

# Negligible impacts of early COVID-19 confinement on household carbon footprints in Japan

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Rapid and large-scale changes in household consumption patterns during the COVID-19 pandemic can serve as a natural experiment to explore the environmental outcomes of changing human behavior. Here, we assess the carbon footprint of household consumption in Japan during the early stages of the COVID-19 pandemic (January-May 2020), which included moderate confinement measures. COVID-19 confinement measures in Japan, and associated lifestyle change, did not have a significant effect on the overall household carbon footprint compared with 2015-2019 levels. However, there were significant trade-offs between individual consumption categories, with carbon footprint increasing for some (e.g. eating at home), while declining (e.g. eating out, transportation, clothing, entertainment) or remaining relatively unchanged for others (e.g. housing). Furthermore, carbon footprint patterns between age groups were largely consistent with 2015-2019 levels. However, changes in food-related carbon footprints were visible for all age groups since March, and in some cases since February.

**Keywords:** Decarbonization, Input-output analysis, Greenhouse gas emissions, Natural experiment

## INTRODUCTION

The coronavirus disease 2019 (COVID-19) emerged in the late 2019<sup>1</sup>, and has since caused an unprecedented disruption of social and economic activity globally. Billions of people were forced to change on short notice their behavior and lifestyle, including how they live, work and socialize. Responses to the COVID-19 outbreak have varied significantly between countries, reflecting the very different national approaches and policies seeking to prevent or mitigate

49 the spread of the disease. Some of the most common measures have included  
50 tele-commuting, scaling down (or even halting) of economic activity (e.g.  
51 services, industry), and stay-at-home orders of variable severity between  
52 countries<sup>2</sup>. Although a wide array of different control measures has been  
53 applied, at the time of writing this paper according to the World Health  
54 Organization (WHO), there have been nearly 83.3 million confirmed cases in  
55 220 countries<sup>3</sup> and a second and third wave of infections in many countries.

56  
57 Since the early phases of the pandemic, studies have noted that these major  
58 changes in human activity have had important economic and social  
59 ramifications<sup>4,5</sup>. This in turn seems to have had significant implications for the  
60 environment through the disruption of aggregate demand and global trade<sup>62</sup>.  
61 For example, studies have estimated substantial short-term decreases in  
62 Greenhouse Gases (GHGs) emissions<sup>6,7</sup> nationally and globally, as well as  
63 locally in some emission hotspots<sup>8-11</sup>. However, the observed changes in  
64 socioeconomic activity might have more pronounced and long-term  
65 environmental implications, for example by derailing current progress to (or  
66 providing new opportunities for) energy transitions and decarbonization<sup>12,13,37</sup>.  
67 Furthermore, many of the actual environmental outcomes seem to vary  
68 substantially between countries, depending on their different approaches to  
69 containment measures<sup>14-15</sup>. Most of the studies mentioned above have  
70 explored the environmental outcomes of the COVID-19 pandemic through  
71 measuring directly environmental variables or identifying macro-level patterns  
72 associated with changes in aggregate economic and social activity. It can thus  
73 be argued that they such studies have mainly adopted a production  
74 perspective.

75  
76 However, there has been very little evidence of the possible environmental  
77 outcomes of the COVID-19 pandemic from a micro-level or consumer  
78 perspective, for example, by exploring quantitatively shifts in consumption  
79 patterns due to changes in the lifestyles of individuals and/or households. In  
80 the past, many studies have used such a lens to explore the direct links  
81 between the lifestyles of individuals/households, their consumption choices and  
82 impact on the environment<sup>16,17</sup>, e.g. carbon footprints of current and future  
83 lifestyles in the UK<sup>18</sup>, USA<sup>19</sup>, China<sup>20,21</sup>, and Japan<sup>22</sup>, among others. Other  
84 studies have identified the very diverse factors mediating the environmental  
85 impacts of lifestyles and consumption practices such as household type<sup>23</sup>,  
86 income/wealth (and related inequalities)<sup>24-28</sup>, and demographic processes (e.g.  
87 aging)<sup>29-31</sup>.

88  
89 At the same time it has been argued that by transitioning to more sustainable  
90 lifestyles such as those characterized by lower mobility and/or consumption,  
91 could have major environmental benefits by decreasing overall energy  
92 consumption, GHG emissions and environmental degradation<sup>29,32-34,17,35</sup>. For  
93 example studies have pointed to the environmental dividends that a voluntary  
94 “downsizing” of the lifestyle has, without necessarily compromising the quality  
95 of life<sup>36,37</sup>. However, despite the wealth of micro-level studies exploring the  
96 environmental outcomes of observed (and not simulated) lifestyle changes,  
97 these studies tend to have a piecemeal approach by focusing on small  
98 populations and/or distinct practices (e.g. mobility, dietary transitions)<sup>38</sup>.

99 Conversely most studies exploring the environmental outcomes of large-scale  
100 lifestyle changes have either relied on simulations or long-term historical data<sup>39</sup>.

101

102 Based on the above, the aim of this paper is two-fold. First it assesses the  
103 changes in the direct and indirect GHG emissions associated with household  
104 consumption (carbon footprint) due to the large-scale lifestyle shifts during the  
105 early stages of the COVID-19 pandemic. Second, by viewing these shifts  
106 through the lens of a natural experiment<sup>40</sup>, it critically discusses the implications  
107 of possible large-scale lifestyle changes for decarbonization. This reflects the  
108 emerging view of many environmental scientists that the COVID-19 pandemic  
109 is an unprecedented natural experiment (e.g. Global Human Confinement  
110 Experiment)<sup>40</sup> that can provide profound insights about the environmental  
111 outcomes of large-scale changes in human activity due to its extensive and  
112 rapid effects on socioeconomic activity and human behavior<sup>40</sup> (Anthropause).

113

114 This study focuses on Japan, which offers an ideal setting in terms of its  
115 significant contribution to anthropogenic climate change, its distinct  
116 demographic/socioeconomic characteristics, and its response to the outbreak  
117 using much milder control policies compared to other countries. On the one  
118 hand, Japan is the world's 3<sup>rd</sup> largest economy and 5<sup>th</sup> largest GHG emitter,  
119 with a highly affluent and consumerist society. On the other hand Japan had a  
120 relatively unique response to the early COVID-19 outbreak, which did not entail  
121 a full and strict lockdown, instead influencing the restriction of usual behavior  
122 through mild measures<sup>41</sup>. This makes Japan arguably a better proxy of a more  
123 "reduced activity" lifestyle compared to most other developed countries that  
124 endured more severe measures. Furthermore, Japan has been undergoing  
125 profound demographic changes in terms of aging, with the proportion of  
126 persons >65 years old increasing from 10% in 1985 to 28.1% in 2018 (one of  
127 the highest such fractions in the world)<sup>42</sup>. This makes Japan an ideal setting to  
128 explore the age-differentiated environmental outcomes of lifestyle change,  
129 considering the observed trends towards higher affluence, consumerism, and  
130 population ageing in many parts of the developed and developing world<sup>17</sup>.

131

132 In summary, we assess the carbon footprint of lifestyle changes for the period  
133 January-May 2020 across a set of constituents of household consumption for  
134 different age groups, and compare it with 2015-2019 levels. We use  
135 Environmental Extended Input-output (EEIO) analysis and data from a  
136 nationally representative sample around 7,500 households, collected monthly  
137 by the Statistics Bureau, Ministry of Internal Affairs and Communications of  
138 Japan. The study period consists of three relatively distinct time intervals  
139 characterized by (a) lack of any marked lifestyle change (January-February),  
140 (b) moderate visible lifestyle change (March), and (c) more pronounced  
141 changes during an initially partial and subsequently national state of emergency  
142 (7 April-25 May) (**Figure S1**, Supplementary Material).

143

## 144 **RESULTS**

145

### 146 **Carbon footprint fluctuation and trade-offs**

147 **Figure 1** shows the total carbon footprint associated with the different  
148 components of household consumption in Japan for 2020 (red lines) compared  
149 to 2015-2019 levels (green/yellow areas), and the major constituent of each  
150 consumption component for 2020 (pie charts). Overall, the results suggest that  
151 the total carbon footprint has not changed throughout the period of January-  
152 May 2020 compared to the five previous years (2015-2019). Indeed, the total  
153 monthly carbon footprint for 2020 (red line) has remained within the window  
154 of the carbon footprint of household consumption in the period 2015-2019  
155 (green area) (**Figure 1T**). However, it is possible that lifestyle change  
156 decreased slightly the carbon footprint for the months of April and May  
157 considering that it reaches the upper bound of the 2015-2019 carbon footprints  
158 for these months.

