these results may look different in countries with lower or wider-ranging incomes.

other hand, while fish also provides a large share of household food CF (≈15% of household food CF, excluding restaurant consumption), we observe roughly double consumption expenditure differences. We note that fish, whether it is wild caught or farmed, has a much lower CF per weight than beef across global production systems.[26,48] Indeed, fish is similar in CF to many pork and poultry production systems. However, as shown in Note S6 and Table S4, the GHG emission intensities per JPY of fish is high when compared with pork and poultry. This indicates that fish is expensive for the quantity consumed. Thus, the consumption of fish can be seen as one of the major differentiators of GHG footprints among households. We note that Japan's beef and veal consumption is lower than the Organization for Economic Co-operation and Development (OECD) average 6.2 kilograms (kg)/capita in Japan versus 15.5 kg/capita in average in OECD nations in 2005,[49] and the percentage of meat CF is much higher than the percentage of calories (8.5%[50]).

High-CF households are distinguished not by heavy meat consumption, but rather by more consumption of fish and vegetables (which are lower-CF foods than beef), alcohol, confectionery, and restaurant visits. Compared with low-CF households, high-CF households spend on average 3.3 times more on alcohol, 2.0 times more on confectionery, and 2.0 times more on restaurants than low-CF households (note: our estimate of the CF of restaurant meals includes ingredients but will be slightly higher than equivalent home-cooked meals because they include emissions associated with operating a restaurant such as lighting and cooking).

In order to further investigate the differences between high- and low-CF households by diet, we perform a decomposition analysis (Figure 4). The average CF because of fish consumption (560 $kgCO_2eq$ [equivalent]/year), vegetables (670 $kgCO_2eq$/year), and restaurant meals (770 $kgCO_2eq$/year) are major drivers of differences between the highest and lowest quartiles. Meat contributes just 9% of the difference (280 $kgCO_2eq$/year) between the mean highest- and lowest-quartile diets.

DISCUSSION

Our investigation across a large sample of households shows that meat consumption is not strongly different in higher-income households but is consumed at relatively similar levels across income groups. Indeed, meat expenditure is not strongly concentrated in a few households but is relatively similar in homes with low- and high-GHG footprints. Therefore, it is hard to target to any particular group to reduce meat CF. What differentiates the highest and lowest CF households is rather spending patterns in unexpected categories: fish, vegetables, alcohol, confectionery, and dining out. Wealth and geography, to a limited degree, explain variations in household diet CFs.

Most of our analysis in the main text is based on a prefecture-level multi-regional input-output model with CO_2 emission. However, non-CO_2 emissions account for a significant share of the CF of food. In this study, it was not possible to include these non-CO_2 emissions because there is not sufficient data on non-CO_2 emissions at the prefecture level by commodity. Hopefully, this data gap will be filled in the future. We have conducted the same analysis using a national-level (not prefecture-level) input-output table with CO_2 and non-CO_2 emissions, and it also supports our argument. These results are presented here and in Figures S1–S3.

Setting aside the prefecture-level model and instead using the national-level model, we can confirm that our conclusions still hold when including non-CO_2 gasses. Therefore, our results would only be incorrect if the CH_4 (or N_2O, etc.) intensity of industries varies at the prefecture level. In larger countries, this could occur. However, in Japan, food-production technology is relatively homogeneous across the country. Our results could be affected by this model limitation because there is substantial variation in the emissions intensity of non-CO_2 gasses in agricultural production across the country. As prefecture-level multi-regional input-output databases have only recently become available,[29] we encourage the research community to undertake this subregional analysis of dietary emissions to gain understandings of the multiple geographic complexities of food's environmental impacts.

The findings still unquestionably support the conclusion that meat is a high-CF food and that all households have considerable margin to reduce their household diet CF by reducing red meat consumption in favor of lower-CF foods. We have also found that fish consumption is another large driver of household CF (≈15% of household food CF, excluding restaurant consumption). The household diet CF related to fish can be reduced by shifting consumption toward lower-intensity CF fish options (to stay within nutritional guideline recommendations).

Another relevant point is the prevalence of vegetarian households. In this study, we observed that <1% of households were purely vegetarian. This sample size is too small to offer any statistically significant insights at the province or national level.

