**Article:**
Kanemoto, K., Moran, D., Shigetomi, Y. et al. (2019) Meat consumption does not explain differences in household food carbon footprints in Japan. One Earth, 1 (4). pp. 464-471. ISSN: 2590-3322

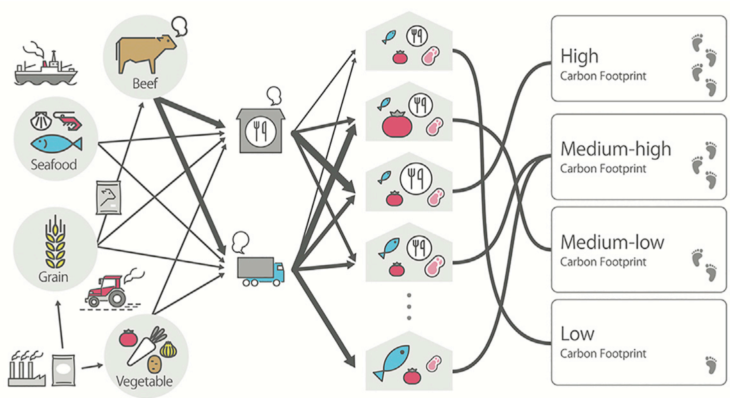
https://doi.org/10.1016/j.oneear.2019.12.004

Article

One Earth

# 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.

Kanemoto et al., 2019, One Earth *1*, 464–471

https://doi.org/10.1016/j.oneear.2019.12.004

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

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https://doi.org/10.1016/j.oneear.2019.12.004