159  
160 <<Insert Figure 1 here >>

161  
162 When looking at the disaggregated carbon footprint for individual consumption  
163 categories, as expected, there are large overall the carbon footprint declines  
164 for activities affected by the confinement measures such as eating out (**Figure**  
165 **1I**), entertainment (**Figure 1S**) and clothing (**Figure 1O**). On the contrary, as  
166 expected, the carbon footprint for most consumption categories associated with  
167 eating at home increased substantially (**Figure 1A-H**). For all these  
168 consumption categories the footprint changes from 2015-2019 levels are very  
169 pronounced for March and April, which signify the months of major lifestyle  
170 change. However, the footprints for these consumption categories increased  
171 rapidly in May, which signifies the end of the confinement measures, through  
172 not reaching the levels of previous year.

173  
174 The total transport-related emissions (both direct and indirect) followed similar  
175 trajectories as the five years before the outbreak (albeit a bit elevated in  
176 January-February), but fell well below the levels of previous years during April  
177 and May, when the confinement measures affected travelling patterns for large  
178 segments of the population (**Figure 1Q**). This decline is mainly due to  
179 decreases in gasoline consumption for private vehicles, which fell 18% below  
180 the lowest emission levels of the five previous years. This seems to imply that  
181 even without mandatory control measures, Japanese residents decreased  
182 substantially their private vehicle using even during the Golden Week in May,  
183 which is the major holiday period in Japan.

184  
185 Surprisingly, despite this reduced activity lifestyle, the carbon footprint of  
186 housing-related consumption categories such as accommodation, electricity,  
187 gas, heating, and sewerage remained largely within the range window of the  
188 past five years with some small exceptions (**Figure 1K-N**). Albeit the carbon  
189 footprint of most these consumption categories hovered at the higher end of  
190 the past footprint spectrum (except for gas), especially during the confinement  
191 measures, they did not show any significant variation despite the larger amount  
192 of time that residents spent at home. The reason might have been the  
193 decreasing demand for space heating due to the regular seasonal warming  
194 from March have weekended the COVID-19' impact on housing related  
195 emission, rather than any unusually high temperatures compared to previous  
196 years (**Figure S2**, Supplementary Material). The carbon footprint of other

197 household consumption categories such as medical services and education,  
198 were close to past footprint levels, with the former staying at the higher end of  
199 the spectrum and the latter at the lower end of the spectrum (**Figure 1P, R**).

200  
201 These patterns suggest two major things. First, despite the major lifestyle  
202 changes, the aggregate carbon footprint of household consumption seems to  
203 have remained relatively constant compared to previous years, with some signs  
204 of slight increase. However, there were very pronounced and changes in the  
205 carbon footprints of some consumption sub-component, which started  
206 bouncing back to the levels of previous years very rapidly after the lift of the  
207 state of confinement measures, such as eating out, clothing and entertainment.

208  
209 <<Insert Figure 2 here >>

210  
211 <<Insert Figure 3 here >>

212  
213 <<Insert Figure 4 here >>

#### 214 **Age-differentiated carbon footprints.**

215 **Figure 2** and **4** show the carbon footprint of non-food and food household  
216 consumption categories respectively, differentiated by age group. **Figure 3**  
217 provides a more disaggregated view of the age-differentiated emissions related  
218 to the demand on energy, sewage and transportation.

219  
220 Consistent with aggregate carbon footprint trends (**Figure 1**), the carbon  
221 footprint for most non-food household consumption categories remained almost  
222 within previous years' footprint limits for all age groups. However, there have  
223 been some major differences between consumption categories as explained  
224 below.

225  
226 First, similar to the aggregate carbon footprint (**Figure 1**), the largest carbon  
227 footprint decreases observed during the pandemic across all age groups are:  
228 clothing (**Figure 2F**), transportation (**Figure 2H**), and communication,  
229 entertainment and relaxation (**Figure 2J**). For these consumption categories  
230 their 2020 emission levels started falling below the 2015-2019 levels from  
231 March 2020 onward (since the early parts of outbreak in Japan), and further  
232 reduced very significantly in the subsequent months across all age groups.

233  
234 Second, the age-differentiated carbon footprints for housing and related energy  
235 use (**Figure 2A-D**) seem to have remained within the previous years' footprint  
236 limits during the pandemic period, despite major changes in working conditions  
237 (i.e. promotion of remote working) and socialization activities (i.e. request by  
238 Japanese government to avoid crowding). Regardless of the month and age  
239 group, the main elements of housing-related emissions are from electricity and  
240 natural gas (**Figure 3**), which might explain the increase by age in **Figure 2D**.  
241 When looking in more detail energy use patterns (**Figure 2B-D, Figure 3**), as  
242 temperature increases into the spring season, heating demand decreases  
243 appreciably. Interestingly, emissions linked to sewage show a slight increase  
244 in April 2020 among age groups >45 years old compared to previous years, but  
245 it is not clear why this happens. While it could be due to increased hand

246 washing for sanitary purposes, the lower than average sewage emission in May  
247 for all groups might challenge this hypothesis.

248  
249 Third, we observe a pronounced decline in transportation-related emissions in  
250 May, when the confinement measures affected travelling patterns for large  
251 segments of the population, and especially groups between 40-64 years old.  
252 Interestingly the transportation emissions of younger groups in May are similar  
253 to previous years, while much more reduced for elderly groups, possibly  
254 implying normalization of travelling activities for the former during Golden Week  
255 (which is the main holiday period in Japan) and continuation of a more “reduced  
256 activity” lifestyle for the latter.

257  
258 When looking more closely into the different food consumption categories,  
259 some interesting patterns emerge (**Figure 4**). First, although the confinement  
260 measures were implemented in April and May, changes in food-related carbon  
261 footprints were visible for all age groups since March, and in some cases since  
262 February (see below), considering that Japan was one of the first countries to  
263 record COVID-19 infections. While it is possible that some of the increase  
264 consumption (and related carbon footprint for some food categories) came from  
265 panic buying in February and March as possibly implied by the increased  
266 footprint of starchy and processed food that reached the emission levels of  
267 previous years (**Figure 4A, F**), there have also been very visible increases  
268 during April-May 2020 from more perishable items such as red meat, eggs and  
269 dairy, and fresh vegetables and fruit (**Figure 4C-E**). There is a marked and  
270 consistent increase in the carbon footprint of eating at home across all age  
271 groups, with the April 2020 levels being consistently higher than the highest  
272 related footprint of the past five years. In contrast, there are exactly the opposite  
273 consistent patterns for the carbon footprint of eating out (**Figure 4B**). However,  
274 we have to point that we cannot infer through these results whether dietary  
275 change took place during the confinement measures, and its effect on GHG  
276 emissions. This is because all of the distinct food categories in **Figure 4** relate  
277 to eating in, as in the FIES survey expenses for “eating in” is divided across  
278 food item categories. However, in the FIES survey “eating out” is captured as  
279 a single block expense category not differentiated by food item. In other words,  
280 the results of **Figure 4** should not be used to elicit whether dietary change  
281 occurred, and the associated changes in emissions.

282  
283 Finally, when looking more closely the footprint of the different age groups we  
284 see some interesting patterns. The most important is that despite some  
285 differentiation in the footprints of individual age groups for some specific  
286 consumption categories, there is no major change in group ranking/order for  
287 the aggregate footprint and almost all individual consumption categories,  
288 except for transportation demand. This suggests that no age group altered  
289 disproportionately its behavior during the period of confinement measures, when  
290 compared to behavior in previous years, and only the younger household  
291 cannot wait for going out in May but the elderly generation still lead a “reduced  
292 activity” lifestyle.

293  
294

## DISCUSSION

### Negligible carbon footprint impacts of lifestyle change

The results strongly imply that lifestyle change during the COVID-19 outbreak period did not have an appreciable effect on the carbon footprint of household consumption in Japan, apart from a small decline below past levels for May (**Figure 1**). This finding based on micro-level data comes in contrast to macro-level studies suggesting that in the same period the decline in economic activity and trade around the world during the COVID-19 outbreak precipitated large overall declines in production-side GHG emissions<sup>8,43-46,62</sup>.

This suggests the rather different trajectory of GHG emissions patterns from the household sector, compared to other economic sectors, at least during the early months of the COVID-19 pandemic (February–May 2020). However, we cannot preclude the possibility of more substantial emission reductions in the medium-to-long term due to reduced household consumption influenced from a possible economic downturn on the aftermath of the COVID-19 outbreak<sup>47</sup>.

Lifestyle change has had relatively consistent effects on age-differentiated carbon footprints. Even though the absolute carbon footprint levels are higher, on average, for more elderly groups, there does not seem to be any major shift in the ranking of carbon footprints between age groups (**Figure 2** and **4**). It is worth noting, that elderly groups have the highest per capita carbon footprints, especially for energy-related categories regardless of the month and the year (e.g. pandemic vs. regular year). This generally higher emissions of elderly households has been pointed in other studies in Japan<sup>29,31,48</sup>, and is mainly due to due to higher heat needs and cooking<sup>49</sup>. In our case, the transport-related emissions of elderly households remain low level even after the emergency declaration in May, while the total footprint is not significantly affected as neither emissions from electricity and food consumption show a substantial decline compared to previous years.

