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Driving forces underlying sub-national carbon dioxide emissions within the household sector and implications for the Paris Agreement targets in Japan

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HIGHLIGHTS

- Household CO_2 emissions in 47 prefectures of Japan were decomposed into six drivers.
- Demographics, household energy usage, and emission intensities were considered.
- Prefectural differences in driver importance were clarified for 1990–2015.
- Only seven prefectures reduced emissions through changes in energy usage.
- Local policy interventions need to consider differences among drivers to be effective.

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ABSTRACT

This study investigated insights into reducing energy-related CO_2 emissions in households by examining individual socio-economic drivers at a sub-national level. Specifically, the logarithmic mean Divisia index technique was used to decompose CO_2 emission trends into six drivers in all 47 prefectures of Japan during the period from 1990 to 2015. Drivers included the change in the number of households (household effect), distribution of households (distribution effect), household size (size effect), per-capita household energy consumption (consumption effect), household energy choice (choice effect), and sectoral CO_2 emission intensity (intensity effect). The results showed that, in contrast to size and the distribution effects, the number of households had a positive, significant effect on CO_2 emissions, indicating that recent demographic trends are responsible for the increase in CO_2 emissions observed in most of the prefectures during the study period. With regard to effects related to consumption and choice, CO_2 emissions due to changes in lifestyle dropped in only seven prefectures and reductions due to changes in sectoral energy choice were seen in only two prefectures in 2015. The intensity effect boosted the emissions of these prefectures the most in 2015 because of the shutdown of nuclear power plants due to the Great East Japan Earthquake. Further, we identified those prefectures that needed to reduce their per-capita energy consumption level in order to attain the reduction targets for household CO_2 emissions in 2030 from 2015, given projected changes in demographic trends and recent and projected emission intensities. In order to achieve reductions in total CO_2 emissions in line with the Paris Agreement, it is important to prioritize national and local policy interventions for the transfer of new household energy technologies, upgrade household appliances, and encourage people to limit energy consumption in light of the differences in these key drivers in each prefecture.

1. Introduction

Mitigation of climate change is one of the most critical global concerns. To address the issue, in November 2016, the Government of Japan ratified the Paris Agreement, which aimed to control greenhouse gas (GHG) emissions and limit the increase in global average temperature from the pre-industrial level to 2 °C by 2100. As part of its commitment to the Paris Agreement, Japan agreed to a 26% reduction

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in GHG emissions by 2030 compared to 2013 levels [1]. According to recent estimates, Japan is the fifth largest GHG and carbon dioxide (CO_2) emitter in the world [2]. Consequently, the responsibility for achieving the reduction target pledged by Japan is significant for global climate mitigation. Considerable socio-economic restructuring will be required to achieve the reduction target, as the target markedly exceeds the previous goal set out in the Kyoto Protocol (i.e., a 6% GHG emission reduction during 2008–2012 compared with 1990 levels).

Reduction of CO_2 emissions in particular should be prioritized because they account for approximately 90% of the GHG emissions generated by Japan. The structure of energy-related CO_2 emissions by sector (Scope 1 + Scope 2) is as follows. The industrial sector has been Japan's largest emitter of CO_2, but its emissions have decreased since 1990 [3]. Conversely, energy-related CO_2 emissions from the residential sector have exhibited an increasing trend in the period 1990–2013, even though the government launched initiatives such as the "Team Minus 6%" campaign which was directed at saving energy in line with the Kyoto Protocol [4]. Although residential CO_2 emissions started to decrease during 2014–2015, further reductions are considered urgent in order to satisfy the requirements of the stricter emission target (39.4% reduction by 2030 compared to the national target pledged for the Paris Agreement) [5]. In order to overcome the obstacles posed by residential sector emissions, meticulous policy measures focused on reducing emissions need to be implemented. Importantly, such measures need to consider the major socio-economic drivers governing the changes in past emissions.

This study aims to investigate how residential CO_2 emissions have varied in response to driving forces, and to examine the importance of implementing regional abatement to reduce residential CO_2 emissions in Japan, as a case of a nation which is facing a variety of demographic issues and high levels of urbanization. Japan has one of the most rapidly aging population in the world, and a very low fertility rate compared to other nations [6]. For example, the proportion of people over the age of 65 in the total population was 27.3% in 2015, while the average proportion of elderly people in other economically developed nations was 17.6% [7]. However, the degree of demographic changes within this aging society varies among prefectures. The population of the three most urbanized areas in Japan[1] accounted for 53.9% of the total population in 2015, and these populations are expected to keep increasing while those of other areas decrease [8]. On the other hand, the rate of aging is, and will remain, higher in rural prefectures than in more urbanized regions [9]. It is therefore important to assess the impact of population concentration in an aging society on changes in residential CO_2 emissions across prefectures. Further, we also aim to identify what kind of abatement should be prioritized in order to reduce the emissions by individual prefectures more effectively based on the results. However, no studies have examined trends in residential CO_2 emissions in Japan, although a few studies have been conducted on Japanese CO_2 emissions from the service sector [10] and the transport sector [11].

Index decomposition analysis (IDA) has been demonstrated as being effective in identifying the key drivers of direct environmental burdens [12]. The first application of IDA was to assess energy consumption by the industrial sector before 1980 [13]. Since then, numerous studies have examined the drivers for energy consumption and energy-related CO_2 emissions at national levels (e.g., China [14], UK [15], Spain [16], US [17], South Korea [18], Iran [19], Latvia [20], The Philippines [21], and Colombia [22]). With respect to regional differences in economic growth, energy efficiency, mix of energy resources, and demographics, some studies have attempted to compare the drivers of change in CO_2 emissions among nations or prefectures in certain areas using IDA. Ang and Goh [23] performed a comparison among ASEAN countries with respect to different drivers of carbon intensity related to electricity generation, and highlighted policy changes that should be implemented in order to reduce national CO_2 emission. Chapman et al. [24] identified the key drivers for changes in CO_2 emissions and energy portfolio trends in six Northeast Asian countries. Fernández González et al. [25] found different trends in the decomposition results for changes in CO_2 emissions by the EU27 group of nations during 2001–2008. Moutinho et al. [26] integrated 21 European countries into four groups geographically, and showed the forces driving their emissions, particularly stressing the impact of changes in the structure of the mix of means of producing energy. Román-Collado and Morales-Carrión [27] analyzed the drivers for changes in regional CO_2 emissions during 1990–2013 in groups of countries with a focus on differences in income growth and emissions in Latin America, and suggested policy changes for achieving optimal emission reduction for the drivers for each group. At the subnational level, China has mainly shed light on its vast territory, which has significant regional differences in natural resource endowments and levels of industrialization and economic development, and so differing factors driving CO_2 emissions across regions [28]. Jiang et al. [29] demonstrated how the emission reduction targets of individual provinces should be customized by considering the economic development of each prefecture and previous studies on decomposing national, regional, and provincial CO_2 emissions in China. Similarly, Li et al. [30] and Wang and Feng [31] analyzed the individual drivers for changes in energy-related CO_2 emissions for the 30 provinces in China, and found different trends in the drivers at the national and provincial levels. Wang et al. [28] examined differences in the industrial aggregate carbon intensity among the 30 provinces, and revealed that the regions with higher levels of economic development perform better.

Although fewer studies have been conducted to date than in other sectors [13], IDA has been adopted to examine the factors underlying CO_2 emissions by the residential sector. O'Mahony et al. [32] broke down residential CO_2 emissions in Ireland for the period 1990–2007 and found that improvements in energy intensity and the emission coefficient could reduce total emissions despite a significant increase in the number of households. Xu et al. [33] presented a decomposition analysis for residential CO_2 plus methane and nitrogen monoxide emissions for the period 1996–2011, as well as emissions from other final-demand sectors in China. They found that increased per-capita energy use was the dominant driver in increased emissions, and that this was due to extended life expectancy and changes in lifestyle. Donglan et al. [34] examined differences in energy-related CO_2 emissions between urban and rural residential areas in China from 1991 to 2004. They found that changes in energy intensity and income distribution played large roles in the decline in household CO_2 emissions in urban China and its increase in rural China. In addition, they showed that the effect of population on CO_2 emissions was opposite in urban and rural China. Zang et al. [35] working at the regional level, which has not yet been addressed sufficiently, highlighted the effects of urbanization and household demographics, income, and emission coefficient on CO_2 emissions in Shanxi, China from 1995 to 2004. Feng et al. [36] elucidated both national and regional CO_2 emissions associated with household consumption in China from 1952 to 2002 with respect to the effects of changes in population, household expenditures, and CO_2 emissions, using an impact, population, affluence, and technology (IPAT) framework [37]. Other studies have presented the structure of embodied (direct and indirect) CO_2 emissions associated with household consumption by structural decomposition analysis (SDA) [38] using input-output tables for the UK [39], US [40], and China [41], for example.

