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Original Article

Lifestyle changes overweighing technology improvement in household decarbonization: evidence from Japan during 1990-2020

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Abstract

Given that over 70% of global greenhouse gas emissions (GHG) stem from consumption, it is essential to promote lifestyle changes among end users and reduce emissions embedded in the upstream supply chain. We investigated the long-term (1990-2020) changes in household carbon footprints from such final users in Japan. Through factor decomposition, we found that the contribution of increasingly green technologies to household decarbonization is diminishing with time. In contrast, lifestyle changes - such as the shift to green products and services, as well as a reduction in overall demand - are becoming the main driver. Additionally, unlike most developed countries, the share of GHG emissions from food expenditures in Japan does not show a declining trend, highlighting the need to upgrade the domestic food supply chain and promote smart services for decarbonizing both homemade meals and eat-out preferences. Our long-term database can provide references to encourage sustainable behaviors and help Japanese policymakers evaluate the effectiveness of current efforts.

Keywords: Household carbon footprints, food-related wastes, urban social infrastructure, smart food services, smart eating habits, Japan

INTRODUCTION

Mitigating greenhouse gas (GHG) emissions is considered an urgent global priority due to the significant impacts of climate change. Many countries have committed to achieving a long-term carbon neutrality goal[1]. In October 2020, the then Prime Minister declared that Japan would become a carbon-neutral society by 2050[2]. Among the global GHG emissions, 72% are consumption-induced emissions[3]. This calls for tracking such emissions induced by final users (long-term changes and cross-sectional structures) and their possible drivers.

The concept of carbon footprint is utilized to quantify such consumption-induced GHG emissions. Carbon footprint refers to the mass of GHG emissions released through a supply chain or the life cycle of a product and is most appropriately calculated using life cycle assessment or input-output analysis[3]. Using a global multi-regional input-output (MRIO) model based on the Global Trade Analysis Project (GTAP) database, Hertwich and Peters[3] calculated the carbon footprints from final consumption for 73 nations and 14 aggregate world regions and reported that 72% of GHG emissions were related to household consumption. Following the European Commission's encouragement of member states to combine national and international climate change mitigation measures with local environmental policies, Ivanova *et al.* developed an inventory of carbon footprints associated with household consumption for 177 regions in 27 EU countries using the MRIO[4,5]. They revealed the spatial heterogeneity of embodied GHG emissions in multi-regional countries within the EU. Based on the distribution of carbon footprints within the EU in 1999 and 2015, Hardadi *et al.* suggested that reducing income inequality within a region would lead to reduced GHG emissions[6].

As a driver of reducing such carbon footprints, lifestyle changes have attracted the attention of researchers worldwide[7-13]. Studies have been conducted on the effects of pro-environmental behavior changes and environmental awareness[14,15]. In certain countries, studies have focused on income inequality as a factor that causes heterogeneity in the distribution of carbon footprints due to differences in lifestyle and environmental awareness within a country[16-19]. An increasing number of studies have analyzed the effects of various sociodemographic differences among people within a country on household carbon footprints based on large data analyses that combine detailed household consumption microdata and input-output tables[20-27]. Among those, lifestyle changes in eating habits have been discussed[28-30] especially in developing countries such as China[31,32] and Brazil[33].

The role of lifestyle changes among all drivers of carbon footprint reduction has also been discussed, especially in several important reviews in this field. These lifestyle changes usually contain dietary habits, transportation options, and other preferences that may reduce household energy use, as well as living spaces. Researchers investigate the former part by looking into individuals' motivations, the impacts of adopting a low-carbon lifestyle, and the strategies for managing the undesirable consequences of these changes[34,35], and investigate the latter part by looking at energy service demand changes in buildings[36]. Ivanova *et al.* summarized the mitigation options of household carbon footprints, together with their impacts[37]. They found that while there is cross-sectional diversity in consumption, the major mitigation options are relatively limited to technological changes, such as using energy-saving home appliances and the modal shift to energy-saving cars. If there are long-term changes in consumer preferences or policies such as taxing the final users, the effect of different drivers may change. Furthermore, Cap *et al.*, with a focus on the EU27, found that while technological change can substantially reduce emissions, the reductions are ultimately insufficient to achieve the 1.5-degree target, leading to a moderate overshoot globally in 2050[38]. The critical role of household lifestyle transformation is highlighted in future mitigation pathways as well.

Although there are many studies on cross-sectional differences in carbon footprints and their driving factors, limited studies have focused on chronological changes. Even when studies have a time-series perspective, they focus primarily on changes in the cross-sectional CF distribution[39-41]. Few studies have examined the effects of technological change or other factors over time on the carbon footprints of the final users. Nansai *et al.* compared the rate of change between two points in time with a decomposition[42]. They concluded that the measures to reduce carbon footprints from consumer goods, whose consumption composition ratio is growing rapidly, are important. However, the longitudinal change in that paper is a relatively short period of 5 years.

Therefore, in this study, in order to provide a relatively long-term perspective of consumption-based greenhouse gas emissions, we investigated the long-term (1990-2020) changes in household carbon footprints in Japan. We then decomposed the factors (changes in technology structure, consumption structure, and total consumption) driving GHG emission changes in each period. Our long-term database will allow Japanese policymakers to evaluate the effectiveness of the current efforts to reduce household carbon footprints. The sub-sector-level results can also clarify the sources of household carbon footprints and provide references to encourage sustainable behaviors.

