Demographic transition hinders climate change mitigation in the aging and shrinking Japanese residential sector

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Demographic transition hinders climate change mitigation in the aging and shrinking Japanese residential sector

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Summary:

The residential sector is one of the major sources of greenhouse gases, and as such it is key for achieving decarbonization targets. However, very diverse household characteristics affect energy use and emissions at the household level. Furthermore, demographic transitions characterized by ageing and shrinking in both total and household size can have enduring effects for some of these household characteristics at the societal level. Here, we explore how demographic transitions in Japan may affect the long-term emissions in the residential sector based on the scenarios to the year 2040. First, we draw from a large-scale survey conducted by the Japanese government (9,996 households) to develop a nuanced typology of households using an integrated clustering approach. This helps us identify high variability in emissions and adoption of emission mitigation technologies between households with different characteristics. We found that household size and age both play important role in terms of emissions. Finally, through different scenarios we identify that indeed the projected demographic transitions with the increasing prevalence of smaller and more elderly households in Japan will likely hinder emission mitigation in the residential sector, imposing significant constraints for achieving decarbonization in the long-term.

Keywords: Aging society; Demographic transition; Emission characteristics; Carbon mitigation; Data mining.

Introduction

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

However, in the post-Paris Agreement era there have been strong calls to also design effective emission mitigation plans on the final demand-side. For example, several campaigns have been sought to promote the uptake of green technologies and transition to low-carbon lifestyles[8-10], especially for the residential sector[10-15]. Household sector accounts for both a large fraction of final energy consumption and total greenhouse gas (GHG) emissions and have high GHG emission mitigation potential[16-19]. For example, the US residential sector directly and indirectly contributed for nearly 80% of total indirect GHG emissions [8,20,21]. In Japan, residential consumption are responsible for >60% of total GHG emission[22-24], with expected contribution for nearly 50% of the emission reduction commitment under the Paris Agreement [25]. Despite the increasing number of efforts to boost household-level decarbonization measures[25-27], the sector is facing two major challenges on the effective design and decarbonization measures implementation.

First, it is widely accepted that emission mitigation technologies targeting households or individual consumers are not universally appealing considering the variability of household demand[28,29], technology acceptance levels[30,31], and affordability[32,33] across demographic groups, which are essentially dictated by consumer/household characteristics. At the same time demand-side emission mitigation efforts need to consider issues of fairness (e.g. climatic justice[19,34], inequality[13,35]), feasibility[36,37], and effectiveness. The design of feasible and effective measures is highly relying on a good understanding of household consumption preference, and how they are affected by household characteristics. Previous studies have identified household characteristics such as income, age, composition and location as key factors affecting energy demand and consumption behaviors[38-43,41,44-46]. For example, affluent families and elderly families tend to have higher energy consumption[19,33,4749], while household size is a major determinant of domestic energy consumption[48]. Furthermore, certain lifestyle decisions also vary between genders and generations, with for example households with school-aged children having higher electricity demand for lighting and elderly households for TV[46]. The above translate to that households with different characteristics have different GHG emissions and acceptance of end-use energy technologies (primarily due to their differentiated needs and financial status)[49,50].

Second, it is important to know that the promotion and adoption of decarbonization measures for households are closely links with multiple unfolding demographic, socioeconomic, and environmental transitions[7,11,51]. One of the most importance demographic transitions is the population ageing and shrinking that affect, among others, household composition, age distribution, and size, and essentially lifestyles. As a result a result, the population ageing and shrinking has major implications for the adoption of energy end-use measures[48], and achieving sustainability in general[52]. Population ageing is now visible in most developed countries and an increasing number of developing countries[16,18,53-56] (see **Figure S1**, **Supplementary Material**),

having major ramifications for energy use and GHG emissions many parts of the world[55,57-60].

Faced by these two challenges, previous studies have explored the consequences of household characteristics and demographic change on energy technology adoption and GHG emissions, but often with mixed findings due to methodological differences and limited data availability[40,60-66]. Generally, there is a wide acceptance that small households with higher income, elderly members, and small size households are more likely to have higher GHG emissions, partially due to the scale effect of household energy consumption and lifestyles such as the longer time spent in-home among elderly[13,40,67-69]. Here, household shrinking make shareability of energy decreased since its scale effect declines[18,70-72], which is of increasing interest in depopulation and household size shirking countries.

The above make a strong case for detailed household-level studies estimating differentiated emissions reduction potentials taking into consideration the effects of household characteristics and technology acceptance rates. However, there are some very important knowledge gaps that have complicated such studies in the past. First, there is often a lack of nuance when creating household taxonomies. Although many household-level studies on energy use and GHG emission have been conducted across different grouping (e.g. divided by income, age, family size, or specific lifestyles and energy consumption behaviors) this is usually discussed from one specific dimension (i.e. different income or age groups, etc.). Furthermore, this is usually based on experience and the focus of the study, rather than a nuanced understanding of multiple intersecting household characteristics. Second, whether the promotion of emission mitigation measurements can really realize their expectation still remind questionable, since promoting high efficiency end-use technology are not sure that be accepted to each household [21,73-78]. Third, there is a general lack of robust studies exploring how demographic transitions intersect with decarbonization efforts at the household level, despite the clear trends towards population ageing and shrinking in many of the largest emitting economies.

Although many studies have explored how this heterogeneity in household characteristics affects both energy use patterns[79,80] and adoption of mitigation technologies[80,81], most studies have relied on mono-dimensional and/or subjective divisions across household characteristics. For example, although many studies find generally higher emissions of richer, aging and small size of household[9,82-84]. Under the classic framework of household-feature analysis, the emission features are manually being grouped and ignored if they derived similar emission features, such as income level and age of reference person. This single-dimension grouping is apt to provide biased information or loss some. For example, richer household are found emit more emission than poor, while their higher emission may be driven from richer household having larger household size or they are elder citizen,etc. The

mismatching from household grouping and emission features lay potential uncertainty for following measurements generation.

Here we first estimate household carbon emissions across income and age groups with different household size, then we discuss how household characteristics and demographic transitions affect the adoption of climate change mitigation technologies at the household level, and their potential effect on emissions. Our focus is Japan, as it makes for an ideal case considering that it is the 3rd largest economy globally, the 5th largest GHG emitter, has made a recent political commitment towards decarbonization by 2050[85] and has experienced strong demographic transitions in recent decades. Regarding the latter, single-member households already account for 34.6% of the entire population in 2015 (expected to increase to >50% by 2035[86]), while the population aging and shirking rates are some of the highest in the world[40,64,65]. Collectively the above can provide valuable information for other major economies that are increasingly facing deep demographic transitions[52] in the next few decades.

