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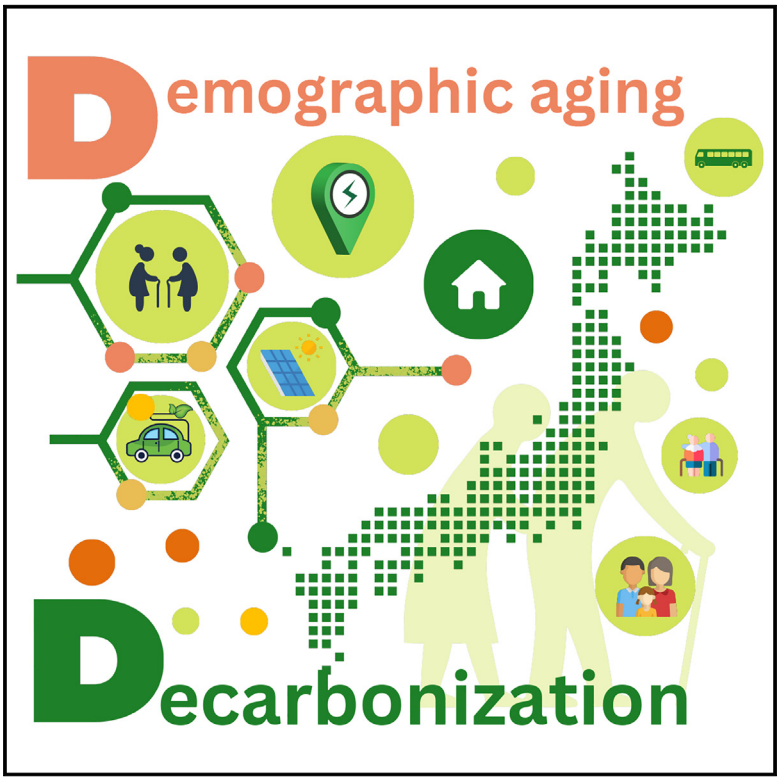
Demographic transitions hinder climate change mitigation for Japan's shrinking and aging households

Graphical abstract



Highlights

- Multiple household characteristics affect energy use and emissions
- Differentiated climate change mitigation technology adoption rates among groups
- Demographic transitions pose challenges for emission reduction by 2040 in Japan
- Tailored strategies are needed for effective climate action in the household sector

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In brief

In their study, Long et al. analyze Japanese household energy consumption and emissions. The research finds people's age, household size, and income to be associated with emissions and the adoption of green technologies such as photovoltaics and new energy vehicles. It shows that demographic transitions associated with household aging and shrinking can have significant ramifications on climate change mitigation efforts in the household sector.

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Demographic transitions hinder climate change mitigation for Japan's shrinking and aging households

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SCIENCE FOR SOCIETY In the quest for a sustainable future, understanding the relationship between demographic change and climate change becomes paramount, as demographic shifts directly impact energy consumption patterns and the effectiveness of interventions. This study reveals how demographic transitions in Japan influence household-level energy consumption and greenhouse gas emissions. Different household types exhibit varied patterns in emissions and the adoption of green technologies such as photovoltaics and new energy vehicles. This is shaped by factors such as people's age, household size, and income. Demographic transitions toward smaller and elderly households will complicate achieving decarbonization in the household sector. The work emphasizes that a sustainable, low-carbon future requires a deep understanding of societal shifts and needs. It calls for tailored approaches in the household sector to manage climate change, particularly in societies experiencing demographic transitions.

SUMMARY

The household sector is a major source of greenhouse gas (GHG) emissions and is key to achieving decarbonization targets. Household characteristics, influenced by demographic transitions such as population aging and shrinking, have a profound impact on energy use and emissions. This study explores how demographic changes in Japan may affect long-term emission mitigation in the household sector through the adoption of photovoltaics (PVs) and new energy vehicles (NEVs) under various scenarios for 2040. Using a comprehensive survey of 9,996 households, we develop a nuanced typology of households to understand variations in emissions and mitigation technology adoption. Household size and age emerge as key factors influencing emissions. The findings reveal that the increasing prevalence of smaller and elderly households may impede emission mitigation efforts in Japan, posing substantial obstacles to achieving long-term decarbonization goals in the household sector.

INTRODUCTION

Containing the increase in global average temperature to well below 2°C above pre-industrial levels requires substantial cross-sectoral efforts.[1] These efforts include extensive reductions in the use of fossil fuels and the promotion of electricity generation through renewable and carbon-neutral pathways.[2,3] Many of these efforts have focused on the supply side (e.g., industrial and energy generation sectors) and have emphasized increasing energy efficiency[4,5] or finding/mobilizing green and renewable energy sources.[6,7]

However, in the post-Paris-Agreement era, there have been strong calls to also design effective emission mitigation plans for the final demand side. For example, there have been increasing efforts to promote the uptake of green technologies and enable the transition to low-carbon lifestyles,[8–10] especially in the household sector.[10–15] The reason for this is that households, by accounting for a large fraction of final energy consumption and total greenhouse gas (GHG) emissions, have a high emissions mitigation potential.[16–19] For example, the household sector in the US contributes nearly 80% of total GHG emissions,[8,20,21] encompassing both direct emissions from home energy use and indirect emissions due to the consumption of goods, services, and secondary energy (e.g., electricity). In Japan, the household sector is responsible for >60% of total GHG emissions[22–24] and is expected to contribute nearly 50%

of the emission reduction commitment under the Paris Agreement.[25] Despite the intense efforts to boost household-level decarbonization measures in many countries,[25–27] the household sector poses two major challenges to their effective design and implementation.

First, it is widely accepted that emission mitigation technologies that target households or individual consumers are not universally accepted due to the variability in household demand,[28,29] technology acceptance levels,[30,31] and affordability[32,33] across demographic groups. At the same time, such mitigation efforts need to consider issues of fairness (e.g., climatic justice,[19,34] inequality[13,35]), feasibility,[36,37] and effectiveness. Here, "climatic justice" refers to fair treatment for all for climate change mitigation, such as promoting equitable access to technologies and designing inclusive policies, while "inequality" denotes unequal energy consumption and emissions across socioeconomic groups, emphasizing disparities and the need for tailored mitigation approaches. Arguably, the design and implementation of feasible and effective mitigation measures for the household sector are highly reliant on a good understanding of household consumption preferences and how such preferences are affected by household characteristics. Previous studies have identified that very diverse household characteristics, such as income, age, composition, and location, can affect energy demand and consumption behavior.[38–46] For example, affluent families and elderly families tend to have higher energy consumption,[19,33,47,48] and household size can also determine household energy consumption.[49] Furthermore, certain lifestyle decisions vary between age groups. For example, households with school-aged children have a higher electricity demand for lighting while elderly households have a higher electricity demand for TV.[46] Such patterns imply that households with different demographic and socioeconomic characteristics also have different GHG emissions and levels of acceptance of end-use energy technologies, not least due to their differentiated needs and financial status.[48,50]

Second, the promotion and adoption of decarbonization measures for the household sector do not happen in isolation. Rather, they are closely linked to multiple unfolding demographic,[51,52] socioeconomic, [9,53] and environmental transitions.[7,11,54] One of the most critical demographic transitions is population aging and shrinking, which affects, among others, household composition, age distribution, size, and lifestyles, with major implications for the adoption of end-use energy measures[49] and sustainability in general.[55] Population aging is now observed in most developed countries and a growing number of developing countries[16,18,56–59] (see Figure S1, supplemental information), and it has significant ramifications for energy use and GHG emissions.[58,60–63]

Facing these two challenges, though previous studies have explored the consequences of household characteristics and demographic change for energy technology adoption and GHG emissions, they have often obtained mixed results due to methodological differences and limited data availability.[40,63–69] In general, there is a wide acceptance that households with higher income, elderly members, and small sizes are more likely to have higher GHG emissions, partially due to the scale effect of household energy consumption and lifestyles (e.g., the longer time spent at home among elderly individuals).[13,40,70–72] Furthermore, household shrinking might prevent the effective scaling up of relevant mitigation measures,[18,71,73,74] which is particularly important for countries experiencing shrinking in household numbers and sizes. These facts suggest the strong need for detailed studies that estimate differentiated emissions reduction potentials within the household sector, taking into account the effects of household characteristics and technology acceptance in the context of demographic transitions. However, there are some very important challenges and knowledge gaps.