Additionally, we suggest further options. First, our household-level analysis indicates the distribution of food-related

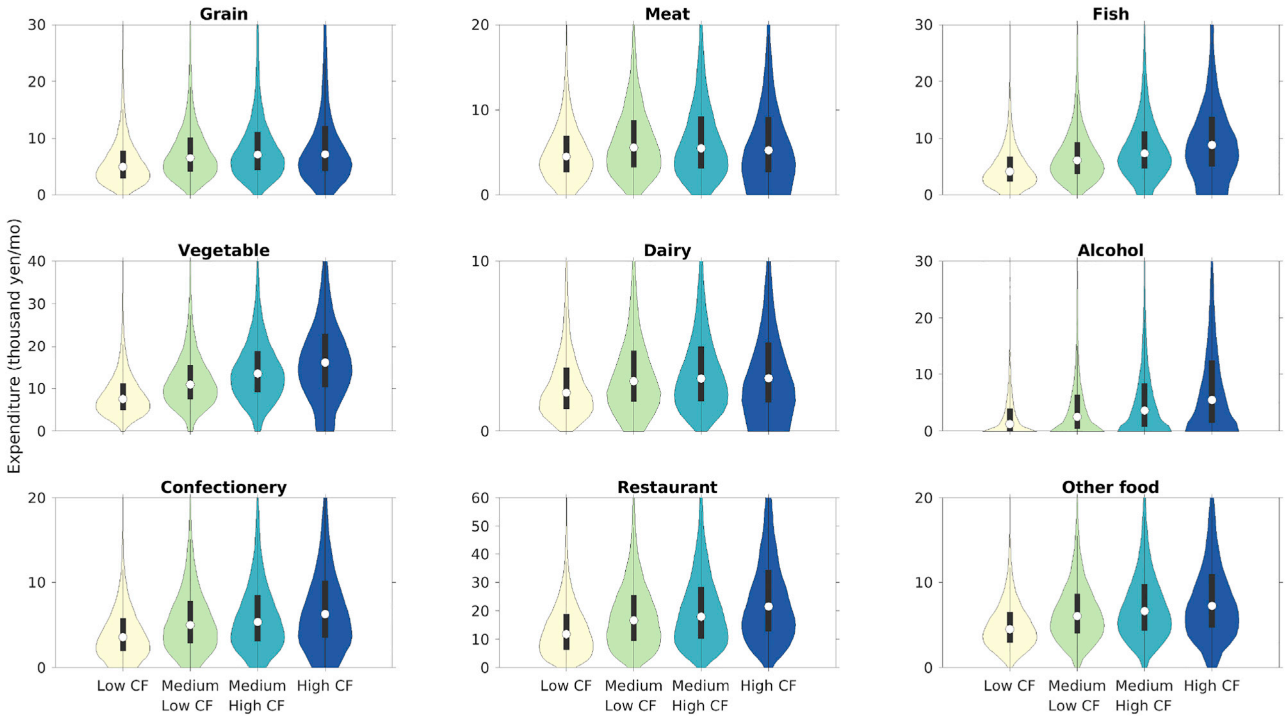

Figure 3. Violin Plot of Consumption Expenditure by CF Group

For most food categories, including meat, the consumption profile is similar between low-, medium-, and high-CF households. However, for alcohol, fish, confectionery, and restaurant meals, there is a clear difference in spending between low- and high-CF households. Shaded areas show the distribution of expenditure on selected food categories; the width indicates frequency. For each of the distributions, the white dot indicates the mean and the lower and upper ends of the black bar indicate the 2.5 and 97.5 percentiles.

CF can vary by region, so region-specific policies may be effective. Second, because household wealth is correlated with higher food-related CFs, income- or wealth-based policies, such as luxury tax on food, measures to prevent food waste, better consumer labeling,[51] or carbon offset schemes, could help reduce excessive consumption or mitigate the dietary CF of wealthy households. Finally, as it is not widely known or discussed that alcohol, confectionery, and restaurants meals in fact substantially differentiate high-CF households, simply communicating this message could provide surprising and helpful information to households seeking to reduce their dietary CF.