Through a data mining and multi-dimensional cluster method we develop a household taxonomy across six groups using data from a large national household survey on energy consumption and emissions. For each of the identified groups we explore the adoption rates and performance of the two major emission mitigations measures currently promoted in Japanese households, namely roof solar photovoltaics (PV) and new-energy vehicles (NEV)[87-90]. For the six study groups we explore patterns for the year 2017-2018, and future trajectories up to the year 2050 based on the expected demographic transition in Japan.

Main text

Differentiated emission patterns between groups

The clustering analysis performed using the least absolute shrinkage and selection operator (LASSO) model which identifies five most important variables (from a total of 27 variables) affecting direct energy use and related GHG emissions, including income, household size, average household age, driving demand and whether the household contains children. We use these variables to create a household taxonomy consisting of six groups that have the largest disparity in direct energy use and related emissions. **Figure S5** in the **Supplementary Material** provides a detailed description of each of the six groups in the taxonomy.

Figure 1A compares the emission between the six household groups. Here, we found that high-income households with children (HFK) have the highest emissions compared to the any other groups. In addition to the income, we found that lower-income elderly single person households (LES) and lower-income single person

households (ULS) have even higher per capita emissions than (see pink bars in **Figure 1A**).

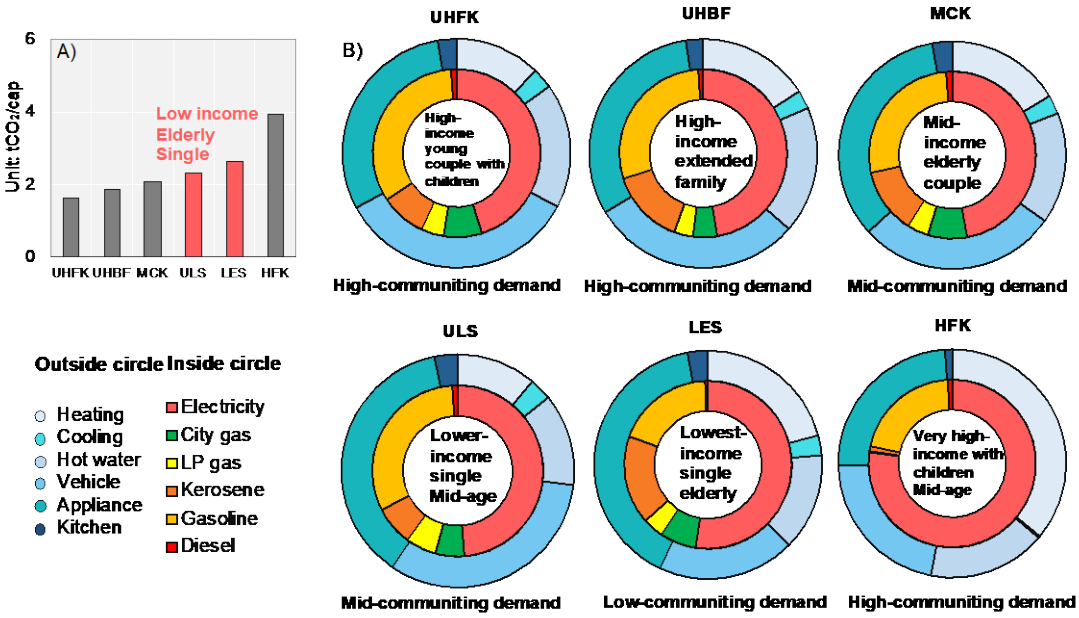

Figure 1: **Per capita household emissions across six household groups.** Panel (A) shows the total per capita household emissions for each of the six groups. Panel (B) shows a decomposition of the household emissions by household activity (outer circle) and fuel (inner circle)

Figure 1B suggests that home appliances and vehicles account for the highest share of household emissions for all groups. For each group except for the high-income households with children (HFK), emissions from appliances and vehicles account for >60% of overall emissions. However, for the HFK group space heating is the largest source of emissions (36.4%), followed by appliances (24.5%) and vehicles (21.9%). For the lower-income elderly single person household (LES) group and the lower-income single person households (ULS), appliances account for most of the emissions, followed by space heating. When we zoom into the three groups outlined above, for household with children (e.g. UHFK and UHBF), >30% of their emissions are from vehicles indicating their propensity for a more car-oriented lifestyle.

When looking at the fuel consumption, we found large kerosene demand for space heating from the lower-income elderly single-person households (LES), although electricity generally tends to be the main fuel for space heating for most groups, especially in mountainous regions of the country. This indicates the strong dependance of LES group on less efficient fuel for space heating. In contrast, emissions from space heating for HFK group account for a large fraction of the total emissions but their emissions are mainly from electricity-based heating and the

electricity-related emissions are as much as 2.16 times greater than the LES group. This first part of results provides two important clues for next step analysis. Firstly, from the total emission across six groups, the highest income with highest commute demand is found with the highest level of emission. However, the second highest does not turn into second rich group. Two other group featured by aged family member above 60 years old (LES), lowest (LES) and second lowest (ULS) income, and single household (both LES and ULS's average household member are 1) are also found with higher per capita emission. Therefore, if the LES and ULS takes large ratio of total population, the mitigation effort of them can not been neglected. Second, although the listed three groups (HFK, LES, ULS) are found with higher emission, the reason that contributed to that (see emission source mix in **Figure 1B**) are different. For example, the space heating of HFK take the majority responsibility of highest emission, while the LES and ULS shows their appliance contribute mostly.

Emission mitigation potential analysis from limited samples

To mitigate household emission, the next step analysis is conducted for revealing the current green technology promotion and its mitigation performance. Here, we estimate mitigation potential of adoption of emission mitigation measure (namely PV and NEV) for each household group. PV and NEV are two major household green technology applied in Japan. However, the current PV and NEV promotion still located early-stage and demands for further development, which result in limited samples in our survey dataset. Although it seems not statistical-significant, we still think our current limited sampling could provide some interesting clues to describe the current dilemma and even the possibility. For example, **Figure 2A** suggests that most households have lower per capita emissions through adopting PV, except for the lower-income single person households (ULS), where households with PV emit up to >53.8% than those households without PV. To note, the electricity consumption from PV is not included in total emission, the reason of higher emission of LES that adopted PV is contributed by two reasons: firstly, the sample number of PV adoption in LES is the smallest which reflect the PV promotion of this groups still insufficient (6.9% of total PV adoption but LES only has 2%). Second, the household that adopted PV are found with higher ratio of electric appliance highest demand of water heating demand (e.g. everyday bath). Conversely, per capita emissions from households adopting PV are 15.1% and 17.7% lower than households not PV for groups with larger sizes such as high-income households with children (UHFK) and high-income extended family households (UHBF).