METHODS

Creating the long-term household carbon footprint database

To track the long-term changes (every five years from 1990 to 2020) in household carbon footprints, we created a long-term carbon footprint database for Japan, with its overview illustration shown in Supplementary Figure 1.

The steps are listed as follows.

- *Deflating (making long-term household consumption comparable)*

The data source of household expenditure in this paper is the Family Income and Expenditure Survey[43]. We converted the nominal value of household consumption (average JPY per household per year) in each period to the real value by the consumer price index[44]. The real JPY value of household consumption in all periods is then mapped by standardized categories covering all goods and services. For each category (the i-th category of good or service), time series data of household consumption ($\lambda_{i,t}$) were obtained in real monetary terms for every fifth year from 1990 to 2020 (t = 1990, 1995, 2000, 2005, 2011, 2015, and 2020). For the mapping of categories (three levels of granularity, 12 in Level 1, 43 in Level 2, and 54 in Level 3), see Supplementary Table 1.

- *Carbon footprint based on nominal household consumptions*

The household carbon footprint of the i-th category of good or service in year t ($E_{i,t}$) is calculated by multiplying the nominal consumption amount of the i-th category of good or service in year t by the corresponding nominal GHG emission intensity (per unit of nominal monetary value). Its data source is the Embodied Energy and Emission Intensity Data for Japan Using Input-Output Tables[45]. The household carbon footprint in all periods is then mapped by standardized categories. For each category, time series data of household carbon footprint (E_{it}) were obtained for every fifth year from 1990 to 2020.

- *Carbon footprint per real household unit*

For each category in each period, the nominal household carbon footprints ($E_{i,t}$) were divided by the real household consumption ($\lambda_{i,t}$). The carbon footprint per real household consumption unit ($e_{i,t}$) in the i-th category of good or service in year t was then obtained.

Based on these variables, we examined the driving factors by factor decomposition analysis in the next section.

Factor decomposition analysis

The factor decomposition for the changes in household carbon footprints is formulated as follows,

$$\begin{aligned} \Delta E_{t,t+5} = E_{t+5} - E_t &= \boldsymbol{e}'_{\boldsymbol{t+5}}\lambda_{t+5}\boldsymbol{c}_{\boldsymbol{t+5}} - \boldsymbol{e}'_{\boldsymbol{t}}\lambda_t\boldsymbol{c}_{\boldsymbol{t}} \\ &= \underbrace{\underbrace{(\boldsymbol{e}'_{\boldsymbol{t+5}}\lambda_{t+5}\boldsymbol{c}_{\boldsymbol{t+5}} - \boldsymbol{e}'_{\boldsymbol{t}}\lambda_{t+5}\boldsymbol{c}_{t+5})}_{\substack{\text{Change in CO}_2\text{ emission intensity} \\ \text{of consumption goods}}}}_{\text{Changes in technology structure}} \\ &\quad + \underbrace{\underbrace{(\boldsymbol{e}'_t\lambda_{t+5}\boldsymbol{c}_{t+5} - \boldsymbol{e}'_t\lambda_t\boldsymbol{c}_{t+5})}_{\text{Change in total consumption}} + \underbrace{(\boldsymbol{e}'_t\lambda_t\boldsymbol{c}_{t+5} - \boldsymbol{e}'_t\lambda_t\boldsymbol{c}_{\boldsymbol{t}})}_{\substack{\text{Change in comsumption} \\ \text{composition}}}}_{\text{Changes in consumer lifestyles}} \end{aligned} \qquad (1)$$

where $E_t = \sum_i e_{i,t} \cdot \lambda_{i,t}$ refers to the real carbon household footprints in year t; $\boldsymbol{e}'_t$ refers to a row vector with each element $e_{i,t}$ equaling to the GHG emission intensity of the i-th category of good or service in year t; $\lambda_t = \sum_i \lambda_{i,t}$ refers to the average total consumption per household in year t; and $\boldsymbol{ct}$ refers to a column vector with each element $c_{i,t}$ equaling to the share of the household consumption of the i-th category of good or service in year t (namely, $\lambda_{i,t}/\lambda_t$).

Based on this equation, the change in household carbon footprints between year t and year $t + 5$ is decomposed into three factors: (1) the effect of change in emission intensity; (2) the effect of change in total consumption; and (3) the effect of change in consumption composition ratio. The first factor shows the changes in the GHG emission structure due to the technological changes across the supply chain. The second and third factors show the changes in lifestyle in the overall households.

