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The Life Cycle Carbon Emissions Caused by Households in Japan: Current Status and Long-term Perspectives

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1. Introduction

1.1. Background

Global annual greenhouse gas (GHG) emissions have risen dramatically since the start of the industrial revolution and caused a series of adverse effects such as climate change. As the 26th Conference of the Parties to the United Nations Climate Change Framework Convention (COP26), a global summit that aims to fight against climate change, ended on November 13, 2021, most major emitting countries have announced their carbon reduction or carbon neutrality targets by mid-21st century. To achieve these targets, the carbon emissions from the household sector need our attention, as households can produce emissions directly through at-home activities like heating, cooking, and indirectly through upstream emissions associated with the production of consumption items, and consequently, the household sector accounts for a considerable proportion of the total carbon emissions. From 1982 to 2007, the energy consumption of the residential sector in Japan has doubled while the population has increased by only 10%[1)]. Accordingly, the same trend of increase in carbon dioxide (CO_2) emissions caused by households has followed, where CO_2 emissions from the household sector in Japan have increased significantly since 1990[2)]. Therefore, to achieve the nation's carbon neutrality by 2050, an ambitious target declared by Prime Minister Yoshihide Suga in October 2020[3)], it is urgent to fully understand the household-induced carbon emissions, which is essential to address the reduction targets.

Following existing studies, here we consider household carbon emissions as "the emissions of individuals or their families to meet the demands of their existence and development under certain socio-economic conditions, which includes both direct and indirect emissions[4)]". Direct emissions can be defined as emissions related to direct household fuel use, including gasoline, gas, etc. On the other hand, the indirect emissions are those resulting from the whole lifecycle of products and services for the household[5)] from the raw material acquisition to the final disposal phase. Therefore, most studies estimate household carbon emissions from the consumption side, Yosuke Shigetomi et al, present the impacts of changes in the composition of Japanese households on GHG emission structures using current consumption-based accounting on the commodity sectors[6)]. Also, Yosuke Shigetomi et al, investigate insights into reducing energy-related CO_2 emissions in households by examining individual socio-economic drivers at a sub-national level[7)]. Similarly, Yin Long et al, evaluate city-level indirect household carbon emissions[8)].

For estimating household emissions, existing studies tend to consider different kinds of factors. Bastien Girod et al., build a model for changes in household greenhouse gas emissions due to higher income[9)], and Underwood, A. J. tries to understand the role of demographic change in household carbon emissions using an EIO-LCA model[10)]. Asumadu-Sarkodie, S. et al., argued that low carbon technology could help to reduce environmental pollution[11)]. Büchs, M., et al., try to examine the impact of different socio-economic factors such as education, gender, etc. on household indirect and total emissions[12)].

As the deadline for the reduction target of 2030 raised by the Japanese government looms, it becomes more and more important to understand current household carbon emissions and to examine the possibility of the attainment of Japan's 2030 reduction targets. Moreover, changes in lifestyles including consumer behavior are a prerequisite for sustaining reductions in GHG emissions and for bridging the emissions gap[13)], thus it is necessary to quantify and understand the impact of these changes.

1.2. Research gap

In most existing studies on household carbon emissions, there is a lack of process-based inventory data of household commodities. According to Zhang et al, studies using input-output data tend to lack reliability when forecasting long-run effects. However, by using process-based inventory data, studies could reflect the effects of the entire life cycle[14)]. Besides, distant future scenarios such as 2050 scenarios for household emissions seem to be overlooked. Most importantly, few studies have addressed the quantitative impact of changes in consumer behavior on expenditure.

1.3. Research objective

This study mainly aims 1) to estimate current household-induced CO_2 emissions by using process-based inventory data and to understand the impact of the COVID-19 pandemic based on the results; 2) to explore the possibility of the attainment of Japan's reduction targets in 2030 based on the results obtained by using 2030 inventory data; 3) to examine how will consumer behavioral changes affect future household carbon emissions in the distant future by setting different expenditure scenarios in 2050.

2. Method and data

2.1. Life cycle assessment (LCA)

Life cycle assessment is a method used to evaluate the environmental impact of a product through its life cycle encompassing extraction and processing of the raw materials, manufacturing, distribution, use, recycling, and final disposal[15), which can be explained simply as 'from cradle to grave'.

An initial approach to completing a life cycle assessment is a process-based LCA method. In a process-based LCA, one itemizes the inputs (materials and energy resources) and the outputs (emissions and wastes to the environment) for a given step in producing a product[16)].

2.2. Inventory database for environmental analysis (IDEA)

IDEA is a database developed by JEMAI and AIST which mainly uses national statistics as its data source and aims to model the environmental impacts of all Japanese businesses comprehensively with a high resolution[17)]. The inventory data is obtained through the method of process-based LCA.

2.3. The microeconomic data

The consumption data of households is obtained from the Family Income and Expenditure Survey (FIES)[18)] conducted every month by the Japanese government. The price data for each commodity is obtained from the Retail Price Survey[19)] and Consumer Price Index[20)] which are also conducted by the Japanese government.