### Trade-offs among consumption categories

Lifestyle change does not seem to have precipitated uniform and proportional changes in carbon footprints across consumption categories. Instead, there seem to be a substantial variation in carbon footprint patterns among consumption categories, with the main observed carbon footprint trade-offs observed between consumption categories associated with eating at home (major increase) and eating outside, transport, clothing and entertainment (major declines). Surprisingly, and with few exceptions, the “reduced activity” lifestyle does not seem to have affected substantially the carbon footprint of housing, despite the opposite trends being visible in some other developed countries<sup>50</sup>.

Despite people spending more time at home, the lack of any major changes in the carbon footprint of housing (and other related consumption categories) might be explained by the timing (spring) and seasonality of energy consumption in Japan<sup>31</sup>. Heating and cooling are the largest contributors of

344 housing-related emissions in Japan<sup>31</sup>, but the mild weather during late spring  
345 in Japan reduces the need for both heating and cooling, as it is also quite  
346 evident in past footprint patterns for these categories (**Figure 1K-M**). It is worth  
347 mentioning that the 2020 spring period did not experience any abnormal  
348 warming, with the average temperatures being rather similar to past years  
349 (**Figure S2**, Supplementary Material). However, we cannot preclude that a  
350 “reduced activity” lifestyle could increase housing-related carbon footprint  
351 during the winter or summer due to the higher demand for heating and cooling  
352 respectively.

353

354 The most pronounced carbon footprint shifts are linked to changes in eating  
355 habits, and especially the large increase in eating at home. This seems to have  
356 negated any carbon footprint gains from other consumption categories due to  
357 lifestyle change, with these changes being largely consistent between all age  
358 groups (**Figure 4**). Despite some evidence of precautionary food purchasing  
359 during the early part of the outbreak (i.e. indicated by carbon footprint increases  
360 for processed and starchy food in February and March), the subsequent  
361 increase in consumption and carbon footprints of perishable food items shows  
362 a rather clear-cut change in eating habits during the study period. This is quite  
363 visible in the large increase of the carbon footprint of emission-intensive food  
364 categories such as red meat, dairy and eggs<sup>39</sup>, especially after March. Even  
365 though it is not possible to confirm possible dietary change from this highly  
366 aggregated data, such shifts might have happened, and can have major  
367 environmental ramifications considering that Japan imports most of these food  
368 items from other countries<sup>51</sup>.

369

### 370 **Implications for decarbonization**

371 Before exploring the implications of this study for decarbonization efforts  
372 through the lens of a natural experiment, we should first acknowledge two  
373 important points. First, as outlined in the Introduction Japan offers a rather  
374 interesting case for exploring the ramifications of reduced social and economic  
375 activity, as the confinement measures were rather moderate and largely  
376 voluntary<sup>41</sup>. Thus, compared to other countries they could in theory reflect  
377 better a possible switch to a “reduced activity” lifestyle. However, at the same  
378 time Japan has some specific characteristics that might affect generalization to  
379 a degree. These include its mild spring, relatively small homes, and lower  
380 reliance on car use, especially in large metropolitan areas such as Tokyo where  
381 a large proportion of the population resides.

382

383 That said, our results suggest that contrary to other economic sectors and  
384 geographical contexts<sup>8,43-46,62</sup>, there seem to be no obvious short-term  
385 environmental benefits from the lifestyle change in the Japanese household  
386 sector during the COVID-19 confinement measures. In our mind this has a  
387 major ramification when seeking to contribute to decarbonization through  
388 lifestyle change, in that environmental benefits might not materialize simply by  
389 adopting a “reduced activity” lifestyle. In fact, the evidence suggests that there  
390 was a simultaneous shift in consumption patterns, which seems to have  
391 practically negated any environmental benefits, at least in the short-term.  
392 Furthermore, the quick bounce of carbon footprints to pre-confinement levels  
393 strongly implies that any changes might be easily reversible.



394

395 This seemingly minor environmental effect of this involuntary change in  
396 consumption patterns across all age groups seems to be in stark contrast with  
397 the pronounced positive environmental outcomes of voluntary lifestyle  
398 changes<sup>36,37</sup>. In this sense we see two major ramifications of our results for  
399 influencing decarbonization through lifestyle change. First, in our mind it re-  
400 affirms the real importance of education to foster more sustainable lifestyles  
401 and prolonged shifts in consumption patterns<sup>17,39,52</sup>, if lifestyle change is to  
402 contribute meaningfully to decarbonization efforts. Second, considering the  
403 larger per capita footprints of the ever-increasing elderly population, future  
404 decarbonization efforts through lifestyle change should focus on emission-  
405 intensive household demand, such as space and water heating, and private car  
406 using.

407

408

### 409 **Future perspectives**

410 Future studies should seek to bridge some of the limitations of this study.  
411 Methodologically these include the inability to consider properly the carbon  
412 intensities of imported goods and the consumption of single-person households  
413 (see Limitations in Methods). The former would require the development of  
414 multi-regional input-output (MRIO) tables that have high sectoral resolution and  
415 employ recent datasets that can capture well national economic structure,  
416 going beyond simple calculations based on GDP change. This is to our best  
417 knowledge a major research gap for Japan, with most current studies unable to  
418 use such high-resolution MRIOs<sup>22,53</sup>. The latter would possibly require  
419 dedicated primary data collection campaigns from nationally representative  
420 single-person households, as these are not considered in the underlying  
421 consumption datasets collected by the Japanese government and used in this  
422 study (see Methods).

423

424 More broadly studies should seek to explore the effects of different confinement  
425 measures on GHG emission changes due to lifestyle changes. Arguably, as  
426 outlined in the introduction Japan's confinement measures have been rather  
427 mild compared to other developed countries, which in our mind make them a  
428 better approximation of "reduced activity" lifestyles. However, comparative  
429 studies across different countries could provide a better micro-level evidence  
430 of how the "Anthropopause" has affected the environment, which would  
431 complement better the emerging studies from the macro-level<sup>54-56</sup>.

432

## 433 **EXPERIMENTAL PROCEDURES**

434

### 435 **Resource availability**

436

#### 437 **Lead contact**

438 Further information and requests for resources should be directed to and will  
439 be fulfilled by the lead contact, Yin Long at [longyinutokyo@gmail.com](mailto:longyinutokyo@gmail.com)

#### 440 **Materials availability**

441 This study did not generate new unique materials.

#### 442 **Data and code availability**

443 The dataset used for this paper has been uploaded to the figshare data  
 444 repository, where it is freely available  
 445 (<https://doi.org/10.6084/m9.figshare.14211989.v1>).

446  
 447 **Carbon footprint of household consumption**

448 Household consumption emits GHGs both directly and indirectly. The direct  
 449 emissions are due to the actual consumption of fuel such as natural gas and  
 450 petroleum products by households. Indirect emissions refer to the emissions  
 451 embodied in the different goods and services consumed by households such  
 452 as food and consumer products. Thus, the total carbon footprint of household  
 453 consumption ( $E^i$ ) is estimated as the sum of direct ( $E_d^i$ ) and indirect emissions  
 454 ( $E_{cf}^i$ ) (Eq.1).

455  
 456 
$$E^i = E_d^i + E_{cf}^i \quad (1)$$

457  
 458 In this study we estimate the total carbon footprint of household consumption  
 459 for the period January-May 2020, and compare it with 2015-2019 levels to  
 460 identify the effect of lifestyle changes during the first COVID-19 confinement  
 461 measures in Japan. The GHGs considered in the calculations include CO<sub>2</sub>,  
 462 CH<sub>4</sub>, N<sub>2</sub>O, HFCs, PFCs, SF<sub>6</sub> and NF<sub>3</sub>.

463  
 464 **Indirect emissions**

465 Many studies have argued for the importance of tracking indirect emissions  
 466 when evaluating the environmental consequences of household  
 467 consumption<sup>57-61</sup>. Indirect emissions can be estimated through Environmental  
 468 Extended Input-output (EEIO) analysis<sup>29,53,62-64</sup>, which involves the use of an  
 469 economic input-output table (IO-T). IO-Ts have been originally used to estimate  
 470 economic transactions among industrial sectors<sup>65-67</sup>. However, subsequently  
 471 they have found applications in environmental impact assessment, as a means  
 472 of tracking indirect energy flows and emission transfer.