We specified the GHG emission intensity by considering the domestic and import consumptions, as well as the direct GHG emissions from household energy consumption and indirect GHG emissions induced by other household consumptions. The GHG emission intensity of the i-th category of good or service in year t ($e_{i,t}$) is calculated as follows.

$$e_{i,t} = \mathbf{i}'\left(\widehat{\mathbf{E}_t}\left(\mathbf{I} - \left(\mathbf{I} - \widehat{\mathbf{M}_t}\right)\mathbf{A}_t\right)^{-1} + \widehat{\mathbf{Ed}_t}\right)\mathbf{f}_{i,t} \qquad (2)$$

where $\mathbf{i}'$ refers to the unit (row) vector; $\left(\mathbf{I} - \left(\mathbf{I} - \widehat{\mathbf{M}_t}\right)\mathbf{A}_t\right)^{-1}$ refers to domestic Leontief inverse in year t; $\mathbf{E}_t$ refers to the vector of GHG emission intensity (GHG emissions per unit of producer's price output) in year t; $\mathbf{Ed}_t$ refers to the diagonalized matrix of direct CO_2 emission intensity of energy goods in year t; $\mathbf{f}_{i,t}$ refers to one unit of the purchaser's price of the i-th consumer good (a vector consisting of the i-th consumer good and its associated distribution margin).

Based on this equation, the first part of the emission intensity $\left(\widehat{\mathbf{E}_t}\left(\mathbf{I} - \left(\mathbf{I} - \widehat{\mathbf{M}_t}\right)\mathbf{A}_t\right)^{-1}\right)$ can measure the effects of energy-derived carbon dioxide emissions, while the second part of the emission intensity $\left(\widehat{\mathbf{Ed}_t}\right)$ can measure the effects of other greenhouse gases (such as methane) after 2000.

Comparison with other research methods

Previous studies on carbon footprints have mainly focused on the cross-sectional distribution (one-year or several-single-year estimation using MRIO). In contrast, as an important feature of our study, the effects of long-term changes (30-year data from 1990-2020 with comparable prices) in both consumer lifestyles and production technologies on household carbon footprints are investigated in this paper.

Many previous studies have used MRIO to clarify the international distribution of GHG emissions induced by a country's final consumption. The input coefficient a_{ij}^{rk} defined in MRIO indicates the input amount of the *i*-th good in country r that is intermediately requried to produce one unit of the *j*-th good in country k. Certain *i*-th goods necessary for producing the *j*-th good in country k are input from other countries (for example, country m). The two input coefficients a_{ij}^{rk} and a_{ij}^{mk} indicate the share of the intermediate demand for the *i*-th good in country k between countries r and m.

In contrast, the input coefficient a_{ij} in the domestic input-output table indicates the amount of input of the *i*-th good required for the unit production of the *j*-th good on an engineering basis. Leontief called this coefficient a_{ij} the technological coefficient. Leontief defined the "state of technology" at that time by measuring the amount of the *i*-th good technologically required to produce the *j*-th good, independent of which country supplies it.

Thus, the input coefficients of the MRIO and domestic IO tables have different meanings. Hence, the policy implications are also different. Analysis using MRIO has the following implications: (1) showing the size of household carbon footprints from different sectors may help people to realize and avoid their high-carbon behaviors; and (2) knowing the regional distribution of carbon footprints in supply chains can help track the emission sources. However, a time-series comparison of analyses using domestic IO makes it possible to comprehensively evaluate the effects of technological change in multiple sectors. Because changes in the scope of technology usually do not occur in the short term, it is better to analyze the effects of technological changes from a relatively longer time span (approximately 30 years). The novelty of our research, which has not been fully discussed in previous studies, lies in the long-term and comprehensive verification of the impacts of emission reduction technologies.

Limitation

The carbon intensity vector is directly from 3EID, where the intensity was compiled based on purchaser price criteria in each release. The carbon intensity of imported products is assumed to be the same as that of Japan's products. Additionally, the 3EID contains multiple non-CO_2 greenhouse gases from the agriculture sectors. The potential of negative emissions from the forestry sector, together with the long-term changes caused by the land use type changes, is not included in this paper.

RESULTS

Long-term changes in real GHG emission intensity

Table 1 shows the changes in average GHG emissions per real-term JPY consumed for all goods and services (with subcategory-level details provided in Supplementary Table 2) from 1990 to 2020.

The average intensity of energy-derived CO_2 emissions, which can be compared over the 30 years, peaked in 1995 and showed a downward trend until 2005, but then rose again in 2011 when the Great East Japan Earthquake occurred. However, the CO_2 emission intensity in 2011 was not as high as it was in 1995 and has been declining since then. The reason for the increase in CO_2 emission intensity in 2011 is that, after the accident at the Fukushima Daiichi Nuclear Power Plant, most of the nuclear power plants stopped

Table 1. Long-term changes in GHG emission intensity in Japan

Unit: g-CO_2-eq per JPY (real-term)	1990	1995	2000	2005	2011	2015	2020
GHG total				3.5933	3.9977	3.6861	3.6340
Energy-derived	3.1710	3.6832	3.5179	3.3599	3.6207	3.3466	3.2816
Methane-derived				0.1071	0.1569	0.1477	0.1536
Other sources				0.1263	0.2201	0.1918	0.1988

Notes: the real value of JPY normalized to the 2015 price level; the average GHG intensity for subcategories is shown in Supplementary Table 2.

operating, and thermal power generation took over as the main electricity supply technology. However, the reduction in CO_2 emission intensity by 2020 was achieved, possibly as a result of the introduction of the feed-in tariff system in 2012 and the promotion of renewable energy use.

On the other hand, the average intensity of GHG emissions caused by methane gas, which has been captured since 2005, increased during 2005-2011 and has not shown a downward trend since then.

