ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Quantifying the carbon footprint reduction potential of lifestyle choices in Japan

ENVIRONMENTAL RESEARCH
LETTERS

CrossMark

OPEN ACCESS

RECEIVED
27 July 2020

REVISED
6 April 2021

ACCEPTED FOR PUBLICATION
27 April 2021

PUBLISHED
21 May 2021

LETTER

Quantifying the carbon footprint reduction potential of lifestyle choices in Japan

Yosuke Shigetomi[1], **Keiichiro Kanemoto**[2,*], **Yuki Yamamoto**[1] **and Yasushi Kondo**[3]

[1] Graduate School of Fisheries and Environmental Sciences, Nagasaki University, 1-14 Bunkyo-machi, Nagasaki 852-8521, Japan
[2] Research Institute for Humanity and Nature, 457-4 Motoyama, Kamigamo, Kita-ku, Kyoto 603-8047, Japan
[3] Faculty of Political Science and Economics, Waseda University, 1-6-1 Nishi-waseda, Shinjuku-ku, Tokyo 169-8050, Japan
[*] Author to whom any correspondence should be addressed.

E-mail: keiichiro.kanemoto@gmail.com

Keywords: household carbon footprint, lifestyle choices, Japan, MRIO, regression analysis

Supplementary material for this article is available online

Abstract

Numerous studies have investigated the hotspots for reducing carbon emissions associated with household consumption, including reducing household carbon footprints (CFs) and greener lifestyle choices, such as living car-free, eating less meat, and having one less child. However, estimating the effect of each of these actions requires the simultaneous consideration of lifestyle choices and household characteristics that could also affect the household CF. Here, we quantify the reduction in household CFs for 25 factors associated with individual lifestyle choices or socioeconomic characteristics. This study linked approximately 42 000 microdata on consumption expenditure with the Japanese subnational 47 prefecture-level multi-regional input–output table, which are both the finest-scale data currently available. We improved the accuracy of household CF calculations by considering regional heterogeneity, and successfully estimated the magnitude of household CF reduction associated with individual lifestyle choices and socioeconomics. For example, it was found that moving from a cold region to a region with mild climate would have considerable potential for reducing the CO_2 emissions of a household, all other factors being equal. In addition, a household residing in a house that meets the most recent energy standards emits 1150 kg less CO_2 per year than if they reside in a house that meets previous energy standards. Ownership and use of durable goods also had the potential for reducing the CO_2 emissions of a household; a normal-sized car, a personal computer, a compact car, and a bidet were associated with CO_2 emissions of 922, 712, 421, and 345 kg per year, respectively. The findings therefore have important implications for climate change mitigation and policy measures associated with lifestyle.

1. Introduction

The consumption of goods generates direct and indirect (i.e. lifecycle) environmental and resource impacts in their supply chains. In recent decades, the impacts of goods and services have been widely assessed in consumption-based accounting as 'footprints' (Wiedmann and Lenzen 2018, Heinonen *et al* 2020). Studies of environmentally extended input–output analysis (IOA) have shown that daily household consumption is the dominant contributor to greenhouse gas (GHG) footprints (i.e. carbon footprint (CF)), accounting for around two-thirds of global carbon emissions (Hertwich 2011, Ivanova *et al* 2016). Numerous studies have therefore investigated the important consumption drivers of the household CF, and examined what personal actions could reduce this footprint effectively, such as living car-free, eating less meat, and having fewer children (Wynes and Nicholas 2017, Vita *et al* 2019, Ivanova *et al* 2020). Some of these studies focused on household characteristics to identify which attributes of a household contribute most to household CFs, and most established that higher-income households have larger footprints than lower income households (Wiedenhofer *et al* 2018). These studies mainly examined the effect of each household characteristic on the household CF.

It is also important to consider the specific consumption choices in conjunction with the household attributes being controlled for. For instance, high-income households in a city would increase their CF by using more electric appliances, and decrease their footprint by avoiding car travel because of the well-developed public transport infrastructure in cities.