473  
 474 In the EEIO model, the relationship between final consumer demand and its  
 475 environmental impacts can be expressed through Equation (2):

476 
$$X = (I - A)^{-1}F \quad (2)$$

477 ...where  $X$  is the vector of domestic production,  $I$  is the identity matrix,  $A$  is the  
 478 input coefficient matrix, and  $F$  is the vector of final demand. When the effects  
 479 of imported goods are considered, then the emission intensity of economic  
 480 sectors is instead calculated using the  $(I - A^d)^{-1}$  type, which refers to inverse  
 481 matrix coefficients of "non-competitive import type" used for analysis when the  
 482 input ratios of imports vary between sectors<sup>68</sup>. When considering the effect of  
 483 imports, Equation (2) is modified into Equation (3):

484 
$$X = (I - A^d)^{-1}F^d \quad (3)$$

485 ...where  $A^d$  and  $F^d$  represent the vectors of domestic input coefficients and  
 486 domestic final demand respectively. Then, by combining with the household  
 487 consumption inventory, indirect emissions embodied in consumption are  
 488 quantified following Equation (4):

489 
$$E_{cf}^i = \sum_{j=1} e_j^i * (I - A^d)^{-1} * Ep^i \quad (4)$$

490 ...where  $E_{cf}^i$  indicates the household carbon footprint by consumption item  $i$ ;  
 491  $Ep^i$  refers to monetary consumption on consumption item  $i$ ;  $e_j^i$  is the direct  
 492 emission intensity of consumption item  $i$ 's GHG emission  $j$ . By multiplying the  
 493 Leontief Inverse Matrix, the direct emission intensity is converted into indirect  
 494 emission intensity, i.e.  $\sum_{j=1} e_j^i * (\mathbf{I} - \mathbf{A}^d)^{-1}$  denoting the indirect emission  
 495 intensity of item  $i$ .

496

### 497 **Direct emissions**

498 Direct emissions are due to the use of fossil fuel, such as natural gas and other  
 499 petroleum products. For this study we include the emissions associated with  
 500 the use of city gas (pipe gas), liquefied petroleum gas (LPG), kerosene and  
 501 gasoline. Japanese households do not use coal directly, while kerosene is an  
 502 important fuel for space heating especially in the mountainous regions<sup>49</sup>. The  
 503 direct emission is estimated through Equation (5),

$$504 \quad E_{y,m}^{dr} = \sum_{i=1} e_t^i * Ep_{y,m}^i * Upc_{y,m}^i \quad (5)$$

505

506 ...where  $E_{y,m}^{dr}$  indicates the total direct household emissions in year  $y$  month  
 507  $m$ ,  $Ep^i$  the direct monetary on fuel  $i$ ,  $Upc_{y,m}^i$  the unit price of fuel  $i$  in year  $y$   
 508 month  $m$ , and  $e_t^i$  the emission intensity of fuel  $i$  in year  $y$  derived from the  
 509 Agency for Natural Resources and Energy by year<sup>69,70</sup>.

510

511 To analyze direct emission by household activities, we merged the four direct  
 512 emission types with the indirect emission inventory, and reclassified sectors  
 513 according to household demand. In more detail, gasoline emissions are merged  
 514 with other transportation-related indirect emission into the "Transportation and  
 515 communication" sector, city gas and LPG in gas-related emissions with indirect  
 516 up-stream emission, and kerosene into the "Other heating and lighting" sector.

517

### 518 **Datasets and Input-Output Tables**

519 The base data for household consumption used to calculate the indirect and  
 520 direct emissions comes from the monthly Family Income and Expenditure  
 521 Survey (FIES)<sup>71</sup>, conducted monthly across Japan by the Statistics Bureau,  
 522 Ministry of Internal Affairs and Communications. The FIES follows a  
 523 standardized approach to capture the expenditures of a nationally  
 524 representative sample of 7,500 households per month across the country.

525

526 The data for the indirect emission intensity of household consumption comes  
 527 from the Embodied Energy and Emission Intensity Data for Japan Using Input-  
 528 Output Tables (3EID), a database of Japan's sectoral intensity of life-cycle  
 529 environmental burdens. This is constructed from the Input-Output Tables for  
 530 Japan using a EEIO model developed by Nansai et al (2002)<sup>72,73</sup>. Even though  
 531 the original model was developed in 2002, it is updated regularly based on the  
 532 Japan official input-output table. For our calculations we used the GHG  
 533 emission intensity for each final demand sector included in the last updated  
 534 version of the 3EID, developed for the year 2015.

535

536 We select the 3EID, which is a single-regional input-output (SRIO) table, rather  
 537 than a multi-regional input-output (MRIO) table for two reasons: (a) higher  
 538 sectoral resolution; (b) most recent data availability. In more detail, the 3EID

539 has a much higher sectoral resolution (390 sectors) when compared with other  
540 MRIOs such as WIOD (56 sectors) and EXIOBASE (200 sectors), which is  
541 closer to the structure of the FIES that contains 500 consumption categories.  
542 This allows for a more comprehensive and fine-grain analysis of consumption  
543 changes in the Japanese household sector, which provides a much better  
544 corresponding between categories between model and data (see below).  
545 Furthermore, the 3EID model has more recent data availability compared to  
546 other SRIOs with similar sectoral resolution such as Eora (401 commodities).  
547 In particular while both 3EID and Eora produce recent data, the latter produces  
548 data that is an extension of estimates based on GDP and other information.  
549 Thus, it does not reflect the latest Input-Output table structure information for  
550 Japan, which is necessary considering the span of our study (2015-2020).

551

### 552 **Calculation procedure**

553 First, we extract from the 3EID dataset the data for the 390 sectors for the year  
554 2015, as well as the corresponding emission intensities<sup>72,73</sup>. Second, we match  
555 categories of the 3EID and FIES, as the classification of industries in the 3EID  
556 database differs from the classification of consumption elements in the FIES  
557 expenditure data. We matched the data following the general approach outlined  
558 in Jiang et al. (2020)<sup>22</sup>, as shown in Table S1 (Supplementary Material) that  
559 includes the major categories and cross—matching of FIES and 3EID. It should  
560 be noted that there is no perfect match between the categories of the 3EID and  
561 the FIES. Some 3EID categories such as waste management that are not  
562 distinct household components in FIES are linked to consumption-relevant  
563 items such as municipal services. However, to avoid mismatching we have  
564 excluded some of the FIES miscellaneous expenses such as allowances and  
565 donations that cannot match well with 3EID sectors. According to our estimates,  
566 the average consumption ratio of these miscellaneous expenses was 4.65% for  
567 the study months in 2020, which represents a rather minor fraction of overall  
568 household consumption.

569

570 Third, we calculate changes in prices between years adjusting for inflation and  
571 Consumer Price Index (CPI). Here, we applied the constant price of 2015  
572 according to the annual inflation data derived from the World Bank<sup>74</sup>. Monthly  
573 average CPI is obtained from the Statistics Bureau of Japan<sup>75</sup>.

574

575 Fourth, we aggregate the obtained inventory of the 495 indirect emission items  
576 and 4 direct emission items into 19 footprint elements, by month and age group  
577 (see Table S2, Supplementary Material for 2020 levels). To understand  
578 convergences and divergences with past emission patterns, we compare each  
579 footprint elements per month and age group for 2020, with the maximum and  
580 minimum such values between 2015 and 2019 (footprint range window).

581

582 Finally, it is worth mentioning that some of the interannual variation in emissions  
583 might be due to confounding factors related to climate and the economy. To  
584 test whether such confounding factors might have had an important effect on  
585 the results, we check for the study period in 2020 changes for three  
586 confounding factors related to the national economy and climate, namely GDP,  
587 household income, Engel's coefficient (i.e. proportion of income spend on  
588 food), and temperature. Overall, we find that these factors remain relatively

589 constant between years, with no unnatural peaks or declines in the study period  
590 compared to previous years (**Figure S3-S5**, Supplementary Material).

591

### 592 **Methodological limitations**

593 Despite the high resolution of consumption categories and data quality, this  
594 study has three main limitations, namely (a) the inability to apply distinct carbon  
595 intensities for imported goods, (b) an inability to capture single-person  
596 households, (c) the assumption of constant technology since 2015, and value  
597 chain configurations since the onset of the COVID-19 pandemic.

598

599 First, the 3EID is an emission inventory generated through the Japanese SRIO  
600 table. This inherently means that the emission intensities used in this study  
601 reflect only domestic goods (and their value chains). We also apply these  
602 domestic emission intensities for imported goods, which inserts some level of  
603 uncertainty to our results. As outlined above, despite the higher sectoral  
604 resolution and data quality expected by adopting the 3EID model, this omission  
605 might underestimate the actual carbon footprint, as goods imported in the  
606 domestic market tend to have longer value chains, and thus higher GHG  
607 emissions when compared to similar domestic goods<sup>76</sup>. However, apart from  
608 the Global Link Input-output for 2005<sup>73</sup>, to the best of our knowledge no input-  
609 output table in the Japanese context has included multi-regional economic  
610 interactions or other similar data in an appropriate manner. This inability to  
611 consider properly emissions from imported good remains a broader gap in the  
612 literature in recent decades.