Long-term changes in carbon footprints

Figure 1 shows the changes in the energy-derived carbon footprints per household from 1990 to 2020. The annual energy-derived carbon footprints per household peaked at 12.8 ton-CO_2 in 1995 and declined to 9.9 ton-CO_2 in 2020.

Over the 30 years, the three dominant categories that have contributed most to household carbon footprints are food expenses, utility expenses (including electric bills and gas fees), and automobile-related expenses. The carbon footprint from the electricity bills increased significantly, from 19% in the 1990s to 26% in 2005 and 37% in 2020.

Table 2 shows the total carbon footprint including energy-derived GHGs, methane-derived GHGs, and GHGs from other sources (nitrous oxide, fluorocarbons, organic fluorine compounds, sulfur hexafluoride, and nitrogen trifluoride). From 2005 (when all GHG emissions can be comparable), the downward trend has been maintained since 2011. Remarkably, the total carbon footprints in 2015 and 2020 were lower than that in 2005, despite the GHG intensity per unit spent (as shown in Table 1) being higher in 2015 and 2020 compared to 2005. This indicates that Japanese households may have shifted to a lower-demand lifestyle.

Specifically, after deflation, the real annual total expenditure has been decreasing over time, as shown in Figure 2. Given such a downward trend in total real household expenditure and an upward trend in GHG intensity, the decreasing total carbon footprints can be explained as a result of lifestyle change.

At the subcategory level, part of them (e.g., expenditure related to automobiles) has been increasing since 2005 and the rest of them (e.g., electricity bills) has been decreasing. The GHG intensity of the expenditure related to automobiles shows a decreasing trend, and the GHG intensity of electricity bills shows an increasing trend (See Supplementary Table 2). Thus, the changes seen in the long-term time series of 30 years can be the result of a complex combination of technological changes (changes in GHG intensity) and changes in people's lifestyles (changes in total expenditure and expenditure structures). Therefore, the decomposition of the overall changes into these factors is important.

Another aspect worth noting from Figures 1 and 2 is the carbon footprint for food expenses. Despite the continuous decrease in expenditure on food, energy-derived carbon footprints for food expenses remain

Table 2. Long-term changes in total carbon footprints per household in Japan

Unit: t-CO2-eq per household per year	1990	1995	2000	2005	2011	2015	2020
Energy derived	11.05	12.77	11.74	11.03	11.41	10.43	9.88
Methane derived				0.35	0.49	0.46	0.46
Other sources				0.41	0.69	0.60	0.60
GHG total				11.79	12.60	11.49	10.94

Notes: due to the data access, before 2000, the total carbon footprints were calculated only for carbon dioxide derived from energy sources.

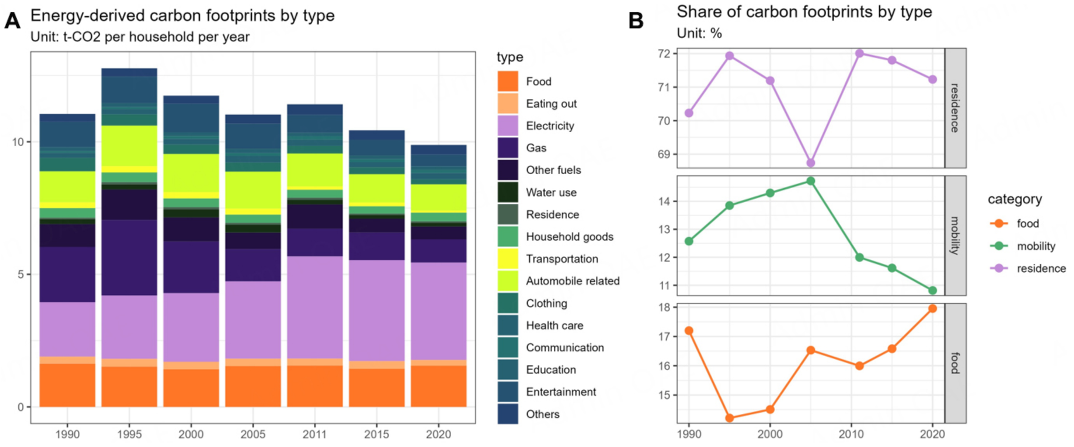

Figure 1. Long-term changes in energy-derived carbon footprints in Japan [by type in (A) and their shares in (B)].