First, there is a lack of nuanced household taxonomies, as most studies have relied on household taxonomies across single dimensions (e.g., grouping by income, age, family size, or specific lifestyles and energy consumption behaviors). Furthermore, grouping and taxonomy decisions are often arbitrary and based on researchers' experience and the focus of the study rather than a strong understanding of how multiple intersecting household characteristics affect energy consumption and emissions. For example, although studies have explored how heterogeneity in household characteristics affects energy use patterns[75,76] and the adoption of mitigation technologies,[76,77] most studies have relied on taxonomies that are unidimensional and/or subjective. Examples are studies finding generally higher emissions from more affluent, elderly, and smaller households[9,78–80] that rely on a manual approach and/or subjective decisions for the division of the groups. This approach might create biases or fail to provide nuanced information about the factors affecting energy use and emissions, which in turn might prevent the development of appropriate mitigation policies.

Second, despite the clear trends toward population aging and shrinking in many of the highest-emitting economies, there is a general lack of robust studies exploring how demographic transitions intersect with decarbonization efforts in the household sector. Although some studies have explored historical patterns in how population aging and shrinking have affected energy use and GHG emissions,[51,53] there are few studies that have provided comprehensive and robust projections.[9,81] One significant challenge here is the difficulty of combining population projections with data on household-level mitigation technology adoption and energy consumption patterns.

Here, we explore how demographic transitions associated with population aging and shrinking might affect long-term climate change mitigation and decarbonization efforts in the household sector. First, we use data mining and a multi-dimensional clustering approach to create a household taxonomy to understand differentiated technology adoption and emission patterns within the household sector. We use data from an extensive national household survey on energy consumption and emissions (which also includes detailed information on private transport). Second, we match this taxonomy with future population projections to estimate how demographic transitions influence the adoption of climate change mitigation technologies at the household level and their potential effect on emissions from the household sector as a whole. We do so for a series of adoption and energy production scenarios for the year 2040.

We focus on Japan, which is an ideal case study. Japan is currently the third-largest economy and the fifth-largest GHG emitter globally, and has recently made strong political

commitments to decarbonize by 2050.[82] The country is also experiencing profound demographic changes that are expected to accelerate. Single-person households already account for >35% of the entire population (expected to increase to >50% by 2035[83]), while the national population aging and shrinking rates are some of the highest in the world.[40,67,68] For each of the identified household groups, we explore the adoption rates and performance of the two main emission mitigation measures currently promoted in Japanese households, namely roof solar photovoltaics (PVs) and new energy vehicles (NEVs).[84–87] For the six study groups, we explore patterns for the 2017–2018 period and future trajectories up to 2040 based on the expected demographic transitions in Japan. Overall, this study can provide valuable information for other major economies that are increasingly facing profound demographic transitions[55] in the next few decades.

RESULTS

Differentiated emission patterns between groups

The clustering analysis performed, using the least absolute shrinkage and selection operator (LASSO) model, identified the five most important variables (from a total of 24 variables) affecting direct energy use and related GHG emissions. These variables included income, household size, average household age, driving demand, and whether the household contains children (see Table S1, supplemental information). We use these variables to generate a household taxonomy that consists of six groups that have the largest disparity in direct energy use and related emissions. Figure S2 in the supplemental information provides a detailed description of each of the six groups in the taxonomy.

Figure 1A compares the emissions across the six household groups. Here, we find that middle-aged, very high-income households with children (HFK) have the highest emissions compared with any other group. In addition to income, we find that lower-income, elderly single-person households (LES) and lower-income, single-person households (ULS) have even higher per capita emissions than middle-income (MCK) and higher-income (UHFK) groups (see the pink bars in Figure 1B). It is also notable that high-income extended families (UHBF) exhibit emissions levels that are relatively high, falling between the aforementioned two groups.

Figure 1B suggests that home appliances and transport account for the highest share of household emissions for all groups (see the outer circle in Figure 1B). For each group, except for the HFK group, emissions from appliances and vehicles account for >60% of overall emissions. However, for the HFK group, space heating is the largest source of emissions (36.0%), followed by appliances (24.3%) and transport (21.7%). For lower-income elderly single-person households (LES) and lower-income single-person households (ULS), appliances account for most emissions, followed by transport and space heating. Notably, Figure 1B shows that for households with children (e.g., HFK, UHFK, and UHBF), >30% of their emissions are from transport, indicating their higher propensity for a more car-oriented lifestyle.

Examining fuel consumption (see the inner circle of Figure 1B), we find great kerosene demand for space heating from lower-income elderly single-person households (LES) and high-income extended families (UHBF). Although electricity generally tends to be the main fuel for space heating for most groups, kerosene is also very prevalent, especially in the mountainous regions of the country.[88,89] In contrast, a large fraction of the emissions of the HFK group come from space heating. However, this group's emissions are mainly from electricity-based heating, while the electricity-related emissions are as much as 2.17 times greater than those of the LES group.

Overall, the results above provide two important clues for our subsequent analysis. First, examining the total emissions of each of the six groups, we see that groups with higher income and high driving demand generally tend to have the highest levels of emissions. However, the groups with the second-highest levels of emissions are not necessarily those with high income; rather, they are single-person households and/or dominated by elderly people. For example, low-income single-person elderly households (LES) and low-income single-person middle-aged households (ULS) have notably high per capita emissions. This finding provides an initial hint that the unfolding demographic transitions toward an aging and shrinking population create certain pre-conditions for high per capita emissions considering the current trends in Japan.

Second, the factors that influence the emissions of the four highest-emitting groups (i.e., HFK, LES, UHBF, and ULS) differ significantly (see Figure 1B). For example, space heating dominates the emission profile of HFK, while appliance use dominates the emissions profiles of LES and ULS. Conversely, a significant fraction of the emissions of UHBF come from kerosene for space heating (17%) and gasoline due to high dependence on private transport (31%). These findings can be explained by the fact that 78% of the households characterized as UHBF come from mid- and small-sized cities away from large metropolitan areas (see Table S2, supplemental information). Hence, one plausible explanation could be the longer commuting distances to employment centers in metropolitan areas. Additionally, lifestyle factors in these regions, such as a higher reliance on personal vehicles due to less accessible public transportation, might contribute to increased transport emissions.

Adoption of green technologies and emission mitigation potential

PVs and NEVs are the two most popular types of green technologies currently promoted and adopted by Japanese households. Although their penetration rates are low for some groups (especially for NEVs) (Table S6, supplemental information), it is crucial to understand their current adoption rates and emissions mitigation potential before understanding how demographic transitions might affect them. To note, in our examination of emissions differentials between NEV adopters and non-adopters, the comparison was conducted exclusively among households that possess at least one vehicle, thereby providing a more accurate assessment of the impact of NEVs on household emissions.