As shown by Donglan et al. [34] and Feng et al. [36] above, considering regional differences in population growth and rises in income level at a local scale is important for further reducing energy-related CO_2 emissions in a nation's residential sector. Xu and Ang [42] also

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[1] Based on the reference by the Ministry of Internal Affairs and Communications, the Tokyo area (Tokyo, Kanagawa, Saitama, and Chiba prefectures), Kinki area (Osaka, Kyoto, Hyogo, and Nara prefectures), and Tokai area (Aichi, Gifu, and Mie prefectures) are the most urbanized areas in Japan.

identified demographics, climate, technology, lifestyle and structure as key indicators of how residential energy consumption relates to CO_2 emissions. These indicators vary and should be therefore underpinned by regional differences when implementing emission abatement. Trends in how key drivers for energy-related CO_2 emissions differ regionally in nations other than Chin have not yet been sufficiently documented.

Against this backdrop, this study investigates how much residential CO_2 emissions are affected by changes in population and household structure, energy consumption behavior, and CO_2 emission intensity across all of Japan's 47 prefectures using IDA. To the best of our knowledge, this case study in Japan is the first attempt to highlight regional differences in drivers that strongly affect energy-related CO_2 emissions in the residential sector at a sub-national level in a developed nation. Further, we present insights for continued CO_2 emission reduction in Japan and other nations which are likely to experience similar demographic and energy trends by applying IDA to all of the regions. The reminder of this paper is organized as follows: Section 2 explains the methodology and data, Section 3 presents the results and discussion, and Section 4 concludes the paper.

2. Methodology and data

Several approaches can be used in implementing IDA to assess energy-related CO_2 emissions, including the Shapley-Sun decomposition method [43], the Laspeyres index, the arithmetic mean Divisia index (AMDI), and the logarithmic mean Divisia index (LMDI) [44,45]. In this study, we used the LMDI approach to decompose energy-related CO_2 emissions from residential sectors in the 47 Japanese prefectures in consideration of the availability of perfect decomposition (without residual terms) and the results obtained from a number of previous studies [12].

2.1. Decomposition of the household CO_2 emissions of 47 prefectures

Xu and Ang [42] proposed two major consumption units for households and energy end-uses, and posited a hybrid model combining these that can be used as an activity indicator of residential energy consumption. In Japan, growth in the total number of households has occurred more rapidly than the increase in the total population [46]. This trend varied among prefectures and occurred primarily because of an increase in one- and two-person households, combined with the effect of an aging society with fewer children [47]. Considering both changes in the population and changes in the number of households as energy consumption units is thus important when analyzing the structure of household CO_2 emissions at a prefecture level.

We selected changes in the number of households as the indicator, and decomposed the household CO_2 emissions by prefecture as follows:

$$C=\sum_{i=1}^{M}\sum_{j=1}^{N}H\frac{H_i}{H}\frac{P_i}{H_i}\frac{E_i}{P_i}\frac{E_{ij}}{E_i}\frac{C_{ij}}{E_{ij}}=\sum_{i=1}^{M}\sum_{j=1}^{N}HS_iW_iI_iV_{ij}U_{ij} \tag{1}$$

where C denotes the household CO_2 emissions by prefecture. H and H_i denote the total number of households in a prefecture, and the number of households by attribute i, respectively. P_i denotes the number of people belonging to household attribute i. E_i and E_{ij} denote the energy consumption by attribute i, and the energy consumption for energy commodity j by attribute i, respectively. C_{ij} denotes the CO_2 emissions generated from energy commodity j by attribute i. The upper summation limits M and N represent the number of household attributes and energy commodities, respectively. In this study, we defined i = 1 to 6 for six age groups (cohorts) of householders (1: ≤34, 2: 35–44, 3: 45–54, 4: 55–64, 5: 65–74, 6: ≥75) (M = 6), and j = 1 to 5 to denote five residential energy commodities (1: "kerosene," 2: "liquefied petroleum gas (LPG)," 3: "city gas," 4: "electricity," 5: "heat supply") (N = 5). There are 47 prefectures in Japan. On the right-hand side of Eq. (1), $S_i = H_i\ /\ H$ refers to the distribution of households in the prefecture (e.g., the proportion of older households to total households in a rural prefecture is more than that in an urban area). $W_i = P_i/H_i$ describes the household size (average number of people in the household). $I_i = E_i/P_i$ is the per-capita energy consumption, and $V_{ij} = E_{ij}/E_i$ refers to the energy choice (e.g., gas is used more often than kerosene as a fuel for heating households). $U_{ij} = C_{ij}/E_{ij}$ denotes CO_2 per unit of energy consumption, i.e., the CO_2 emission intensity. Note that U_{ij} for all i is the same because it is not possible to identify which energy source was used by each household. H, S_i, and W_i represent factors reflecting the impact of demographic trends, with a focus on trends in both household composition and population. I_i and V_{ij} reflect changes in consumer behavior of energy consumption. Finally, U_{ij} indicates the energy mix for the residential sector, being influenced by changes in the way energy is produced, particularly household electricity.

Based on Eq. (1), we decomposed changes in energy-related CO_2 emissions from residential sectors into six different factors by prefecture: overall number of households (household effect), distribution of householder age (distribution effect), household size (size effect), per-capita energy consumption (consumption effect), household energy choice (choice effect), and sectoral CO_2 emission intensity (intensity effect). We identified each one's effect on energy-related CO_2 emissions by prefecture using Eqs. (2)–(8) for the multiplicative decomposition approach [45].

$$D_{tot}=C^{(T)}/C^{(0)}=D_{house}D_{dist}D_{size}D_{cons}D_{choice}D_{int} \tag{2}$$

$$D_{house}=\exp\left(\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{(C_{ij}^{(T)}-C_{ij}^{(0)})/(\ln C_{ij}^{(T)}-\ln C_{ij}^{(0)})}{(C^{(T)}-C^{(0)})/(\ln C^{(T)}-\ln C^{(0)})}\ln\left(\frac{H^{(T)}}{H^{(0)}}\right)\right) \tag{3}$$

$$D_{dist}=\exp\left(\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{(C_{ij}^{(T)}-C_{ij}^{(0)})/(\ln C_{ij}^{(T)}-\ln C_{ij}^{(0)})}{(C^{(T)}-C^{(0)})/(\ln C^{(T)}-\ln C^{(0)})}\ln\left(\frac{S_i^{(T)}}{S_i^{(0)}}\right)\right) \tag{4}$$

$$D_{size}=\exp\left(\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{(C_{ij}^{(T)}-C_{ij}^{(0)})/(\ln C_{ij}^{(T)}-\ln C_{ij}^{(0)})}{(C^{(T)}-C^{(0)})/(\ln C^{(T)}-\ln C^{(0)})}\ln\left(\frac{W_i^{(T)}}{W_i^{(0)}}\right)\right) \tag{5}$$

$$D_{cons}=\exp\left(\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{(C_{ij}^{(T)}-C_{ij}^{(0)})/(\ln C_{ij}^{(T)}-\ln C_{ij}^{(0)})}{(C^{(T)}-C^{(0)})/(\ln C^{(T)}-\ln C^{(0)})}\ln\left(\frac{I_i^{(T)}}{I_i^{(0)}}\right)\right) \tag{6}$$

$$D_{choice}=\exp\left(\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{(C_{ij}^{(T)}-C_{ij}^{(0)})/(\ln C_{ij}^{(T)}-\ln C_{ij}^{(0)})}{(C^{(T)}-C^{(0)})/(\ln C^{(T)}-\ln C^{(0)})}\ln\left(\frac{V_{ij}^{(T)}}{V_{ij}^{(0)}}\right)\right) \tag{7}$$

$$D_{int}=\exp\left(\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{(C_{ij}^{(T)}-C_{ij}^{(0)})/(\ln C_{ij}^{(T)}-\ln C_{ij}^{(0)})}{(C^{(T)}-C^{(0)})/(\ln C^{(T)}-\ln C^{(0)})}\ln\left(\frac{U_{ij}^{(T)}}{U_{ij}^{(0)}}\right)\right) \tag{8}$$

where the superscripts T and 0 indicate the target year and base year, respectively. Due to limitations in data availability, the target years for analysis were set as 1990 (T = 0), 1995 (T = 1), 2000 (T = 2), 2005 (T = 3), 2010 (T = 4), and 2015 (T = 5). D_{tot} represents the ratio of the total CO_2 emissions in year T to that in the base year. D_{house}, D_{dist}, D_{size}, D_{cons}, D_{choice}, and D_{int} denote the household effect, distribution effect, size effect, consumption effect, choice effect and intensity effect, respectively. Those effects and D_{tot} always take positive values. Ratios higher (lower) than unity for the household effect, size effect, consumption effect, and intensity effect indicate an increase (decrease) in the number of households, household size, and per-capita energy consumption. Ratios higher (lower) than unity for the distribution effect and choice effect imply shifts towards an increase (decrease) in the proportion of carbon-intensive households and energy commodities used in households, respectively. Finally, ratios higher (lower) than unity for the intensity effect generally imply an increase (decrease) in the share of fossil fuels used in electricity generation.