613

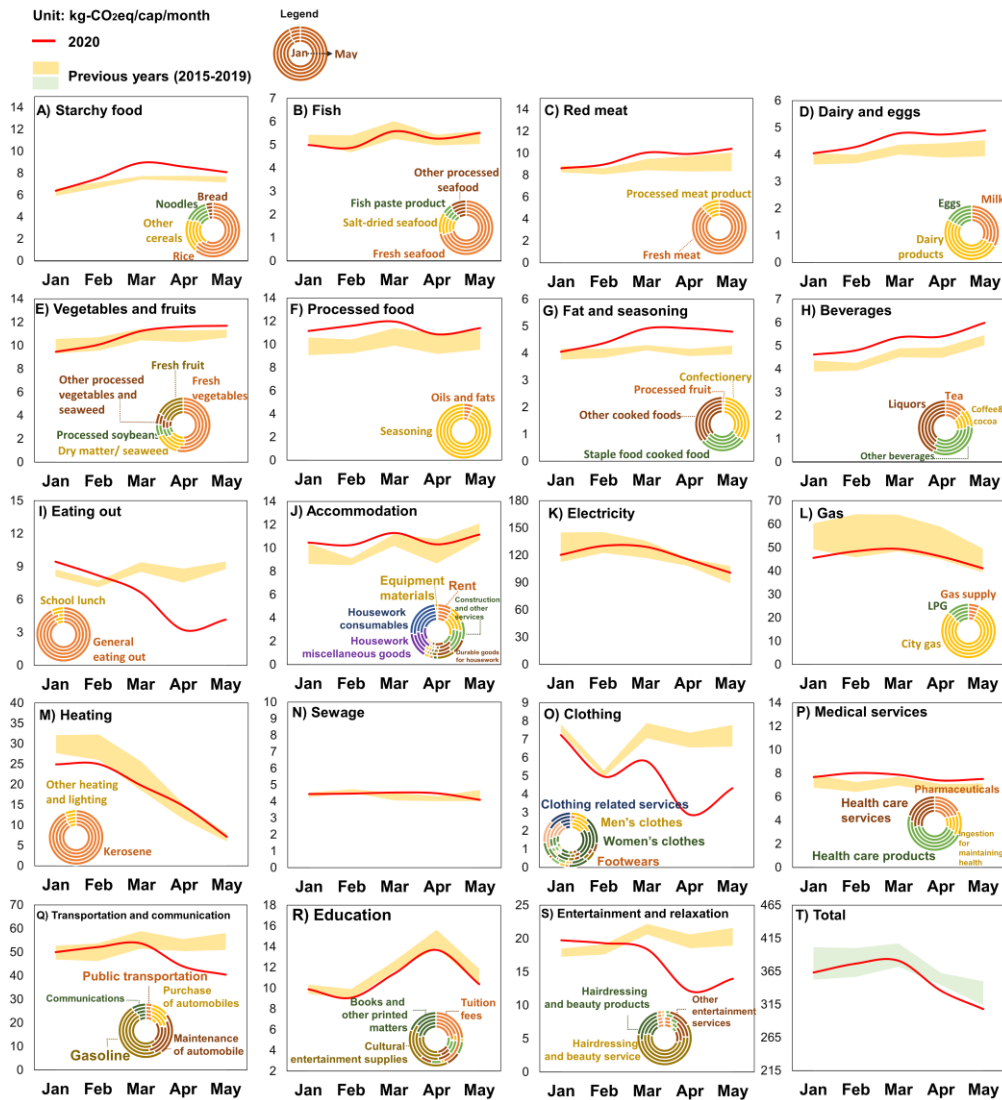
614 Second, the underlying FIES datasets used in this study do not capture single-  
615 person households, as the most recent sample used in this study only contains  
616 households with two and more members. Even though single-person  
617 households are very prevalent across all age groups in Japan<sup>71</sup>, they tend to  
618 be more prevalent across younger age groups<sup>77</sup>, which are generally  
619 associated with lower per capita emissions in the country (see also Results). At  
620 the same time single-person households are associated with higher per capita  
621 emissions in Japan<sup>77</sup>. This means that it is difficult to predict what is the actual  
622 effect of this omission from our calculations, in terms of overestimation,  
623 underestimation or balancing out. Thus, considering the relatively large  
624 prevalence of single-person households in the Japanese society<sup>78</sup>, some  
625 caution should be exerted when generalizing the results of the analysis.

626

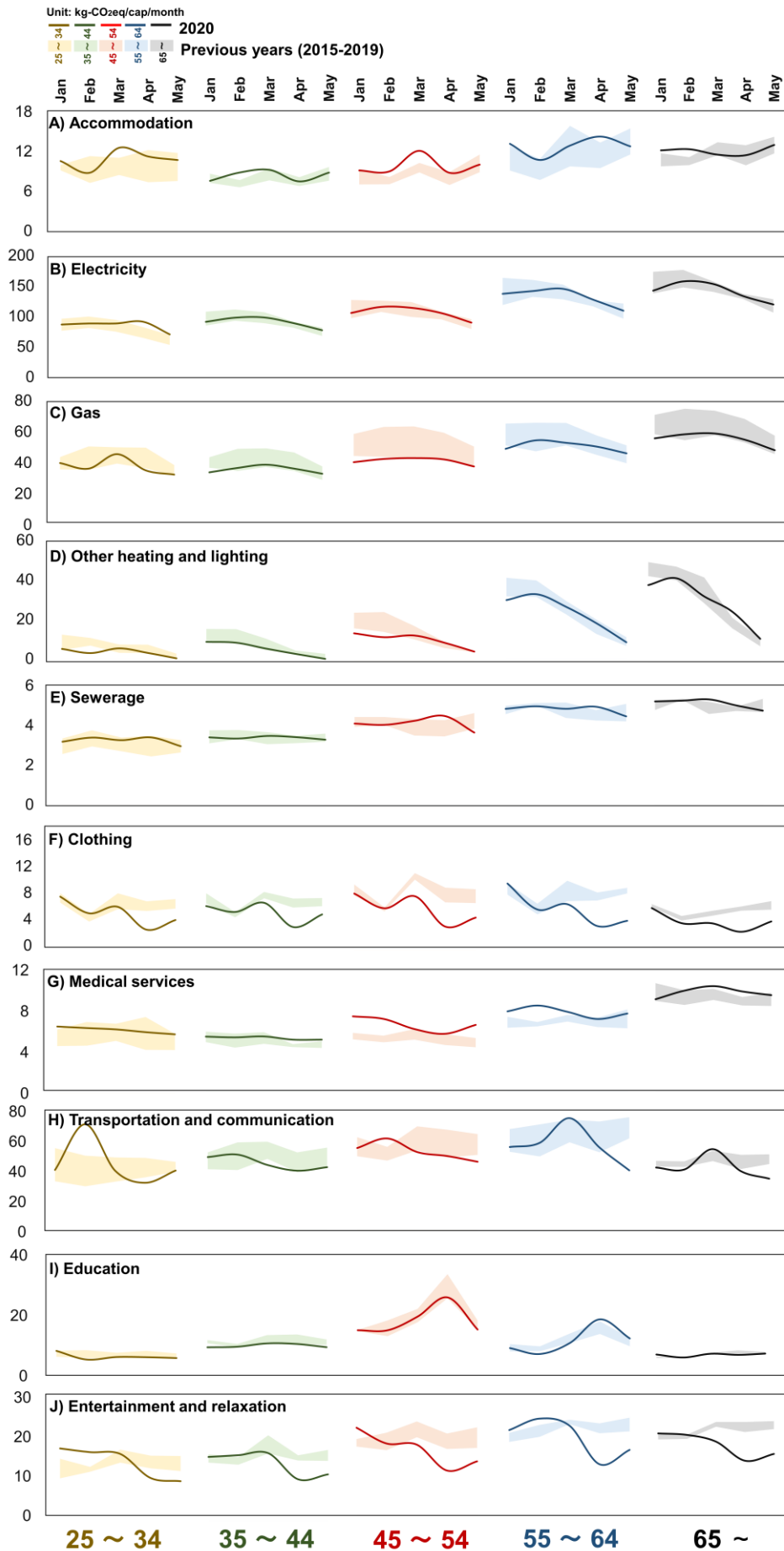
627 Third, considering that 3EID data is for 2015 it might be that technology effects  
628 might lead to the over- or under-estimation of the carbon footprints when  
629 applied for other years<sup>73,79</sup>. Still we believe that these changes might be  
630 relatively marginal considering that the technology improvement needs a  
631 comparatively longer time to manifest<sup>80</sup>. One interesting phenomenon might be  
632 the effect of COVID-19 in production and trade chains, considering the severe  
633 economic disruptions. It is rather difficult to predict the effects of such changes  
634 for household carbon footprints in Japan. Considering the exclusion of imported  
635 carbon intensities in our analysis as explained above they will not affect the  
636 results of this analysis. In any case we expect them in reality to be marginal as  
637 the confinement measures it is highly possible that most materials were  
638 supplied to the market before the confinement measures, and thus non-food