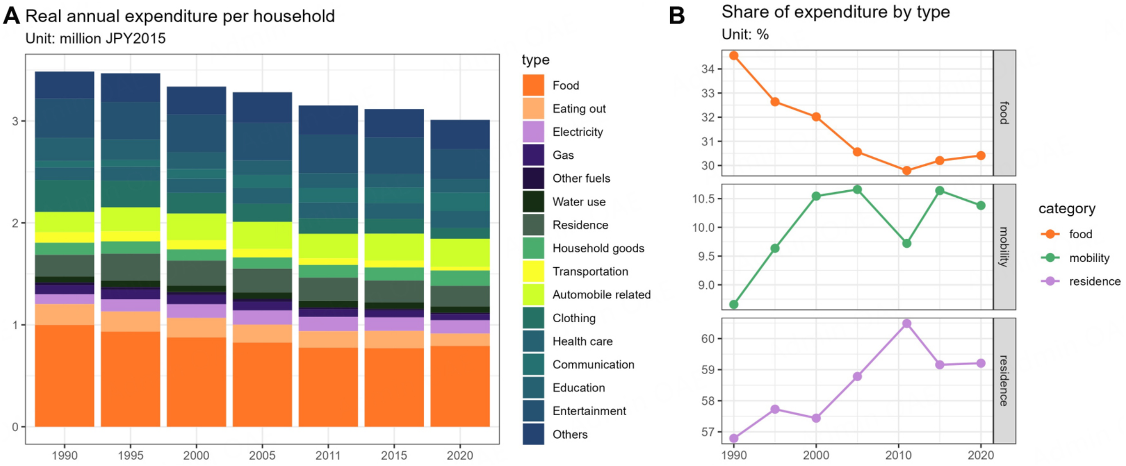

Figure 2. Long-term changes in the real annual expenditure per household in Japan (by type in (A) and their shares in (B)].

almost the same. Food expenditure per household decreased from 1995 to 2015 in both absolute values and expenditure structures, but increased slightly in 2020. This may be due to significant lifestyle changes due to the COVID-19 pandemic; however, this phenomenon requires further research. In addition, the carbon footprints from food expenses would be greatly affected by methane gas, which has been added to the calculation since 2005.

Results of the factor decomposition analysis

This section shows the results of a factor decomposition analysis of the changes in household carbon footprints in Japan during 1990-2020. Among the results of factor decomposition analysis, the subcategory results of all GHG emissions are shown in Supplementary Table 3 and the subcategory results of energy-derived CO_2 emissions are shown in Supplementary Table 4.

Figure 3 shows the decomposition results of the changes in the carbon footprints (total GHG and energy-derived CO_2 emissions) from total household expenditure during 1990-2020, including three factors (emission intensity, total consumption, consumption composition) where the factor emission intensity further divided into energy-derived, methane-derived, and other sources. The carbon footprint for electricity consumption increased in the 1990s due to lifestyle changes (changes in consumption composition), and increased again in the 2000s due to the factor of emission intensity, but decreased after 2011 due to the decrease in total consumption amount. The diminishing impact of technology improvement on the mitigation of household carbon footprints highlights a contrast with the rising contribution of lifestyle changes. Similar to the findings of Cap *et al.* in the EU, what may lie behind the decreasing technology improvement factor in Japan can be the saturation of early low-carbon technology adopters and the lower rate of efficiency improvements along with the technology maturities[38]. There are also barriers to integrating matured renewable power generation into the grid at lower costs and higher efficiency[46], as well as challenges for industries to fully utilize a greener electricity supply[47]. These factors hindered a further decarbonization in household energy consumption.

Figure 4 shows the factor decomposition of changes in carbon footprints from energy-related household expenditures. The carbon footprint from electricity consumption increased in the 1990s mainly due to lifestyle changes (changes in consumption composition). Subsequently, in the 2000s, it kept increasing significantly due to the increase in CO_2 intensity. However, after 2011, the carbon footprint from electricity consumption has been decreasing. Especially in the last five years, such a decrease was driven by both the decrease in consumption amount and the decrease in CO_2 intensity, with the former overweighing the latter factor. On the other hand, the carbon footprints from gas consumption decreased significantly from 1995 to 2005, driven by the decrease in CO_2 intensity. Since 2005, it has continued to decline because of lifestyle changes (a decrease in the consumption composition ratio). Different from the carbon footprints from electricity consumption, changes in lifestyle were the factors that drove the increase in the carbon footprints from gas consumption until 2005, but after 2005, these changes contributed to a reduction in carbon footprints. Moreover, the factor of technological change (changes in CO_2 intensity) was the main driver of the emission reduction from 1995 to 2005.

Figure 5 shows the factor decomposition of changes in carbon footprints from other major expenditures (in level 1 categorization). From the perspective of lifestyle factors, technological change factors, or both, the carbon footprints for all categories that occupy a larger share of household expenditures (food, transportation, and other leisure expenditures) have maintained a declining trend, especially since the 2000s. Among these, the transportation-related carbon footprints dropped from 2005, driven by both technology improvement and lifestyle changes. In the early 2000s, the Japanese government began incentivizing hybrid and electric vehicles, supported by tax incentives and subsidies. Initiatives such as the development of dedicated bike lanes and bike-sharing programs (e.g., "Docomo Bike Share" in major cities) contributed to a shift toward greener personal mobility. However, we can observe an exception for the increasing trend in the carbon footprints from food expenses. In particular, in the last five years, the results show that the carbon footprints in those categories have increased due to lifestyle and technological changes. In addition, Table 2 also suggests that food expenditures may be the main source of methane-derived GHG emissions.