Table 1
Demographic and energy statistics for Japan in 1990–2015.

	Year					
	1990	1995	2000	2005	2010	2015
Total number of households [$\times 10^3$ households]	40,670	43,900	46,782	49,063	51,017	52,154
Total population [$\times 10^3$ people]	1,21,545	1,23,646	1,24,725	1,24,973	1,24,573	1,22,858
Fraction of households aged ≤ 34 years [%]	20.5	20.8	20.3	18.6	16.1	14.7
Fraction of households aged 35–64 years [%]	74.2	72.7	71.2	70.1	69.8	68.6
Fraction of households aged ≥ 65 years [%]	5.4	6.5	8.4	11.3	14.1	16.7
Average household size [people]	2.99	2.82	2.67	2.55	2.44	2.36
Per-capita energy consumption [GJ/y]	16.7	19.8	20.7	21.9	21.1	17.5
Fraction of energy provided by electricity [%]	53.2	54.5	55.2	58.5	62.0	61.7
Fraction of energy provided by LPG and city gas [%]	25.0	23.7	23.2	20.3	20.4	22.6
Fraction of energy provided by kerosene and heat [%]	21.8	21.8	21.6	21.2	17.7	15.7

2.2. Dataset

H for each year was retrieved from the national population statistics database [46]. The other demographic data, H_i and P_i, were calculated using Population Census data and consumer expenditure survey data [48] as follows. The NSFIE describes monthly consumption expenditures for energy commodity k (“gas”, “electricity”, “other heating costs”) per household for household attributes according to the age of the householder. The total number of households in the NSFIE is inconsistent with H, because the former values are based on survey data. H_i could therefore be determined by multiplying the number of households in the NSFIE by H, as follows:

$$H_i = H \times \frac{h_i}{\sum_{i=1}^{M} h_i} \tag{9}$$

where h_i denotes the number of household attributes i in the NSFIE. P_i was estimated using Eq. (10), because the summed product of H_i and the average household size by attribute, s_i, $\sum_{i=1}^{M} H_i s_i$, is inconsistent with the total population, P, in the Population Census of Japan (2016).

$$P_i = P \times \frac{H_i s_i}{\sum_{i=1}^{M} H_i s_i} \tag{10}$$

In order to determine E_i and E_{ij}, we calculated the annual market share of energy item k among households in each prefecture from the NSFIE (e.g., households with inhabitants ≥ 65 years-old are more likely to purchase electricity than households with inhabitants aged 35–44 years-old in Tokyo), as shown by

$$Q_{ik} = \frac{H_i e_{ik}}{\sum_{i=1}^{M} H_i e_{ik}} \tag{11}$$

where e_{ik} denotes the consumption expenditure for energy item k by attribute i in the NSFIE. Then, we obtained the market share of energy commodity j, Q_{ij}, from Q_{ik}, by associating “gas,” “electricity,” and “other heating costs” with “liquefied petroleum gas (LPG)” and “city gas,” “electricity,” and “kerosene” and “heat,” respectively. Data for the amount of energy consumed (E_j) and the relative CO_2 emission intensity (U_j) for commodity j were obtained from the energy statistics (Energy Consumption Statistics by Prefecture). E_{ij} was calculated by multiplying E_j by Q_{ij}. Thus, E_i represents $\sum_{j=1}^{N} E_{ij}$. U_{ij} is assumed to be equal to U_j.

2.3. Demographic and energy consumption trends during 1990-2015

Here we demonstrate the trends in the drivers for all prefectures (i.e., at a national level) during the period 1990–2015. As shown in Table 1, the total number of households increased continuously until 2015, even though the total population started declining after 2005. Due to increased age and decreased fecundity, the proportion of households with householders aged ≤ 34 and 35–64 decreased by 5.8% and 5.6%, respectively. On the other hand, the proportion of households with householders aged ≥ 65 increased from 5.4% to 16.7% from 1990 to 2015. Reflected in these demographic trends is a decrease in the average household size, which shifted from 2.99 to 2.36 people, a decrease of about 21%. Conversely, per-capita consumption of energy increased from 1990 to 2005, before decreasing slightly in 2010, partly because of the global economic crisis during 2007–2009. In 2015, per-capita energy consumption decreased again by 17.5 GJ/y, although this was still 5.0% higher than in 1990. This large decrease from 2010 levels was likely influenced by changes in people’s perceptions of energy-saving measures after the Great East Japan Earthquake in 2011 [49]. Thus, compared to 2005, the way in which people used household energy in Japan appeared to improve with respect to energy consumption. Interestingly, in terms of household energy composition, electricity became more widely used, and other energy sources, such as gas, kerosene, and other heating use declined. This trend implies that kerosene, which used to be popular for heating, was being replaced by heaters using LPG and city gas. Moreover, compared to gas heaters, electric appliances, such as heaters and air-conditioners, have become more pervasive in recent decades.

2.4. Estimation of future consumption effect for each prefecture in 2030

The Government of Japan committed to a 39.4% reduction in household CO_2 emissions by 2030 compared to 2013 levels, as part of the Paris Agreement [5]. This target can be translated to mean a 32.0% reduction compared to 2015 levels. For this reduction target, we used the IDA described in Section 2.1 to examine how much each prefecture should reduce its household CO_2 emissions on a per-capita basis under the following three extreme conditions.

First, we assumed that all prefectural CO_2 emissions will be reduced by 32.0% in 2030 compared to 2015 levels. We then estimated the size of the total population and age of householders in each prefecture for each year until 2035 [50]. The demographic data were capable of estimating the household effect, distribution effect, and size effect for the period 2015–2030. Next, we assumed that household energy choice among prefectures will be constant. In other words, the choice effect is 1 for all prefectures in 2015–2030.

In order to estimate future CO_2 emission intensities, we considered the following three cases. The first, or “outlook case,” assumes the emission intensity based on the future composition of electricity generation in 2030 that is predicted to meet the emission reduction target for the Paris Agreement in the Long-term Energy Supply and Demand Outlook [51]. According to the outlook, renewable energy technologies such as photovoltaic generation will grow to 22–24%, resulting in a lower CO_2 emissions due to electricity generation in 2030 than in 2013. The emission intensity can be approximated to be 2.56×10^{-3} t-CO_2/GJ.[2] We therefore replaced the emission intensity associated with

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[2] The amount of electricity generation and the amount of its CO_2 emissions

electricity generation in 2015 among prefectures with this value under the assumption that all of the regions' electricity generation composition would be the same. In addition, we also assumed that the electricity generation methods employed in 2030 would be the same as the methods employed in 2010 ("2010 case") and 2015 ("2015 case"). This is because we want to examine the impact of the drastic change in the composition of electricity generation due to the shutdown of almost all nuclear power plants since 2011, based on those two years. Thus, the intensity effects between 2015 and 2030 were determined based on the emission intensity for the three different methods of electricity generation and those for kerosene, LPG, city gas, and heat in 2015. Finally, we estimated the consumption effect using the values of the other effects and CO_2 emissions in 2015–2030 based on Eqs. (2)–(8).