2.4. The Framework for estimating and predicting household carbon emissions

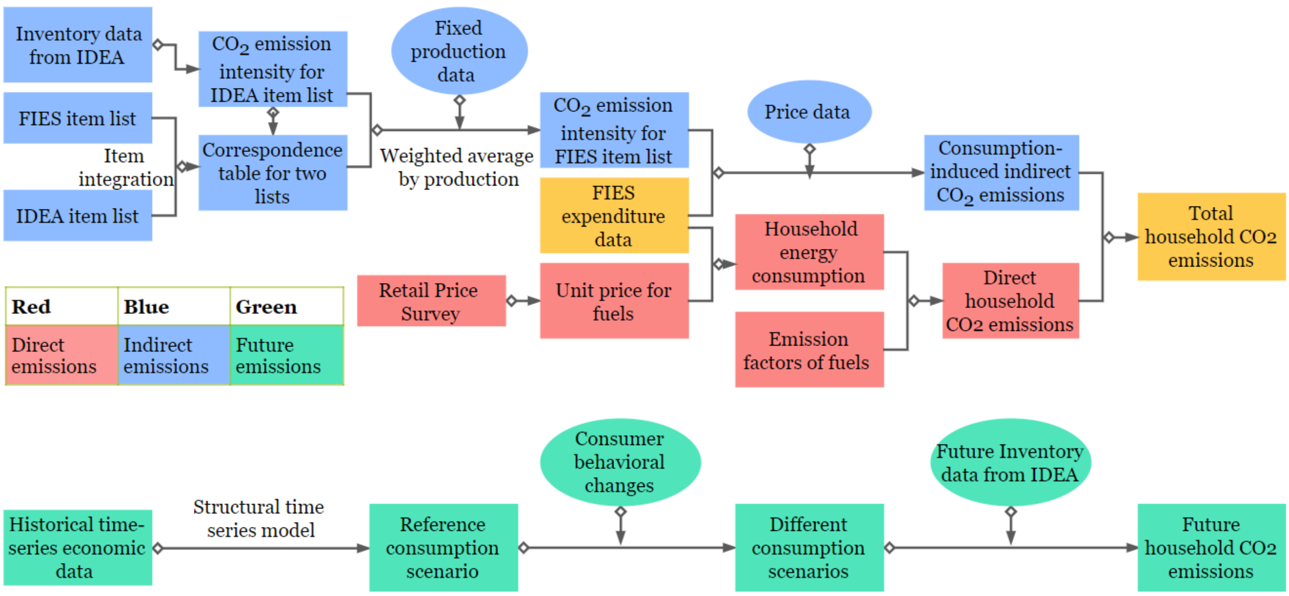


Fig. 1. Workflow for household CO_2 emissions estimation and prediction

For estimating current emissions, first, I obtained the carbon emission intensity data, which was generated by process-based inventory data from IDEA v.3.1, and then, considering that I need use expenditure data from FIES to conduct the calculation, it was necessary to match the IDEA item list with the FIES item list. Therefore, a correspondence table was made, which allowed me to match all 495 commodities in the FIES list that may embody carbon emissions with items in the IDEA list. However, I noticed that the items in the correspondence table might not be a simple one-to-one relationship (e.g. for item 'edible oil' in the FIES list, the corresponding 4-digit items in the IDEA list included 'vegetable oil', 'animal fat', and 'edible oil processing', which could even be subdivided into more 6-digit items). Thus, the intensity data must be weighted, and here I used the fixed production data for the commodities to calculate the weighted average emission intensity data. After this step, I obtained the emission intensity data for all commodities in the FIES list. The intensity data represents how much carbon emissions will be produced when consumed per basic unit of a commodity. I subsequently used the price data to transfer the money from FIES expenditure data to the basic unit. And finally, we could multiply the intensity data with the consumed amount of each commodity, and I estimated the consumption-induced carbon emissions. On the other hand, to calculate the direct household carbon emissions caused by the combustion of fuel such as city gas, I took similar steps while I obtained the unit prices of fuel from the Retail Price Survey. Eventually, I summed up direct and indirect emissions and aggregated total household carbon emissions at current status.

For predicting future emissions, firstly, historical data from 2000–2019 of household expenditure (obtained from FIES), household disposable income (also obtained from FIES), and commodity price (obtained from Consumer Price Index and Retail Price Survey) were used in estimation under a time series model, and I obtained the expenditure data which represents the reference scenario. Considering one of the goals of this study is to explore how will household emissions change in the distant future under the impact of consumer behavior changes, I set up different scenarios to describe household expenditure in 2050 based on varying degrees of consumer behavior change. And finally, I managed to use future inventory data from IDEA with household expenditure data in different scenarios to forecast several pathways of household carbon emissions in 2050. The details of future scenarios are explained in Section 3.

2.5. Model for the prediction of future household expenditure

Structural Time Series Model (STSM) for expenditure prediction[21)] was used for the prediction of future household expenditure.

$$exp_t = \mu_t + \lambda_t + \pi p_t + \tau y_t + \nu_t \qquad \nu_t \sim NID(0, \sigma_\nu^2) \tag{1}$$

Where exp_t is the natural logarithm of real household expenditure for each category; μ_t is a trend component that represents the impact of non-economic factors, including technological advances, consumer preferences, lifestyles, etc., which are difficult to be quantified, and thus suitable data is not available in most cases; λ_t represents the seasonal component; p_t is the natural logarithm of real price, while y_t is the natural logarithm of real household disposable income, these two variables represent the regression component; π and τ are unknown regression coefficient to be estimated; ν_t is a random white noise disturbance term.

The reason for choosing STSM lies in that this model allows for the examination of the relationship between expenditure, income, and prices and a stochastic underlying trend and allows for stochastic seasonality so that, along with the stochastic trend, are included in the following long-run expenditure model[21)]. Compared to other models like ARMA and ARIMA, which focus on the characteristics of the dataset of expenditure such as auto-regression and moving average, STSM is more comprehensive as it attempts to quantify the contributions of the economic drivers (income and price) and non-economic factors to determining household expenditure.

3. Future expenditure scenarios

3.1. Three scenarios

Considering that one of our goals is to examine how will consumer behavioral changes affect future household carbon emissions in the distant future by setting different expenditure scenarios in 2050, three scenarios for 2050 were set. Although we can only roughly estimate changes in household carbon emissions through these three future scenarios, it is enough for conducting scenario analysis based on different degrees of consumer behavior changes here.

- Reference scenario: This is a scenario which is set only based on the estimation result from the structural time series model, the consumer behavior can be regarded as the same as the trend of the past 20 years (2000–2019), and no extra influence of consumer behavioral changes are taken into consideration.
- Scenario A: This is a scenario where I try to adapt the impact of large-scale consumer behavior changes on the reference scenario, which means, for example, much more household consumers gain environmental awareness in the future scenario compared to the reference scenario. These consumer behavior changes are reflected on expenditure by 10 categories.
- Scenario B: Compared to Scenario A, the only difference lies in that a smaller scale of consumer behavior change occurs in this scenario.

3.2. Assumption for all scenarios

Given some limitations, the expenditure was estimated by 10 different categories including 1) Food, 2) Housing, 3) Fuel, light & water charges, 4) Furniture & household utensils, 5) Clothing & footwear 6) Medical care, 7) Transportation & communication, 8) Education, 9) Culture & recreation, 10) Others. But it is the data for each commodity that could be used in estimation. Thus, the first common assumption is that the ratio of each commodity in the same category will remain the same with the base year 2019. In this way, the future expenditure data of each category can be distributed to each commodity according to the same proportion in 2019. Also, when setting the values to quantify the impact of consumer behavior changes on future household expenditures, the second assumption is that the impact is equal for all items in the category that will be affected, which means that the rate of change will apply to expenses of all these items.

Moreover, the only future inventory data provided by IDEA is for 2030, but my purpose is to estimate the impact of consumer behavior change on household carbon emissions in the scenarios of 2050. And the linear extrapolation methods seems not feasible due to data limitation, for the only data of two different year that I have are not capable to make the extrapolation convincing. Therefore, the third assumption is inventory data for commodities will remain constant from 2030 till 2050.

3.3. Assumption for changes in different categories

- Food

I mainly focus on two kinds of food when setting the scenarios, animal-based food, foods that come from an animal source such as beef, pork, poultry, dairy, and eggs, and plant-based food, foods that come from plants sources such as fruits and vegetables. According to Westhoek et al., there will be a reduction in animal-based consumption such as eggs, porks, etc., by 25%/50%, due to a shift to a plant-based diet[22]. Similarly, Ivanova et al., reveal the reduced share of meat and dairy, and compensated by other kinds of food[23]. These studies provide the evidence for less animal-based food consumption and conversely plant-based food consumption, as a substitute for the latter to some extent, will be more in the scenarios. For plant-based diet and calories, Pimentel et al., reveal a whole plant-based diet is more sustainable than a meat-based diet when the daily quantity of calories consumed is kept constant in both diets[24]. Brown, Derrick D., claims appropriately designed and managed vegetarian diets contain foods nutritionally sufficient for health, well-being, and physical performance[25].

- Fuel, light & water charges

According to Lee et al[26]., here I assume that the penetration rate of net-zero energy houses and all-electric houses will increase significantly in Scenario A and Scenario B as consumers' preference towards these houses become stronger, compared to the status quo. Consequently, the consumption of electricity will increase dramatically, but for other fuels, their consumption will be decreased sharply.

- Furniture & household utensils and Clothing & footwear

Hancheng Dai et al., when estimating the future expenditure patterns of China, explained that consumption on these two categories, as people's environmental awareness, would become higher and consequently low-carbon consumption patterns are favored, will tend to decreased[27]. Therefore I set some reduction in these two categories in Scenario A and Scenario B.