There are a number of potential sources of uncertainty in our results. The first is the price effect, i.e., that the analysis treats monetary and physical values as equivalent. For example, an organic vegetable costing 200 JPY would be treated as having twice the CF of the identical conventional item costing 100 JPY.[52,53] Looking at a range of descriptive statistics (see Note S4), we do observe some price effects, but in the case of Japan, they are not severe and most food is bought and sold at relatively stable mean prices. Second, the price effect may be more serious for imported goods because imported products can be much cheaper or much more expensive than domestic equivalents. Japan has a strong and relatively unified national culture, so the country's 127 million residents may display a more homogeneous diet profile than the population in other, more culturally diverse, countries. The consumption expenditure survey does not distinguish domestic from import products. Therefore, in this study, we cannot reconcile the differences. Third, uncertainty is introduced regarding the reliability of the economic input-output data,[54–56] the accuracy of the consumer survey (including both misreporting and the fact the survey only covers the period of September to November), and potential aggregation and classification error effects in the input-output table and mapping of expenditure data to the input-output classification.[57–61] Finally, another source of uncertainty is the "restaurants" expenditure category. The analysis has a single category for expenditure at restaurants. It could be possible that this masks a wide variation and that some individuals or restaurants are more heavily meat-intensive than others. Our analysis assumes that all restaurant expenditure has a homogeneous meat intensity, but in fact, the GHG intensity of restaurant meals could vary. In this study, we cannot attempt to quantify the uncertainty in the restaurant-meal meat intensity.

EXPERIMENTAL PROCEDURES

We integrate Japanese household-level consumption data and multi-regional input-output analysis. Existing literature only uses country-level input-output analysis or bottom-up life-cycle assessments to uncover the foods' CF of countries, regions, and a small sample of households. In this study, we first show a large number of households' food-related CF.

Input-output analysis has two main advantages: (1) tracing an infinite number of supply chains and (2) covering all products and services within an economy. Although many studies in the input-output analysis community use a single-country input-output table and therefore cannot distinguish the regional

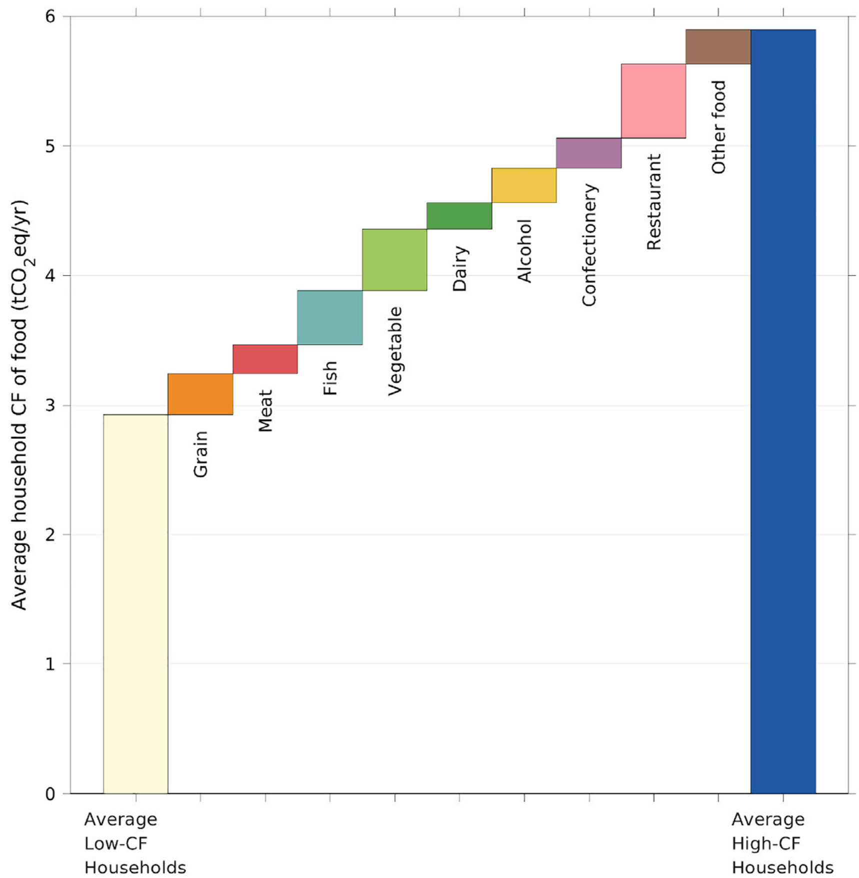

Figure 4. Differences between the Average Household in the Lowest-CF Quartile and Average Household in the Highest-CF Quartile