2.5. Limitations of this study

This study has the following limitations due to the lack of data that can be applied to the above methodology. One limitation was a discrepancy in the timescales used for the demographic data and energy data. NSFIE data and Population Census data are published every five years, while Energy Consumption Statistics by Prefecture data are available annually. We also assumed that data for the market shares of energy commodities between 1994 and 2014 were equal to those between 1990 and 2015. Specifically, we used the NSFIE in 1994, which is the oldest available data source, to explain the market shares in 1990. In addition, we obtained consumption expenditures for energy commodities for households with two or more people on the NSFIE. In other words, I_{ij} and V_{ij} do not reflect the consumption patterns of energy commodities in one-person households in each prefecture.

It is also essential to take into account not only Scopes 1 and 2 but also Scope 3 for CO_2 emissions generated through supply chains associated with household consumption (i.e., household carbon footprint [52]) at the regional level in order to examine further opportunities to reduce emissions. Examining the differences in the key drivers for household carbon footprint at the sub-national level using structural decomposition analysis could extend the perspectives of this study, although the data limitation should be overcome (i.e., time-series of embodied emission intensity at the prefectural level are not available).

Finally, for estimating future consumption effects by prefecture in 2030 under projected demographic trends, we assumed that the choice effect will not change from 2015 to 2030. This implies that people's preferences for household energy would not change, perhaps because energy prices and technologies were constant in 2015. Macroeconomic policies and conditions such as quantitative easing and deflation could affect energy prices and people's income, which may result in changes in household energy usage that contribute to the consumption and choice effects. However, this study does not consider these exogenous factors due to the difficulty of estimation based on rigid evidence.

3. Results and discussion

3.1. Drivers of changes in household CO_2 emissions in Japan from 1990–2015

Fig. 1 shows the time-series impact of the six factors examined in this study on changes in total CO_2 emissions for Japanese households for the period 1990–2015, quantified using the LMDI. The results show that total household CO_2 emissions in Japan increased in all of the targeted periods except in 2005–2010. Changes in the number of households (household effect) have continued to increase CO_2 emissions since 1990. In contrast, changes in household size (size effect) and the distribution of households (distribution effect) contributed to a sustained decrease in CO_2 emissions, which is likely due to the influence of recent demographic trends such as an increase in one-person households and a reduction in household size due to an aging society with fewer children. Changes in per capita energy consumption (consumption effect) as well as the household effect were important drivers underlying the increase in CO_2 emissions until 2005. However, subsequently, CO_2 emissions due to the consumption effect dropped from 2005 to 2015, implying that households attempted to save energy and use more energy-efficient appliances. As mentioned above, household energy savings were likely affected by changes in consumer behavior in response to the financial crisis in 2008 and the Great East Japan Earthquake in 2011. Changes in sectoral energy choice (choice effect), the decision of which household energy commodity people are likely to use, contributed to increases in CO_2 emissions from 1990, but these were relatively small. In other words, household energy efficiency did not improve through changes in energy resource consumption and their associated CO_2 emission intensities. Finally, changes in sectoral CO_2 emission intensity (intensity effect) boosted CO_2 emissions after 2000, mainly because the emission intensity for electricity started to increase from that time. The intensity effect was the largest driver for CO_2 emissions in 2015, mainly because all of Japan's nuclear power plants were taken off-line in 2011 due to the Great East Japan Earthquake. As a result, dependency on fossil fuels increased rapidly.

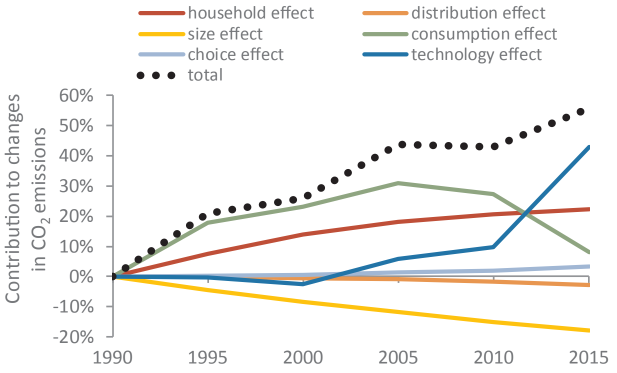

Fig. 1. Decomposition of energy-related CO_2 emissions from households and driving forces from 1990 to 2015 compared with 1990 levels.

3.2. Regional trends in household CO_2 emission between 1990 and 2015

None of the prefectures' CO_2 emissions dropped to levels lower than in 1990 during 1995–2015, even though 2015 was three years after the target date proposed by the Kyoto Protocol. Fig. 2(a) shows changes in the proportion of emissions by prefecture between 1990 and 2015. Among the 47 prefectures, Fukui, Ishikawa, Shiga, Ehime, and Tokushima Prefectures showed the largest emission increases of 102, 98.6, 91.4, 85.6 and 81.8%, respectively (Fig. 2(a)). Conversely, changes in emissions from Nagano, Shimane, Okinawa, Yamanashi, and Mie Prefectures were the lowest at 19.9, 25.9, 27.3, 29.5, and 33.0%, respectively. Thus, the difference in the proportion of increases in emissions between Fukui (the highest) and Nagano (the lowest) was more than fivefold.

Let us now elaborate on the breakdown of household CO_2 emissions by prefecture in 1990–2015, as shown in Fig. 2(b)–(g) (retrieved from the results for 2015 in Fig. A2). The household effect by prefecture (Fig. 2(b)) had a positive and significant effect on CO_2 emissions in all prefectures, especially in Okinawa (49.6%), Shiga (47.4%), Saitama (42.1%), Chiba (39.1%), and Aichi (37.4%). These results clearly showed the impact of household density on CO_2 emissions, particularly

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(footnote continued)
are estimated to be approximate 1.065 trillion kWh and 360 million t-CO_2/y, respectively [51]. The national emission intensity due to electricity generation in 2010 and 2015 were 3.43×10^{-3} t-CO_2/GJ and 2.39×10^{-3} t-CO_2/GJ, respectively. Therefore, the estimated intensity is between the values for 2010 and 2015.

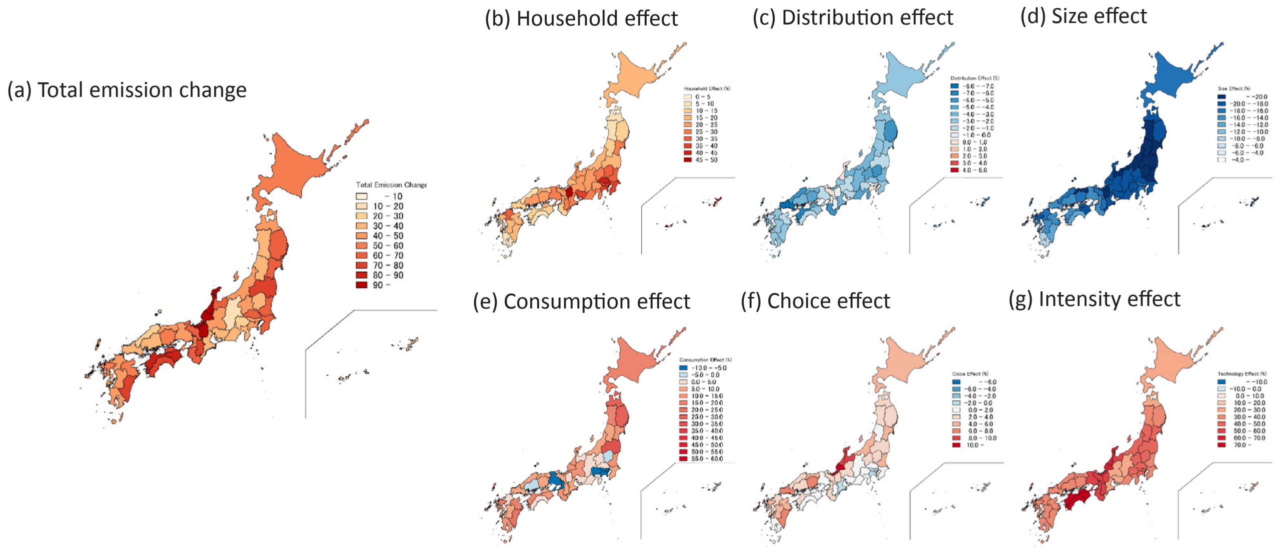

Fig. 2. (a) Changes in total household CO_2 emissions by prefecture in 1990–2015 and impacts of the six study factors on household CO_2 emissions by prefecture in 1990–2015: (b) household effect, (c) distribution effect, (d) size effect, (e) consumption effect, (f) choice effect, and (g) intensity effect.