Previous studies have examined the relationship between household income and carbon and energy footprints using econometric approaches (e.g. Lenzen *et al* 2006, Baiocchi *et al* 2010, Wiedenhofer *et al* 2013, Jiang *et al* 2020). While these analyses provided insights into reduction policies related to CFs, the sample sizes used were small because only the average expenditure in each area was utilized, which meant that the spatial resolution was insufficient for accurately characterizing factors that impact the household CF (Ivanova *et al* 2017). The use of aggregated (e.g. country- or regional-level) data is problematic because it can lead to misspecification and/or biased estimates (Theil 1954, Orcutt *et al* 1968, Clark and Avery 1976). To deal with these problems of data aggregation, some studies used datasets containing data from a large number (e.g. more than 1000) of households (Ala-Mantila *et al* 2014, 2016, Baiocchi *et al* 2015, Ottelin *et al* 2015, 2019, Fremstad *et al* 2018, Gill and Moeller 2018, Koide *et al* 2019, Li *et al* 2019), or large datasets were constructed for analysis (Jones and Kammen 2014). For example, Fremstad *et al* (2018) utilized a quarterly panel dataset with approximately 28 000 households in the US and found that CFs could potentially be reduced through an economy of scale, which provides opportunities for carbon-intensive goods to be shared. Jones and Kammen (2014) applied econometric models to approximately 30 000 household consumption expenditures in national household survey data linked to US postal codes. They also clarified the relationships between household CFs and US socioeconomic and typological factors, such as population density, the number of rooms in a house, and the age of a house, all of which can influence consumption. However, due to the national input–output model adopted, the CF estimates obtained in these studies did not reflect differences between subnational regions with regard to the technologies and supply chains that produced the consumption goods and services.

In this study, we examined the relationship between household characteristics (e.g. socioeconomic, geographic, and demographic measures) and household CFs in Japan using a rich dataset. The dataset was constructed by combining a subnational multi-regional input–output model (MRIO) with micro-survey data, which included 25 characteristics for approximately 42 000 households. To our knowledge, this is the largest and most accurate dataset currently available in Japan. We also set a goal of quantifying the CF reduction for each lifestyle choice. The findings of this study can, therefore, provide more detailed insights into the factors that potentially affect the household CF, with useful policy implications for GHG emissions reductions associated with changes in lifestyles as demand-side solutions (Seto *et al* 2016, Creutzig *et al* 2018).

2. Methods

2.1. Data for detailed estimations of household CF

The household CF is derived from direct carbon emissions from fossil fuel combustion (i.e. driving a car) and indirect carbon emissions associated with household electricity use and the production of goods and services consumed through household supply chains (i.e. passenger car manufacturing) (Weber and Matthews 2008). In a review, Tukker *et al* (2010) examined income level, household size (number of family members per household), geographic location, house type, automobile ownership, food consumption patterns, international (and interregional) trade, and social and cultural differences as the key determinants of the household CF. In addition, they found that for economically developed nations, the most critical consumption categories affecting the household CF were food and beverages, mobility, housing, and products that use energy, such as household appliances. This result has been corroborated by other studies (Hertwich 2005, 2011, Huppes 2006, Tukker and Jansen 2006, Ivanova *et al* 2016, 2017, Shigetomi *et al* 2017). Based on these studies, we quantified the spatial attributes of household CFs in Japan in detail, and conducted a regression analysis of household energy and CFs based on previous studies.

The variables used for the regression analysis and their definitions and sources are listed in table 1. The household consumption expenditures used to estimate the CF and most of the explanatory variables were retrieved from the microdata of the Japanese National Survey of Family Income and Expenditure (NSFIE) for the year 2004, with special permission from the Ministry of Internal Affairs and Communications, Japan (MIC). The dataset consists of information on 60 058 households. The population density, *Density*, was determined for each city where the household is located. The numerator of *Density*, i.e. total population, was obtained from the 2004 Basic Resident Registration of Japan (MIC 2011); in this way the population data corresponded to the microdata of the NSFIE. The denominator, i.e. area of each region, was calculated using geographical information system data provided by the National Land Numerical Information, and downloaded from the Ministry of Land, Infrastructure, Transport and Tourism (MLIT 2020). House type was classified as an apartment or freestanding house; the dummy variable value for *House* is 0 (apartment) or 1 (freestanding house). Since the Japan Meteorological Agency (2017) does

Table 1. Descriptive statistics: cross-sectional data for 2004.