Decomposition analysis revealing the dietary differences between the average household in the lowest-CF quartile and average household in the highest-CF quartile. Meat is one of the smallest differentiators between the lowest- and highest-CF households.

disparities, this study uses Japan's 47-prefecture-level multi-regional input-output analysis.[27] In addition, we use household-level microdata as an alternative to a national final demand vector in an input-output table. The original microconsumption data in 2004 is from the National Survey of Family Income and Expenditure conducted by the Statistics Bureau of Japan. The survey provides the aggregated version of household consumption data in their website, but in this study, we used the household-level survey results from ∼60,000 households, obtained by special permission. The data sampling and collection was carried out by the Statistics Bureau of Japan. To avoid the bias of the sampling of cities and type of households, they use stratified sampling. In addition to household consumption expenditure, they collected data on income, savings, address, possession of durable goods, household composition of household, etc. The microconsumption data have several limitations in analyzing dietary pattern. For example, the dataset is only suitable for household-level analysis and aggregated restaurant consumption. Other dietary assessment methods allow us to analyze individual-level and detailed food intake from the restaurant consumption.[62] However, the consumption stage is useful for footprint analysis, not epidemiological study, because of the connection to supply chain model, and we do not need to consider food waste. Therefore, our datasets have an advantage in the data sampling process, accompanied information about household, and are a good match with CF analysis. The direct carbon emissions data are from energy balance tables[63] and official GHG emissions reports for each prefecture (see Note S5 for details) and Embodied Energy and Emission Intensity Data for Japan Using Input-Output Tables (3EID) for the national level.[64,65] We analyzed the potential drivers of household food CF using prefecture-level CO_2 and national-level CO_2 CH_4, and N_2O (see Note S1). Our method follows the basic Leontief demand-pull model, which has been well described before.[66,67] The food-related CF of household h is defined as follows,

$$F_h = \sum_{j \in \text{food}, i, r, s} f_i^r L_{ij}^{rs} y_{j,h}^s, \qquad \text{(Equation 1)}$$

where f refers to factor inputs (i.e., GHG emissions per unit of production), L is the Leontief inverse, y is consumption expenditure, i and j are sectors of origin and destination, and r and s are the exporting and importing region, respectively. We aggregate the original 82 food-related consumption items from the household consumption survey (which provides 320 expenditure categories in total) into the 80-sector classification used in the multi-regional input-output tables. We assume that imported products are produced with the same technology as the domestic market. We note that the survey asked respondents to document their consumption from September to November. We estimate consumption activity of a year based on the monthly average expenditure data.

Because households contain different numbers people, we cannot directly compare households. Table S2 presents that the number of members in household (i.e., household size) is significantly correlated with CF in the supporting information. In addition, family components with respect to age would vary the household's CF (e.g., an increase in the ratio of working adults is associated with a decline in their CF, contrasting with that of elderly people; shown in Table S2). Therefore, we normalized CF of foods for household h using average calorific intake by age and sex as follows,

$$C_h = \frac{F_h}{\sum_{k=1}^{9} \left(n_{h,k}^M c_k^M + n_{h,k}^W c_k^W \right)}, \qquad \text{(Equation 2)}$$

where n is a number of persons within a household, c is the average calorific value of a person per year, the superscripts M and W refer to men and women, and k is the kth age group. The age groups are: 0–6, 7–14, 15–19, 20–29, 30–39, 40–49, 50–59, 60–69, and 70+. We get average energy intake (kcal) by sex, age, and year from National Health and Nutrition Survey.[50]

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.oneear.2019.12.004.

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AUTHOR CONTRIBUTIONS

K.K., Y.S., D.M., and Y.K. designed the research. K.K. and Y.S. conducted the analysis. K.K. prepared the figures. K.K., D.M., C.R., Y.S., and Y.K. wrote the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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