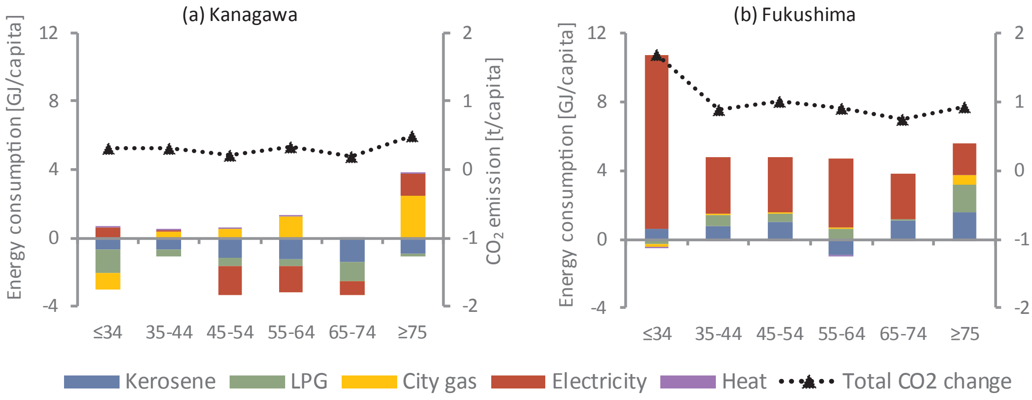

Fig. 3. Changes in the per-capita energy consumption for different energy sources and per-capita CO_2 emission between 1990 and 2015 in (a) Kanagawa and (b) Fukushima.

in Shiga, Saitama, and Chiba, which have been developed as “bedroom communities” for workers in the urban prefectures of Tokyo and Osaka. Aichi is one of the most economically powerful prefectures in Japan, and its population and number of households have been increasing [46]. These trends imply that CO_2 emissions will likely increase, not only in the heavily urbanized regions, but also in the surrounding suburban prefectures as they experience rapid population concentration. Although Okinawa is not an economically urbanized prefecture, it is the only prefecture that has undergone a natural increase in its number of households and its population. In contrast, the distribution effect by prefecture (Fig. 2(c)) caused decreasing CO_2 emissions in all prefectures except Ishikawa (0.8%), Kanagawa (0.3%), and Kyoto (0.1%), although the increase in emissions from these three prefectures was negligible. The largest decrease due to the distribution effect was apparent in Yamaguchi Prefecture (−7.2%), followed by Ehime (−6.3%), Shimane (−5.3%), Tochigi (−5.2%), and Iwate (−5.2%) Prefectures. There was no large difference in the degree of increase in young (≤34 years-old) and elderly (65–74 and ≥75 years-old) households compared to other prefectures. These trends were generally reflected in the size of the drop in middle-aged households (35–44, 44–54, and 55–64 years old), which were likely to consume more energy due to their high income and household size compared to other households. Examining the household size effect by prefecture (Fig. 2(d)), it can be seen that CO_2 emissions decreased in all prefectures. The most marked size effect was observed in Yamagata Prefecture (−22.1%), followed by Fukushima (−22.0%), Akita (−21.7%), Miyagi (−21.3%), and Niigata (−21.3%) Prefectures. While Fukushima ranked 15th lowest in 2010 compared to 1990 levels, its large drop by 2015 was likely attributable to a decrease in young and middle-aged households with children after the Fukushima nuclear power plant accident. Nearly 50,000 mostly younger people living in Fukushima moved to other prefectures after the accident [53], markedly decreasing its average household size between 2010 and 2015.

The largest consumption effect by prefecture (Fig. 2(e)) was observed in Fukushima Prefecture (33.2%), followed by Iwate (29.5%), Aomori (29.0%), Miyazaki (24.2%), and Akita (18.7%) Prefectures. Most prefectures experienced an increase in their CO_2 emission due to the consumption effect. Prefectures in the Northeast region (where the five listed above are located) were marked higher than prefectures in other regions. However, there were seven prefectures where the consumption effect caused a reduction in CO_2 emissions in 1990–2015. For example, Kanagawa Prefecture reduced CO_2 emissions by −9.9%, followed by Yamanashi (−7.7%), Tokyo (−7.6%), Hyogo (−5.9%), and Osaka (−5.8%). Importantly, most of these prefectures are in the most urbanized areas in Japan. In order to investigate the consumption effect, we compared the results obtained for Kanagawa and Fukushima Prefectures, which have the lowest and highest contributions from the consumption effect, respectively. Fig. 3 shows a breakdown of the changes in both per-capita energy consumption and total CO_2 emissions for each household attribute between 1990 and 2015 in (a) Kanagawa and (b) Fukushima Prefectures. For Kanagawa Prefecture, the per-capita energy consumption for most of the attributes decreased, except in ≥75-year-old households. This trend is mainly associated with a decrease in kerosene and LPG consumption and an increase in city gas consumption. A reduction in electricity consumption was observed among three age cohorts of householders (35–44, 45–54, and 65–74 years-old). The ≤34 and 65–74 year-old households could decrease city gas consumption by using electricity. The contribution of lifestyle changes for these age groups was therefore considered to be relatively small. On the other hand, in Fukushima Prefecture, among all of the household attributes examined, the per-capita energy consumption increased, mainly due to an increase in electricity consumption and a decrease in the average household size. However, this trend was already observed between 1990 and 2010 in this prefecture, as well as in Iwate and Miyagi Prefectures, which were the most seriously damaged by the Great East Japan Earthquake in 2011. Thus, the earthquake did not have a negative impact on electricity consumption in the prefectures affected by the earthquake.

We next turn to the choice effect by prefecture (Fig. 2(f)). CO_2 emissions increased in Fukui (12.7%), Toyama (9.4%), Ishikawa (9.2%), Okayama (6.8%), and Yamaguchi (6.8%), but choice also contributed to a slight reduction in emissions in two prefectures (Okinawa and Mie). The increase in the range of emissions by prefecture due to the choice effect, however, was quite small compared to the consumption effect. Finally, the results obtained for the intensity effect by prefecture (Fig. 2(g)) showed an increase in CO_2 emissions in all prefectures, especially in Kagawa (77.6%), Kochi (77.0%), Tokushima (76.0%), Ehime (74.0%), and Fukui (69.0%). This is mainly dependent on the regional characteristics of electric power generation by electricity companies in the regions they serve. While the contributions of the other effects on emissions were not marked, total emissions for Fukui, Kagawa, Tokushima, and Ehime Prefectures showed the highest growth due to the intensity effect.

3.3. Potential for reducing household CO_2 emissions through lifestyle changes and changes in demographic trends

Of the six factors that contribute to household CO_2 emissions (Fig. 2), the consumption effect and the choice effect depend on consumer behavior in household energy usage. On the other hand, the household effect, the distribution effect, and the size effect represent exogenous impacts of demographic trends on emissions in the prefectures, implying that it would be quite difficult to control those effects by implementing policy changes and changing consumer behavior. Further, the intensity effect is influenced largely by the structure of electric power generation in a region. We therefore attempted to identify which prefectures succeeded in mitigating household CO_2 emissions in 1990–2015 by adopting “greener” consumer behavior, i.e., through exogenous factors, such as changing demographic trends and/or the structure of power generation.