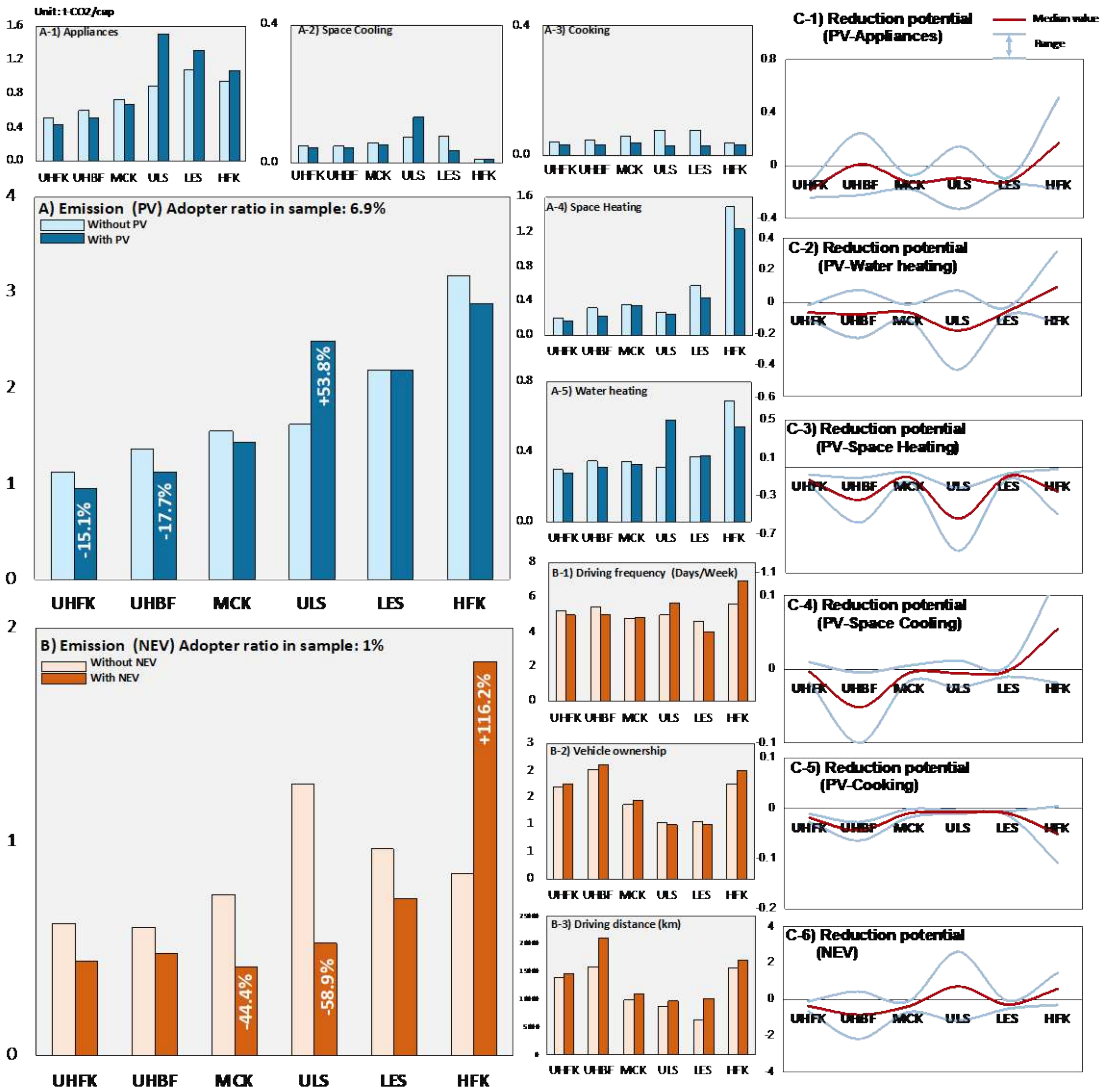

Figure 2. Direct emissions reductions in 2017-2018 for each household group considering the adoption and not adoption of PV and NEV. Panel (A) highlights differences in direct per capita emissions for each household group adopting and not-adopting residential PV. The five sub-panels (A1-A5) indicate the differences in direct per capita emissions for each group for PV adopters and non-adopters for different household activities. Panel (B) highlights the difference in direct per capita emissions from vehicle use for each household groups adopting and not adopting NEV. The three sub-panels (B1-B3) indicate differences in direct per capita emissions between NEV adopters and non-adopters based on driving frequency, driving distance, and vehicle ownership. Panel (C) estimates the effects of PV and NEV adoption on direct per capita emissions for each household group for different activities (C1-C6). The lines present the coefficients of the OLS estimations in each group, where the red lines indicate the average effect and blue lines denote the lower or upper confidence intervals at 95% confidence level. These are patterns for 2017-2018 based on data from Japanese household energy use survey (HEUS) (see Methods).

Therefore, the reasons for these patterns depend by group. In particular, the PV adopters within the lower-income single person households (ULS), the lower-income

elderly single person households (LES), and the high-income households with children (HFK) tend to have higher emissions from appliance use than non-adopters (**Figure 2A-1**). This is also visible for water heating for the ULS group (**Figure 2A-5**). But generally, PV adopters for all other groups tend have lower per capita emissions for other household activities compared to non-adopters. PV adoption in groups characterized by higher family sizes (whether extended or nuclear families) such as UHFK, UHBF or even HFK, has higher emissions reduction potential for all household activities. These groups with larger families will benefit from adopting PV to significantly offset their consumption of electricity or the other fuels, especially from space heating and water heating. Generally, the PV adopted household's annual energy consumption is 32.2GJ while without PV is 40.5GJ. However, the total PV installation ratio of sample data is only 6.9%. Therefore, although the PV already show its energy conservation potential, the current PV adoption is still insufficient in Japan, especially for the LES and ULS group. And to the further promotion of PV in Japan, the home appliance efficiency improvement of LES and ULS should also be conducted simultaneously.