- Transportation & communication

According to Shaheen, S. et al., car sharing could cause a considerable reduction in personal vehicle uses[28]. And based on the IEA Net Zero Scenario, a sustained modal shift from car trips to active and public travel – as well as from air travel to rail is required[29]. These studies can support my assumption on less personal vehicle use-related consumption and more public transportation-related consumption in Scenario A and Scenario B.

- Housing, Medical care, Education, Culture & recreation and, Others

For these categories, whose expenditures are less sensitive to consumer behavior changes it is difficult to judge the expenditures will increase or decrease due to lack of evidence. For example, housing expenditure is basically related to economic factors such as housing rent. As a result, I assume they will be the constant with Reference Scenario in Scenario A and B.

The details of these scenarios are shown in **Table 1**.

Table 1

Assumptions in the three scenarios.

Expenditure	Food	Housing	Fuel, light & water charges	Furniture & household utensils	Clothing & footwear	Medical care	Transportation & communication	Education	Culture & recreation	Others
Reference Scenario given by model	-	-	-	-	-	-	-	-	-	-
Scenario A: Large Consumer behavior change	Animal-based: -75%; Plant-based: +50%	-	Electricity: +75%; Fuel: -90%	-50%	-50%	-	Personal vehicle use-related: -75%; Public transportation-related: +50%	-	-	-
Scenario B: Small consumer behavior change	Animal-based: -50%; Plant-based: +25%	-	Electricity: +50%; Fuel: -60%	-25%	-25%	-	Personal vehicle use-related: -50%; Public transportation-related: +25%	-	-	-
Behavioral change interpretation	A shift to plant-based diet and reduction of animal-based consumption (e.g. beef, pork, poultry, dairy and eggs)	No changes	Penetration of net zero energy house (ZEH) and all-electric house: less expense on fuel and more on electricty;	Less expense on furniture due to environmental awareness	Less expenses due to environmental awareness	No changes	Less expense related to personal vehicle use due to car-sharing and a shift to public transportation	No changes	No changes	No changes
Note: all consumption changes are based on Reference Scenario										

4. Results

4.1. Results of current emissions

Annual household consumption-induced CO_2 emission per household in 2020 considering product life cycle is approximately 10.977 t-CO_2, including both direct and indirect emissions.

Note that only items that may cause emissions will be considered here. For each category of consumption expenditure, the results of consumption expenditures and induced CO_2 emissions in 2020 are shown in **Fig. 2**. I noticed that the proportions of most categories, such as food, education, medical care, etc., are similar in expenditure and emission. On the other hand, for categories like Fuel, light & water charges, the proportions are very different between expenditure and emission. The possible reason might be different unit prices and emission intensities for household commodities.

As is known to us, the year 2020 is very special due to the COVID-19 pandemic, resulting in a large scale of people's lifestyles and consumer behavior changes, for example, a shift to remote working and remote learning. And the impact on consumer behavior can even extend to the long-term future[30]. To gain a deeper understanding of the current situation and the impact of COVID-19 on household expenditures and emissions, I then estimated emissions for the past 5 years (2015–2019). After making some comparisons, the results are shown in the figures below.

From **Fig. 3** we can find several categories such as food suffer decreases with varying degrees, and simultaneously other categories remain constant with expenditure level of past years. And the trend for indirect emission shown in **Fig. 4** is quite similar to the expenditure. **Fig. 5** shows the direct household CO_2 emissions and except for gasoline, emissions from other fuels seem rather stable in the past few years. Possible considerations include that the people tend to drive out much less due to the pandemic, causing a considerable decrease in consumption of transportation, which intuitively means less gasoline consumption. For other fuels, they are more sensitive to factors such as temperature, because they are used for heating at home in most cases. Consequently, their consumption and emissions would not change similarly with gasoline under the impact of consumer behavior changes.

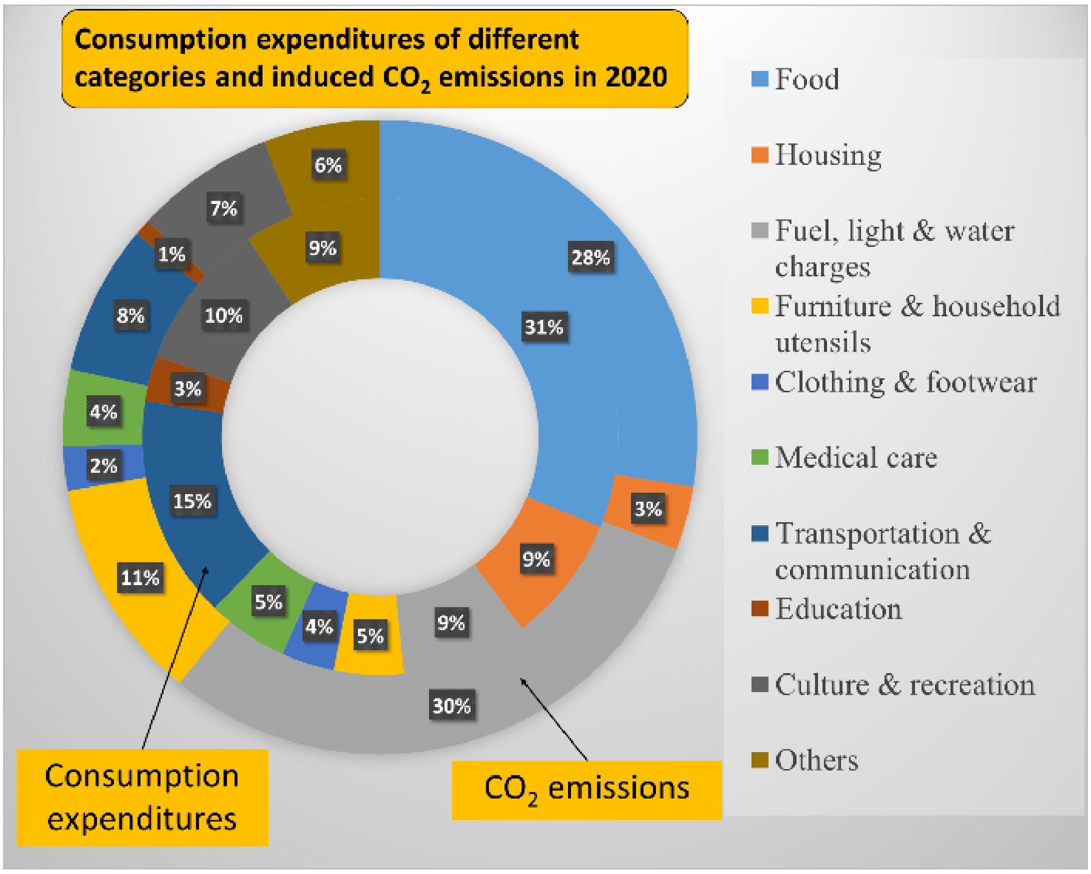


Fig. 2. Consumption expenditures and induced CO_2 emissions per household in 2020