**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.

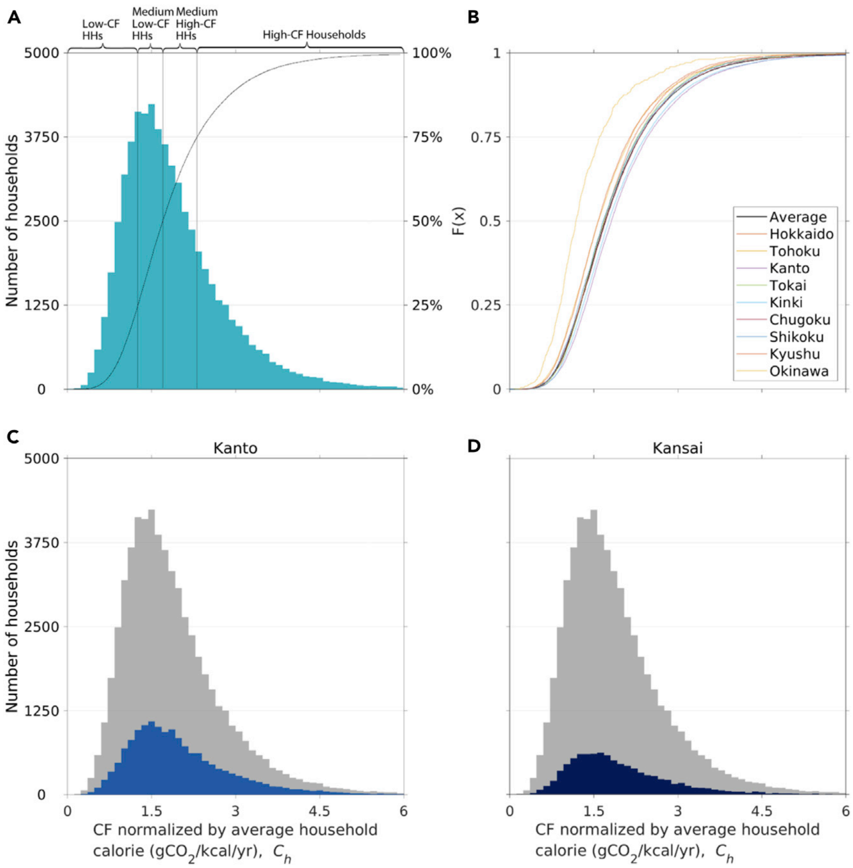


**Figure 1. Frequency Distribution of Food-Related Carbon Footprint**

(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

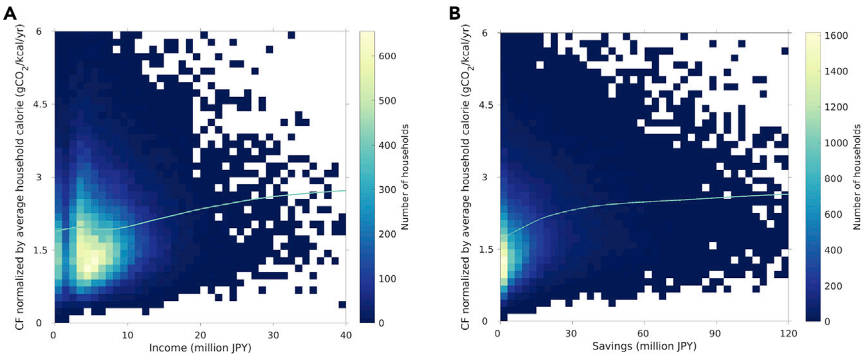


**Figure 2. Relationship between Food-Related CF and Income and Saving**

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

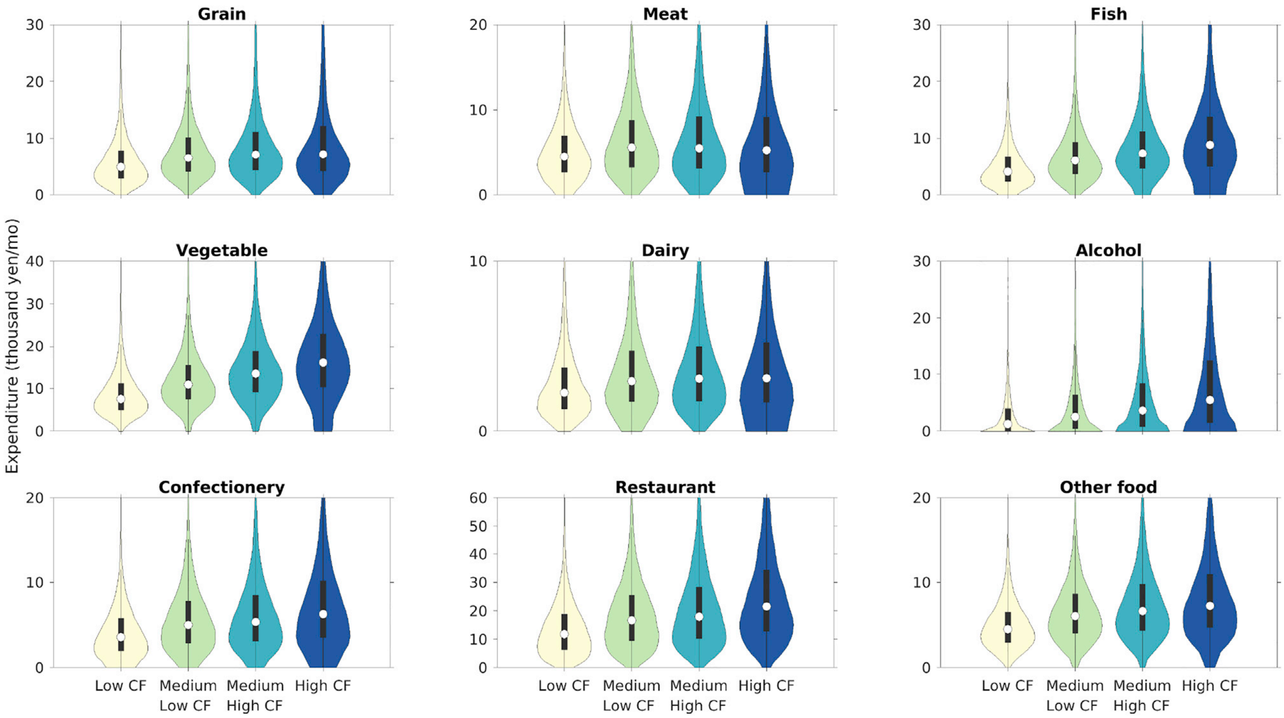


**Figure 3. Violin Plot of Consumption Expenditure by CF Group**

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

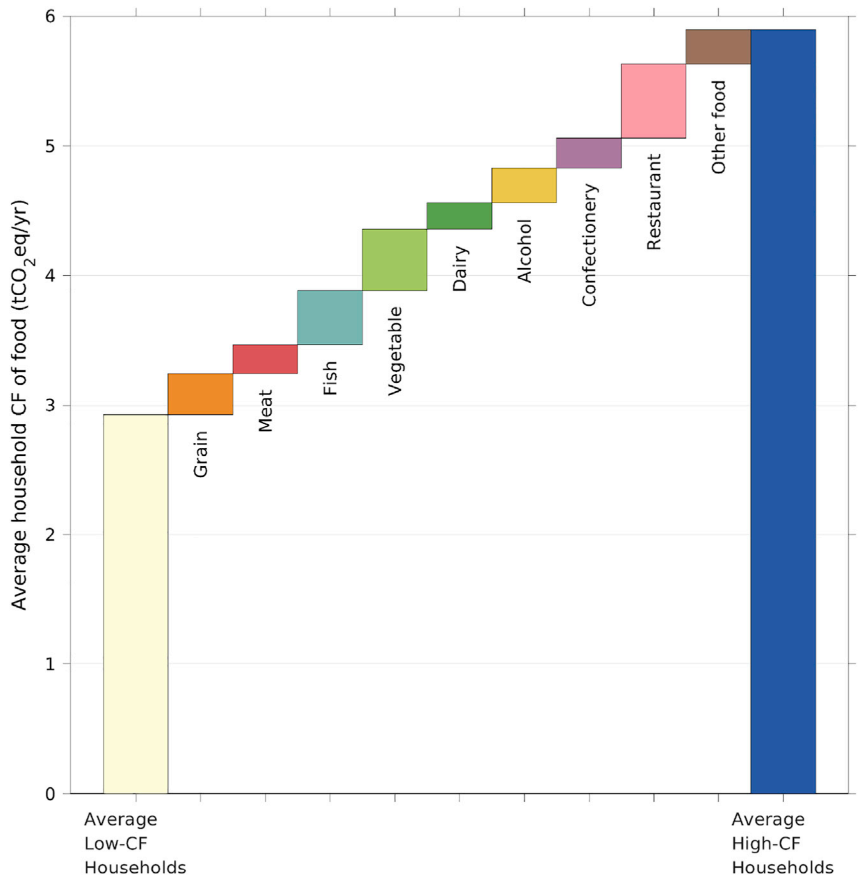


**Figure 4. Differences between the Average Household in the Lowest-CF Quartile and Average Household in the Highest-CF Quartile**

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,

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

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 $k$th 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.

## ACKNOWLEDGMENTS

This work was supported by the Research Institute for Humanity and Nature project no. 14200135 and the Japan Society for the Promotion of Science through its Grant-in-Aid for Young Scientists (A) 15H05341. We wish to thank Marco Springmann and Ken'ichi Matsumoto for valuable comments.