Figure 2B shows the emission reduction effect of NEV adoption for the six household groups. To note, the samples only show 1% of NEV adopter, therefore the results from NEV may also biased due to insufficient data. However, the current NEV adopter still can show some important clues for future promotion. Firstly, the results show that the adoption of NEV tend to lower the emissions for all groups, with the only exception being the very high-income households with children (HFK), for which emissions more than double (116.2% higher). This reflects the generally high levels in terms of driving distance, driving frequency, and vehicle ownership (Figure 2B1-3). Beyond the generally high transport demand within this group, many households are also highly likely to own multiple cars. For the other groups, households adopting NEVs tend to emit significantly less. It is also interesting to see that households adopting NEVs tend to have above average driving distances but lower per capita emissions than those without NEV (Fig 2B-3). This is particularly evident in single and lower-income household groups such as the MCK and the ULS groups, where per capita emissions from for NEV-adopting households are 44.4% and 58.9% lower than those from households without NEV. In contrast, the average driving distances for the MCK and ULS groups are 10,871 km/year and 9,667 km/year, which lower than the average driving distance by 21.6% and 15.2% respectively. Therefore, the lower-income and single households such as those in the MCK, ULS, and LES groups tend to have higher emission reduction potential in terms of the NEV adoption.

Figure 2C outlines the estimated effects of PV and NEV adoption on per capita emission from various activities for each group. We observe relatively significant emission reduction potentials for the high-income extended family households (UHBF), lower-income single person households (ULS) and lower-income elderly single person households (LES) through the adoption of either PVs or NEVs. In

contrast, for the very high-income households with children (HFK) the results do not suggest a significant emission reduction potential except for cooking. Again, this reflects what was mentioned above that for this group the adoption of these technologies might be followed by greater energy use, negating any emission mitigation benefits. Tables S4-5 in the Supplementary Material provide the emission reduction estimates for each group and activity.

Effects of demographic transition on emissions

In the previous section we estimated the current per capita mitigation potential of green technology adoption for household groups with different characteristics. Here, we explore the overall future reduction potential considering the expected demographic change over the period 2025-2040, This is done through regressions on group-level per capita emissions for different scenarios (see "**Research Approach"**).

Figure 3a-f show for each household group the projected differences in their contribution to future emissions from the residential sector based on different population structure. Here, we consider the future household structures under two scenarios (i.e. baseline: using current demographic mix and dynamic: using dynamic demographic promotion). When trying to understand the factors dictating the differences between the two scenarios outlined above, **Figure 3g-j** suggest that for each of the future study years the emissions from the increasing prevalence of single and elderly households (i.e. ULS and LES) are countered by the reduced prevalence of households with larger household sizes (i.e. UHFK and UHBF). However, although during the demographic transition between 2025 and 2040 the emissions from the increasing prevalence of LES grows by 34.7%, the emission reduction caused by the decreased prevalence of UHFK and UHBF grow by 10.5% and 7.1%. When considering these trends, the results suggest that emission mitigation efforts in the residential sector will be hindered by the increasing emissions from the single and ageing households.

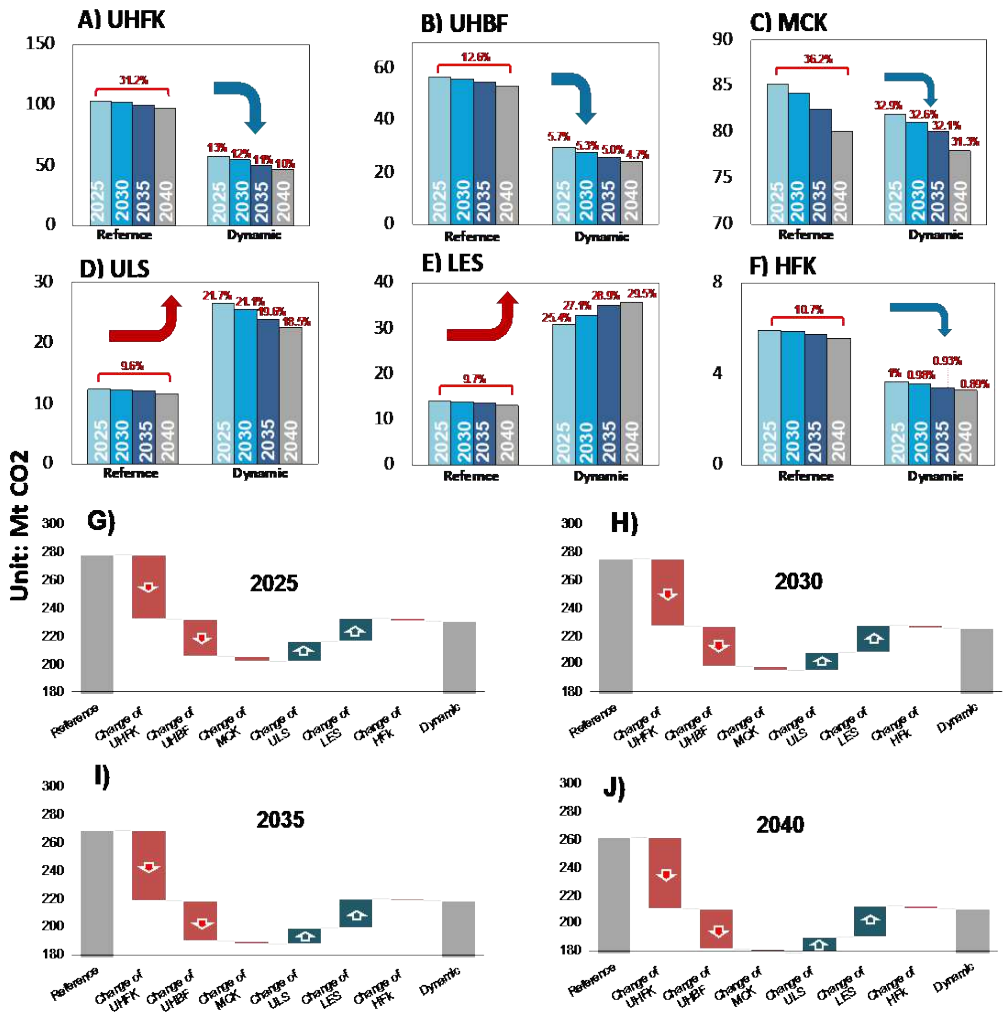

Figure 3: **Effects of demographic change on direct emissions from the residential sector.** **Panel (A-F)** show the direct emissions for each group for the baseline reference scenario and the dynamic population structure scenario (see "**Research approach**" for scenario description and underlying assumptions). Percentages above bars indicate the expected fraction of each household group in the total population for the specific year (i.e. all percentages for the reference scenario add up to 100%, while all the percentages for the same year in the dynamic scenario add up to 100%). Fractions of household groups in the reference scenario are assumed to be the same as for 2017-2018, while fractions for each group and year for the dynamic scenario are allocated following the process outlined in "Future prevalence of study groups". Panel (G-J) explain for each year which group changes explain the differences levels between the baseline reference scenario and the dynamic scenario.