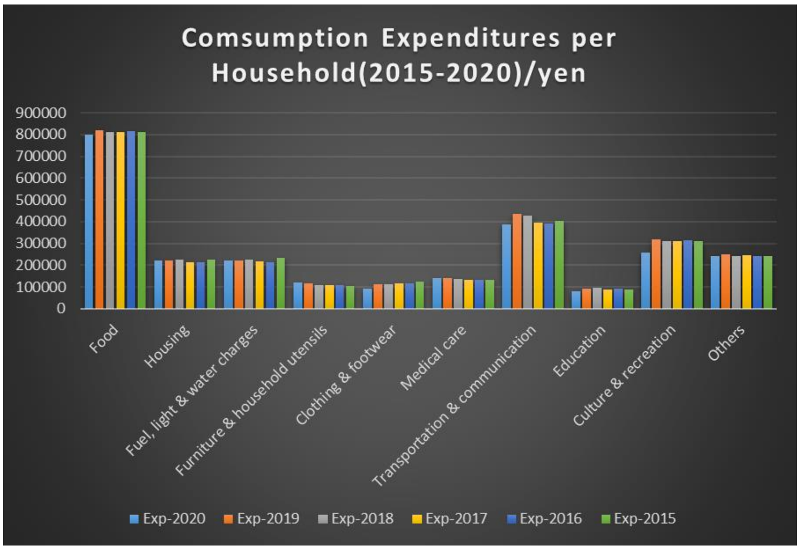


Fig.3. Consumption expenditures by each category per household for 2015–2020

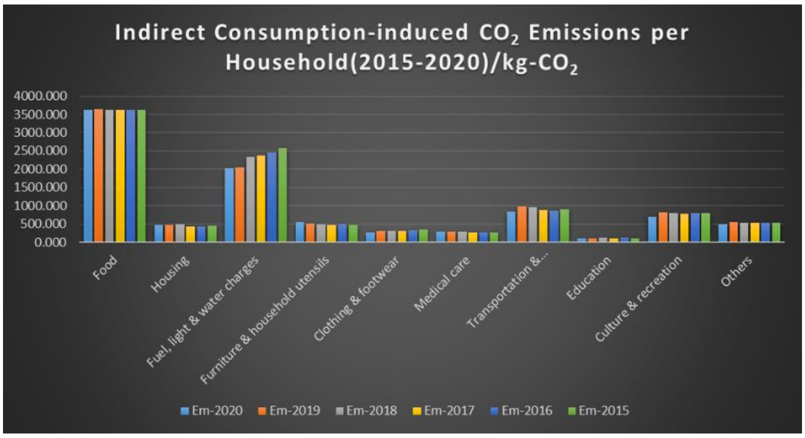


Fig. 4. Indirect consumption-induced household CO_2 emissions per household for 2015–2020

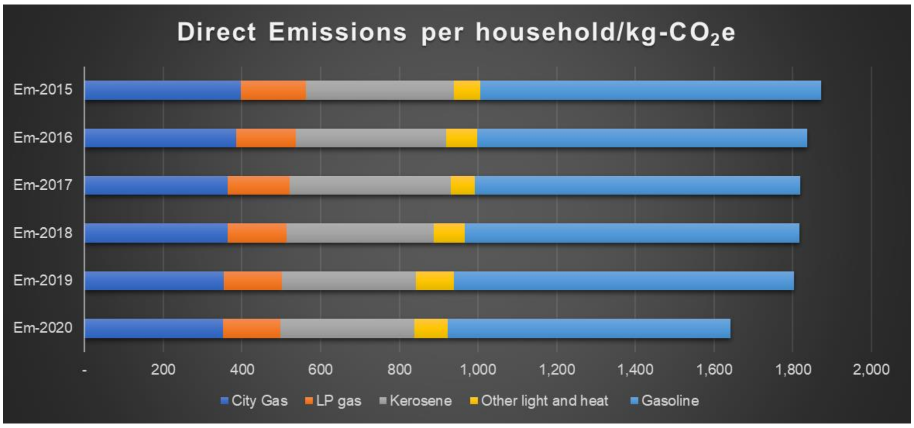


Fig. 5. Direct household CO_2 emissions of different fuels per household for 2015–2020

4.2. Results of future emissions

First, considering that the STSM contains regression components, time-series data of variables (Price and Income) extended to the target year is needed. The disposable income and price for each category are estimated till 2050 through STSM, the results are shown in **Fig.6** and **Fig.7**. And then these extended time-series data are used in expenditure estimation and the results are shown in **Fig.8.**

We can find from **Fig.6** that the disposable income is at a relatively stable level from 2000 to 2050, while the prices for each category have varying trends. Categories include Food, Fuel, light & water charges, Medical care, and Others will have a significant increase in their price, while categories include Housing, Furniture & household utensils, Culture & recreation will decrease significantly and the rest will remain relatively stable compared with the price in 2020 level.

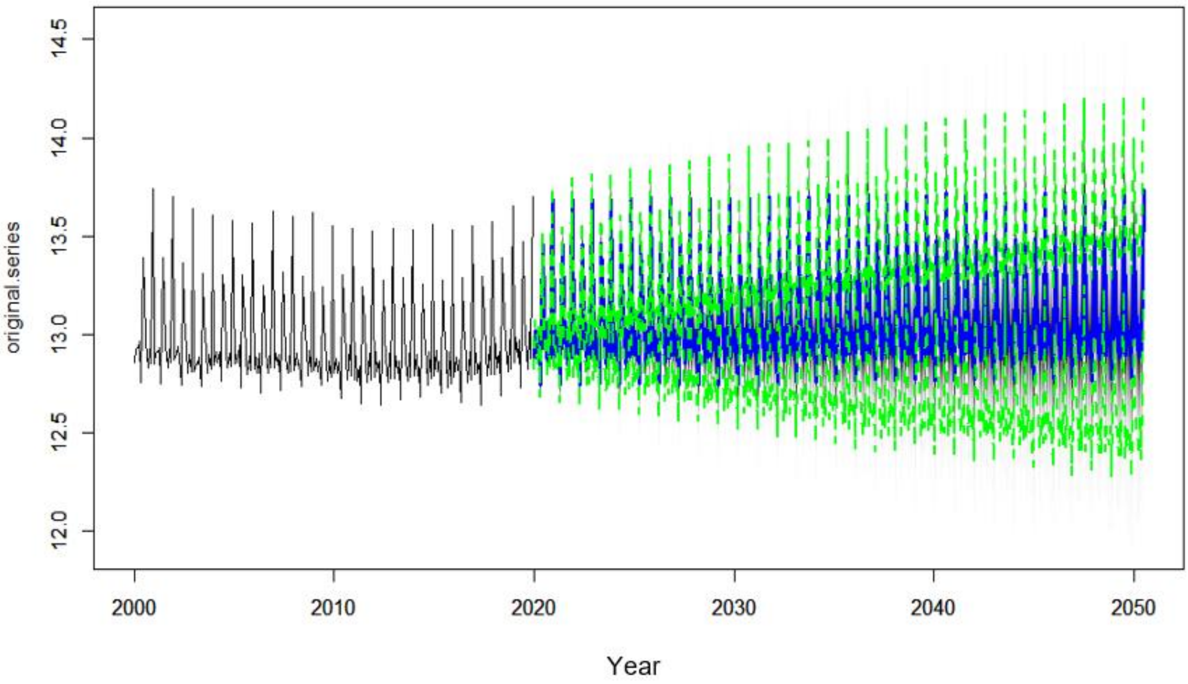
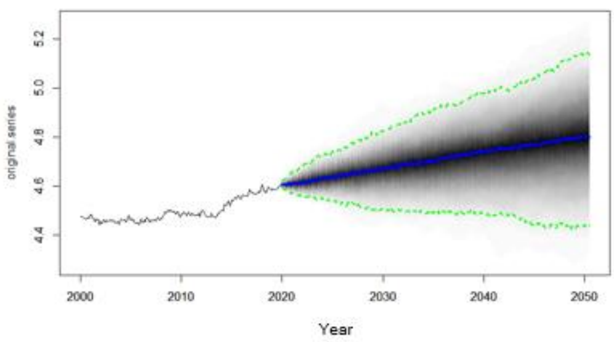
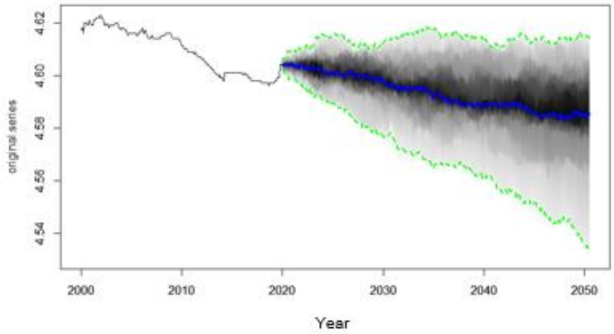