Figure 2A suggests that most household groups that adopt PVs have lower per capita emissions than their counterparts. For example, the per capita emissions of households adopting PVs are 16.0% and 27.3% lower, respectively, than those of households without PVs for groups with larger sizes, such as

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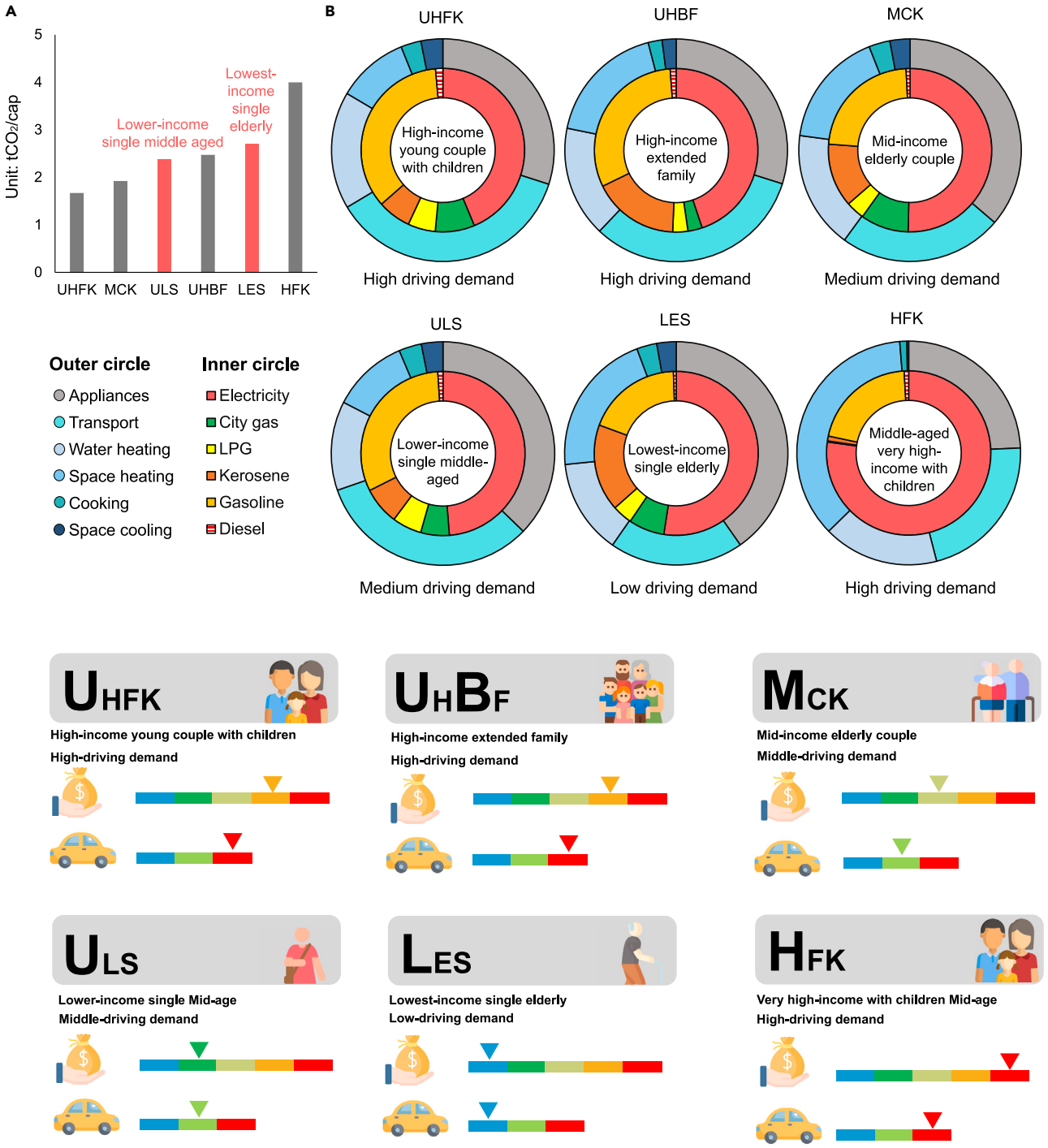

Figure 1. Per capita household emissions for the six household groups

(A) shows the total per capita household emissions from each of the six groups in our taxonomy. (B) shows a decomposition of household emissions by household activity (outer circles) and fuel (inner circles).

high-income households with children (UHFK) and high-income extended family households (UHBF). The exception is lower-income single-person households (ULS) and low-income single-person elderly households (LES). For ULS, the PV adopters emit >55.8% more than non-adopters. Notably, here, the in-house electricity consumption from PV is not included in the total emissions. Furthermore, the emissions of households adopting PVs are marginally higher than those of non-adopters within the LES group (Figure 2A). This relatively counter-intuitive result might be due to two factors: (1) low overall PV adoption rates

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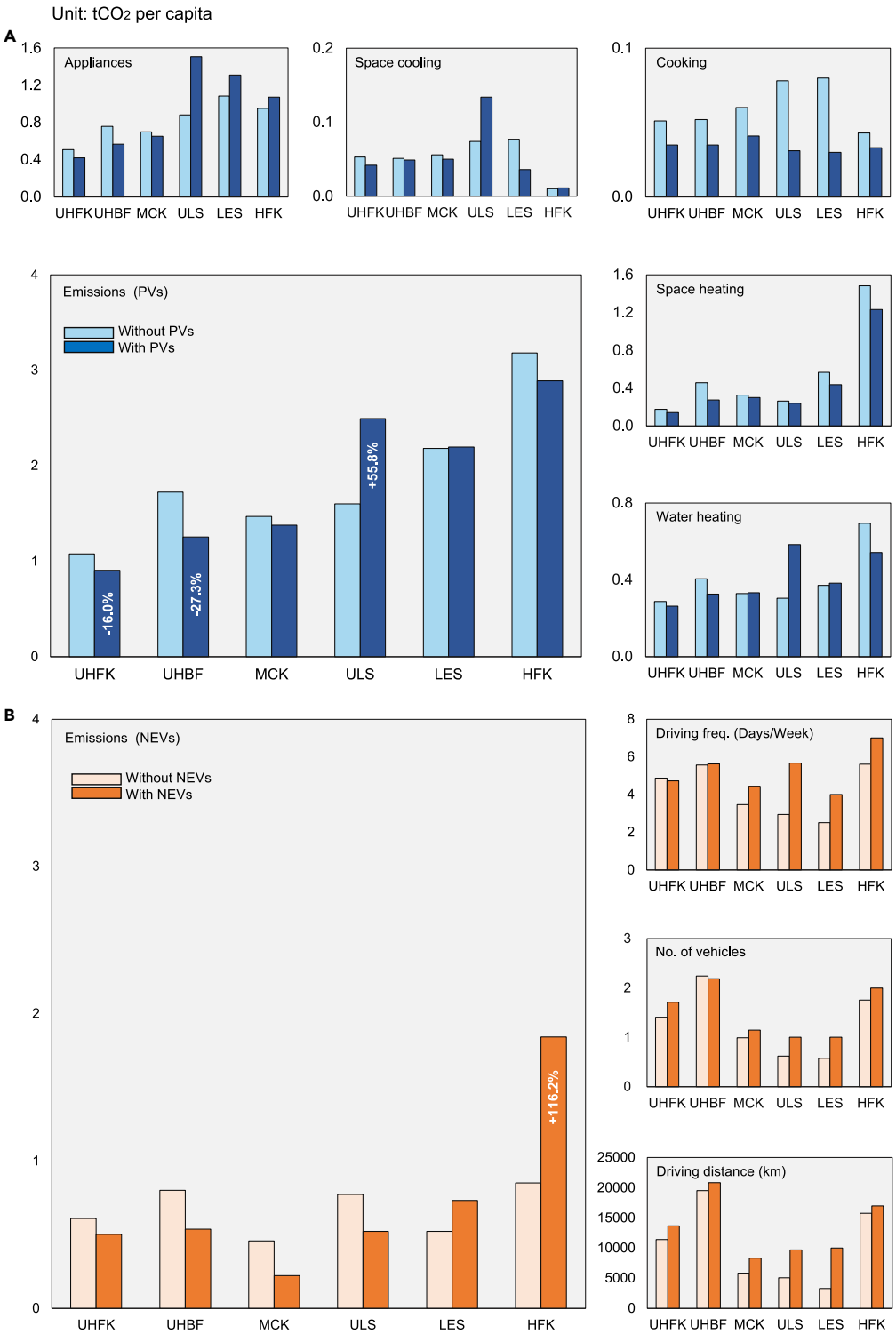

Figure 2. Direct emission reductions for the six household groups due to the adoption of PVs and NEVs (in 2017–2018)

(A) highlights the total differences in direct per capita emissions for PV adopters and non-adopters within each household group, while the five sub-figures indicate the differences in direct per capita emissions between PV adopters and non-adopters for different household activities. (B) highlights the total difference in direct per capita transport emissions for NEV adopters and non-adopters within each household group, while the three sub-figures indicate differences in direct per capita emissions between NEV adopters and non-adopters based on driving frequency, driving distance, and the number of vehicles owned per household.