639 items (and possibly food items with long lives such as starchy and processed  
 640 food) will not have been affected by any changes in production value chains  
 641 due to existing stocks.  
 642  
 643  
 644  
 645

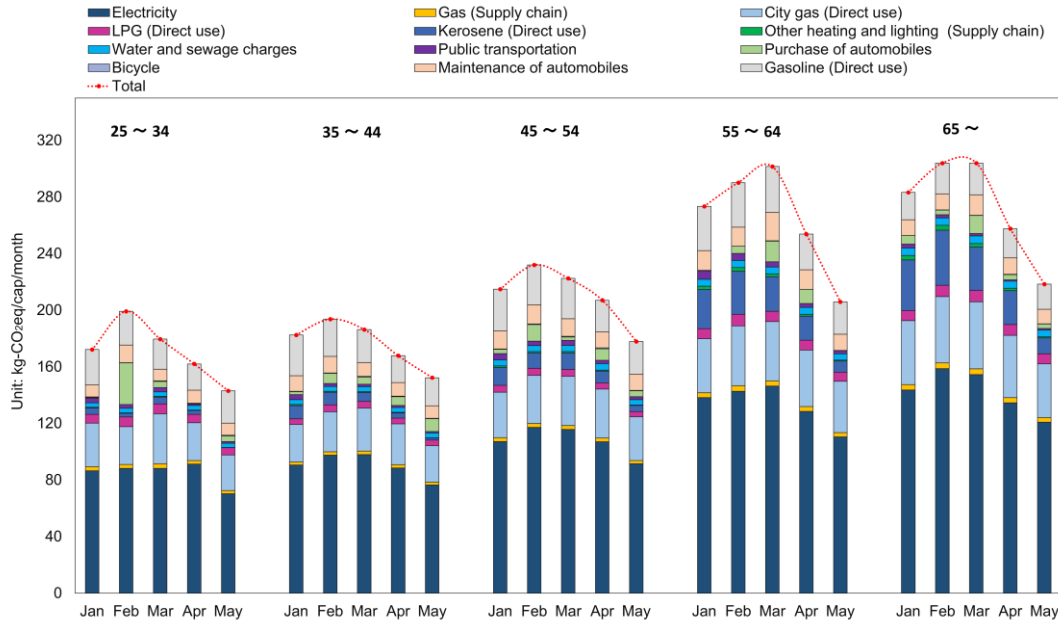
### Figure Legends



646  
 647  
 648 **Fig.1 Total carbon footprint of household consumption (in kg-CO<sub>2</sub>eq/cap).**  
 649 The red line indicates the 2020 GHG emissions for the different household  
 650 consumption categories for each corresponding month. The yellow and green  
 651 areas indicate the emissions ranges for the past five years (2015-2019). Pie  
 652 charts indicating the main emission sources for each consumption category.

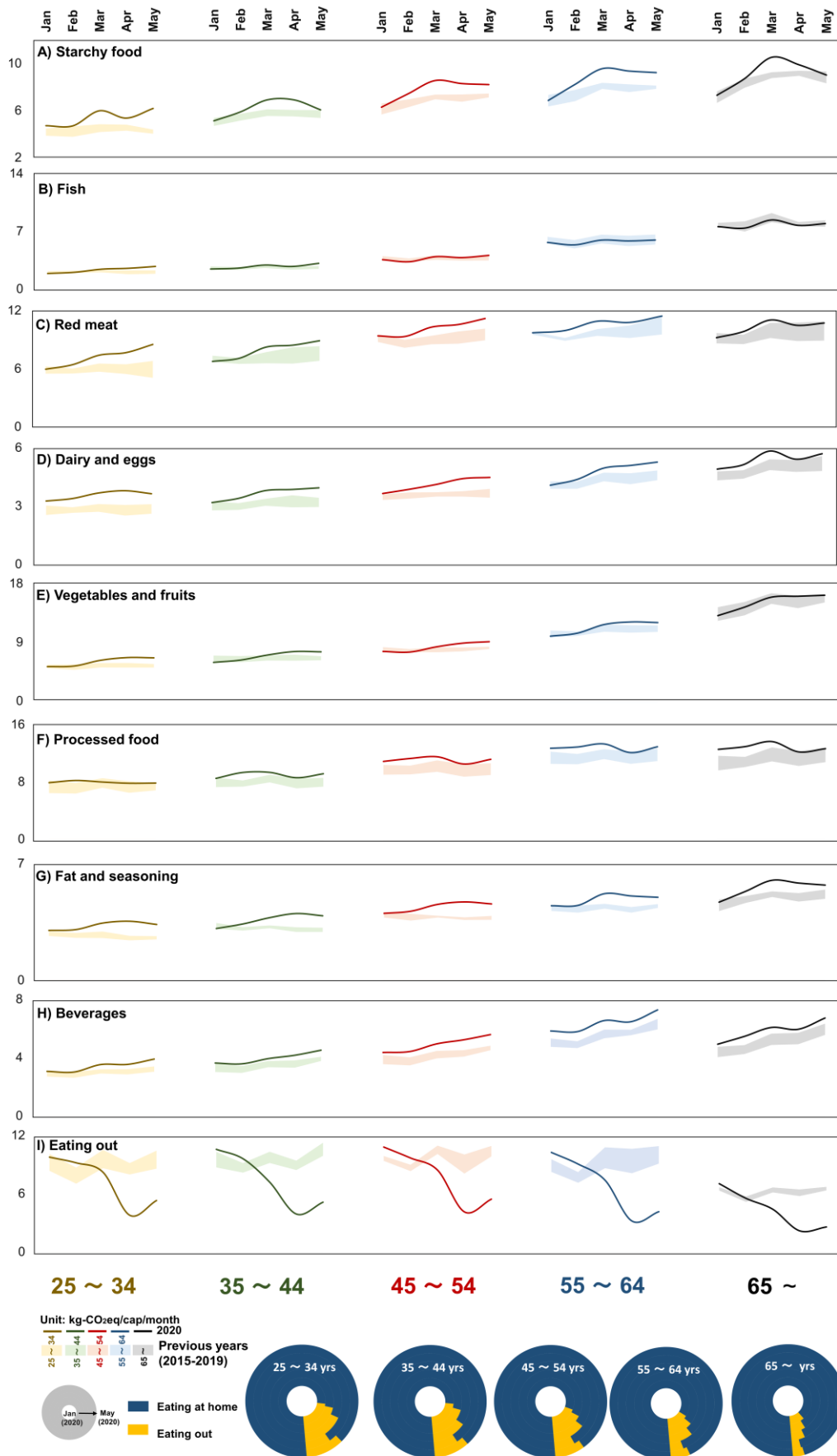


654 **Fig.2 Carbon footprint of non-food consumption categories**  
 655 **disaggregated by age group** (in kg-CO<sub>2</sub>eq/cap). The lines indicate the 2020  
 656 GHG emissions for the different non-food household consumption categories  
 657 for each corresponding month. The shades indicate the emissions ranges for  
 658 the past five years (2015-2019).  
 659



660 **Fig.3 Carbon footprint components for housing, sewage and**  
 661 **transportation by age group** (in kg-CO<sub>2</sub>eq/cap).  
 662  
 663





664  
 665  
 666

**Fig.4 Carbon footprint of food consumption categories disaggregated by age groups (in kg-CO<sub>2</sub>eq/cap).** The lines indicate the 2020 GHG emissions for

667 the different food-related household consumption categories for each  
668 corresponding month. The shades indicate the emission ranges for the past  
669 five years (2015-2019). The concentric circles at the pie charts indicate for each  
670 age group the proportion of eating at home (dark blue) and eating out (light  
671 blue) to the food-related carbon footprint by month starting from January (inner  
672 circles) to May (outer circles).  
673

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679

## 680 **AUTHOR CONTRIBUTIONS**

681 Y.L. and G.A designed the study. Y.L. conducted the analysis. Y.L and A.G.  
682 wrote the first draft of the manuscript. K.K., D.G and G.A revised the manuscript.  
683  
684

## 685 **DECLARATION OF INTERESTS**

686 The authors declare no competing interests.  
687

688

## 689 **REFERENCES**

- 690
- 691 1 WHO (2020). Report of the WHO-China Joint Mission on Coronavirus  
692 Disease 2019 (COVID-19)
  - 693 2 Habersaat, K. B., Betsch, C., Danchin, M., Sunstein, C. R., Böhm, R., Falk, A.,  
694 Brewer, N. T., Omer, S. B., Scherzer, M., Sah, S., *et al.* (2020). Ten  
695 considerations for effectively managing the COVID-19 transition. *Nature*  
696 *Human Behaviour*.
  - 697 3 WHO (2020). Coronavirus disease (COVID-19) pandemic.
  - 698 4 Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F.,  
699 Schmidt, A. L., Valensise, C. M., Scala, A. & Quattrociocchi, W. J. P. o. t. N. A.  
700 o. S. (2020). Economic and social consequences of human mobility  
701 restrictions under COVID-19. *117*, 15530-15535.
  - 702 5 Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M. & Stanton, C. J.  
703 P. o. t. N. A. o. S. (2020). The impact of COVID-19 on small business  
704 outcomes and expectations. *117*, 17656-17666.
  - 705 6 Guan, D., Wang, D., Hallegatte, S., Davis, S. J., Huo, J., Li, S., Bai, Y., Lei, T.,  
706 Xue, Q. & Coffman, D. M. (2020). Global supply-chain effects of COVID-19  
707 control measures. *Nature Human Behaviour*, 1-11.
  - 708 7 Le Quéré, C., Jackson, R. B., Jones, M. W., Smith, A. J. P., Abernethy, S.,  
709 Andrew, R. M., De-Gol, A. J., Willis, D. R., Shan, Y., Canadell, J. G., *et al.*

710 (2020). Temporary reduction in daily global CO<sub>2</sub> emissions during the  
711 COVID-19 forced confinement. *Nature Climate Change* 10, 647-653.