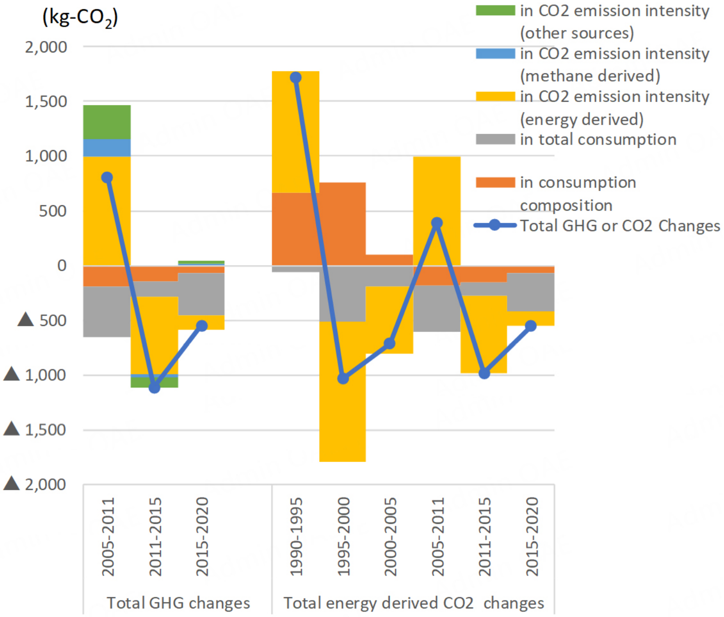

Figure 3. Factor decomposition of changes in carbon footprints from total expenditure.

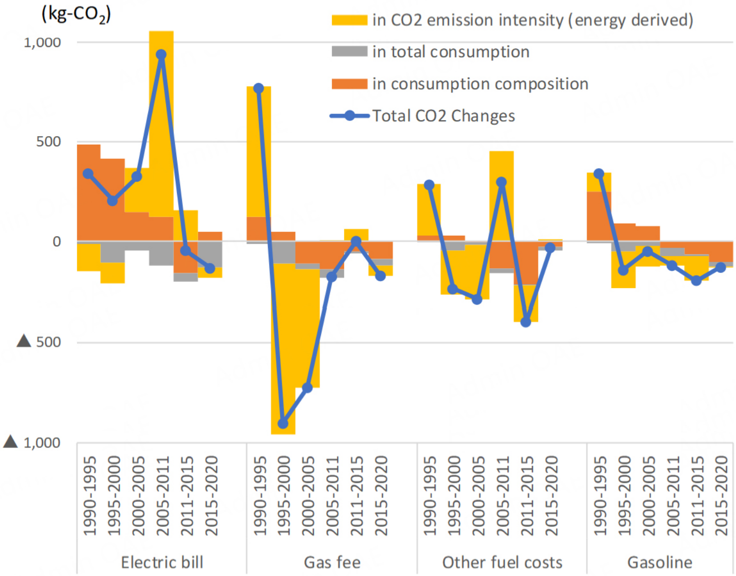

Figure 4. Factor decomposition of changes in carbon footprints from energy-related household expenditures.

Thus, we show the further decomposition results of food-related carbon footprint in Figure 6, including all GHG (including the impact of methane gas) at a more detailed level (by level 2 classification category).

The carbon footprints from most food expenditure subcategories increased during 2005-2011, mainly driven by technological factors (increased GHG intensity). Thereafter, it decreased during 2011-2015 due to the improvements in the food production technologies (decrease in GHG intensity), and subsequently, increased until 2020, mainly driven by the lifestyle change factors (increase in the consumption composition factor). Among them, the decrease in the carbon footprint from seafood expenditure was largely attributed

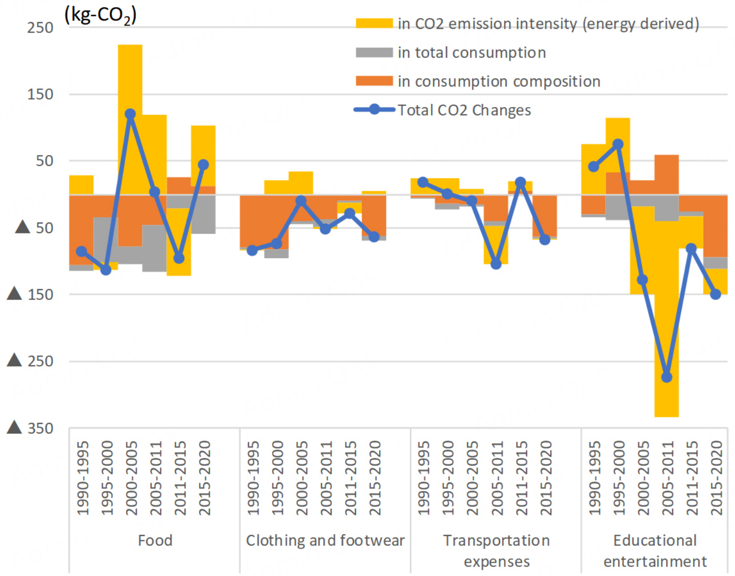

Figure 5. Factor decomposition of changes in carbon footprints from other major expenditures (in level 1 categorization).