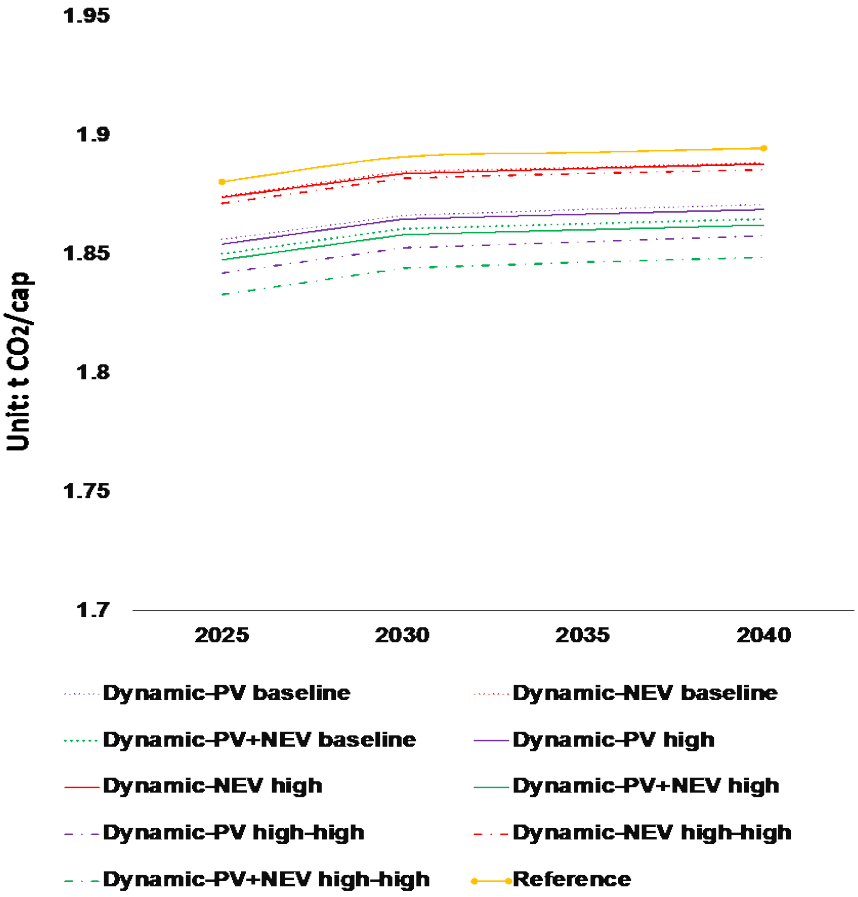

Figure 4: Effects of PV and NEV adoption rates on residential sector emissions. The yellow line depicts emissions for the entire residential sector assuming for each year both the same distribution of household groups as in 2017-2018 and PV/NEV adoption rates for each group as in 2017-2018. All other lines depict emissions from the entire residential sector using the distribution of household groups estimated for the dynamic scenario in each year (**Figure 5**) and different levels of PV and NEV adoption (see "**Estimation of future mitigation potential**").

Figure 4 shows the per capita emissions from the residential sector considering different levels of emissions mitigation technology adoption. The underlying household group allocation here is the population scenario here is the dynamic scenario, with dots line in purple, red and green shows the projected per capita emission after demographic transition with current adoption of NEV, EV or both. The solid lines show the projected per capita emission with a higher rate of technology adoption. The dash lines show the projected per capita emission with the highest rate (the most optimistic scenario) of technology adoption.

The results indicate that, in the coming decades, while the total direct emission from the Japanese household sector would likely gradually decline (mainly due to the declining population, see **Figure 3**), the actual per capita emissions will increase for practically each scenario (**Figure 4**). This reflects the strong expected demographic transition in Japan.

Furthermore, PV and NEV are not always receiving an expected reduction potential in some groups (See **Figure 2**) by total. For example, group ULS and LES do not see much reduction potential by introducing PV, because ULS has higher demand on electric appliance, cooling, and hot water because of the elderly are sensitive to temperature variance but most of them keep their out-of-date home appliance for more than 15 years old[91], and thus more emissions are generated. Furthermore, both elder and single household will select wooden living environment, featured by a worse isolation living condition. Therefore, in both winter and summer those families need more energy to keep the in-house temperature comfortable. Similarly, HFK also shows a limited reduction expectation by adopting NEV. The reason is high income core family often have multiple vehicles and featured by the highest frequency driving frequency (7 days/week), by introducing the NEV will not significantly lower the per capita emission from vehicles like other groups. Therefore, although PV and NEV are two of most promising end-use green technology, the reduction potential varies among household groups and may not receive much difference in certain groups, which provides vital information of groups-target promotion of green technologies. Detailed discussion about reduction potential of PV and NEV in different household segments can be found in **Figure S7 Supplementary Material**.

In the **Figure 3K**, we give out one more step to answer to what extent the household per capita emission will be affected by introducing PV and NEV aggregating the potential emission changes brought by future demographic transition. The reference line denotes a slightly upward trend of per capita emissions after demographic transition by excluding any additional technology adoption. The emission intensity is estimated to grow from 1.880 to 1.894 tCO_2/cap (about 1.4%) at the reference level. Under the baseline scenario, adoption of PV and NEV can reduce the emission intensity by 0.03 tCO_2/cap (about 1.6%) in 2025, 2030, 2035, and 2040. However, due to the higher penetration rate of residential PV, it shows a slightly greater emission mitigation potential than NEV by 0.018 tCO_2/cap. In addition, under optimistic scenarios, with technology adoption, the emission intensity decreases by 0.033 tCO_2/cap (high scenario) and 0.047 tCO_2/cap (high-high scenario). According to our definition of optimistic scenarios, higher penetration rates of technologies prove effective to lower emission intensity, and the potentials under high and high-high scenario are about 79% and 156% higher than the baseline scenario.

Overall, due to the trend of aging and depopulation, holding the penetration rate of technologies constant, the emission mitigation potential declines across all scenarios in 2025, 2030, 2035, and 2040, and thus will potentially lead to an upward emission intensity in Japan's future. More efforts are needed to offset the excessive part and then reduce the overall emission level of the whole society, by overlapped pressure from both 2030 NDCs and well as zero emission target in 2050.