## 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.

Received: February 11, 2019
Revised: September 18, 2019
Accepted: December 2, 2019
Published: December 20, 2019

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ONEEAR, Volume *1*

# Supplemental Information

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

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# Supplemental Information

## Note S1: The resolution of input-output table and $CH_4$, and $N_2O$ emissions

One of limitation is sector resolution of input-output table. Even though original household-level consumption data have 320 sector product classification, we need to aggregate it to 80 sectors to fit Japan's multi-regional input-output classification. In addition, Japan's 47 multi-regional input-output analysis do not include $CH_4$, and $N_2O$ emissions. To verify these limitations, we also replicate figure 3 using Japan's national input-output table that has about 400 sectors and $CO_2$, $CH_4$, and $N_2O$ satellite accounts. We confirmed that the main findings derived from Figures 1, 2, and 3 are basically consistent with Figures S1, S2, and S3.

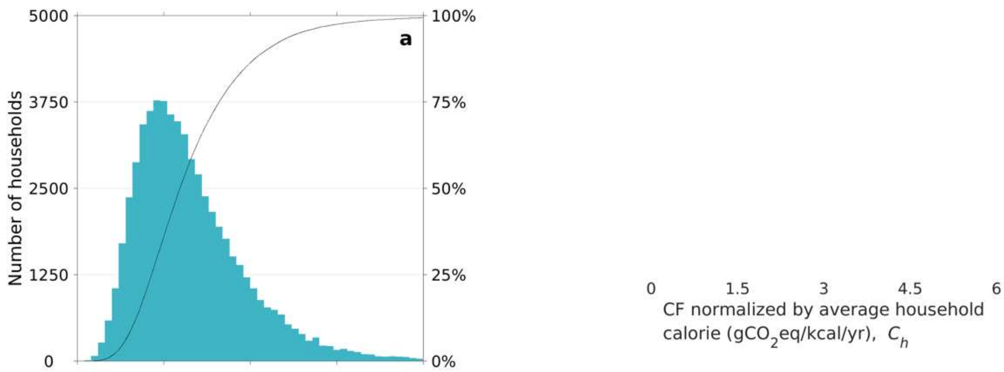


Figure S1: Frequency distribution of food-related carbon footprint (CF) of 60,000 households in Japan. Filled curve and left axis show number of households, right axis and line show cumulative relative frequency. Values are food-related CF normalized by average household calorie by regions and national average.

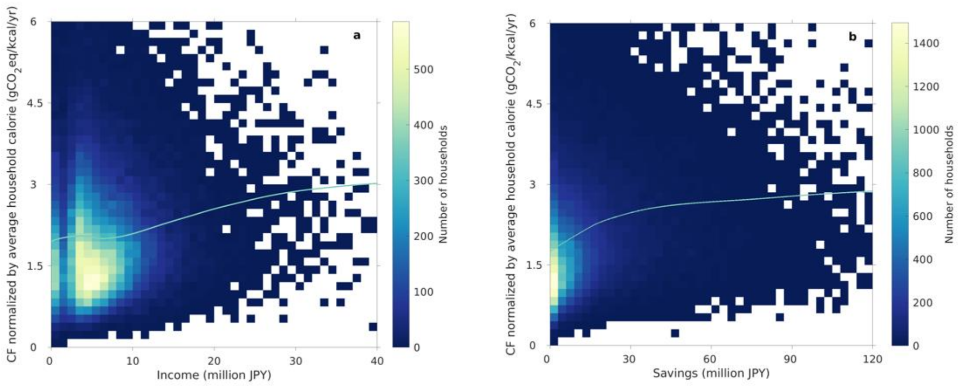


Figure S2: Density scatterplot (brighter pixels contain more observations than darker pixels) of income (A) and savings (B) versus household CF normalized by average household caloric consumption. Lines show a nonparametric regression curve.