712 8 Kanniah, K. D., Kamarul Zaman, N. A. F., Kaskaoutis, D. G. & Latif, M. T.  
713 (2020). COVID-19's impact on the atmospheric environment in the  
714 Southeast Asia region. *Science of The Total Environment* 736, 139658.

715 9 Long, Y., Huang, D., Lei, T., Zhang, H., Wang, D., Yoshida, Y. J. T. R. P. D. T. &  
716 Environment (2020). Spatiotemporal variation and determinants of  
717 carbon emissions generated by household private car. 87, 102490.

718 10 Liu, Y., Huang, L. & Onstein, E. (2020). How do age structure and urban  
719 form influence household CO<sub>2</sub> emissions in road transport? Evidence  
720 from municipalities in Norway in 2009, 2011 and 2013. *Journal of Cleaner  
721 Production*, 121771.

722 11 Berman, J. D. & Ebisu, K. (2020). Changes in U.S. air pollution during the  
723 COVID-19 pandemic. *Science of The Total Environment* 739, 139864.

724 12 Kuzemko, C., Bradshaw, M., Bridge, G., Goldthau, A., Jewell, J., Overland, I.,  
725 Scholten, D., Van de Graaf, T. & Westphal, K. (2020). Covid-19 and the  
726 politics of sustainable energy transitions. *Energy Research & Social  
727 Science* 68, 101685.

728 13 Steffen, B., Egli, F., Pahle, M. & Schmidt, T. S. (2020). Navigating the Clean  
729 Energy Transition in the COVID-19 Crisis. *Joule* 4, 1137-1141.

730 14 Bahmanyar, A., Estebasari, A. & Ernst, D. (2020). The impact of different  
731 COVID-19 containment measures on electricity consumption in Europe.  
732 *Energy Research & Social Science* 68, 101683.

733 15 Rugani, B. & Caro, D. (2020). Impact of COVID-19 outbreak measures of  
734 lockdown on the Italian Carbon Footprint. *Science of The Total  
735 Environment* 737, 139806.

736 16 Tukker, A., Cohen, M. J., Hubacek, K. & Mont, O. J. J. o. I. E. (2010). The  
737 impacts of household consumption and options for change. 14, 13-30.

738 17 Wiedmann, T., Lenzen, M., Keyßer, L. T. & Steinberger, J. K. J. N. c. (2020).  
739 Scientists' warning on affluence. 11, 1-10.

740 18 Baiocchi, G., Minx, J. C. & Hubacek, K. (2010). The impact of social factors  
741 and consumer behavior on CO<sub>2</sub> emissions in the UK: A panel regression  
742 based on input-output and geo-demographic consumer segmentation  
743 data.

744 19 Bin, S. & Dowlatabadi, H. (2005). Consumer lifestyle approach to US  
745 energy use and the related CO<sub>2</sub> emissions. *Energy Policy* 33, 197-208.

746 20 Ding, Q., Cai, W., Wang, C. & Sanwal, M. (2017). The relationships between  
747 household consumption activities and energy consumption in china—An  
748 input-output analysis from the lifestyle perspective. *Applied Energy*.

749 21 Hubacek, K., Guan, D., Barrett, J. & Wiedmann, T. (2009). Environmental  
750 implications of urbanization and lifestyle change in China: Ecological and  
751 Water Footprints. *Journal of Cleaner Production* 17, 1241-1248.

752 22 Jiang, Y., Long, Y., Liu, Q., Dowaki, K. & Ihara, T. (2020). Carbon emission  
753 quantification and decarbonization policy exploration for the household  
754 sector - Evidence from 51 Japanese cities. *Energy Policy* 140, 111438.

755 23 Shigetomi, Y., Nansai, K., Kagawa, S. & Tohno, S. (2018). Fertility-rate  
756 recovery and double-income policies require solving the carbon gap  
757 under the Paris Agreement. *Resources, Conservation and Recycling* 133,  
758 385-394.

- 759 24 López, L., Arce, G., Morenate, M. & Zafrilla, J. (2017). How does income  
760 redistribution affect households' material footprint? *Journal of Cleaner*  
761 *Production* 153, 515-527.
- 762 25 Golley, J. & Meng, X. (2012). Income inequality and carbon dioxide  
763 emissions: The case of Chinese urban households. *Energy Economics* 34,  
764 1864-1872.
- 765 26 Hubacek, K., Baiocchi, G., Feng, K., Castillo, R. M., Sun, L., Xue, J. J. E.,  
766 *Ecology & Environment* (2017). Global carbon inequality. 2, 361-369.
- 767 27 Hubacek, K., Baiocchi, G., Feng, K. & Patwardhan, A. J. N. c. (2017). Poverty  
768 eradication in a carbon constrained world. 8, 1-9.
- 769 28 Wiedenhofer, D., Guan, D., Liu, Z., Meng, J., Zhang, N. & Wei, Y.-M. (2017).  
770 Unequal household carbon footprints in China. *Nature Climate Change* 7,  
771 75.
- 772 29 Shigetomi, Y., Nansai, K., Kagawa, S. & Tohno, S. (2014). Changes in the  
773 carbon footprint of Japanese households in an aging society.  
774 *Environmental science & technology* 48, 6069-6080.
- 775 30 Shigetomi, Y., Matsumoto, K. i., Ogawa, Y., Shiraki, H., Yamamoto, Y., Ochi,  
776 Y. & Ehara, T. (2018). Driving forces underlying sub-national carbon  
777 dioxide emissions within the household sector and implications for the  
778 Paris Agreement targets in Japan. *Applied Energy* 228, 2321-2332.
- 779 31 Long, Y., Yoshida, Y., Meng, J., Guan, D., Yao, L. & Zhang, H. J. A. e. (2019).  
780 Unequal age-based household emission and its monthly variation  
781 embodied in energy consumption—A cases study of Tokyo, Japan. 247,  
782 350-362.
- 783 32 Abdul-Manan, A. F. N. (2015). Uncertainty and differences in GHG  
784 emissions between electric and conventional gasoline vehicles with  
785 implications for transport policy making. *Energy Policy* 87, 1-7.
- 786 33 Grischkat, S., Hunecke, M., Böhler, S. & Haustein, S. (2014). Potential for  
787 the reduction of greenhouse gas emissions through the use of mobility  
788 services. *Transport Policy* 35, 295-303.
- 789 34 Saner, D., Heeren, N., Jäggi, B., Waraich, R. A. & Hellweg, S. (2013). Housing  
790 and mobility demands of individual households and their life cycle  
791 assessment. *Environmental science & technology* 47, 5988-5997.
- 792 35 O'Neill, D. W., Fanning, A. L., Lamb, W. F. & Steinberger, J. K. J. N. s. (2018).  
793 A good life for all within planetary boundaries. 1, 88-95.
- 794 36 Vita, G., Ivanova, D., Dumitru, A., García-Mira, R., Carrus, G., Stadler, K.,  
795 Krause, K., Wood, R., Hertwich, E. G. J. E. R. & Science, S. (2020). Happier  
796 with less? Members of European environmental grassroots initiatives  
797 reconcile lower carbon footprints with higher life satisfaction and income  
798 increases. 60, 101329.
- 799 37 Jackson, T. J. J. o. I. E. (2005). Live better by consuming less?: is there a  
800 "double dividend" in sustainable consumption? 9, 19-36.
- 801 38 Capstick, S., Lorenzoni, I., Corner, A. & Whitmarsh, L. J. C. m. (2014).  
802 Prospects for radical emissions reduction through behavior and lifestyle  
803 change. 5, 429-445.
- 804 39 Dubois, G., Sovacool, B., Aall, C., Nilsson, M., Barbier, C., Herrmann, A.,  
805 Bruyère, S., Andersson, C., Skold, B., Nadaud, F. J. E. R., *et al.* (2019). It  
806 starts at home? Climate policies targeting household consumption and  
807 behavioral decisions are key to low-carbon futures. 52, 144-158.