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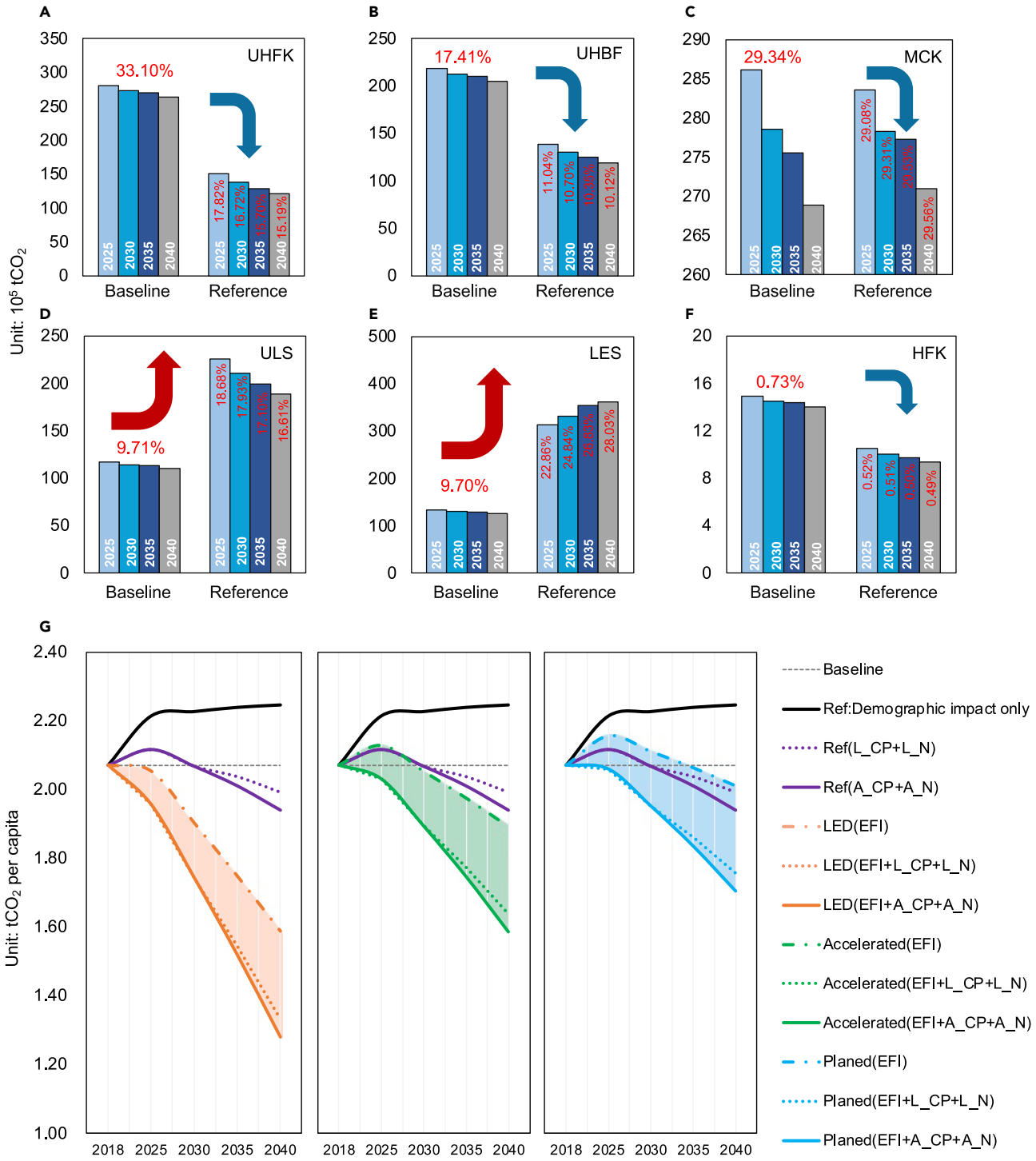

Figure 3. Effects of demographic change on direct emissions from the household sector

(A)–(F) show the direct emissions of each group under the baseline scenario and the reference scenario (dynamic population structure scenario) (see "research approach" for the scenario descriptions and underlying assumptions). The percentages presented above the bars in the figures denote the projected contribution of each household group to the total carbon emissions from the household sector for a given year, with the sum of the contributions from all groups equating to 100% for any specified year within the scenario, and the values for the baseline scenarios are the average values among analyzed years. The fractions of household groups under the baseline scenario are assumed to be the same as for the 2017–2018 period, while the fractions for each group and year under the reference scenario are allocated following the process outlined in "future prevalence of the study groups." (G) depicts the per capita emissions for the overall household sector from 2018 to 2040 under 12 scenarios of adoption of different mitigation technologies. The black line indicates the emission increase caused by

(legend continued on next page)

within these groups (possibly due to low homeownership), which might result in an insufficient sample for analysis (Table S6, supplemental information); and (2) the specific combination of activities and fuels, which might not (see below).

The reasons for these differences in emission patterns depend on the group. In particular, PV adopters in lower-income single-person households (ULS), lower-income elderly single-person households (LES), and middle-aged very high-income households with children (HFK) tend to have higher emissions from appliance use than non-adopters (Figure 2A). This result is also observable for water heating, as well as water heating for the ULS group. However, PV adopters in all other groups generally tend to have lower per capita emissions from other household activities compared with non-adopters. PV adoption in groups characterized by larger family sizes (whether extended or nuclear families), such as UHFK, UHBF, or even HFK, is associated with a higher emission reduction potential for all household activities. These groups with larger families tend to benefit from adopting PVs to offset their consumption of electricity or the use of other fuels, especially for space heating and water heating.

Figure 2B shows the emission reduction effect of NEV adoption for each of the six household groups. Importantly, the current NEV adoption rates for most groups are <2% (Table S6, supplemental information), which may affect the accuracy of the results and should be taken into account. However, there are some exciting insights already observable for future promotion efforts, especially in the context of demographic transitions. First, the results show that the adoption of NEVs tends to lower the total direct emissions for most groups because the use of NEVs reduces the fossil fuel consumption of traditional vehicles. Nevertheless, for middle-aged very high-income households with children (HFK), direct emissions double when NEVs are adopted (116.2% higher), which is also the case for low-income single-person elderly households (LES). For the former, this finding reflects the generally high levels of NEV adopters in terms of driving distance, driving frequency, and the number of vehicles owned (Figure 2B). Beyond the generally high transport demand within this group, many HFK households are also highly likely to own multiple cars. Conversely, for LES, this increase in emissions reflects the generally higher distance driven by NEV adopters, as households in this group tend to own only one car. For the other groups, households adopting NEVs tend to emit significantly less, with some interesting patterns within groups. Lower-income (ULS) and mid-income (MCK) households adopting NEVs have higher driving frequencies and distances compared with those without NEVs, which is completely different compared with higher-income groups (i.e., UHFK and UHBF). This finding might reflect both the fact that NEVs purchased by lower-income groups will be used as the main vehicles and the possibly lower fuel cost of driving such vehicles, which might be more affordable for lower-income groups. For example, in terms of the average driving distances of the LES and ULS groups, households with NEVs drive approximately 10,000 km/year and 9,667 km/year, respectively, and these distances are higher than those driven by households without NEVs in the respective groups by 205% and 91.5%, respectively.