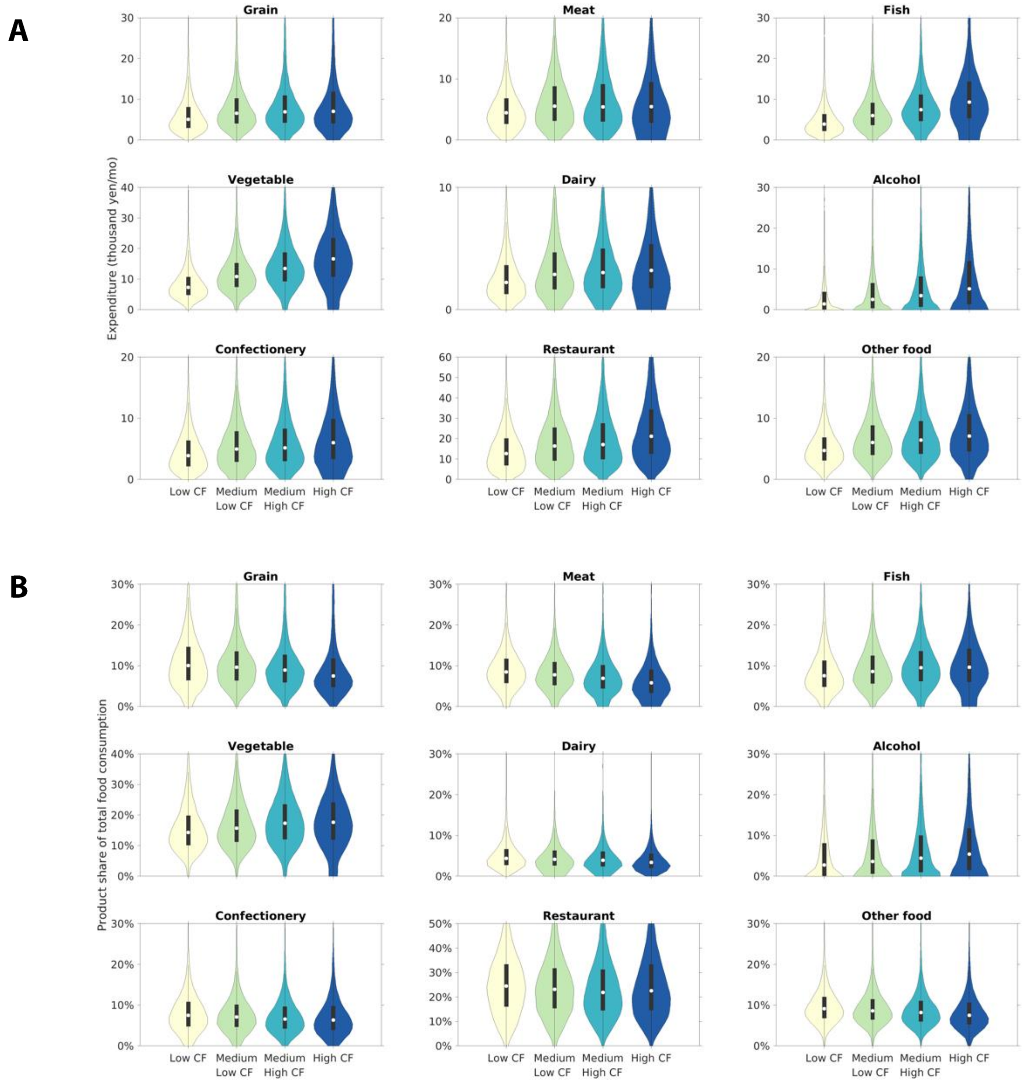


Figure S3: Food consumption absolute volume (A) and relative volume (B) for high food-related CF, medium-high, medium-low, low CF of households using about 400 sector-level Japan's national input-output table.

## Note S2: The distribution of consumption for each food consumption category

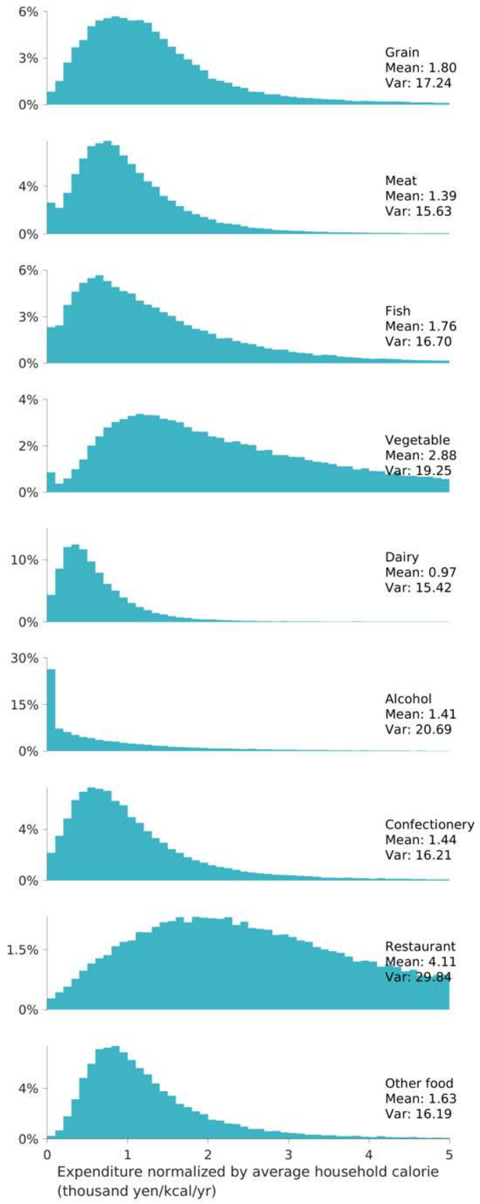


Figure S4: Distribution of consumption expenditure normalized by average household calorie. The coefficient of variation of alcohol varies most, followed by grain, restaurant, fish, and vegetable. Meat and dairy have the lower value of the coefficient of variation.

**Table S1: Two-sample Kolmogorov-Smirnov test results between 9 Japan's regions.** Okinawa and Chugoku are significantly different from other regions and therefore it is consistent with Figure S3.

| | Hokkaido | Tohoku | Kanto | Tokai | Kinki | Chugoku | Shikoku | Kyushu | Okinawa |
|---|---|---|---|---|---|---|---|---|---|
| Hokkaido | | 0.0608 | 0.0774 | 0.0215 | 0.0639 | 0.0368 | 0.0244 | 0.0633 | 0.3193 |
| | | (0.0000) | (0.0000) | (0.2696) | (0.0000) | (0.0201) | (0.3588) | (0.0000) | (0.0000) |
| Tohoku | | | 0.1245 | 0.0637 | 0.105 | 0.0746 | 0.057 | 0.0131 | 0.2672 |
| | | | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.6935) | (0.0000) |
| Kanto | | | | 0.0708 | 0.028 | 0.0547 | 0.0769 | 0.1284 | 0.3848 |
| | | | | (0.0000) | (0.0002) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Tokai | | | | | 0.0507 | 0.0209 | 0.0223 | 0.0633 | 0.3234 |
| | | | | | (0.0000) | (0.1041) | (0.1671) | (0.0000) | (0.0000) |
| Kinki | | | | | | 0.0348 | 0.0564 | 0.1063 | 0.3588 |
| | | | | | | (0.0010) | (0.0000) | (0.0000) | (0.0000) |
| Chugoku | | | | | | | 0.0273 | 0.0778 | 0.3317 |
| | | | | | | | (0.1165) | (0.0000) | (0.0000) |
| Shikoku | | | | | | | | 0.0595 | 0.3144 |
| | | | | | | | | (0.0000) | (0.0000) |
| Kyushu | | | | | | | | | 0.2664 |
| | | | | | | | | | (0.0000) |
| Okinawa | | | | | | | | | |

Note: Values in parentheses are p-value.