DISCUSSION

The nuanced understanding of energy consumption and emission patterns, as well as of the propensity to adopt green technologies, are pre-requisites for designing effective and fit-for-purpose measures to influence transitions to low-carbon lifestyles, and eventually achieve the decarbonization of the residential sector[67,92,93]. This is because household characteristics (e.g. age, income, household composition) not only affect energy use and emissions [21,9], but also the acceptance of different emission mitigation technologies[95,9]. At the same time, demographic transitions might alter drastically some of these household characteristics (e.g. age, composition) at the national scale, essentially affecting the overall emissions of the residential sector[58,66]. With many societies around the world currently experiencing rapid and deep demographic transitions exemplified by population shrinking and/or ageing (see Introduction), it becomes critical to understand how these transitions will affect the prevalence of households with different characteristics (and essentially different energy use and emission profiles, and propensity to adopt mitigation strategies).

These realisations have influenced us to adopt a multi-stage approach to (a) develop a multi-dimensional household typology in relation to their energy use and emissions (**Figure 1**), (b) estimate the current emissions variability and potential emissions savings for each group based on the adoption and non-adoption of mitigation technologies (PV/NEV) (**Figure 2**), (c) explore senitivity of future emissions estimations for the residential sector in the face of unfolding demographic transitions, based on different scenarios about the prevalence of different household groups in the future population (**Figure 3**), and (d) assess the effects of variable PEV and NEV adoption rates between groups, on residential sector emissions in the context of future demographic transitions (**Figure 4**). Below we discuss some of the major observations and implications for each of these points.

For (a) we observe that while income affects both the emissions and the adoption of mitigation technologies, other demographic factors such as age and household composition play equally important roles. Sometimes these characteristics may exhibit endogenous correlations, having a synergistic effect on household emissions. This is evident by the fact that it is not always the higher-income households emitting more, but that sometimes also lower-income households may have high emissions due to, for example, reliance on low-efficiency appliances[94]. Our integrated clustering analysis found that for Japan family size, number of children, average age, income per capita, and driving frequency factors affect significantly energy use and direct emissions and were thus used to develop a household typology that explains between their trends in the Japanese residential sector (**Figure 1**).

For (b) we find that the adoption of PV and NEV has different emission mitigation potential across the different household groups (**Figure 2**). This mostly reflects the energy demand variability for the different household activities for each group (**Figure 1**). Although the PV and NEV adopters have mostly lower emissions compared to non-adopters, there are some exceptions. In particular, in some groups PV adopters exhibit

higher emissions from appliance use (**Figure 2A**). This possibly indicates the existence of rebound effects in that although PVs are adopted for energy savings, the adopting households might end up increasing electricity use, and thus associated emissions[95,96]. Although we also observe higher emissions from NEV adopters in some groups, it is not clear-cut whether this is due to rebound effects. Although in some cases the driving distance and car use might be higher for adopters (**Figure 2B-1** and **2B-3**), vehicle ownership also tends to be higher (**Figure 2B-2**).

For (c), we observe the sensitivity of future emission projections for the residential sector, to the prevalence of different household types in the future population (**Figure 3**). We argue that in the context of the profound demographic transitions currently observed in Japan and other developed countries (see Introduction), multi-dimensional household typologies, such as the one developed in this study, can increase the accuracy of emissions projections. This can be appreciated when understanding the cascading effects of ageing. Firstly, currently 47.1% households in in Japan can be characterized as aged (>65 years old), of which 57.8% consist of less than 2 persons[91]. After reaching the retirement age (currently 65 years old in Japan), household income tends to decrease significantly, as they depend on pensions that are much lower than salaries. This reduces both their ability to adopt emission mitigation technologies such as PV or NEV (**Figure 2**), and increases their dependency on low-efficiency home appliances. According to the survey conducted by the Ministry of Economy, Trade and Industry (METI), the ageing household owned more outdated appliances than younger generation and some appliances have been used for over 15 years or above. These collectively increase the emissions of such households to levels almost comparable to the emissions of households with higher sizes and incomes (**Figure 1**), only standing below of very high-income households[11,13].

For (d) we see signs that the expected demographic transition towards older and smaller households, will likely pose constraints in emissions mitigation from the residential sector. It seems that regardless of the PV and NEV adoption scenario, the per capita emissions slightly increase over time (**Figure 4**). This is indeed driven by the increasing numbers of these types of households in the future population (Figure 3), which both tend to have relatively high emissions (**Figure 1**) and comparatively lower adoption rates of emissions mitigation technologies (**Figure 2**). Considering the above it becomes obvious that in order to achieve decarbonization in the residential effort there should be a conscious effort to enable such groups reduce their emissions, through a combination of measures that seek to enhance the efficiency of their energy use[97] and reduce the emission intensity of their energy sources[66,94].

METHODOLOGY

Research approach

For this study we follow four main research steps: (a) delineate study groups through developing a household taxonomy (Step 1), (b) estimate household emissions for the

study groups (Step 2), (c) identify adoption patterns for emission mitigation options for each group, and estimate emissions for adopters and non-adopters for each group (Step 3), and (d) simulate future adoption and emissions considering the ongoing demographic transition. **Figure S2** in the Supplementary Material summarizes the research approach.

During Step 1 we develop a taxonomy of the study households through data mining and a multi-dimensional cluster method (see "**Integrated-clustering Method").** We use household-level data from the Japanese household energy use survey (HEUS) conducted by the Ministry of the Environment (MOE) over the period 2017-2018, after appropriate treatment (see "**Data preparation"**). This marks a major departure from conventional approaches that group households across specific characteristics for emission estimation, which is usually performed through expert judgment and across single dimensions/characteristics. This type of conventional grouping can provide misleading information, as it does not consider the multiple dimensions affecting emissions (see Introduction). For example, higher-income households tend to have higher emissions compared to lower-income households, although this may be also driven by the fact that the former use more efficient appliances and houses with higher energy needs[98,99]. Such mismatching may introduce uncertainties in emissions calculation[100].

For this reason, our study groups households across five dimensions: (a) income, (b) household size, (c) average age of household members, (d) driving demand and (e) children. These five household characteristics form the basis of the study group taxonomy and are identified through the Least Absolute Shrinkage And Selection Operator (LASSO) method, after the filtered characteristics expected to significantly affect the variations of per capita emission across households (**Figure S3**, **Supplementary Material**). The household characteristics evaluated through the LASSO method are selected and filtered by matching variables from survey data with variables in existing studies[69,98], resulting in a more nuanced household taxonomy across six household groups (**Figure S4, Supplementary Material)**.