Effects of demographic transitions on emissions

In the previous section, we estimated the current per capita mitigation potential (in 2017–2018) of green technology adoption for the six household groups. Here, we explore the overall future reduction potential, considering the expected demographic change over the 2025–2040 period and structural changes in the energy systems through regressions on group-level per capita emissions under different scenarios (see "research approach").

Figures 3A–G show, for all six groups, the projected differences in their contribution to future emissions from the entire household sector based on different population structures, for the *baseline scenario* and the *reference scenario*. In the *baseline scenario*, we assume the current demographic structure for 2040, meaning that the proportion of the six household groups within the overall population remains constant. In contrast, the *reference scenario* anticipates dynamic demographic changes, adjusting for shifts in these proportions over time. Moreover, the analysis extends to four additional scenarios, as illustrated in Figure 3G with purple, orange, green, and blue lines. These scenarios not only reflect dynamic demographic evolution but also incorporate a variety of mitigation measures and structural adjustments in the energy system, offering a broader perspective on potential future developments.

When trying to understand the factors dictating the differences among the different scenarios outlined above, Figures 3A–3F and the black line in Figure 3G suggest that for each of the future study years, the emissions from the increasing prevalence of single-person and elderly households (i.e., ULS and LES) cannot be fully countered by the reduced prevalence of households with larger household sizes (i.e., UHFK and UHBF). Thus, while the total direct emissions from the household sector in Japan are likely to gradually decline owing to the declining population (as shown in Figures 3A–F), the actual average per capita emissions are projected to increase (see the black line in Figure 3G). This finding reflects the strong expected demographic transitions in Japan. Due to the demographic transitions between 2025 and 2040, the emissions from the increasing prevalence of LES and ULS households in the national population will contribute to over 21.1 million and 9.2 million more tonnes of CO_2 on average per 5 years, respectively, while the decreasing prevalence of UHFK and UHBF households will make their emissions decline by only approximately 13.7 million and 8.3 million tonnes of CO_2 on average per 5 years, respectively.

When considering these trends and the differentiated adoption rates of mitigation technologies outlined in the previous

demographic changes (reference scenario), while the four groups of scenarios (in purple, orange, green, and blue lines) reveal the reduction potential brought by multiple combinations of decarbonization measures and ambition levels (see scenario explanation in "research approach" and Section S4, supplemental experimental procedures). Here, L_CP refers to a linear recurrence scenario in 2040, where we assume that the achievement of the emission reduction target will be achieved in 2050, considering the integration of the clean grid and PVs, while L_N refers to realizing the same target with the NEV technology adopted in the future scenario. Additionally, A_CP and A_N denote the "ambitious target" in which Japan achieves the 2050 emission reduction target in advance (in 2040) with the adoption of the clean grid and PVs and utilizing NEV technology, respectively.

section, the results suggest that emission mitigation efforts in the household sector will be hindered by the increasing prevalence and related emissions of single-person and elderly households. Specifically, this is because PVs and NEVs do not constantly show substantial emission reduction potential for groups such as ULS and LES, which are expected to become more prevalent in the future population (see Figure 2). This is because ULS households have a higher demand for electric appliances, space cooling, and water heating, as elderly people are sensitive to temperature variance and mostly use out-of-date home appliances (sometimes for more than 15 years). [41,90] Furthermore, both elderly and single-person households tend to live in houses characterized by worse thermal insulation (e.g., wooden buildings).[91] Therefore, in both winter and summer, such families will need more energy to ensure in-house temperature comfort. Similarly, NEV adoption might not have significant mitigation benefits for the HFK group compared with other groups because such high-income nuclear families often have multiple vehicles and the highest driving frequency (7 days/week). A detailed discussion about the reduction potential of PVs and NEVs in different household segments can be found in Figure S3 in the supplemental information.

The results indicate that in the forthcoming decades, while the total direct emissions from the household sector in Japan are likely to gradually decline owing to the declining population (Figures 3A–F), the actual average per capita emissions for the household sector are projected to increase by 8.5% between 2018 and 2040, considering the expected changes in household structure in the reference scenario if any additional technology adoption is excluded (see black line in Figure 3G). However, if we follow the linear target scenario, the adoption of PVs (as well as lower grid emission factors) and NEVs can reduce emissions by 0.26 tCO_2 per capita (approximately 11.4%) in 2040. Due to the anticipated higher mitigation potential of household PVs in the future, they are expected to offer a slightly greater emission reduction, by an additional 0.01 tCO_2 per capita, compared with NEVs. Additionally, under the ambitious target scenario, where technology adoption is further accelerated, the emission intensity is projected to decrease by 0.31 tCO_2 per capita. Overall, due to this trend of population aging and shrinking, although penetration rates of mitigation technologies are expected to grow (alongside improvements in energy efficiency in appliances and energy production), the mitigation expectations will be partially countered.

DISCUSSION

Arguably, the nuanced understanding of energy consumption and emission patterns, as well as the propensity to adopt green technologies, is a prerequisite for designing effective and fit-for-purpose measures to influence transitions to low-carbon lifestyles and to ultimately achieve decarbonization in the household sector.[70,92,93] This is because household characteristics, such as age, income, and household composition, affect not only energy use and emissions[9,21] but also the acceptance of different emission mitigation technologies.[9,93] At the same time, demographic transitions might drastically alter some of these household characteristics (e.g., age, composition) at the national scale, essentially affecting the overall emissions of the household sector.[61,69] With many countries around the world currently experiencing rapid and profound demographic transitions, as exemplified by population shrinking and/or aging[55] (see also the introduction), it has become critical to understand how these transitions will affect the prevalence of households with different characteristics, which essentially dictate different energy use and emission profiles and different propensities to adopt mitigation strategies.

Recognizing the complexity of household energy consumption and emissions, we adopted a multi-stage approach to: (1) develop a multi-dimensional household typology in relation to households' energy use and emissions (Figure 1), (2) estimate the current variability in emissions and potential emission reductions for each group based on the adoption and non-adoption of mitigation technologies (specifically PVs and NEVs) (Figure 2), and (3) explore the sensitivity of future emission estimations for the household sector in the context of unfolding demographic transitions, and projected the variance in per capita emissions by considering technological development and demographic change (Figure 3). In the remainder of this section, we provide an overview of our key findings and their implications.

Regarding the first stage, it is apparent that income has an impact on both emissions and the adoption of mitigation technologies. However, various demographic factors, including age and household composition, also exert a considerable influence. It is plausible that these characteristics may demonstrate endogenous correlations, leading to a synergistic effect on household emissions. This is evidenced by the fact that higher-income households do not always emit more and that many lower-income households sometimes have high emissions as well, possibly due to their reliance on low-efficiency appliances.[94] Our integrated clustering analysis demonstrates that in Japan, family size, the number of children, average age, income per capita, and driving frequency are major factors that affect energy use and direct emissions. These factors have been employed to develop a household typology that provides insights into trends in the Japanese household sector, as illustrated in Figure 1.