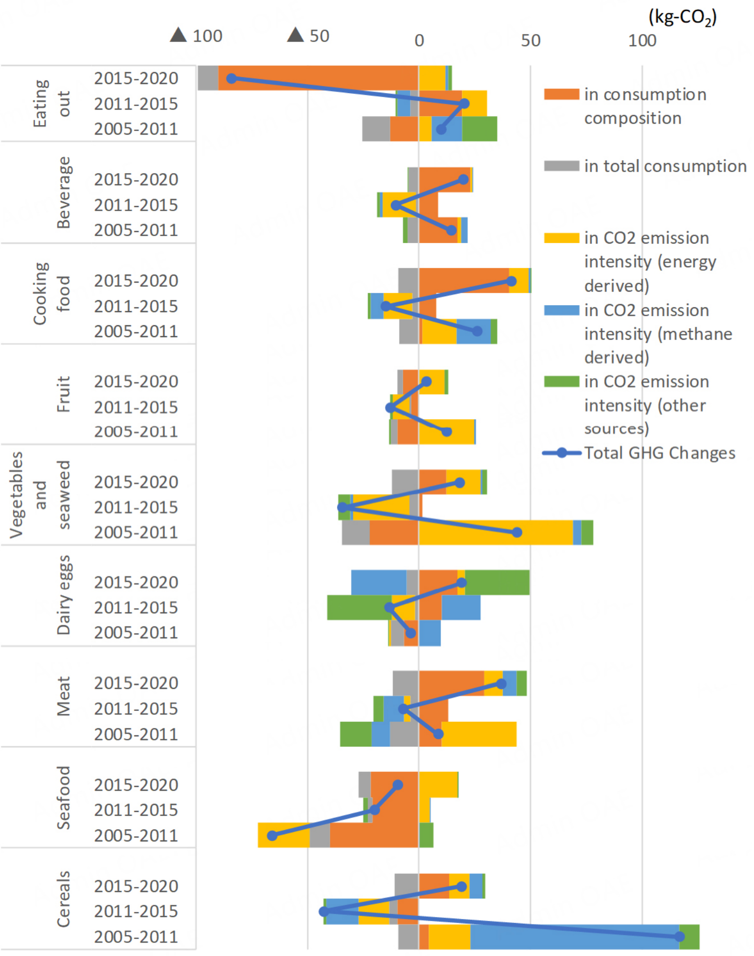

Figure 6. Factor decomposition of changes in carbon footprints from food-related expenditures.

to the consumption composition factor, whereas the increase in the carbon footprint from meat was also greatly driven by this factor. This indicates that the household consumption of seafood has not increased the overall carbon footprint, while the household consumption of meat positively contributed to the overall carbon footprint, especially in recent years. On the other hand, the carbon footprint from eating out expenditure has been increasing, driven by both technology and consumption composition factors; however, by 2020, it decreased significantly due to the decrease in consumption composition.

In summary, the carbon footprints from food expenditures increased from 2005 to 2010 due to the increase in the CO_2 emission factor (probably due to a lower share of nuclear power generation after the Fukushima accident, leading to a more emission-intensive household electricity supply). However, improvements have been observed since 2015. From 2015 to 2020, the majority of food expenditure shifted from industry foods (eating out) to homemade foods (cooking), and their carbon footprints changed accordingly. During this period, the carbon footprints of food expenditures (especially cooking) increased significantly, driven by changes in consumption patterns. The COVID-19 pandemic further influenced this shift, as household eating habits moved from eating out to eating at home. Additionally, lifestyle changes emerged, e.g., increased reliance on convenient foods. This also aligns with previous research[28,48] that the most pronounced carbon footprint shifts were linked to changes in eating habits (the large increase in eating at home). The amount reached a level that has negated those carbon footprints from other consumption categories due to lifestyle changes. What is behind the complex trend of food-related carbon footprints shown in Figure 5 might be such shifting lifestyle preferences between cooking at home and eating out.

According to Figure 5, carbon footprints from total food expenditure, especially in the most recent five years, increased due to CO_2 intensity. This can be inferred as the result of an increase in the CO_2 intensity of most subcategories, along with the increase in the shares of those subcategories in the overall food expenditure (the CO_2 intensity of cooking increased from 1.419 (g-CO_2 per JPY) in 1990, to 1.821 in 2011; decreased to 1.704 in 2015, and increased again to 1.773 in 2020). Diet shift has been suggested by multiple studies[49,50] to reduce CO_2 intensities or food-related household carbon footprints. More effective use of convenience foods has attracted attention as they can make the dining tables of the elderly and disabled more effort-saving and nutrition-rich[51] while reducing the CO_2 intensity. To enhance the domestic food supply chain and reduce emissions, measures are needed to reduce GHG intensity in the supply chain of such convenience foods. Furthermore, investing in urban food infrastructure to include cold chain logistics, together with integrating smart food services, e.g., guiding households to be more willing to use AI cooking devices, to use inventory management APPs, and to support the stores that make efforts to reduce food loss, as we found in Ita *et al.*, can further reduce emissions and food waste[52].

DISCUSSION

By investigating the long-term changes in household consumption with comparable prices, we built a database of long-term household carbon footprints. We found that a declining trend of household carbon footprints has begun to emerge, mainly driven by electrification in buildings, energy conservation behaviors, and a decrease in gasoline consumption in private mobility. Policies supporting more shared mobility options (e.g., improving urban infrastructures such as dedicated bike/walk lanes, promoting car-sharing APPs, *etc.*; both factors in the transportation category), higher standards of energy efficiencies in new buildings (the technology improvement factor in energy-related carbon footprint categories), and public awareness programs (the lifestyle change factor in leisure categories such as clothing and footwear, educational entertainment, *etc.*) can further accelerate the decarbonization of household carbon footprints.