## Note S3: Regression analysis

To understand the variation in food-related CF along with income of households, we conducted a regression analysis, controlling for the factors related to economic (savings), urbanization (population density), demographic (household size and age) and possession of household electric appliances. The regression equation that we used is

$$\ln F_i = \beta_0 + \beta_1 \ln I_i + \beta_2 (\ln I_i)^2 + \beta_3 \ln S_i + \beta_4 (\ln S_i)^2 + \beta_5 \ln P_i + \beta_6 {H_i}^{1/2} + \beta_7 C_i + \beta_8 L_i + \beta_9 E_i + \beta_{10} M_i + \beta_{11} R_i + u_i \quad \text{(S1)}$$

where of $i$ is household, $F$ is food-related CF, $I$ is income (*Income*), $S$ is savings (*Savings*), $P$ is population density (*Density*), $H$ is the number of members in household, $C$ is the ratio of children aged between 6 and 18 years old (*Child*), $L$ is the ratio of working adults aged between 19 and 64 years old (*Adult*), $E$ is the ratio of elderly people aged more than 65 years old (*Elderly*), $M$ is the number of microwaves possessed (*Microwave*), $R$ is the number of refrigerators possessed (*Refrigerator*), $u$ is error term, and $\beta_0, \dots, \beta_{11}$ are parameters to be estimated. We adopt a quadratic formula for income $I$ and savings $S$ to capture a nonlinear relationship as shown in Figure 2. All of the above explanatory variables except population density were retrieved from the microdata of NSFIE. The value of population density was estimated by dividing the total population by the square measure where the household lives. The total population was referred to 2004 Basic Resident Register of Japan (https://www.e-stat.go.jp/stat-search/files?page=1&layout=datalist&toukei=00200241&tstat=000001039591&cycle=7&year=20040&month=0&tclass1=000001039601&result_back=1). The square measure was calculated by using the geographical information system (GIS) data provided by National Land Numerical Information download service (http://nlftp.mlit.go.jp/ksj-e/index.html).

In Table S2, Column VI presents the main results obtained from an equation that includes all variables considered in this study using the ordinary least squares (OLS) method. Columns I to V investigate the robustness for each coefficient of the variables used in Column VI. Both Columns I and II, examine the relationship between economic factors and the CF, using the linear and quadratic terms. Column III explores the relationship between population density and CF. Column IV investigates the correlation of variables related to the family component. Column V examines the trends in the number of household electric appliances for food. We checked the variance inflation factor (VIF) for the selected variables, confirming that there is no serious multicollinearity problem (no values exceeded 10).

Table S2: Results of the regression of food-related carbon footprint in OLS estimations.

| Variables | I<br>Income | II<br>Economic | III<br>Population density | IV<br>Family component | V<br>Electric appliances for food | VI<br>All |
|---|---|---|---|---|---|---|
| ln(*Income*) | 0.266*** | 0.339*** | 0.270*** | 0.193*** | 0.314*** | 0.301*** |
| | (0.0583) | (0.0590) | (0.0587) | (0.0505) | (0.0585) | (0.0506) |
| ln(*Income*)$^2$ | 0.0101** | 0.000775 | 0.00985** | 0.0109*** | 0.00454 | -0.00404 |
| | (0.00466) | (0.00471) | (0.00470) | (0.00403) | (0.00468) | (0.00403) |
| ln(*Savings*) | | 0.0590*** | | | | 0.0193** |
| | | (0.00888) | | | | (0.00818) |
| ln(*Savings*)$^2$ | | -0.000351 | | | | 0.00346*** |
| | | (0.000708) | | | | (0.000658) |
| ln(*Density*) | | | -0.0116*** | | | -0.000996 |
| | | | (0.00113) | | | (0.00110) |
| *HouseholdSize*$^{(1/2)}$ | | | | 0.361*** | | 0.356*** |
| | | | | (0.00631) | | (0.00656) |
| *RatioChild* | | | | -0.0645*** | | 0.00832 |
| | | | | (0.0112) | | (0.0113) |
| *RatioAdult* | | | | -0.0939*** | | -0.0555*** |
| | | | | (0.00833) | | (0.00840) |
| *RatioElderly* | | | | 0.0928*** | | 0.0338*** |
| | | | | (0.00702) | | (0.00717) |
| *Microwave* | | | | | 0.0692*** | 0.0234*** |
| | | | | | (0.00613) | (0.00586) |
| *Refrigerator* | | | | | 0.0924*** | 0.0545*** |
| | | | | | (0.00317) | (0.00323) |
| *Constant* | -1.481*** | -1.940*** | -1.414*** | -1.652*** | -1.746*** | -2.103*** |
| | (0.181) | (0.180) | (0.182) | (0.157) | (0.181) | (0.155) |
| Observations | 55,802 | 53,380 | 55,627 | 55,802 | 55,802 | 53,208 |
| Adjusted $R^2$ | 0.260 | 0.275 | 0.261 | 0.325 | 0.277 | 0.349 |

Standard errors calculated by the Huber-White method are in parenthesis.