Table 2 summarizes the impact of changes in demographic trends (household effect × distribution effect × size effect) and lifestyle shifts (consumption effect × choice effect) on household CO_2 emissions by prefecture. “Region” in Table 2 refers to the main areas of Japan, which are mostly serviced by one large electricity company. As shown in column (a) in the table, the household CO_2 emissions in 33 prefectures, i.e., 70% of all prefectures, declined in 2015 compared with 1990 levels due to demographic trends. Interestingly, CO_2 emissions increased in some prefectures (e.g., Kyoto and Nara), even though their populations declined. On the other hand, CO_2 emissions increased markedly in most prefectures with economic centers, such as Tokyo, Kanagawa, Aichi, Fukuoka, and Osaka. Furthermore, CO_2 emissions rose considerably in prefectures with “bedroom communities” that service adjacent economic centers (e.g., Shiga, Saitama, and Chiba Prefectures). It is therefore essential for the inhabitants of these prefectures to further reduce their CO_2 emissions by implementing energy-saving behavior and improving energy efficiency, as they are most likely to absorb immigrants from other prefectures (even though the total population in Japan is shrinking). As for the impact of changes in lifestyle (column (b) in Table 2), only seven prefectures – Kanagawa, Tokyo, Yamanashi, Hyogo, Okinawa, Osaka, and Hiroshima Prefectures – decreased their CO_2 emissions. In other words, 85% of prefectures did not succeed in achieving a less energy-intensive lifestyle compared to 1990. Overall, CO_2 emissions by prefecture in northern Japan (e.g., those in the Hokkaido and Tohoku regions) tended to increase markedly compared to other regions, which was particularly evident for Fukushima, Iwate, and Aomori. Commuter prefectures also increased their CO_2 emissions, reflecting a developing demographic trend, implying that it will become more important for those prefectures to mitigate increases in emissions associated with lifestyle shifts by improving consumption activities related to increased immigration. Finally, there are prefectures whose CO_2 emissions are larger than 1990 levels due to the impact of demographic trends of lifestyle shifts shown in column (c) in Table 2 (i.e., column (a) × (b)); these include Kanagawa, Tokyo, Okinawa and Osaka. This implies that the efforts implemented by these prefectures to mitigate their CO_2 emissions were negated by increases in both household number and population. Thus, for the other prefectures, declines in CO_2 emissions associated with lifestyle shifts and their effect on energy usage would be negated due to general changes in demographic trends. A drastic reassessment of household energy consumption is therefore required in most prefectures in Japan.

3.4. Consumption effect requirements in prefectures to achieve emission reduction targets based on the Paris Agreement by 2030

Finally, we estimated the consumption required to attain the reduction targets for household CO_2 emissions in 2030 compared to 2015 levels (−32.0%), given projected changes in demographic trends and recent and projected emission intensities. With respect to the trajectories of demographic trends projected by the Population Census, both the population and household composition are projected to decrease in all prefectures. Fig. 4 depicts the range of consumption effects necessary to achieve emission reduction targets by prefecture in accordance with the “2010 case,” the “2015 case,” and the “outlook case.” In the figure, diamond and circular symbols indicate the required consumption effect when the emission intensity for electricity generation is based on the 2010 and 2015 levels, respectively. Green lines denote the required consumption effect from the Long-term Energy Supply and Demand Outlook. If the value of the required consumption effect is positive in the figure, the per-capita energy consumption needs to be reduced from the 2015 level to meet the reduction target. On the other hand, the reduction target would be achieved in prefectures in which the value of the required consumption effect is negative, even if their per-capita energy consumption is assumed to be constant at the 2015 level.

In the event that emission intensities in 2030 are the same as those in 2010 (the “2010 case”), the values obtained for the consumption effect are expected to be negative for most prefectures. The prefectures would therefor achieve their emission reduction targets even if per-capita energy consumption does not change from its 2015 level. It should be noted that the 11 prefectures (e.g., Hiroshima, 34 in Fig. 4) in which the emission intensity for electricity generation did not change much between 2010 and 2015 are required to make efforts to decrease their consumption effect even if their emission intensity in 2030 is identical to the 2010 level. In contrast, the values of the consumption effect are positive in all prefectures except for Akita (-2.9%), when we assume an emission intensity in 2030 equal to that in 2015 (i.e., intensity effect = 1) (“2015 case”). This implies that the reduction target could not be achieved only through the expected decreases in demographic trends, even in those prefectures that experienced a decrease in household number and population in 2015.

Table 2
Contributions of demographic trends and lifestyle shifts (from 1990) to energy-related CO_2 emissions from households in 2015.

Pref. no.	Region	Prefecture	(a) Demographic trend	(b) Lifestyle shift	(c) (a) × (b)
			Emissions	Emissions	Emissions
1	Hokkaido	Hokkaido	-2.8%	23.1%	**19.6%**
2	Tohoku	Aomori	-13.3%	**32.7%**	15.1%
3		Iwate	-13.7%	**34.6%**	16.3%
4		Miyagi	-1.0%	17.8%	16.6%
5		Akita	-18.9%	22.0%	-1.0%
6		Yamagata	-13.6%	9.8%	-5.1%
7		Fukushima	-10.0%	**36.4%**	**22.8%**
8	Kanto	Ibaragi	0.2%	18.9%	19.1%
9		Tochigi	-2.5%	1.3%	-1.3%
10		Gunma	-3.6%	7.3%	3.5%
11		Saitama	**10.9%**	4.8%	16.3%
12		Chiba	10.4%	7.7%	18.9%
13		Tokyo	**12.3%**	-7.8%	3.6%
14		Kanagawa	**13.9%**	-10.1%	2.4%
15		Yamanashi	-3.2%	-6.0%	-9.0%
16	Hokuriku	Niigata	-10.2%	12.7%	1.2%
17		Toyama	-7.8%	9.9%	1.3%
18		Ishikawa	-1.2%	20.8%	19.4%
19		Fukui	-7.2%	**28.7%**	**19.4%**
20	Chubu	Nagano	-6.3%	6.4%	-0.3%
21		Gifu	-2.7%	17.0%	13.9%
22		Shizuoka	-3.9%	5.7%	1.5%
23		Aichi	9.7%	0.6%	10.4%
24		Mie	0.2%	6.7%	7.0%
25	Kinki	Shiga	**16.3%**	7.6%	**25.2%**
26		Kyoto	2.8%	8.6%	11.7%
27		Osaka	4.9%	-3.8%	0.8%
28		Hyogo	4.6%	-5.5%	-1.2%
29		Nara	3.1%	11.7%	15.2%
30		Wakayama	-9.5%	13.7%	2.9%
31	Chugoku	Tottori	-8.6%	15.3%	5.4%
32		Shimane	-14.5%	8.4%	-7.3%
33		Okayama	-3.0%	14.6%	11.1%
34		Hiroshima	-1.1%	-0.5%	-1.6%
35		Yamaguchi	-13.1%	14.9%	-0.1% -0.1%
36	Shikoku	Tokushima	-8.5%	12.8%	3.3%
37		Kagawa	-8.0%	9.6%	0.8%
38		Ehime	-10.6%	19.3%	6.7%
39		Kochi	-7.5%	6.3%	-1.7%
40	Kyushu	Fukuoka	5.6%	3.7%	9.5%
41		Saga	-5.3%	22.1%	15.6%
42		Nagasaki	-9.7%	16.1%	4.8%
43		Kumamoto	-1.3%	10.7%	9.2%
44		Oita	-2.9%	22.3%	18.7%
45		Miyazaki	-1.2%	**32.4%**	**30.8%**
46		Kagoshima	-5.5%	13.6%	7.3%
47	Okinawa	Okinawa	**13.4%**	-4.6%	8.2%

The five highest and lowest values are shown in bold and shaded grey, respectively.

Finally, if the emission intensity in 2030 projected by the Government of Japan (“outlook case”), consumption effect values are positive in 24 prefectures. Therefore, it is imperative that those prefectures encourage consumers not only to review their household energy usage but also to introduce more energy-efficient goods to lower their energy consumption. In particular, Aichi (17.3%), Shiga (16.9%), Kanagawa (14.9%), Tokyo (13.6%), Mie (9.8%), Saitama (9.6%), and Chiba (9.5%), each with a 10% or more reductions in the consumption effect, need huge efforts to improve their household energy usage. Aichi, Kanagawa, and Tokyo Prefectures, however, showed a very small increases or even decreases in their CO_2 emissions due to the consumption effect during 1990–2015, as shown in Fig. 2. This implies that it is necessary especially for those prefectures to review their household energy usage to lower consumption but also to prioritize the penetration of greener electricity generation systems, particularly renewable energy beyond the target considered by the government.