Variable	Unit	Obs.	Mean	Median	Std. Dev.	Min.	Max.	Explanation	Reference
Explained									
CF_all	t/household	60 058	14.99	13.39	8.274	0.787	155.4	Annual CF per household for all goods and services	Estimated based on the raw data of NSFIE (MIC 2017) with the 47 prefecture MRIO (Hasegawa *et al* 2015) and energy balance table (METI 2018) in this study.
CF_food	t/household	60 058	2.938	2.759	1.341	0.0312	24.89	Annual CF per household for food	
CF_electricity	t/household	60 058	0.667	0.595	0.372	0	4.477	Annual CF per household for electricity	
CF_gas	t/household	60 058	1.127	1.026	0.667	0	10.97	Annual CF per household for gas	
CF_other heating	t/household	60 058	0.363	0.000	0.836	0	21.74	Annual CF per household for kerosene and heat	
CF_durable goods	t/household	60 058	1.782	1.171	2.427	0	101.6	Annual CF per household for household durable goods	
CF_consumable goods	t/household	60 058	1.469	7.364	1.835	0	114.8	Annual CF per household for household consumable goods	
CF_education	t/household	60 058	0.736	0.000	2.960	0	137.1	Annual CF per household for education	
CF_medicals	t/household	60 058	0.410	0.256	0.622	0	26.06	Annual CF per household for medical products and services	
CF_private transport	t/household	60 058	2.136	1.601	2.244	0	44.77	Annual CF per household for passenger vehicles including motor bikes and passenger cars	
CF_public transport	t/household	60 058	0.753	0.137	1.562	0	43.54	Annual CF per household for public transport	
CF_other services	t/household	60 058	2.605	2.070	2.325	0	56.63	Annual CF per household for information, recreation, rent, and other services	
Explanatory									
Income	10^4 JPY	60 058	608.7	527.0	470.1	0	12 643	Annual household income	NSFIE (MIC 2017)
Savings	10^4 JPY	60 058	1382	760.0	1922	0	50 770	Household savings	NSFIE (MIC 2017)
Density	People/km^2	59 882	2916	930.9	5088	2.746	50 209	Population density where the household is located at the city level	National Land Numerical Information (MLIT 2020)
CDD	C° · day	60 058	6.169	4.876	7.032	0	91.64	Monthly CDDs	Japan Meteorological Agency (2017)
HDD	C° · day	60 058	18.44	4.493	29.86	0	260.7	Monthly HDDs	Japan Meteorological Agency (2017)
Floor	m^2	60 058	122.8	111.5	78.70	7	3300	Gross floor areas in house	NSFIE (MIC 2017)
Built I	(Dummy)	42 382	0.320	1	0.467	0	1	1: when the owned house was built during 1980–1993; 0: otherwise	NSFIE (MIC 20177)
Built II	(Dummy)	42 382	0.133	0	0.339	0	1	1: when the owned house was built during 1994–1997; 0: otherwise	NSFIE (MIC 2017)

(Continued.)

Table 1. (Continued.)

Variable	Unit	Obs.	Mean	Median	Std. Dev.	Min.	Max.	Explanation	Reference
Built III	(Dummy)	42 382	0.165	0	0.371	0	1	1: when the owned house was built in 1998 or later; 0: otherwise	NSFIE (MIC 2017)
House	(Dummy)	60 058	0.757	0	0.429	0	1	1: freestanding house; 0: apartment	NSFIE (MIC 2017)
Child	Person	60 058	0.673	0	0.993	0	6	Number of children aged 0–18 years in household	NSFIE (MIC 2017)
EmployAdult	Person	60 058	1.079	1	0.888	0	6	Number of employed individuals aged 18–64 years in household	NSFIE (MIC 2017)
UnemployAdult	Person	60 058	0.747	1	0.726	0	6	Number of unemployed individuals aged 18–64 years in household	NSFIE (MIC 2017)
Employ65	Person	60 058	0.108	0	0.371	0	3	Number of employed individuals aged more than 65 years in household	NSFIE (MIC 2017)
Unemploy65	Person	60 058	0.478	0	0.729	0	4	Number of unemployed individuals aged more than 65 years in household	NSFIE (MIC 2017)
VehicleNS	Unit	60 058	1.029	1	0.804	0	5	Number of normal sized vehicles (>660 cc)	NSFIE (MIC 2017)
VehicleK	Unit	60 058	0.411	0	0.656	0	5	Number of light vehicles ($\leqslant$660 cc) that a household owns	NSFIE (MIC 2017)
Motorbike	Unit	60 058	0.192	0	0.477	0	5	Number of motor bikes that a household owns	NSFIE (MIC 2017)
AirCon	Unit	60 058	2.218	2	1.739	0	9	Number of air conditioners that a household owns	NSFIE (MIC 2017)
Microwave	Unit	60 058	1.009	1	0.349	0	6	Number of microwaves that a household owns	NSFIE (MIC 2017)
PC	Unit	60 058	0.922	1	0.927	0	9	Number of personal computers that a household owns	NSFIE (MIC 2017)
Fridge	Unit	60 058	1.254	1	0.613	0	8	Number of refrigerators that a household owns	NSFIE (MIC 2017)
TV	Unit	60 058	2.180	2	1.308	0	12	Number of televisions that a household owns	NSFIE (MIC 2017)
Washer	Unit	60 058	1.059	1	0.378	0	5	Number of washing machines that a household owns	NSFIE (MIC 2017)
Bidet	Unit	60 058	0.684	1	0.705	0	7	Number of bidets that a household owns	NSFIE (MIC 2017)