*** p<0.01, ** p<0.05, * p<0.1

## Note S4: The price effect

According to Report of Survey on Trend of Price and Sales of Perishable Food, Statistics Department, Ministry of Agriculture, Forestry and Fisheries, the price of organic or specially cultivated vegetables is 20-150% higher than conventional vegetables. The organic vegetables can variously have a lower or higher carbon footprint than conventional vegetables[1,2]. However, Japan has only 0.17% of organic food compared to national production in 2005 (0.2% for vegetable, 0.06% for fruits, etc. in 2007). European countries have ~15% in Italy etc. and due to this there was need to control the price effect in a similar European case study[3].

Another explanatory variable related to Note S3 is regional price variation. The retail price survey provides Japan's prefecture-level retail price for 58 food and non-food products in 2013. At here, we checked the prefecture-level price variation. Figure S5 shows the coefficient of variation is less than 20% for any products and usually smaller than 10%.

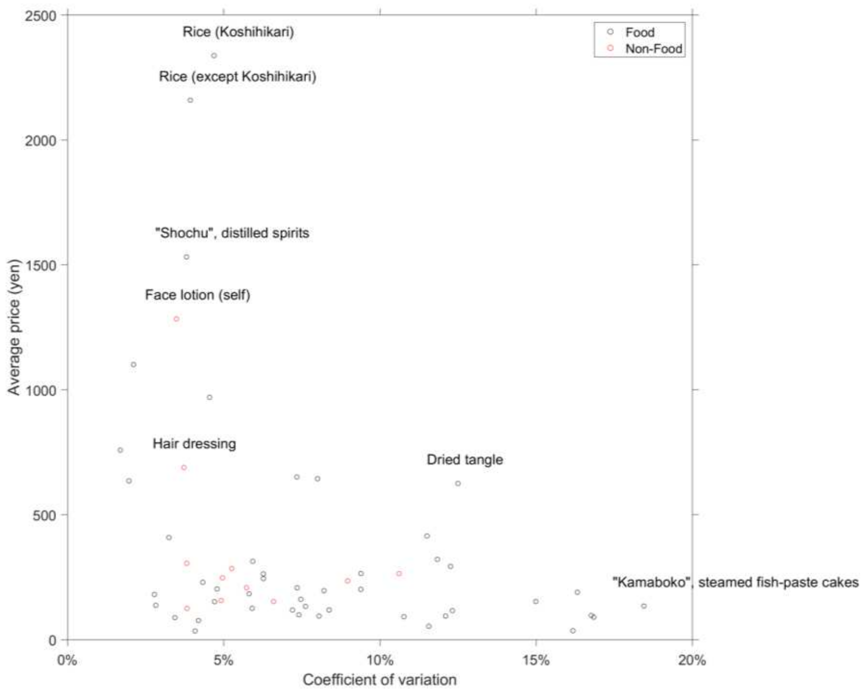


Figure S5: The coefficient of variation and average price scatter figure.

Because of the low ratio of organic products and small regional price difference, we conclude the price effect is relatively low and can ignore it in this study.

## Note S5: Prefecture-level carbon emissions

Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry provide prefecture-level energy balance table, but these tables only do not cover emissions from the whole transport sector and energy transition sectors. Therefore, we contacted Environmental Policy Division for each prefecture to obtain sectoral carbon emissions (see Table S3). Although official carbon emission reporting for each prefecture do not have the detailed sector, we integrated official carbon emission datasets and energy balance tables. We use energy balance table for sectoral ratio and official data for scaling.

Table S3: Data sources of sectoral carbon emissions for each prefecture. We contacted following all official environment divisions and received data by email.

| | |
|---|---|
| Hokkaido | Climate Change Policy Division,<br>Bureau of Environmental Affairs,<br>Department of Environment and Lifestyle,<br>Hokkaido Government |
| Aomori | Environmental Policy Division,<br>Department of Environment and Public Affairs,<br>Aomori Prefecture |
| Iwate | Office of Environment and Residential Life Planning,<br>Department of Environment and Residential Life,<br>Iwate Prefectural Government |
| Miyagi | Environmental Policy Planning Division,<br>Environment and Lifestyle Department,<br>Miyagi Prefectural Government |
| Akita | Climate Change Policy Division,<br>Department of Living and Environment,<br>Akita Prefectural Government |
| Yamagata | Environmental Planning Division,<br>Environment and Energy Department,<br>Yamagata Prefectural Government |
| Fukushima | Environmental Policy Division,<br>Social Affairs and Environment Department,<br>Fukushima Prefectural Government |
| Ibaraki | Environmental Policy Division,<br>Department of Residential and Environmental Affairs,<br>Ibaraki Prefectural Government |
| Tochigi | Global Warming Management Division,<br>Department of Environment and Forestry,<br>Tochigi Prefectural Government |
| Gunma | Sustainable Energy Division,<br>Gunma Prefectural Government |
| Saitama | Global Warming Strategy Division,<br>Department of Environment,<br>Saitama Prefectural Office |
| Chiba | Recycling Society Promotion Division,<br>Environmental and Community Affairs Department,<br>Chiba Prefectural Government |
| Tokyo | Planning Section,<br>Climate Change and Energy Division,<br>Bureau of Environment,<br>Tokyo Metropolitan Government |
| Kanagawa | Environmental Planning Division,<br>Environment Department, |