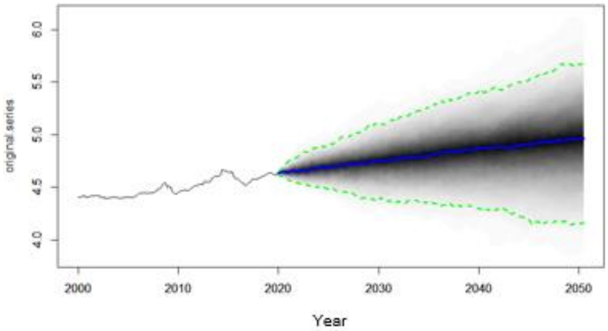
Fig. 6. Disposable household income 2000–2050 (values in the form of natural logarithm)



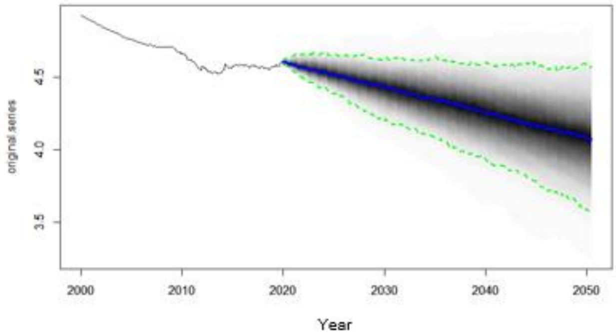
a) Food



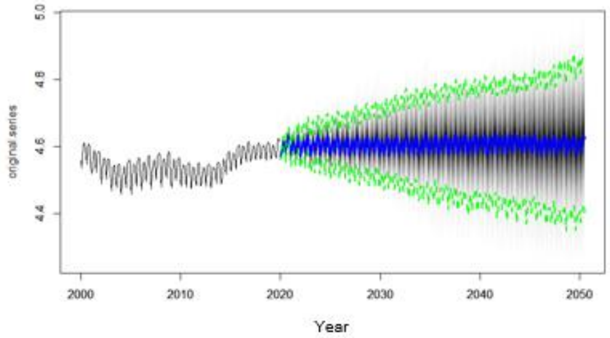
b) Housing



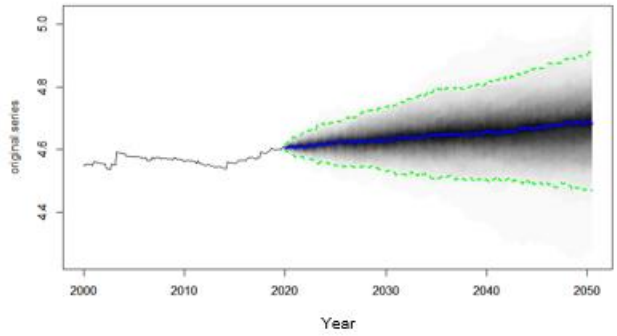
c) Fuel, light & water charges



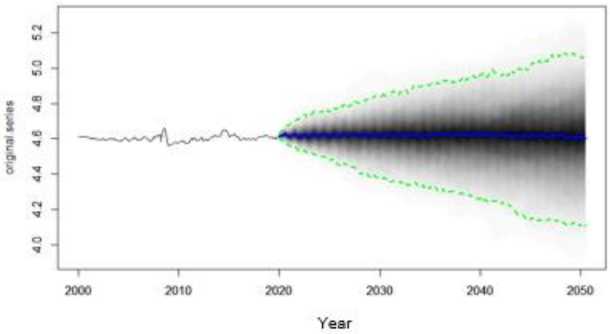
d) Furniture & household utensils



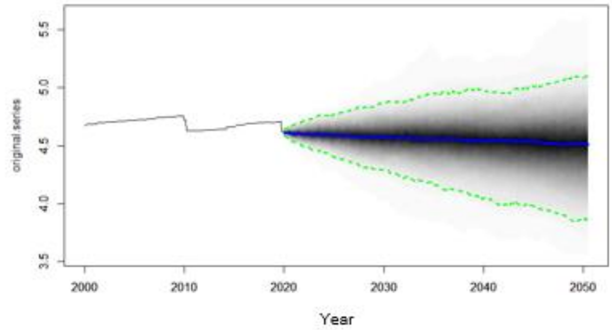
e) Clothing and footwear



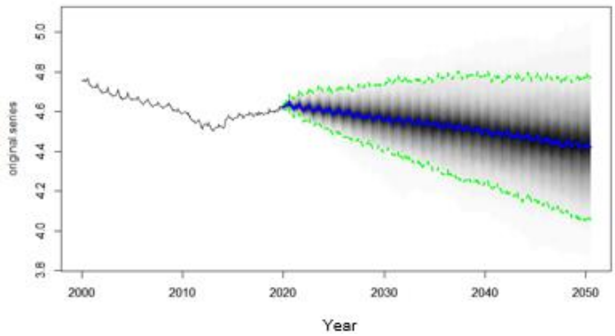
f) Medical care



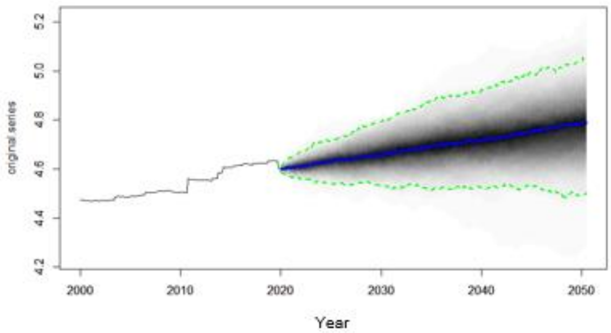
g) Transportation & communication



h) Education

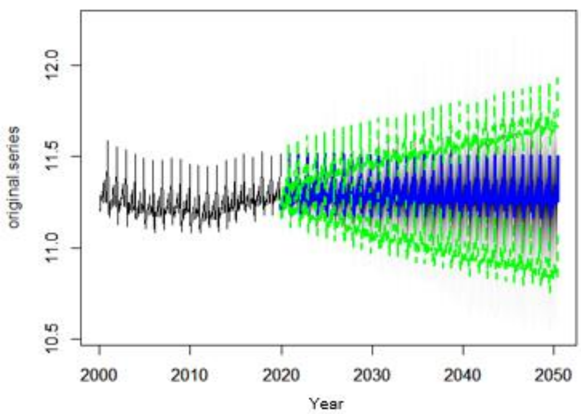


i) Culture & recreation

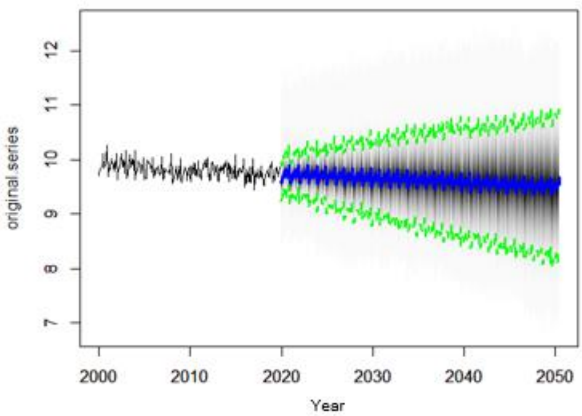


j) Others

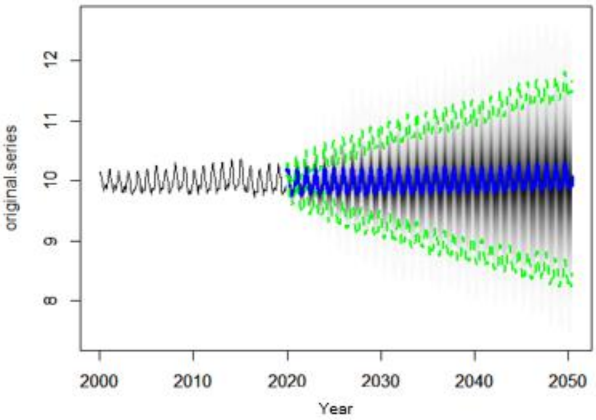
Fig. 7. Price 2000–2050 (values in the form of natural logarithm)