In the second stage, we find that the adoption of PVs and NEVs is both differentiated and has different emission mitigation potentials across the different household groups (Figure 2). This finding is largely attributable to the variability in energy demand for different household activities within each group (Figure 1). Although PV and NEV adopters tend to have lower emissions than non-adopters, there are some exceptions. Notably, in some groups, PV adopters exhibit higher emissions from appliance use (Figure 2A). This finding possibly indicates the existence of rebound effects, whereby households that adopted PVs for energy savings might end up increasing electricity use and associated emissions.[95,96] Similarly, although we observe higher emissions from NEV adopters in some groups, we cannot definitively conclude whether this finding is due to rebound effects. Although driving distance and car use might be higher among adopters in certain cases, the number of vehicles owned tends to be higher as well (Figure 2B). In addition, we find that the emission reduction potential in lower-income groups by adopting NEVs is more prominent than in higher-income groups, but their lower adoption rate underscores a potential barrier to

widespread NEV uptake. Recognizing this disparity, it is crucial for policymakers to consider targeted incentives or subsidies that lower the entry barriers for NEV adoption in low-income households. In conclusion, the current mode of NEV promotion seems to have stimulated only higher-income groups to adopt NEVs (often as a secondary means of mobility), rather than significant adoption toward transport decarbonization. Therefore, policy interventions designed to bridge this adoption gap can play a vital role in accelerating the transition toward a low-carbon economy.

Regarding the third stage, we observe the impact of different household types on future emission projections for the household sector (Figures 3A–3F). We believe that, in the context of the profound demographic transitions currently observed in Japan and other developed countries (see the introduction), multi-dimensional household typologies, such as the one developed in this study, can increase the accuracy of emission projections. This can be appreciated when understanding the cascading effects of aging on emissions and the adoption of mitigation technologies. Currently, 47.1% of households in Japan can be characterized as aged (>65 years old), of which 57.8% consist of fewer than 2 persons.[90] Upon reaching retirement age (which is presently set at 65 years in Japan), household income experiences a substantial decline due to the dependence on pensions, which offer significantly lower remuneration than salaries. This decline in households' income both reduces their ability to adopt emission mitigation technologies such as PVs or NEVs (Figure 2) and increases their dependency on low-efficiency home appliances. According to a survey conducted by the Ministry of Economy, Trade, and Industry (METI), households composed of elderly individuals were found to possess a larger number of outdated appliances compared with younger generations, with some of these appliances being utilized for more than 15 years. These old appliances collectively increase the emissions of such households to levels almost comparable to the emissions of households with higher sizes and incomes (Figure 1), being positioned only below very high-income households.[11,13]

Finally, there are signs that the anticipated demographic shift toward smaller and older households is likely to pose obstacles to achieving emission reductions within the household sector. It appears that irrespective of the scenario of PV and NEV adoption, per capita emissions are expected to exhibit a slight increase over time (Figure 3G). This increase is driven by the increasing numbers of these types of households, which tend to have relatively high emissions (Figure 1) and lower adoption rates of emission mitigation technologies (Figure 2), in the future population (Figures 3A–F). Furthermore, Figure 3G reveals a current disparity between the goals set by the Japanese government (see planned in Figure 3G) and the existing decarbonization pathway designed for developed countries (see low energy demand [LED] in Figure 3G). Even after including a more ambitious scenario (see accelerated in Figure 3G) beyond the Japanese government's documented goals, it is evident that the country is still lagging behind the targets set for developed countries in previous studies, such as the LED scenario. Consequently, to achieve the LED scenario as the next target, the current rate of promotion for PVs and NEVs will need to be accelerated by more than 10 years, which would entail reaching the planned rate of promotion two decades earlier. In light of the observations above, it is obvious that to achieve decarbonization in the household sector, there should be a conscious effort to enable groups in the sector to reduce their emissions. Doing so can be achieved through a combination of measures that seek to enhance the efficiency of their energy use,[97] reduce the emission intensity of their energy sources,[69,94] and accelerate the achievement of planned NEV and PV promotion goals.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by Yin Long (longyinutokyo@gmail.com).

Materials availability

This study did not generate new unique materials.

Data and code availability

The dataset for energy use behavior comes from a nationally representative survey conducted by the Ministry of Environment, Japan. We received special permission to use the raw data, which were analyzed subject to certain confidentiality constraints. The details of the dataset can be accessed from https://www.env.go.jp/earth/ondanka/ghg/kateiCO2tokei.html. The homepage of this representative survey is: http://www.env.go.jp/earth/ondanka/kateico2tokei/index.html. The aggregated results can be found in e-Stat, the portal site of official statistics of Japan: https://www.e-stat.go.jp/stat-search/files?page=1&toukei=00650408&kikan=00650&result_page=1. For the future population projections, we used secondary data collected by the Government of Japan: https://www.stat.go.jp/data/jinsui/index.html. The structure of the population projection data can be found in Table S7 in the supplemental information. For the purpose of replication and transparency, we have uploaded the major body of scripts and intermediate data onto GitHub: https://github.com/wuyi0614/japan-hce-footprint. The repository is publicly accessible, and contains instructions about how to replicate all the results in our paper.

Research approach

For this study, we follow three main research steps: (1) delineate study groups by developing a household taxonomy (step 1), (2) estimate household emissions for the study groups (step 2), and (3) establish different scenarios for projecting future emission reduction potentials for the household groups (step 3). Notably, in step 3, by focusing on the penetration rates of mitigation options and estimating the ratio of adopter and non-adopter households in terms of emission mitigation options, we set up multiple scenario specifications to develop the reduction potential projection. Figure S3 in the supplemental information summarizes the research approach.

In step 1, we develop a taxonomy for the studied households through data mining and a multi-dimensional clustering method (see "integrated clustering method"). To do so, we use household-level data from the Japanese household energy use survey (HEUS) conducted by the Ministry of the Environment (MOE) over the 2017–2018 period, with appropriate processing (see "data preparation"). This approach represents a significant deviation from traditional methods of grouping households based on specific characteristics for emission estimation that typically rely on expert judgment and consider only single dimensions or characteristics. Such conventional grouping approaches may produce inaccurate results by failing to account for multiple dimensions that influence emissions, as highlighted in the introduction. For example, higher-income households tend to also have higher emissions than lower-income households, although this tendency may also be driven by the fact that the former use more efficient appliances and houses with higher energy needs.[98,99] Such a mismatch may introduce uncertainties in the emission calculations.[100]

For this reason, our study groups households across five dimensions: (1) income, (2) household size, (3) the average age of household members, (4) driving demand, and (5) children. These five household characteristics serve

as the foundation for the study's group taxonomy and were identified through the LASSO method after filtering for characteristics expected to have a significant impact on variations in per capita emissions across households (Figure S4, supplemental information). The household characteristics evaluated through the LASSO method are selected and filtered by matching variables from survey data with variables in existing studies,[72,98] resulting in a more nuanced household taxonomy comprising six household groups (Figure S5, supplemental information). Overall, this approach aimed to identify distinct household groups for further analysis by maximizing differences between them while minimizing variations within each group.

In step 2, we estimate the per capita emissions of each household group, using common household expenditures and fuel consumption data from the HEUS outlined above (see "data preparation"). We focus on direct household energy use instead of indirect emissions embodied in goods and services[101,102] (see "estimation of direct emissions"). The results of this analysis are included in the first sub-section of the results. Notably, both of these scenarios assume for each of the six groups the same energy consumption patterns and adoption rates for mitigation options, as estimated for the 2017–2018 period (see steps 1–2).