| | |
|---|---|
| | Environment and Agriculture Bureau,<br>Kanagawa Prefectural Government |
| Niigata | Environmental Planning Division,<br>Department of Civic and Environmental Affairs,<br>Niigata Prefectural |
| Toyama | Environmental Policy Division,<br>Toyama Prefectural Government |
| Ishikawa | Global Warming Preventive Measures and Satoyama Policies Office,<br>Living and Environment Department,<br>Ishikawa Prefectural Government |
| Fukui | Environment Policy Division,<br>Department of Public Safety and the Environment,<br>Fukui Prefectural Government |
| Yamanashi | Energy Policy Division,<br>Energy Bureau,<br>Yamanashi Prefectural Government |
| Nagano | Sustainable Energy Policy Division,<br>Environmental Department,<br>Nagano Prefectural Government |
| Gifu | Environmental management Division,<br>Gifu Prefectural Government |
| Shizuoka | Environmental Policy Division,<br>Environmental Protection Bureau<br>Community and Environmental Affairs Department,<br>Shizuoka Prefecture |
| Aichi | Global Warming Prevention division,<br>Department of the Environment,<br>Aichi Prefectural Government |
| Mie | Global Warming Prevention Division,<br>Department of Environmental and Social Affairs,<br>Mie Prefectural Government |
| Shiga | Global Warming Issues Division,<br>Department of Lake Biwa and the Environment,<br>Shiga Prefecture |
| Kyoto | Global Warming Countermeasures Division,<br>Department of the Environment,<br>Organization of Kyoto Prefectural Government |
| Osaka | Energy Policy Division,<br>Department of Environment, Agriculture, Forestry and Fisheries,<br>Osaka Prefectural Government |
| Hyogo | Environmental Management Bureau, Global Warming Solutions Division,<br>Agricultural & Environmental Affairs Department,<br>Hyogo Prefectural Government |
| Nara | Environmental Policies Division,<br>Nara Prefectural Government |
| Wakayama | Environment and Living General Affairs Division,<br>Environmental Policy Bureau,<br>Environment and Living Department,<br>Wakayama Prefecture |
| Tottori | Environmental Policy Division,<br>Department of the Environment and Consumer Affairs,<br>Tottori Prefectural Government |
| Shimane | Environmental Policy Division,<br>Department of Environment and Civic Affairs,<br>Shimane Prefectural Government |
| Okayama | Alternative Energy and Global Warming Strategy office,<br>Okayama Prefecture |

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|---|---|
| Hiroshima | Environmental Policy Division,<br>Environment and Citizens Affairs Bureau,<br>Hiroshima Prefectural Government |
| Yamanashi | Environmental Policy Division,<br>Environment & Living Department,<br>Yamaguchi Prefectural Government |
| Tokushima | Eco City Division,<br>Environment and Citizens' Affairs Department,<br>Tokushima Prefecture |
| Kagawa | Environmental Policy Division,<br>Environment and Forestry Department,<br>Kagawa Prefectural Government |
| Ehime | Environmental Policy Division,<br>Bureau of Environment,<br>Public Affairs and Environment Department,<br>Ehime Prefecture |
| Kochi | New Energy Promotion Division,<br>Department of Forestry and the Environment,<br>Kochi Prefectural Government |
| Fukuoka | Environmental Preservation Division,<br>Department of Environmental Affairs,<br>Fukuoka Prefectural Government |
| Saga | Environment Division,<br>Department of Citizens and Environmental Affairs,<br>Saga Prefectural Government |
| Nagasaki | Environmental Policy Division,<br>Environmental Affairs Department,<br>Nagasaki Prefectural Government |
| Kumamoto | Environmental Policy Promotion Division<br>Kumamoto Prefectural Government, |
| Oita | Utsukushi Environmental Policy Promotion Division,<br>Life and Environment Department,<br>Oita Prefectural Government |
| Miyazaki | Environment and Forestry Division,<br>Miyazaki Prefecture |
| Kagoshima | Climate Change Policy Division,<br>Environment and Forestry Affairs Department,<br>Kagoshima Prefecture |
| Okinawa | Environmental Restoration Division,<br>Department of Environmental Affairs,<br>Okinawa Prefectural Government |

## Note S6: Greenhouse gas emission intensities

Table S4 is greenhouse gas emission intensities of food products which we used for Figure 4 and Note S1. The original data is from Nansai et al.[4]

Table S4: GHG ($CO_2$, $CH_4$, and $N_2O$) emission intensities (Unit: t-$CO_2$eq/million yen)