During Step 2 we estimate the per capita emissions of each group, for common household activities and fuel use using data from the HEUS survey outlined above (see "Data preparation"). We focus on direct energy use in households (rather than indirect emissions embedded in goods and services[101,102] (see "Emissions estimation"). The results of this analysis are included in the first sub-section of the Results.

During Step 3 we identify for the six study groups the differentiated adoption rates and related emissions for the two major home emission mitigations measurements currently promoted in Japanese households: roof solar photovoltaics (PV) and new-energy vehicles (NEV)[87-90]. NEVs include electric, plug-in hybrid electric, LPG and

fuel cell vehicles. For each group we estimate for the year 2017-2018 total direct emissions and direct emissions by different household activities for households adopting PV/NEV and households not adopting. This analysis is included in the second sub-section of the Results.

Steps 4-5 explore future trajectories of emissions from the residential sector considering the expected demographic transition and adoption of PV and NEV. This is achieved through two scenario analyses for the years 2025, 2030, 2035 and 2040.

The first scenario analysis (Step 4), highlights why it is important to consider properly household structure when estimating future emissions from the residential sector in the face of demographic change. We use two main scenarios for each study year: (a) a business-as-usual scenario that assumes the same household structure as currently (i.e. the proportion of the six groups in the projected population remains the same as in the base year 2017-2018), and (b) a dynamic scenario that varies the proportion of the different groups in the projected population (see “Future prevalence of study groups” below for the allocation method). Both these scenarios assume for each of the six groups the same energy consumption patterns and PV/NEV adoption rates as estimated for the year 2017-2018 (see Step 1-2).

The second scenario analysis (Step 5), highlight what are the emissions due to the differentiated adoption rates of PV and NEV in the face of demographic change. Here, to reflect the demographic change we use the dynamic scenario developed in Step 4, as we believe that it offers a better approximation of the makeup of the Japanese residential sector in the future study years. Then for each household group we establish three PV/NEV adoption scenarios namely: (a) Baseline, (b) Optimistic (High), and (c) Highly optimistic (High-high). The “Baseline” scenario assumes for each household group the same PV/NEV adoption rates as for the base year 2017-2018 (Step 2). The two optimistic scenarios reflect different assumptions for PV and NEV adoption rates through the estimation of different acceptance rates (see “Estimation of Future Mitigation Potential”).

Data preparation

Household emissions can be estimated through top-down or bottom-up approaches. The latter are data-intensive and entail the statistical analysis and aggregation of micro-level data of direct and indirect energy consumption by individual households. The former generally require macro-level data usually derived from input-output tables. 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 level of prefecture in most countries (though there have been efforts to develop such tables at the city-scale with large, however, uncertainty). Furthermore, household

consumption data is generally reported in aggregated form, which complicates analysis. Such data availability challenges usually underpin efforts to estimate accurately energy use and emissions at the household level.

In this study we use household level data collected through the Japanese household energy use survey (HEUS) conducted by the Ministry of the Environment Japan (MOEJ) over the period 2017-2018. 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 (see **Section S1, Supplementary Methods**). This applied to 1,008 records for households: (a) not having valid records about their building space (332 households), (b) showing difference 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) that is >0.01 tCO_2 (676 households). It is important to remove anomalies from these individual emissions categories to avoid possible biases from estimating the emission reduction potentials.

Furthermore, to facilitate the clustering process we select the most relevant variables explaining household emissions contained the HEUS survey and transform them into numeric or categorical variables (**Section S2, Supplementary Methods**). First, we select all relevant quantitative variables after filtering them through comparisons to existing studies[69] that identify significant household characteristics explaining household emissions. This includes variables related to family size, income, energy use, and transportation behavior. This amounts to 65 variables, for which we apply a z-score normalization method to eliminate possible biases (see normalized variables in **Table S1**, **Supplementary Material**).

Integrated-clustering Method. By integrating the 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”). This method is considered to be efficient and appropriate for pattern recognition in household survey data [103,104].

First, we select all the possible quantitative variables related to household energy consumption from the survey and filter them based on the literature[69,94] to identify the significant household characteristics that explain household emissions. We convert the input data from the HEUS survey and fit them on emission per capita data through a LASSO model[105]. The LASSO model is fitted by minimizing the following cost function:

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

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 variable.

The value of λ controls the entry of variables trained by the model. The higher the value of λ, the more variables would have their coefficients be zero. Therefore, this parameter is crucial for the 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 0.0001 to 0.01 (with a step equal to 0.0005) for the optimal model output, we find that 0.026 is the optimal parameter value for the LASSO model that results the highest performance. Then, after applying the LASSO model[105] (see **Figure S3, Supplementary Material**), we keep only 24 variables that have an importance of over 0.05. Table S2 in the Supplementary Material contains the complete list of the selected variables for the subsequent analysis.

Second, we develop the actual household taxonomy. To achieve this we apply the K-means method based on the selected variables, which is one of the prevailing unsupervised learning approaches that fits well in high-dimensional datasets[106]. However, as the K-means clustering cannot automatically produce an optimal number of clusters, we search for the optimal number of clusters iteratively. The performance of the clustering process is assessed through the Silhouette coefficient [107,108]. Additionally, we impose another constraint to ensure that each cluster contains no less than 50 households. The number of clusters obtained through K-means method is 6, which is optimized by maximizing the Silhouette score using the selected variables as a 24-dim input data. This process is described in more details in Figure S4 (**Supplementary Material)**. The clusters are further categorized according to five dimensions, namely household income, household size, average age, driving frequency and whether the household has children, as these are the five most important dimensions affecting emissions recognized in the LASSO model. Figure S4 (Supplementary Material) provides a simplified description of the household taxonomy**.** Table S3 (Supplementary Material) suggests that households are not clustered in specific geographic regions and the distributions is almost random.

To validate the output of the integrated-clustering method, we make comparisons between the clustering and the socioeconomic groups (**Figure S6**, **Supplementary Material)**. In **Figure 3**, the differences in per capita emission among household groups are magnified because 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 the emission per capita as a dependent variable in the analysis, the significant 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 we adopted use a bottom-up emission accounting method. Firstly, energy uses related to Scope 1 and Scope 2 emissions are accounted including various fuels and electricity. Secondly, in terms of various energy types, the survey collects household energy uses and then emissions are estimated on the basis of adjusted emission factors in our previous study. Therefore, the aggregate emission of a household is the sum of all subsidiary emissions from uses of electricity and primary energy, and besides the aggregate emission is consistent with the sum of emissions from household energy demand including electric appliance, transportation, space heating, space cooling, water heating, and etc. The detailed information of carbon emission survey are conducted directly by Ministry of Environment Japan, which can be referred from for further details(*https://www.env.go.jp/earth/ondanka/ghg/kateiCO2tokei.html*).