In step 3, we first show two different emission trends considering demographic factors, namely the baseline scenario with no demographic change up to 2040 and the reference scenario that considers a dynamic population structure scenario due to demographic change. Although the baseline scenario is certainly far from reality, the comparison with the reference scenarios could provide insights into how demographic change can significantly alter household emissions in the country (results are given in Figures 3A–F). In addition, demographic change will not be the only factor that could impact future household emissions. Therefore, we create three further sub-scenarios for projecting how energy efficiency improvement (EFI) for home appliances, and EV and NEV adoption, could impact per capita emissions from the entire household sector considering the demographic make-up of the household sector in the reference (which assumes dynamic population structure). Here, we must note that, according to estimates in the literature on energy consumption in the household sector, the energy intensity (energy consumption per device) of household activities may decrease significantly if the best available technologies are adopted.[103] Furthermore, long-term improvements in the supply chain energy conservation rate will also largely impact energy use and emissions in the household sector.[104] Therefore, the sub-scenarios outlined above consider not only the dynamic demographic transition and the adoption of PVs and NEVs considering future household structure but also EFI in household appliances and changes in power generation efficiency.[104]

Considering the above, these families of sub-scenarios essentially assume that the potential impact on energy use and emissions from the household sector may come from both the consumption side (i.e., home appliance EFI, and consumption behavior change and PV/NEV adoption change due to demographic change) and the production side (i.e., energy efficiency change from power generation). We do this for different ambition levels as described below. First, by referring to the survey on actual CO_2 emissions in the household sector published by the MOE, Japan,[105,106] we set the household appliance EFI target for 2050 according to the official report. To account for the timeframe of our analysis (2040) we separate the target into achieved as planned (i.e., achieved in 2050, and linearly interpolating the progress for 2040) and achieved accelerated (i.e., the 2050 target will be achieved in 2040). This target setting reflects official Japanese governmental reports. Additionally, for better comparison with other previous work, we use one more ambition level from previous work on LED.[103] Thus far, we have two demographic scenarios (baseline, reference) and three ambition sub-scenarios (LED, accelerated, planned).

Finally, we take into account the future penetration rates of PVs and NEVs in the household sector by decomposing the 2030 and 2050 climate targets from the literature in a linear or ambitious (ahead-of-schedule) manner. For the ahead-of-schedule decomposition, it is presumed that the 2050 net-zero target will be achieved earlier, by 2040. This is realized by making a linear decomposition of the original target from 2025 to 2040. More details can be found in Section S4 in the supplemental experimental procedures.

Collectively, the above results in the 12 scenarios explored in Figure 3G. Deeper explanations of the scenarios are included in Table S3 in the supplemental information.

Data preparation

Household emissions can be estimated through top-down or bottom-up approaches. The former generally require macro-level data derived from input-output tables. The latter are more data-intensive, entailing statistical analysis and aggregation of micro-level data on direct and indirect energy consumption by individual households. Although input-output tables can be connected to micro-level consumption data at the household level, they usually have a low resolution up to the prefecture-level in most countries (there are also efforts to develop such tables at the city scale but these are characterized by large uncertainty). Furthermore, household consumption data are generally reported in an aggregated form, which complicates analysis. Such data availability challenges usually underpin efforts to accurately estimate energy use and emissions at the household level.

In this study, we use household-level data collected through the HEUS over the 2017–2018 period. To note, within the context of Japan, a fiscal year conventionally spans from April 1 to March 31 of the following year, aligning with the time frame encompassed by the dataset employed in our study. The HEUS covers a nationally representative sample of 9,996 individual households across all 47 Japanese prefectures, capturing demographic characteristics, socioeconomic status, energy use, and property characteristics.

Initially, after exploring the data, we removed surveys with incomplete or problematic data to avoid possible biases in estimating the emission reduction potentials (see Section S1, supplemental experimental procedures). This applied to a total of 1,008 households that (1) did not have valid records for their building space (332 households) and (2) exhibited differences of >0.01 tCO_2 between the reported total emissions and the sum of emissions estimated for individual household activities (i.e., space heating, space cooling, water heating, appliances, cooking, vehicle use) (676 households).

Furthermore, to facilitate the clustering process, we select the most relevant variables explaining household emissions contained in the HEUS and transform them into numeric or categorical variables (Section S2, supplemental experimental procedures). The selection of all relevant variables is based on existing studies[72] that identify the factors contributing to household emissions. This amounts to 65 variables, including variables related to family size, income, energy use, and transportation behavior, among others. We apply a Z score normalization method to eliminate possible biases (see the normalized variables in Table S4, supplemental experimental procedures).

Integrated clustering method

By integrating supervised and unsupervised learning modules, we develop a simplified two-stage clustering approach to develop a taxonomy of households based on various household characteristics (see step 1, research approach, experimental procedures). We consider the clustering method to be more efficient and appropriate for pattern recognition in household survey data based on the following factors: (1) the use of multiple regression methods requires a clear causality[107]; (2) excessive number of variables in multiple regression methods can increase model noise and reduce accuracy[108,109] and can lead to problems of overfitting and multicollinearity[110]; and (3) clustering is more conducive to highlighting the differences between categories with relatively low algorithmic complexity.[12,111]

First, we select all the possible quantitative variables related to household energy consumption from the survey and filter them based on the literature[72,94] to identify the significant household characteristics that explain household emissions. We convert the input data from the HEUS and fit them to emissions per capita data through a LASSO model.[112] The LASSO model is fitted by minimizing the following cost function:

$$J = \frac{1}{2m}\sum_{i=1}^{m}\left(y_i - \alpha - \sum_j \beta_j x_{ij}\right)^2 + \lambda\sum_j |\beta_j| \qquad \text{(Equation 1)}$$

where m is the total number of observations, α is the intercept, y_i is the dependent variable, λ is a non-negative regularization parameter, and β_j is the coefficient of independent variables.

The value of λ controls the entry of variables trained by the model. The higher the value of λ, the higher the number of variables whose coefficients are zero. Therefore, this parameter is crucial for clustering and can be optimized by minimizing the fitting error, i.e., the mean square error (MSE). By applying a grid searching strategy with values of λ ranging from 0.001 to 0.1 (with a step equal to 0.001) for the optimal model output, we find that 0.006 is the optimal parameter value for the LASSO model, which results in the highest performance. Then, after applying the LASSO model,[112] we retain only 25 variables that have an importance of over 0.04 (see Figure S5, supplemental information). Table S1 in the supplemental information contains the complete list of variables selected for the subsequent analysis.

Second, we develop the actual household taxonomy. To achieve this, based on the selected variables, we apply the K-means method, which is one of the prevailing unsupervised learning approaches that fit well with multi-dimensional datasets.[113] However, as K-means clustering cannot automatically produce an optimal number of clusters, we iteratively search for the optimal number of clusters. The performance of the clustering process is assessed through the silhouette coefficient.[114,115] Additionally, we impose another constraint to ensure that each cluster contains no fewer than 50 households. The number of clusters obtained through the K-means method is 6, which is optimized by maximizing the silhouette score using the selected variables as 25-dim input data. This process is described in more detail in Figure S2 (supplemental information). The clusters are further categorized based on five dimensions, namely household income, household size, average age, driving frequency, and whether the household has children, as these are the five most essential dimensions affecting emissions recognized in the LASSO model. Figure S6 (supplemental information) provides a simplified description of the household taxonomy. Table S5 (supplemental information) suggests that households for a given group are not clustered in a specific geographic region and that their distributions is almost random within the country.

To validate the output of the integrated clustering method, we make comparisons between clustering and socioeconomic groups (Figure S7, supplemental information). In Figure 3, the differences in per capita emissions among household groups are magnified. Given the top five factors affecting emissions outlined above, the clustering method minimizes the intra-group differences and maximizes the inter-group differences. Although we do not directly use emissions per capita as a dependent variable in the analysis, the differences among groups are still identified by the unsupervised learning method.

Estimation of direct emissions

To estimate the household-level emissions for each group, the survey adopted for our study uses a bottom-up emission accounting method. First, energy uses related to scope 1 and scope 2 emissions are accounted for, including various fuels and electricity. Second, in terms of various energy types, the survey collects household energy uses and subsequently estimates emissions on the basis of the adjusted emission factors in our previous study. Therefore, the aggregate emissions of a household are the sum of all subsidiary emissions from using electricity and primary energy. In addition, the aggregate emissions are consistent with the sum of emissions from household energy demand, including electric appliances, transportation, space heating, space cooling, and water heating, among others. The detailed information of the carbon emission survey is collected directly by the MOE of Japan (https://www.env.go.jp/earth/ondanka/ghg/kateiCO2tokei.html).