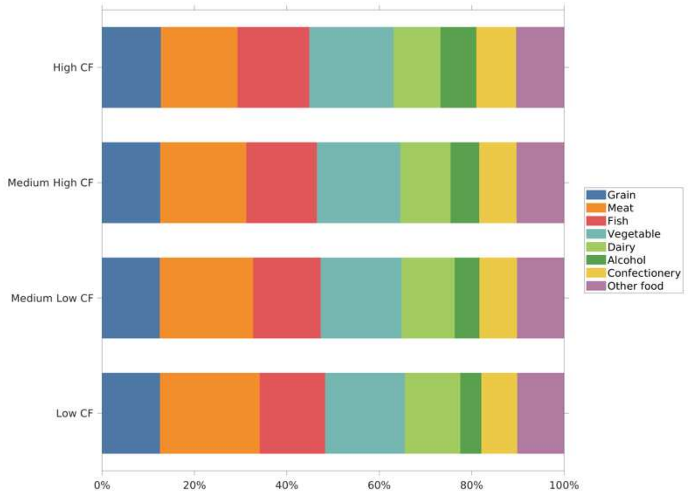
| Item | $CO_2$ | $CH_4$ | $N_2O$ |
|---|---:|---:|---:|
| Rice | 2.11 | 3.09 | 0.54 |
| Wheat, barley and the like | 2.74 | 0.21 | 2.24 |
| Potatoes and sweet potatoes | 1.97 | 0.15 | 1.02 |
| Pulses | 2.07 | 0.19 | 2.59 |
| Vegetables | 2.91 | 0.14 | 0.81 |
| Fruits | 2.36 | 0.12 | 0.65 |
| Sugar crops | 2.30 | 0.30 | 0.70 |
| Crops for beverages | 2.58 | 0.23 | 9.06 |
| Other edible crops | 2.27 | 1.69 | 2.97 |
| Crops for feed and forage | 1.62 | 0.31 | 6.89 |
| Seeds and seedlings | 1.45 | 0.09 | 0.03 |
| Flowers and plants | 7.20 | 0.26 | 0.05 |
| Other inedible crops | 1.33 | 0.10 | 2.64 |
| Dairy cattle farming | 1.85 | 5.91 | 2.34 |
| Hen eggs | 2.31 | 0.44 | 3.09 |
| Fowls and broilers | 2.91 | 0.51 | 3.81 |
| Hogs | 2.47 | 1.39 | 3.35 |
| Beef cattle | 2.25 | 7.74 | 2.90 |
| Other livestock | 2.10 | 0.86 | 1.27 |
| Marine fisheries | 9.14 | 0.25 | 0.03 |
| Marine culture | 4.39 | 0.16 | 0.07 |
| Inland water fisheries and culture | 4.68 | 0.19 | 0.10 |
| Slaughtering and meat processing | 2.26 | 3.29 | 2.72 |
| Processed meat products | 2.24 | 1.36 | 1.12 |
| Bottled or canned meat products | 2.58 | 0.43 | 0.38 |
| Dairy farm products | 3.09 | 2.46 | 0.99 |
| Frozen fish and shellfish | 5.43 | 0.15 | 0.02 |
| Salted, dried or smoked seafood | 4.10 | 0.12 | 0.02 |
| Bottled or canned seafood | 4.14 | 0.12 | 0.05 |
| Fish paste | 3.27 | 0.16 | 0.11 |
| Other processed seafood | 3.23 | 0.11 | 0.04 |
| Grain milling | 2.02 | 2.20 | 0.40 |
| Flour and other grain milled products | 3.13 | 0.32 | 1.24 |
| Noodles | 2.95 | 0.18 | 0.32 |
| Bread | 2.35 | 0.21 | 0.30 |
| Confectionery | 2.49 | 0.24 | 0.26 |

| | | | |
|---|---|---|---|
| Bottled or canned vegetables and fruits | 3.31 | 0.11 | 0.22 |
| Preserved agricultural foodstuffs | 2.22 | 0.09 | 0.21 |
| Sugar | 7.06 | 0.23 | 0.28 |
| Starch | 4.57 | 0.78 | 1.32 |
| Dextrose, syrup and isomerized sugar | 7.61 | 0.49 | 0.68 |
| Vegetable oils and meal | 3.90 | 0.52 | 1.26 |
| Animal oils and fats | 5.97 | 0.86 | 0.65 |
| Condiments and seasonings | 2.77 | 0.16 | 0.21 |
| Prepared frozen foods | 3.07 | 0.51 | 0.40 |
| Retort foods | 2.93 | 0.36 | 0.31 |
| Dishes, sushi and lunch boxes | 2.50 | 0.56 | 0.35 |
| School lunch (public) | 2.04 | 0.51 | 0.33 |
| School lunch (private) | 1.99 | 0.53 | 0.36 |
| Other foods | 3.25 | 0.26 | 0.45 |
| Refined sake | 1.87 | 0.57 | 0.11 |
| Beer | 1.49 | 0.05 | 0.06 |
| Whiskey and brandy | 1.82 | 0.06 | 0.03 |
| Other liquors | 2.07 | 0.14 | 0.06 |
| Tea and roasted coffee | 2.31 | 0.10 | 2.11 |
| Soft drinks | 2.42 | 0.14 | 0.22 |
| Manufactured ice | 4.50 | 0.12 | 0.04 |

## Note S7: Composition of food carbon footprint of households

Figure S6 is the composition of food carbon footprint. The volume of household food CF including restaurant consumption are 3.0, 4.2, 4.9, and 6.0 t-$CO_2$eq/yr for high, medium high, medium low, and low households for each.

**A**




**B**

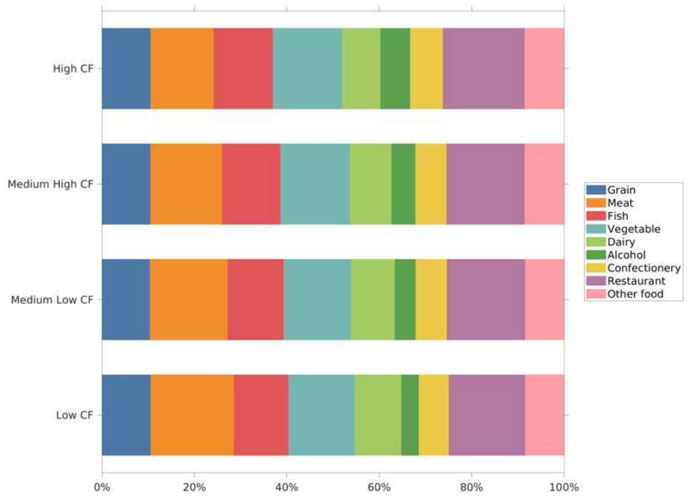



Figure S6. Excluding restaurant (A) and including restaurant (B).

## Supplemental References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2. Clark, M. & Tilman, D. (2017). Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice. *Environ. Res. Lett.* **12**, 064016.
3. Ministry of Agriculture, F. and F. Promotion of Organic Agriculture (2009). Available at: http://www.maff.go.jp/j/study/yuki_suisin/04/pdf/data8.pdf.
4. Nansai, K. *et al.* (2012). Estimates of Embodied Global Energy and Air-Emission Intensities of Japanese Products for Building a Japanese Input − Output Life Cycle Assessment Database with a Global System Boundary. *Environ. Sci. Technol.* **46**, 9146–54.