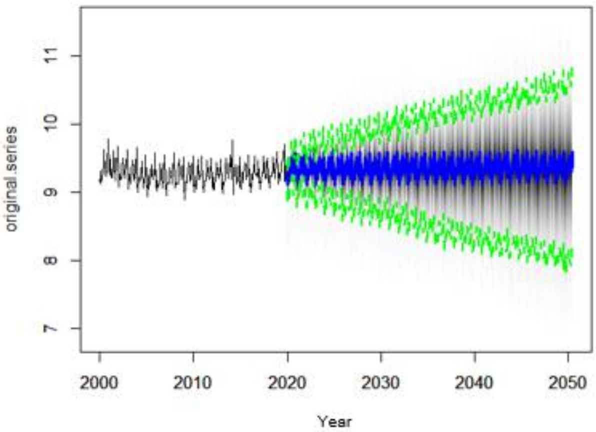
a) Food



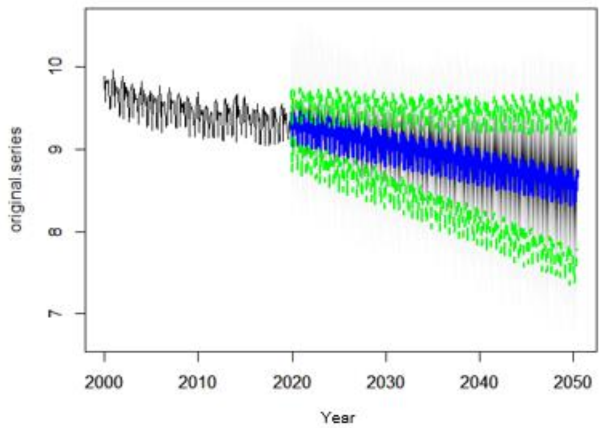
b) Housing



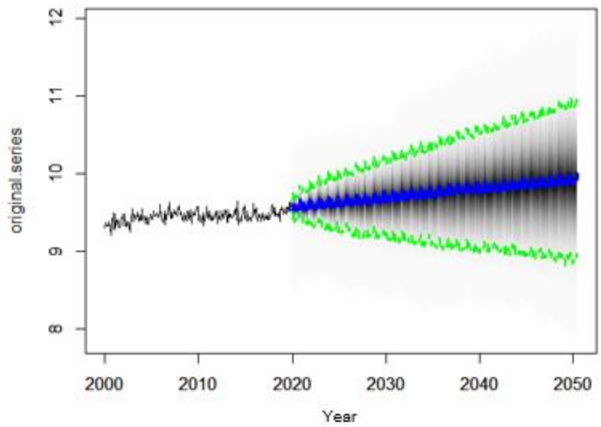
c) Fuel, light & water charges



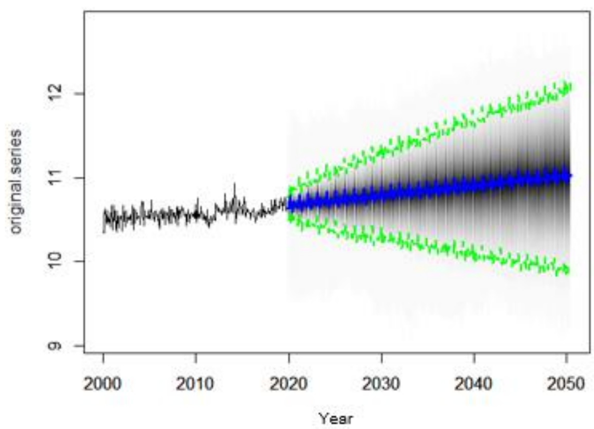
d) Furniture & household utensils



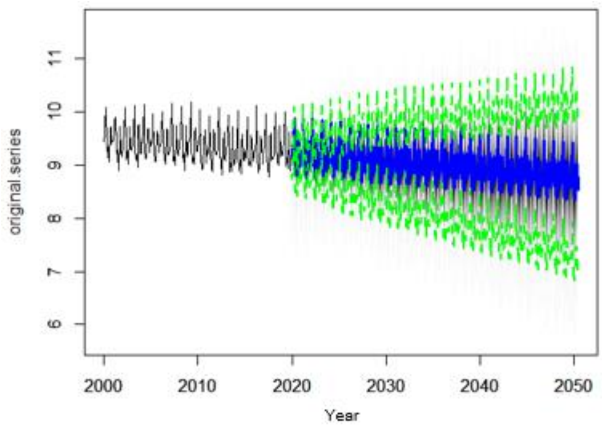
e) Clothing and footwear



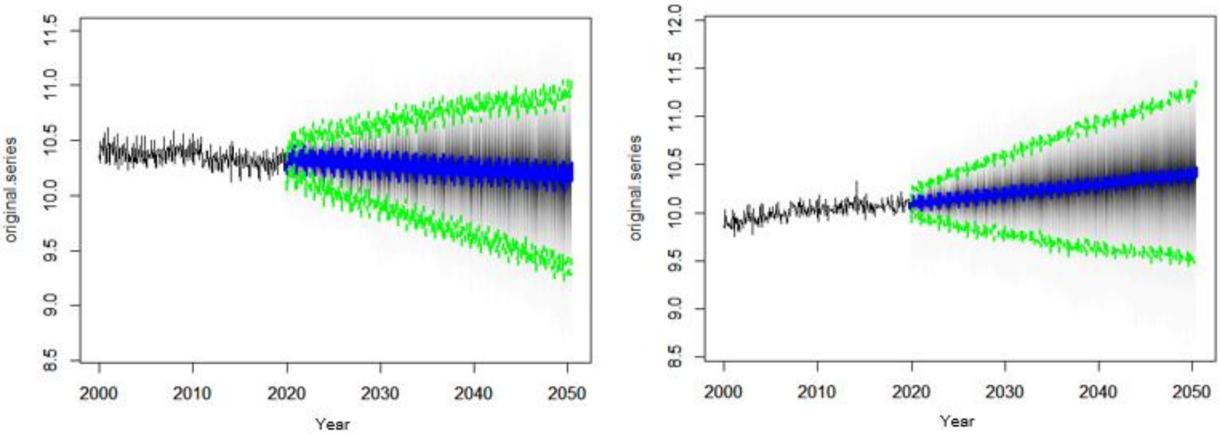
f) Medical care



g) Transportation & communication



h) Education



i) Culture & recreation

j) Others

Fig. 8. Expenditure 2000–2050 (values in the form of natural logarithm)

The blue lines in **Fig. 8** represent the trend of expenditure by different categories in the Reference Scenario. It reveals that household expenditure in several categories such as Medical care will increase while other categories such as Clothing and footwear will suffer an obvious decrease.