Future prevalence of the study groups

To generate the results shown in Figure 3, we conduct two scenario analyses to estimate the future of the studied household groups in 2025, 2030, 2035, and 2040: (1) a "baseline scenario" that assumes that the household structure is the same as it is currently (i.e., there is no demographic transition and the proportion of the six groups in the projected population remains the same as in the base years 2017–2018) and (2) a "demographic transition scenario" that varies the proportion of the different groups in the projected population.

For both scenarios, the projected population data for Japan are provided by the National Institute of Population and Social Security Research (IPSS, https://www.ipss.go.jp/index-e.asp) and we match them with the household taxonomy developed above. We do so by fixing the age and family structures as follows. First, we divide the projected population of 14–84 years old into 15 age groups (i.e., at 5-year intervals), with those ">85 years old" constituting a separate group. Second, we cross-map the family types from the projected population data (i.e., single, couple, single with children, couple with children, and others) to the family types from the survey data (i.e., single, couple, single with children, couple with children, single elderly [>60 years old], couple elderly [>60 years old], large family [family size > 4], and others). The mapping process is described precisely in Section S3 in the supplemental experimental procedures.

To calculate the projected number/population of each household group for 2025, 2030, 2035, and 2040, we measure the distribution of households by age and family type D^k_{ab} for household segment k, where a, b represent the age and family type dimensions for the matrix. In our population projection approach, we establish mapping between age and family type groups from the HUES survey and the National Institute of Population and Social Security for Japan (NIPSSR) population projections. We leverage the NIPSSR population projections to infer population estimates for each combination of age and family type groups identified in the HEUS data, ultimately obtaining prevalence projections for the six household groups by multiplying these estimates by the respective proportions of each age and family type group within each household cluster (see details in Section S3, supplemental experimental procedures). By multiplying by the projection population data P_{abt}, the future number/population for a given household group is calculated through Equation 2 as follows:

$$P^k_t = \sum\sum D^k_{ab} \times P_{abt} \qquad \text{(Equation 2)}$$

Estimation of future mitigation potentials

We obtain the results shown in Figure 3G by using the emissions in the reference scenario as the base (see future prevalence of the study groups, methodology), as it offers a better approximation of the make-up of the Japanese household sector in the future. Then, for each household group, we measure the effects of EFI, and PV and NEV adoption, on household emission intensity and calculate the emission reduction potential due to PVs, NEVs, and lower grid emission factors (see Section S4, supplemental experimental procedures).

We estimate the conditional probability that a household adopts PVs or NEVs, incorporating the dynamics of technological advances and household preferences for technology adoption through logit models, given their pre-adoption features.[116,117] The propensity can be expressed as follows:

$$p(\mathbf{X}) = \Pr(adopt = 1|\mathbf{X}) \qquad \text{(Equation 3)}$$

where $\mathbf{X}$ represents the pre-adoption features of households. The logit regression model is defined as follows:

$$\ln\left(\frac{p(\mathbf{X})}{1 - p(\mathbf{X})}\right) = \beta_0 + \beta_i \mathbf{X}_i + \epsilon_i \qquad \text{(Equation 4)}$$

Notably, PV installation costs or NEV costs are not included in the set of pre-adoption features because the HEUS dataset does not provide detailed information about the adoption time of PV and NEV technologies for households. This lack of information makes it difficult to provide accurate cost estimations for technology adoption.

In this case, we define the *penetration rate* of PVs and NEVs as the ratio of willing-to-adopt households to unwilling-to-adopt households. Because it is not clear whether households are willing to purchase emission mitigation technologies as advanced low-carbon technologies are emerging, we assume that the future willingness of household groups to adopt PVs/NEVs is the same as it is currently. The probabilities of adopting PVs and NEVs range from 0%–91.4% and 0%–44%, respectively, depending on the group, with mean probabilities of 6.9% and 1.3%.

The PV/NEV penetration rate of each household group is calculated as follows. First, we decompose the general penetration rate for the whole

population into subsidiary penetration rates for each household group. The penetration rate χ_k for household group k can be viewed as the accumulated distribution of households possessing higher propensity scores than the threshold x_a. In other words, the percentage of households that are willing to adopt mitigation technologies over the whole population is:

$$\chi_k = \frac{N_k(X|X \geq x_a)}{N_k} \quad \text{(Equation 5)}$$

This equation can also be written as $\chi = 1 - P(X \leq x_a)$, where X is the random variable denoting the propensity score of households for mitigation technology adoption. Therefore, given threshold x_a, households with propensity scores higher than x_a will be considered as adopters in the scenario.

Ultimately, household emission scenario projections take into account factors from two aspects, namely energy intensity decline and mitigation technology adoption. We denote the household emission projection as $E_{t,i}$ (household i's total amount of emissions in year t), and it can be expressed as follows:

$$E_{t,i} = E_{t0,i} - \underbrace{\sum_j^5 R_j A_{ij} EF_{t,j}}_{activity} - \underbrace{\Delta EF_{t,elec} C_{pv} E_{t,elec}}_{electricity} - \underbrace{(1 - C_{nev}) E_{t,nev}}_{vehicle} \quad \text{(Equation 6)}$$

where $E_{t0,i}$ represents household i's total amount of emissions in 2018. The total household emissions in year t are composed of three parts: emissions from activities (except vehicles), electricity consumption, and vehicles. $E_{t,i}$ will be affected by (1) the ratio of energy intensity decline R_j, which is related to the increase in electrification; (2) emission reductions from the lower grid emission factor ΔEF_t and PV adaptation coefficient C_{pv}; and (3) emission reductions from switching to NEVs with the coefficient C_{nev}. In addition, $E_{t,elec}$ denotes emissions from electricity use and $E_{t,nev}$ denotes emissions from vehicles. The estimated emission reduction potentials of PVs and NEVs are listed in Table S6 in the supplemental information.

Limitations and uncertainty

Several limitations should be acknowledged when interpreting the results of this study. First, the use of a single clustering method may affect the robustness of the results. The LASSO model used here was instrumental in identifying influential variables for our analysis (namely income, household size, average household age, driving demand, and presence of children). Although these variables are interdependent to some extent—for instance, household size naturally correlates with the presence of children—our model's focus was on using these variables as distinct classification points. Consequently, the LASSO model's structure emphasized variable selection rather than exploring the complex interactions among them. Acknowledging the importance of these factors, future research should investigate these interactions more thoroughly and test alternative algorithm-based clustering methods, which can be populated with survey data to validate the clustering approach.

Second, we made a series of assumptions that might have introduced uncertainties in the modeling process. For instance, the acceptance thresholds for the adoption of emission mitigation technologies are unlikely to be verified with real-world data. From the perspective of the simulation, the different thresholds indicate only different offset levels (which will not affect our findings). Using different models to estimate acceptance rates may affect the penetration rates of PVs and NEVs in the projection population. In this sense, as the current penetration rates are relatively low, it is difficult to accurately extend our data to 2040, as there is the possibility of major disruptions in the NEV and PV markets.[118,119] Notably, as only 1% of the samples are NEV adopters, the NEV results may be biased due to insufficient data. However, as current NEV adopters can still provide some important clues for future promotion, this survey should be updated every year to provide more data in the future. In contrast, the effects of aging and the increase in single-person households hold great significance for emission patterns. Here, we make assumptions about the constant willingness to purchase PVs and NEVs, which may increase or decrease subject to policy signals, and the availability and price of low-carbon technologies in the future.[120,121] In this case, to reduce model uncertainty, future studies could conduct sensitivity analyses to offer more accurate prediction ranges or primary data collection to precisely describe the willingness of adoption (e.g., through choice experiments or other similar techniques).

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.crsus.2024.100053.

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AUTHOR CONTRIBUTIONS

Y.L. designed the study. Y.L. and Y.W. conducted the analysis. All the authors wrote the first draft of the manuscript and revised the manuscript. A.G. supervised this research.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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