4. Conclusion and policy implications

This study examined six socio-economic drivers for energy-related CO_2 emissions from households in the 47 prefectures of Japan since 1990 using index decomposition analysis. Firstly, we identified how recent demographic changes in Japanese households (the household effect, household distribution effect, and household size effect) contributed to CO_2 emissions within prefectures, as these factors are almost impossible to regulate through initiatives focusing on policy or

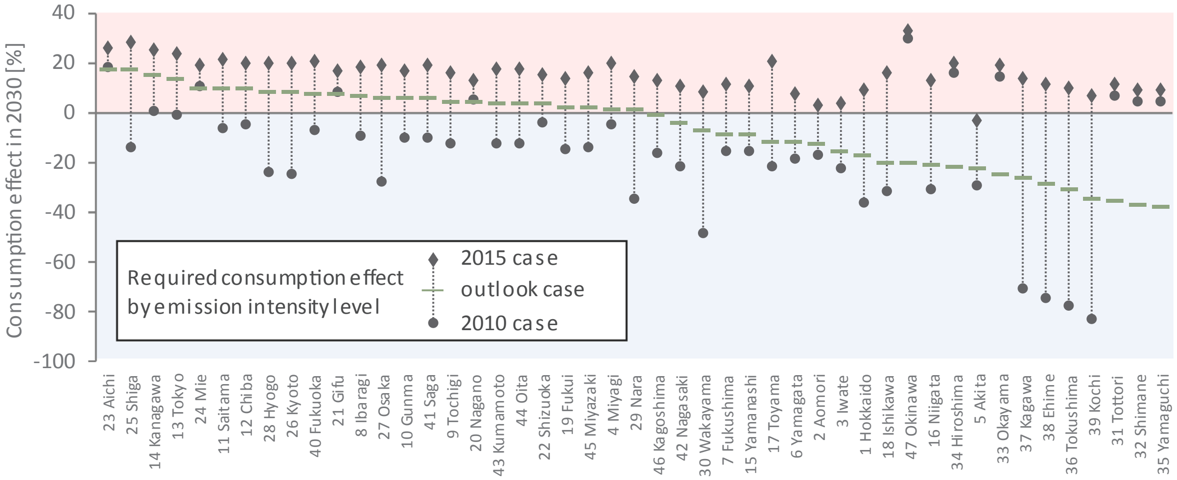

Fig. 4. Consumption effect by prefecture required to achieve emission reduction targets based on the Paris Agreement by 2030. Black diamond and circular symbols and green lines represent the consumption effect value for each prefecture owing to the emission reduction target in line with the Paris Agreement based on the emission intensity levels for the "2010 case," "2015 case," and "outlook case," respectively. Values less than 0 (blue) imply that there is a surplus of per-capita energy consumption from 2015 available for achieving the reduction target. Positive values (red) imply that the consumption effect should be reduced to achieve the reduction target. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

consumer activities. As shown in the results and discussion section, between 1990 and 2015, demographic trends have accelerated increases in total CO_2 emissions. Since the total number of households is projected to keep increasing until 2020, it is essential to consider the impact of future demographic trends on CO_2 emissions, even though the total population has already decreased from 2011 levels [50]. Specifically, we showed that demographic trends in the heavily urbanized regions and "commuter prefectures," or bedroom communities, were responsible for driving CO_2 emissions increases, and also that emissions in more than half of all prefectures decreased. On the other hand, for changes in energy usage (the consumption effect and choice effect) brought about by changes in policy related to CO_2 emissions, only seven of the 47 prefectures showed emission decreases. This implies that even the positive contribution of changes in energy usage to emission reduction was canceled out by the negative impact of demographic trends in heavily urbanized regions like Tokyo. For example, despite the largest reduction of 10.1% due to changes in energy usage in Kanagawa Prefecture, its demographic shifts increased CO_2 emissions by 13.9%. Similarly, while the largest contribution of demographic trends decreasing CO_2 emissions was 18.9% in Akita Prefecture due to high population outflows and a dominance of older households, energy usage patterns in the prefecture increased CO_2 emissions by 22.0% during the same period. These differing trends among prefectures demonstrate that even if a universal mitigation target for CO_2 emissions was adopted throughout the nation, specific policy measures need to be developed for each prefecture to further reduce emissions resulting from the different key drivers. Specifically, the following policy interventions could be prioritized based on the results:

- For those prefectures in which the effect of changes in energy usage had a large impact on increasing emissions while demographic shifts had the effect of decreasing emissions (i.e., 33 out of 47 prefectures), implementing policy interventions to promote shifts toward greener lifestyles is particularly necessary. For example, it is essential to encourage consumers residing in these prefectures to achieve energy savings by using more energy-efficient household appliances. However, compared to less energy-efficient ones, the high initial cost of energy-efficient appliances can hinder their adoption by consumers. To overcome this problem, implementing a subsidy policy for household electric appliances, such as the Home Appliance Eco-Point System executed from 2009 to 2011 in Japan, could contribute to further reductions in CO_2 emissions in those prefectures. Given the demographic trends present in most of these prefectures, such a subsidy policy would likely be effective as senior consumers in small towns were more responsive to the previous Eco-Points System than young consumers [54]. From a lifecycle perspective, implementing policy measures that promote the early replacement of less energy-efficient air-conditioners would also be effective in reducing residential CO_2 emissions [55,56]. Fostering consumers' knowledge about GHG emissions as well as energy savings would also be helpful to encourage them to use less household energy [57].
- For those prefectures in which the effect of demographic changes increased CO_2 emissions despite changes in energy usage decreasing emissions, development of greener housing with improved heat insulation [58], rooftop solar photovoltaic panels [59], and the use of energy-efficient appliances [60] in line with the previous domestic energy plan need to be prioritized [61]. This is because improving energy use through lifestyle changes would have less potential in those prefectures where the consumption effect is already comparatively small. To this end, the Government of Japan recently published the Net Zero Energy House (ZEH) Roadmap to achieve substantial household energy saving [62]. A ZEH is defined as a house that attains an annual net energy consumption of around zero (or less) through the adoption of energy-saving appliances as mentioned above; this standard will be adopted for more than half of all newly constructed houses by 2020. However, although the importance of subsidies and promotion activities as they relate to the construction of ZEHs is noted in the roadmap, how these measures will be implemented is not specified. By considering the effects of demographic changes on CO_2 emissions, the results of this study could be used to earmark those prefectures that most urgently require ZEHs.
- For commuter prefectures such as Saitama and Shiga, the combination of demographic trends and energy usage increased CO_2 emissions significantly. In these prefectures, relatively more attention should be given to implementing the abovementioned improvements in housing and household appliances.

As shown by the data obtained for the intensity effect, the impact of changes to the structure of electric power generation on household CO_2 emissions was particularly significant in all prefectures, particularly those dependent on energy derived from nuclear power. As described in the results and discussion section, under the same levels of per-capita energy consumption in 2015 and energy intensities in 2010, more than half of the prefectures could meet the reduction targets for household CO_2 emissions as set out in the Paris Agreement. However, it seems quite unlikely that Japan's nuclear power plants will resume operation at the same levels as before the Great East Japan Earthquake in the near future [63]. The Japanese government expects improvements in electricity generation toward 2030 in line with the Paris Agreement. It would be impossible, however, for each prefecture to achieve emission reduction targets without intense effort to improve household energy saving and emission intensity even if the current demographic trends that could contribute to emission declines become more significant. Therefore, promoting renewable energy more widely and establishing related policy schemes such as a feed-in-tariffs (FIT) become highly important [64]. Infrastructures with new grid technologies should also be developed to achieve more efficient distribution of electricity [65]. From the consumer's side, the nuclear plant shutdowns prompted liberalization of the electric utilities market in April 2016, which enabled consumers to select which electric utility company they wanted to use to supply their household with electricity. If consumers can purchase household electricity created by power generation facilities that have lower associated CO_2 emission intensities, such as energy produced using renewable energy resources, then the impact of the intensity effect would be reduced. In order to promote such a reduction, it is necessary to foster an understanding among consumers regarding the differences in the structure of power generation and the associated CO_2 emissions, as well as providing consumers with economic incentives to select low-carbon electricity [66]. Overall, in order to achieve substantial reductions in emissions, it is important for society to understand renewable energy from both supply and demand perspectives [67]. Educating consumers could be easier at the prefectural government level than at the national government level, which is a good reason for analyzing regional trends in emission drivers.

Finally, clarifying the structure of energy-related household CO_2 emission trends at the sub-national level, as presented in this study, can help decision makers in local governments to better understand how policy and technology interventions can be employed to mitigate prefectures' emissions. Doing so can lead to effective measures that further reduce long-term emissions to achieve emission mitigation targets under the Paris Agreement in Japan as well as other in nations experiencing similar demographic and industrialized trends.