Estimation of Current Mitigation Potential.

Initially, we estimate the current emission mitigation potential for each group due to the adoption of residential photovoltaics (PV) and new-energy vehicles (NEV) through Ordinary Least Squares models as follows:

$$e_i = \alpha + \beta x_i + \boldsymbol{\gamma}\mathbf{Z}_i + \varepsilon_i \qquad \text{(Eq. 2)}$$

where e_i represents the emissions per capita, x_i is a dummy variable indicating that a household adopts PV/NEV or not, β is the emission mitigation potential coefficient to be estimated, $\mathbf{Z}_i$ represents a vector of control variables (i.e. the 24 variables selected in the LASSO model), α is the intercept and ε_i is the error term. The regressions are performed for each household group in order to estimate differentiated emission mitigation potentials. Table S4-S5 (Supplementary Material) contains the regression results for PV and NEV for each of the six study groups**.**

Future prevalence of study groups

We divide the projected population data for Japan for the years 2025, 2030, 2035 and 2040 provided by the National Institute of Population and Social Security Research (IPSS, https://www.ipss.go.jp/index-e.asp), to match the household taxonomy developed above. This is done by fixing the age and family structures as follows: (a) we divide projected population from 14-84 years old in 15 age groups (i.e. at five years intervals), and those “>85 years old” as a separate groups, and then (b) we cross-map the family types from the projected population data (i.e. single, couple, single with kids, couple with kids and others) to the family types from the survey data (i.e. single, couple, single with kids, couple with kids, single elderly (>60 years old), couple elderly (>60 years old) and big family (exclusive to the others). The mapping process is described precisely in **Section S3**, **Supplementary Methods**.

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_{ab}^{k} for household segment k where a, b represent the age and family type dimensions for the matrix (see details in Section S3, Supplementary Methods). By multiplying with the projection population data P_{abt}, the future number/population for a given household group is calculated through Eq. 3 as:

$$P_t^k = \sum\sum D_{ab}^{k} \times P_{abt} \qquad \text{(Eq. 3)}$$

Estimation of Future Mitigation Potential.

We incorporate the dynamics of technological advance and household preferences on technology adoption through logit models that estimate the conditional probability that a household adopts PV or NEV, given their pre-adoption features[109,110]. The propensity can be expressed as:

$$p(\mathbf{X}) = \Pr(adopt = 1|\mathbf{X}) \qquad \text{(Eq. 4)}$$

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

$$\ln\left(\frac{p(\mathbf{X})}{1-p(\mathbf{X})}\right) = \beta_0 + \beta_i \mathbf{X}_i + \epsilon_i \qquad \text{(Eq. 5)}$$

Notably, PV installation costs or NEV costs are not included in the set of pre-adoption features because the HEUS survey data does not provide detailed information about the adoption time of PV and NEV technologies for households. This makes it hard to give accurate cost estimation on technology adoption.

We also define the penetration rate of PV or NEV that expresses the ratio of the willing-to-adopt households to that of unwilling-to-adopt ones. We use three scenarios by applying different probability thresholds. As the penetration rates of PVs and NEVs are currently relatively low among the households captured in the HEUS survey, the estimated propensity scores are also relatively low. For this reason, data in the HEUS survey is insufficient to estimate the household willingness to purchase PV or NEV because the costs and timing of purchases are not available in the data.

Since it is not clear whether household willingness to purchase mitigation technologies will increase or decrease as advanced low-carbon technologies are emerging, including willingness increases the uncertainty of the modeling. Therefore, we assume that the future willingness of household groups to adopt PV/NEV is the same as currently. The probabilities of adopting PV and NEV range from 0%-91.4% and 0%-44% respectively depending on the group, with the mean probabilities being 6.9% and 1.3%.

We use the penetration rates from the survey data as the baseline scenario and use the following thresholds to define optimistic (high) and very optimistic (high-high) scenarios for PV and NEV adoption. For the high adoption scenario the adoption propensity thresholds are 25% and 10% for PV and NEV respectively, and (b) for the high-high scenario, the adoption propensity thresholds are 15% and 5% for PV and NEV respectively. Here the threshold means the minimum probability that households with estimation probabilities higher than the threshold will be willing to adopt.

Finally, the future emission reduction potential is estimated through Eq. 4:

$$r_t^k = \widehat{\beta^k} P_t^k \left(\frac{N_{adopt=1}^k}{N^k}\right), k = 1, \dots, 6 \qquad \text{(Eq. 4)}$$

where r_t^k is the total emission mitigation potential for household group k in the year t, $\widehat{\beta^k}$ is the estimated emission mitigation potential of PV or NEV for household group k in Eq. (2), P_t^k is the projected population for group *k*, $\frac{N_{adopt=1}^k}{N^k}$ is the penetration rate of PV or NEV for group k. where $N_{adopt=1}$ is the number of households for group who have acceptance probabilities over the scenario threshold, and N is the total number of households for group *k*. In different scenarios, $N_{adopt=1}^k$ varies according to their acceptance probabilities.

Limitations and uncertainty

We acknowledge a series of limitations in this study, which should be taken into consideration when interpreting the results. Firstly, different algorithm-based clustering methods can be tested for robustness, and populated with future survey data to validate the clustering.

Second, we made a series of assumptions that might have inserted 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, while from the perspective of the simulation the different thresholds only indicate different offset levels (which will not affect our findings). Using different models to estimate acceptance rates may affect the penetration rates of PV and NEV in the projection population. In this sense as the current penetration rates are relatively low, it is difficult to accurately extend our data to the year 2040, as there is possibility for major disruptions in the NEV and PV markets [111,112]. In contrast, the effects of aging and increase of single households is of great significance for emission patterns. Here we make assumptions about the constant willingness to purchase PV and NEV, which may increase or decrease subject to policy signals and availability/price of low-carbon technologies in the future [113,114]. In this case, in order to reduce model uncertainty, sensitivity analyses could be further conducted in future studies to offer more accurate prediction ranges, or conduct primary data collection to precisely describe the willingness of adoption (e.g. through choice experiments or other similar techniques).

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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. G.A supervised this research.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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