However, a declining trend of carbon footprints from household food expenditures has not yet emerged. This is because the GHG emission intensity of food production industries in Japan is not declining, and at the same time, household food consumption behavior has shifted to a higher share of convenient food (more industrial food instead of homemade food). Policies supporting decarbonizing the food supply chain, including both ingredients for industrial food and homemade food, and supporting the smart food services that reduce food losses will be crucial.

According to Hertwich and Peters[3], food, residence, and mobility are the three major factors in GHG emissions from household consumption. The latter two factors occupy a larger share in developed countries. The study provides new findings for Hertwich and Peters[3] with evidence from Japan, especially the GHG emissions from households in the early 2000s and before. In Japan, one of the most developed countries, the share of GHG emissions from residences and mobility has been on a downward trend or decreasing in the last 10 years. In contrast, the share of GHG emissions from food expenditures did not (See Figure 2B). Carbon footprints from the consumption of food have become an important issue in Japan. We emphasize that technologies to reduce GHG emissions from consumption, especially from food supply chains, can also be essential in the next decade in developed countries. Japan's experience with lifestyle changes and technological improvements in the past 30 years did reflect its unique context. The urban density (public transport usage), adoption of digital tools, and strong energy-saving practices in households may make Japan different from other countries in a further international comparison across countries.

With the observation of a unique pattern in food-related consumption and carbon footprints in Japan, we looked into services that align with the low overall demand level but help provide households with an overall utility (or well-being) level that is still high (the concept of High-with-Low see[53,54]). The construction of information platforms using ICT and AI and the improvement of management utilizing aggregated information provided the new potential to reduce food loss, waste, and GHG emissions per unit of food production in some recent research[55]. Nakano and Washizu[51] showed that using smart food services can bring sufficient and diverse diets to households. Nakano and Washizu[56] also showed that the smart food system could bring about a new economic cycle. The contribution of such services to food-related emission reduction will be an important direction. It is also worth noting that the method we applied in this paper (factor decomposition analysis) serves the research objective well but also has its limitations. The rich nuance of lifestyle changes could be captured by more advanced econometric techniques. Our future research topic will empirically examine the contribution of a smart food service system to mitigating carbon footprints from household consumption based on such more advanced econometric models.

Other important directions that this paper was not able to sufficiently explore include the investigation across various socioeconomic groups (e.g., income levels, age groups, or regions). High-income and low-income households may have significantly different consumption patterns and lifestyles.

CONCLUSION

In this study, long-term (1990-2020) changes in household carbon footprints in Japan were calculated and the changes were decomposed into the following three factors: changes in technology structure, consumption structure, and total consumption. We found that:

The average intensity of energy-derived CO_2 emissions, which can be compared over the 30 years, peaked in 1995 and showed a downward trend until 2005, but then rose again in 2011 (possibly due to a higher share of fossil fuel power generation after Fukushima Daiichi Nuclear accident) but reduced in 2020 again. Unlike the fluctuations of low-carbon technology development, the real annual total expenditure of Japanese households has been decreasing over the 30 years, leading to a result of annual energy-derived carbon footprints per household peaking at 12.8 ton-CO_2 in 1995 and declining to 9.9 ton-CO_2 in 2020.

Among them, the carbon footprints from electricity bills are largely driven by such long-term technology changes (e.g., in Japan, before and after the Fukushima accident). Household carbon emission reduction can benefit a lot from a cleaner power generation mix.

The factor decomposition results also show that the contribution of increasingly green technologies to household decarbonization is decreasing with time. Lifestyle changes, including not only the shift to green products/services but also to a lower level in overall demand, should be paid more attention to.

Among the main types of household expenditure, a declining trend of household carbon footprints has begun to emerge in transportation options, clothing, and other leisure expenditures. Policies that can further accelerate the decarbonization of household carbon footprints include expanding shared mobility options (e.g., better bike/walk lanes and car-sharing apps), enforcing higher energy efficiency standards for new buildings, and increasing public awareness.

We also found that, unlike most developed countries, the share of GHG emissions from residences and mobility has been on a downward trend in Japan, and more importantly, the share of GHG emissions from food expenditures did not. From 2015 to 2020, the majority of food expenditure shifted from industry foods (eating out) to homemade foods (cooking), with their carbon footprints showing corresponding changes. In this period, the carbon footprints from food expenditures (especially cooking) increased significantly, driven by the consumption composition. Influenced by the COVID-19 pandemic, household eating habits have shifted from eating out to eating at home, and simultaneously, people have undergone lifestyle changes, e.g., using more convenient foods than before. Policies that facilitate the upgrading of domestic food supply chains and the promotion of smart services for decarbonizing both homemade meals and eat-out preferences will be crucial.

DECLARATIONS

Authors' contributions

Made substantial contributions to the conception and design of the study, performed data analysis and interpretation, and drafted the manuscript: Ita S, Washizu A
Performed data acquisition, as well as contributing to manuscript drafting: Ju Y

Availability of data and materials

The data that support the findings of this study are available in the Supplementary Material of this article.

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Conflicts of interest

All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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