808 40 Bates, A. E., Primack, R. B., Moraga, P. & Duarte, C. M. (2020). COVID-19  
809 pandemic and associated lockdown as a “Global Human Confinement  
810 Experiment” to investigate biodiversity conservation. *Biological  
811 Conservation* 248, 108665.

812 41 Normile, D. (2020). Japan ends its COVID-19 state of emergency. *Science*.  
813 42 Japan, S. B. o. (2020). *Statistical Handbook of Japan 2019*. Ministry of  
814 Internal Affairs and Communications, Japan.

815 43 Gillingham, K. T., Knittel, C. R., Li, J., Ovaere, M. & Reguant, M. (2020). The  
816 Short-run and Long-run Effects of Covid-19 on Energy and the  
817 Environment. *Joule* 4, 1337-1341.

818 44 He, G., Pan, Y. & Tanaka, T. (2020). The short-term impacts of COVID-19  
819 lockdown on urban air pollution in China. *Nature Sustainability*.

820 45 Forster, P. M., Forster, H. I., Evans, M. J., Gidden, M. J., Jones, C. D., Keller, C.  
821 A., Lamboll, R. D., Quéré, C. L., Rogelj, J., Rosen, D., *et al.* (2020). Current  
822 and future global climate impacts resulting from COVID-19. *Nature  
823 Climate Change*.

824 46 Huang, X., Ding, A., Gao, J., Zheng, B., Zhou, D., Qi, X., Tang, R., Wang, J., Ren,  
825 C. & Nie, W. J. N. S. R. (2020). Enhanced secondary pollution offset  
826 reduction of primary emissions during COVID-19 lockdown in China.

827 47 Venter, Z. S., Aunan, K., Chowdhury, S. & Lelieveld, J. J. P. o. t. N. A. o. S.  
828 (2020). COVID-19 lockdowns cause global air pollution declines.

829 48 Huang, Y., Shigetomi, Y., Chapman, A. & Matsumoto, K. i. J. E. (2019).  
830 Uncovering household carbon footprint drivers in an aging, shrinking  
831 society. *12*, 3745.

832 49 MOE (2017). *Annual Report on Environmental Statistics*. Ministry of the  
833 Environment Government of Japan.

834 50 Chen, C.-f., de Rubens, G. Z., Xu, X. & Li, J. (2020). Coronavirus comes  
835 home? Energy use, home energy management, and the social-  
836 psychological factors of COVID-19. *Energy Research & Social Science*,  
837 101688.

838 51 FAOSTAT (2020). *Food and agriculture data*.

839 52 Schellnhuber, H.-J., van der Hoeven, M., Bastioli, C., Ekins, P., Jaczewska, B.,  
840 Kux, B., Thimann, C., Tubiana, L., Wanngård, K. & Slob, A. (2018). *Final  
841 Report of the High-Level Panel of the European Decarbonisation  
842 Pathways Initiative*.

843 53 Long, Y., Yoshida, Y., Zhang, R., Sun, L. & Dou, Y. (2018). Policy  
844 implications from revealing consumption-based carbon footprint of major  
845 economic sectors in Japan. *Energy Policy* 119, 339-348.

846 54 Lai, K. Y., Webster, C., Kumari, S. & Sarkar, C. J. C. O. i. E. S. (2020). The  
847 nature of cities and the Covid-19 pandemic.

848 55 Mackenzie, S. H. & Goodnow, J. J. L. S. (2020). Adventure in the age of  
849 COVID-19: Embracing microadventures and locavism in a post-pandemic  
850 world. 1-8.

851 56 Cho, E. (2020). Examining boundaries to understand the impact of COVID-  
852 19 on vocational behaviors. *Journal of Vocational Behavior* 119, 103437.

853 57 Lenzen, M., Wood, R. & Wiedmann, T. (2010). Uncertainty analysis for  
854 multi-region input-output models—a case study of the UK's carbon  
855 footprint. *Economic Systems Research* 22, 43-63.

- 856 58 Wiedmann, T., Lenzen, M., Turner, K. & Barrett, J. (2007). Examining the  
857 global environmental impact of regional consumption activities—Part 2:  
858 Review of input–output models for the assessment of environmental  
859 impacts embodied in trade. *Ecological economics* 61, 15-26.
- 860 59 Lenzen, M., Murray, S. A., Korte, B. & Dey, C. J. (2003). Environmental  
861 impact assessment including indirect effects—a case study using input–  
862 output analysis. *Environmental Impact Assessment Review* 23, 263-282.
- 863 60 Lenzen, M. (1998). Primary energy and greenhouse gases embodied in  
864 Australian final consumption: an input–output analysis. *Energy policy* 26,  
865 495-506.
- 866 61 Wiedmann, T. & Lenzen, M. (2018). Environmental and social footprints  
867 of international trade. *Nature Geoscience* 11, 314-321.
- 868 62 Long, Y. & Yoshida, Y. (2018). Quantifying city-scale emission  
869 responsibility based on input-output analysis – Insight from Tokyo, Japan.  
870 *Applied Energy* 218, 349-360.
- 871 63 Long, Y., Dong, L., Yoshida, Y. & Li, Z. (2018). Evaluation of energy-related  
872 household carbon footprints in metropolitan areas of Japan. *Ecological  
873 Modelling* 377, 16-25.
- 874 64 Shigetomi, Y., Nansai, K., Kagawa, S. & Tohno, S. (2015). Trends in  
875 Japanese households' critical-metals material footprints. *Ecological  
876 Economics* 119, 118-126.
- 877 65 Leontief, W. W. (1936). Quantitative input and output relations in the  
878 economic systems of the United States. *The review of economic statistics*,  
879 105-125.
- 880 66 Leontief, W. (1970). Environmental Repercussions and the Economic  
881 Structure: An Input-Output Approach *The Review of Economics and  
882 Statistics* 52, pp. 262-271
- 883 67 Su, B. & Ang, B. W. (2015). Multiplicative decomposition of aggregate  
884 carbon intensity change using input–output analysis. *Applied Energy* 154,  
885 13-20.
- 886 68 MIC (2015). 2011 Input-output tables for Japan.
- 887 69 Japan, A. f. N. R. a. E. o. (2017). FY2016 Annual Report on Energy (Energy  
888 White Paper)
- 889 70 Long, Y., Yoshida, Y., Zhang, H., Zheng, H., Shan, Y. & Guan, D. J. S. d. (2020).  
890 Japan prefectural emission accounts and socioeconomic data 2007 to  
891 2015. 7, 1-8.
- 892 71 FIES Family Income and Expenditure Survey. Statistics Bureau, Ministry  
893 of Internal Affairs and Communications, Japan.
- 894 72 Nansai, K., Kagawa, S., Kondo, Y., Suh, S., Inaba, R. & Nakajima, K. (2009).  
895 Improving the Completeness of Product Carbon Footprints Using a Global  
896 Link Input–Output Model: The Case of Japan. *Economic Systems Research*  
897 21, 267-290.
- 898 73 Nansai, K., Kondo, Y., Kagawa, S., Suh, S., Nakajima, K., Inaba, R. & Tohno, S.  
899 (2012). Estimates of embodied global energy and air-emission intensities  
900 of Japanese products for building a Japanese input-output life cycle  
901 assessment database with a global system boundary. *Environmental  
902 science & technology* 46, 9146-9154.
- 903 74 Bank, T. W. Inflation, consumer prices (annual %). World Bank Open Data.  
904 75 Japan, S. B. o. (2020). Report on the Consumer Price Index.

905 76 Lee, J., Taherzadeh, O. & Kanemoto, K. (2021). The scale and drivers of  
906 carbon footprints in households, cities and regions across India. *Global*  
907 *Environmental Change* 66, 102205.

908 77 Kawajiri, K., Ihara, T., Hatayama, H. & Tahara, K. (2018). Revealing hidden  
909 CO2 impacts from consequential consumption by matrix analysis:  
910 Application to Japanese single households. *Journal of Cleaner Production*  
911 172, 582-590.

912 78 NIPSSR (2014). Household Projections for Japan 2010-2035 :Outline of  
913 Results and Methods National Institute of Population and Social Security  
914 Research of Japan.

915 79 Nansai, K., Fry, J., Malik, A., Takayanagi, W., Kondo, N. J. R., Conservation &  
916 Recycling (2020). Carbon footprint of Japanese health care services from  
917 2011 to 2015. 152, 104525.

918 80 Mi, Z., Meng, J., Guan, D., Shan, Y., Song, M., Wei, Y.-M., Liu, Z. & Hubacek, K.  
919 (2017). Chinese CO 2 emission flows have reversed since the global  
920 financial crisis. *Nature communications* 8, 1712.  
921  
922