Then, these estimating results are used in building Scenario A and Scenario B. After setting the three scenarios, the expenditure and emissions for 2030 and these 2050 scenarios are estimated. The results are shown in **Fig.9**, and **Fig. 10.** Similar to the current estimation, only items that may cause emissions are considered here.

If we compare the result of 2030 to the result of 2015, the total household emissions will reduce by only 19.5%, and for the household sector defined by the government (including only electricity and three fuels, city gas, LP gas, and kerosene), only a 25.2% reduction, which seems far away from the government's target that a 66% reduction in 2030 compared with the fiscal year 2013.

Comparing results of 2030 and 2050-R, although the intensities for commodities remain the same, when total expenditure increases by about 19.5%, the indirect emissions, however, about 8.0%. The possible reason may be the changes in expenditure structures, which will lead to more expenditure on low-carbon-intensity commodities and conversely less on commodities with high intensity. Moreover, when comparing the three 2050 scenarios, indirect emissions under Scenarios A and B decrease by 9.2% and 5.9%, respectively. But the total emissions gained a more significant reduction by 28.1% and 18.5%, indicating that direct emissions from fuels decrease sharply, which is consistent with our assumption in Scenario A and Scenario B.

In **Fig.10**, it is found that although expenditure changes caused by large-scale consumer behavior changes are set in Scenario A and B, the food category only suffers a slight reduction. Thus, it can be inferred that either the expenditure changes cancel each other out due to some compensating effect within the food category, or the impact of consumer behavior changes is too small to be shown in the food expenditure. Considering the considerate number of affected commodities, I tend to believe the former one.

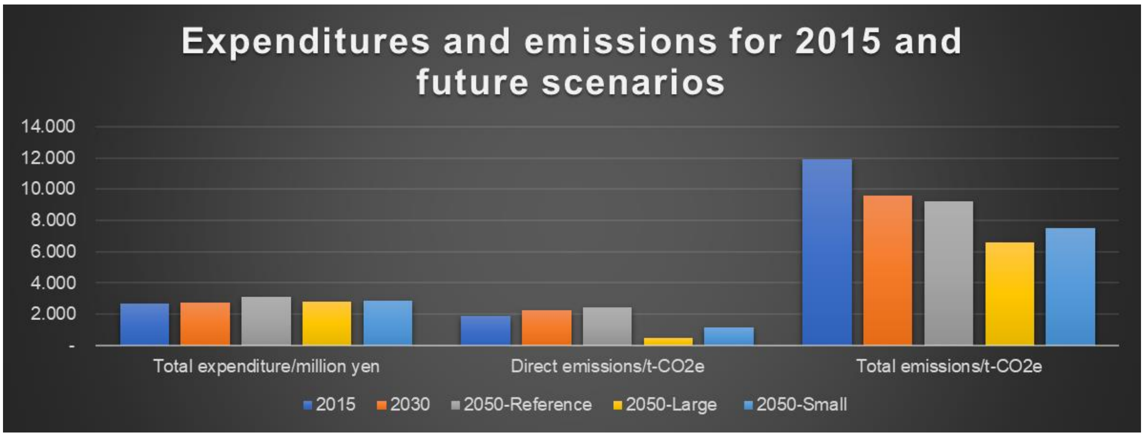


Fig.9 Expenditures and emissions for 2015 and future scenarios

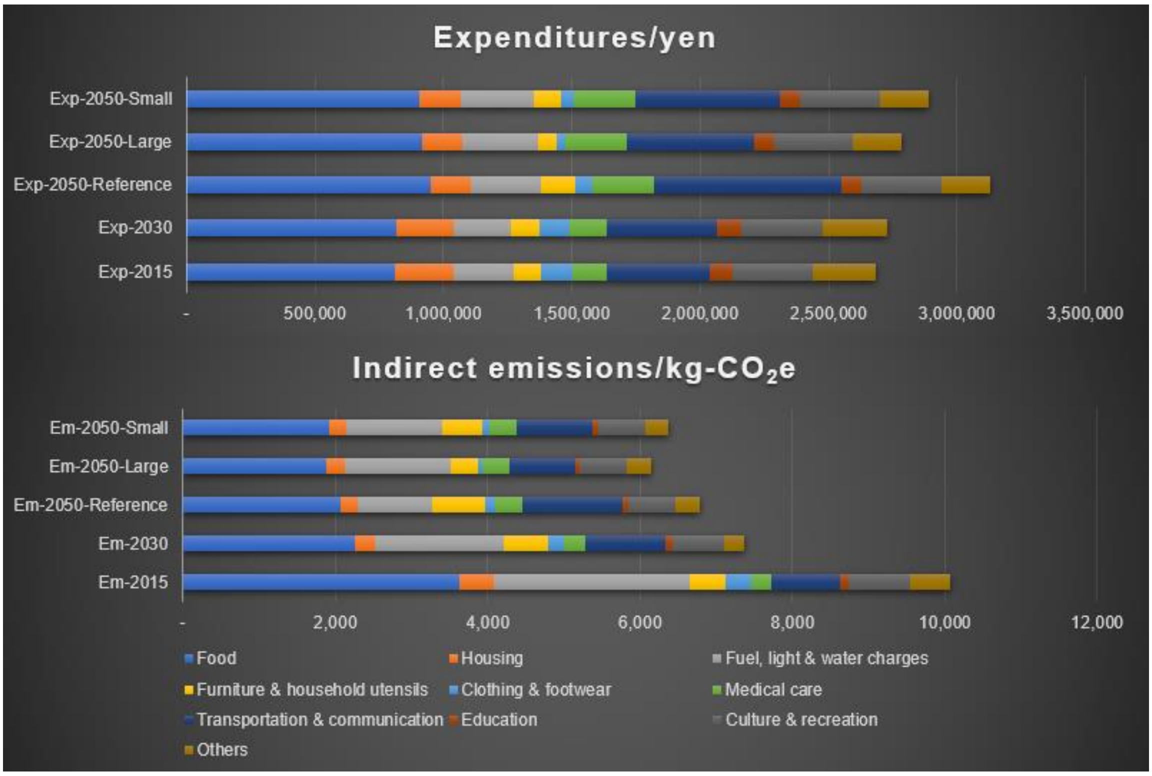


Fig.10 Expenditure and indirect emissions in each category for 2015 and future scenarios

5. Discussion

5.1. Compensating effect within a category

When comparing total household expenditure for 2015–2020, it can be found that these expenditures are relatively close, and even for the year 2020, which seems to be an unexpected result. Due to the COVID-19 pandemic, people's lifestyles changed significantly but total emissions just suffered a slight decrease (4.79%). However, when looking into different categories, some changes in several items like eating out services decreased sharply in 2020, but the whole expenditure of the food category just decreased slightly. And the indirect emissions of the food category follow the same pattern. Thus, it can be indicated that there are some trade-offs among expenditure categories, which is consistent with the result of Yin Long et al[31]. To be more specific, the reduced eating out services are compensated by increases of other items in the same category, such as more consumption of commodities required in at-home cooking. After we set an increase in plant-based food consumption and a decrease in animal-based consumption in Scenario A and Scenario B, more evidence is revealed in the result of 2050 expenditure in the food category, which shows a similar pattern with the year 2020. On the other hand, as is shown in **Table 2**, commodities that have no substitute in the same category such as gasoline suffered the sharpest decline in 2020 compared to other fuels in the fuel category. To sum up, the 2020 case with a slight emission decrease and significant lifestyle changes can be partly explained by the compensating effect within a category.