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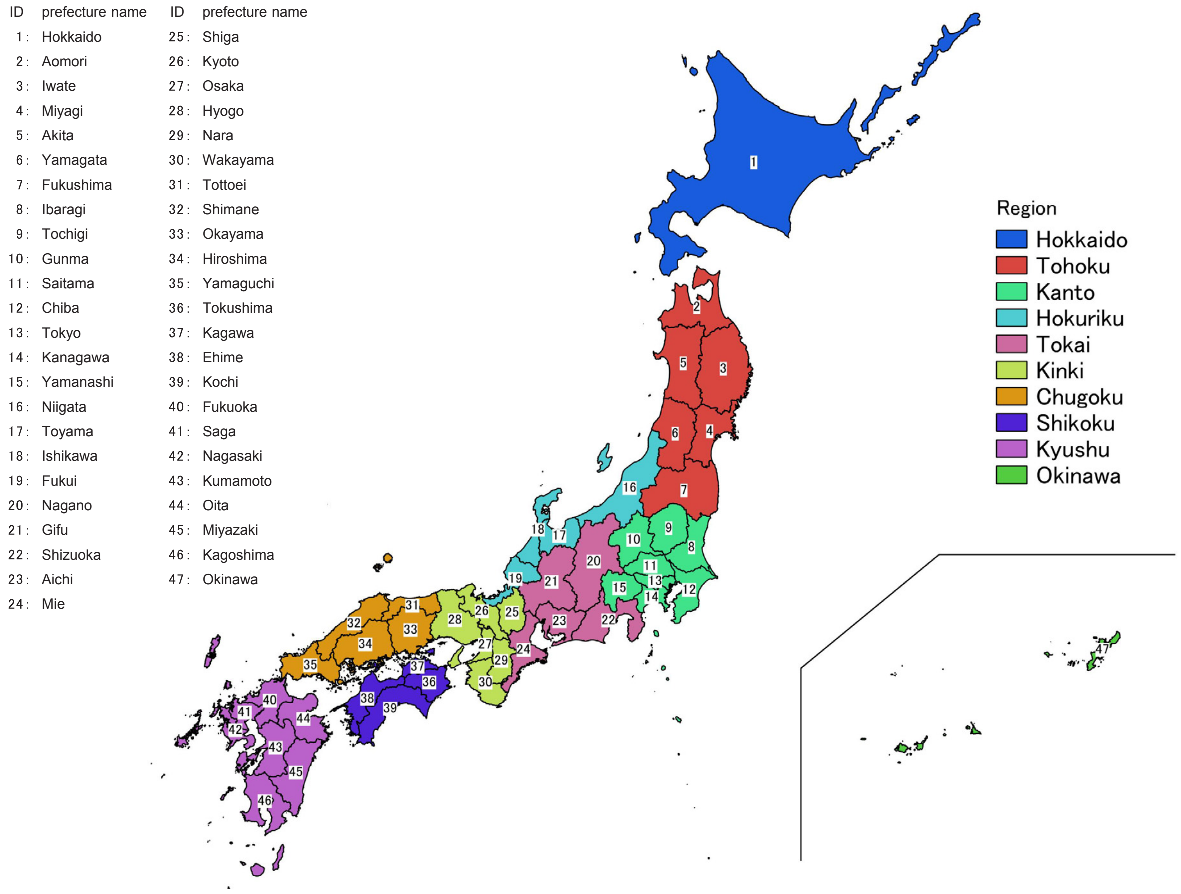
Appendix A.

Figs. A1 and A2 depict the geographical locations of the 47 prefectures in Japan and a breakdown of the time series of the six factors considered in this study by prefecture for the period 1995–2015, compared with 1990 levels.



ID	prefecture name	ID	prefecture name
1 :	Hokkaido	25 :	Shiga
2 :	Aomori	26 :	Kyoto
3 :	Iwate	27 :	Osaka
4 :	Miyagi	28 :	Hyogo
5 :	Akita	29 :	Nara
6 :	Yamagata	30 :	Wakayama
7 :	Fukushima	31 :	Tottoei
8 :	Ibaragi	32 :	Shimane
9 :	Tochigi	33 :	Okayama
10 :	Gunma	34 :	Hiroshima
11 :	Saitama	35 :	Yamaguchi
12 :	Chiba	36 :	Tokushima
13 :	Tokyo	37 :	Kagawa
14 :	Kanagawa	38 :	Ehime
15 :	Yamanashi	39 :	Kochi
16 :	Niigata	40 :	Fukuoka
17 :	Toyama	41 :	Saga
18 :	Ishikawa	42 :	Nagasaki
19 :	Fukui	43 :	Kumamoto
20 :	Nagano	44 :	Oita
21 :	Gifu	45 :	Miyazaki
22 :	Shizuoka	46 :	Kagoshima
23 :	Aichi	47 :	Okinawa
24 :	Mie		

Fig. A1. Geographical locations of the 47 Japanese prefectures.

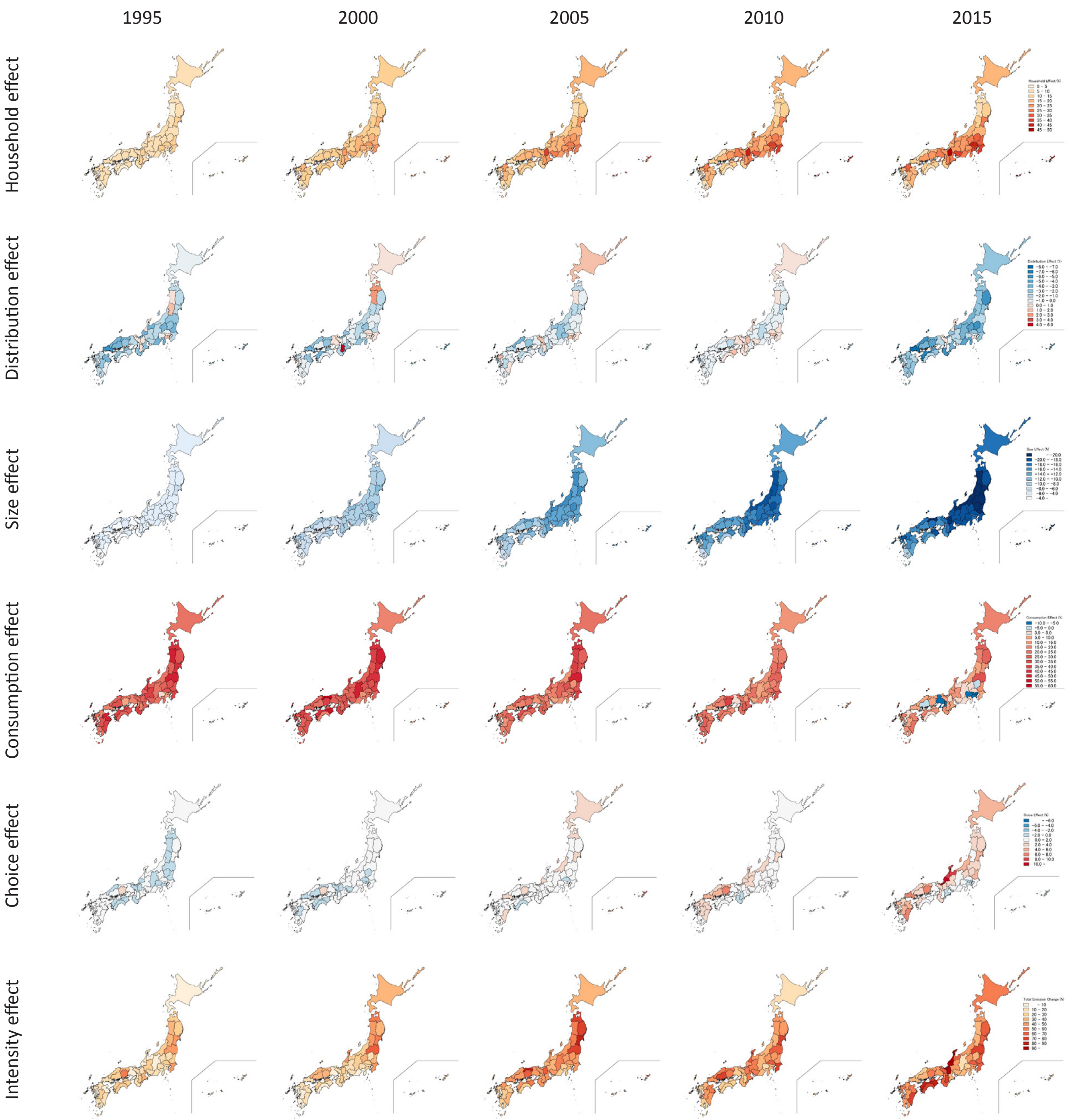


Fig. A2. Time-series analysis of the six study factors by prefecture for the period 1995–2015, compared with 1990 levels.

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