Table 2

Rate of change of direct emissions caused by fuels for 2016–2020

Year	2016	2017	2018	2019	2020
City Gas	-3.04%	-8.72%	-8.53%	-10.96%	-11.60%
LP gas	-8.66%	-4.46%	-9.39%	-10.60%	-11.02%
Kerosene	1.99%	9.51%	-0.44%	-9.27%	-9.26%
Gasoline	-3.23%	-4.41%	-1.77%	-0.24%	-17.16%

5.2. Compare estimation results of current emissions with an emission survey

The Survey of CO_2 Emission Statistics in the Household Sector was conducted every year by the Ministry of the Environment of Japan, and the purpose is to understand the actual situation of CO_2 emissions and energy consumption from households[32], which is consistent with this study. However, the survey only estimates emissions of four items, City Gas, LP gas, Kerosene and, Electricity, which is quite different from our methodology. But still, we can compare the results of these items as a reference. The expenditure data and emission results are shown in **Table 3** and **Table 4**. It is noticed that while the expenditure data for all the items except for LP gas are almost the same, the emissions result have some differences between calculation and survey. Possible considerations include 1) FIES tends to underestimate expenditures due to some sampling issues. 2) different emission factors are used in estimation. 3) different statistical periods: FIES (Jan–Dec), The Survey of CO_2 Emission Statistics in the Household Sector (Apr-Mar). But the reason why LP gas has more consumption in the Survey remains uncertain.

Table 3

Expenditure data used in the calculation and survey[32]

Survey Results	Expenditures-2020 (yen)	Expenditures-2019 (yen)	Expenditures-2018 (yen)	Expenditures-2017 (yen)
City Gas	30000	30000	30000	30000
LP gas	21000	21000	21000	21000
kerosene	12000	13000	13000	14000
Electricity	106000	106000	110000	106000
Calculating Results	Expenditures-2020 (yen)	Expenditures-2019 (yen)	Expenditures-2018 (yen)	Expenditures-2017 (yen)
City Gas	30266	31507	31321	30226
LP gas	19365	19308	19268	20039
kerosene	11769	12626	13780	13042
Electricity	107688	109203	109810	104499

Table 4
Emission result of calculation and survey[32)]

Survey Results	Emissions-2020 (kg-CO_2-e)	Emissions-2019 (kg-CO_2-e)	Emissions-2018 (kg-CO_2-e)	Emissions-2017 (kg-CO_2-e)
City Gas	440	400	400	430
LP gas	170	160	170	180
Kerosene	390	360	370	430
Electricity	1910	1800	2090	2160
Calculating Results	Emissions-2020 (kg-CO_2-e)	Emissions-2019 (kg-CO_2-e)	Emissions-2018 (kg-CO_2-e)	Emissions-2017 (kg-CO_2-e)
City Gas	352	354	364	363
LP gas	147	148	150	158
Kerosene	341	341	374	411
Electricity	1673	1701	1973	2020

5.3. Slight carbon emissions impacts of consumer behavior change

Change rates of total emissions per household are shown in **Table 5**. The impact of consumer behavior changes on several categories may not be as obvious as one might expect or even negligible in some specific cases. This point can be inferred from the result of emission in the year 2020, and the results of the three 2050 scenarios. Both the year 2020 and Scenario A and Scenario B are affected by a considerable degree of consumer behavior changes, but these changes only lead to a slight change in consumption-induced indirect emissions. The main reason can be considered as the compensating effect within the same category. The other possible explanation may include some items are much more sensitive to other factors such as temperature compared to consumer behavior changes. Thus, regardless of the extent of these consumer behavior changes, some items or categories will remain stable in emissions they may cause. And consequently, we can regard the corresponding impacts as slight.

Table 5
Rate of change of total emissions per household for 2016–2020

Year	2016	2017	2018	2019	2020
Rate of change	-1.84%	-0.97%	0.95%	-1.56%	-4.79%

5.4. Implication for consumer behavior compatible with reduction goals

Now we may understand that some consumer behavior changes although they can be considered environmentally friendly, do not necessarily lead to a reduction in carbon emissions. To cooperate with the government to meet emission reduction targets, consumers can turn their preference towards choices that would produce much less direct emissions, such as choosing the all-electric house, following the shift from personal vehicle use to public transportation.

6. Conclusion

As the deadline for the reduction target of 2030 raised by the Japanese government looms, it becomes more and more important to understand current household carbon emissions. This study first uses current expenditure data and inventory data in IDEA to estimate the status quo of household emission, specifically the year 2020, where a large scale of consumer behavior and lifestyle changes occurs. By comparing the 2020 results with 2015–2019 results, some interesting points are revealed, such as compensating effect within one consumption category. Also, other changes in expenditure pattern and emissions in 2020 are specified and interpreted by several possible reasons, based on which we can gain a deeper understanding of household carbon emissions and consumer behavior changes. And then, to explore the possibility of the attainment of Japan's reduction targets for 2030, future inventory data is used to estimate the emission in 2030, while the future expenditure data is obtained by STSM using historical data. The results show that when compared to the year 2015 which can be considered similar to the emissions of 2013, there is only a 25.2% reduction, far from meeting the 66% reduction targets. Finally, keeping the focus on consumer behavior changes, which are applied in setting 2050 scenario, this study tries to quantify the impact of consumer behavior changes on expenditure. After expenditure scenarios are built, it allows us to find several points based on expenditure and emission results from long-term perspectives.

7. Limitation

7.1. Data insufficiency

Considering that 2030 inventory data is used in 2050 estimations due to data insufficiency, the result of emission in 2050 seems to be over-estimated, and the actual result would be less. Besides, the FIES historical data only contains data for households with two or more people, thus one-person households are not considered in this study. The effect of this needs further exploration.

7.2. Lack of rebound effect

Existing studies point out there is possible rebound effects, which can be defined as "The rebound effect is the change in overall consumption and production due to the behavioral or other systemic response to changes in economic variables (income, price and financial gains or costs of product and material substitution) induced by a change in the technical efficiency of providing an energy service." [33)], which are simply interpreted as changes in some products such as animal-based food that will cause changes in the products of the same category such as plant-based food, are not fully grasped in this study. Thus more works need to be done.

7.3. Future Perspectives

Considering that this study when quantifying the impact of consumer behavior changes on expenditure, these values are largely determined subjectively, future studies are needed to raise a more precise and convincing approach for this. Besides, structural changes in commodities types within a category such as the introduction of new products or obsolescence of old products worth to be considering. For instance, maybe insects as food are better compared to common animal-based food in terms of nutritional value, ease of feeding, cost, and impact on the environment, and seem to be promising in the future. Unfortunately, this study cannot estimate this kind of structural change in Food category, and I hope future studies raise a feasible solution to examine the effect.

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