not report city-level temperatures, we estimated the heating degree days (HDDs) and cooling degree days (CDDs) for each prefecture as the simple average of values observed at all the meteorological weather stations within a prefecture.

The NSFIE database lists the year that the house was built (e.g. 2000). In Japan, the law of the standard for home energy saving was passed in 1980, and the heat insulation requirements for housing were amended; for example, energy conservation standards were updated in 1994, 1998, 2013, and 2016. Thus, depending on the year when the house was built, we used three dummy variables to distinguish between the home energy standards. *Built I, Built II*, and *Built III* take on a value of 1 if the house was built during 1980–1993, 1994–1997, and 1998 or later, respectively. The base group of these dummy variables consists of houses built during 1955–1979. Due to the survey design of the NSFIE, the year of construction for a household is listed only if the household owned their house and it was built in 1955 or later. Consequently, data were missing for 17 676 observations, and the number of observations used in our main model was therefore 42 257. In order to use as many observations as possible for each regression equation, those households with missing values were omitted from the analysis, which meant that the number of observations ranged from 42 257 to 60 058 (see tables S4 and S6 (available online at stacks.iop.org/ERL/16/064022/mmedia)). We also analyzed the regression equations by using the smallest 'common' dataset to examine whether omitting households with missing values influenced our regression results (see tables S8 and S9 in the supporting information (SI)).

To obtain the explained variables, we used an MRIO model covering the 47 prefectures in Japan (47MRIO) (Hasegawa *et al* 2015) to estimate the CO_2 emissions embodied per unit of expenditure (CF intensity). The MRIO model is a recent solution for distinguishing the regional differences in technology and supply chain structures. MRIO tables describe economic transactions across multiple regions, and have been adopted to quantify the CF, as well as carbon leakage from rapid development in the recent decade (Wiedmann *et al* 2011, Inomata and Owen 2014, Lenzen *et al* 2017, Naegele and Zaklan 2019). Most recently, Ivanova *et al* (2017) and Ottelin *et al* (2019) used an MRIO model to conduct a regression analysis for estimating household CFs across nations in the European Union (EU). The 47MRIO comprises 80 commodities and 47 prefectures based on 2005 data. Although the targeted year is vintage, the model describes the commodity sectors in more detail than other interregional models (e.g. Chinese MRIO of Mi *et al* 2018 has 30 economic sectors for 30 provinces). Our analysis is the first to combine subnational MRIO and micro-consumption data to analyze the CF of households in Japan.

2.2. Estimating household CFs using a regression model

The household CF, Q_{ij}, due to consumption of commodity j by household i, was quantified based on the IOA (i.e. Leontief demand-pull model; Miller and Blair 2009) using equation (1):

$$Q_{ij} = e_{pj} f_{ij}, \tag{1}$$

where, e_{pj} refers to the total (i.e. direct and indirect) CO_2 emissions per unit consumption expenditure on commodity j in prefecture p where household i lives, and f_{ij} to the consumption expenditure on commodity j by household i. The data for f_{ij} were obtained from the NSFIE, while those for e_{pj} were estimated based on the 47MRIO and sectoral direct carbon intensities, which we will explain below.

The carbon intensity, e_{pj}, can be decomposed into two terms, $e_{pj} = e^{\mathrm{d}}_{pj} + e^{\mathrm{i}}_{pj}$, where e^{d}_{pj} and e^{i}_{pj} are direct and indirect emissions, respectively. To quantify the direct intensity, e^{d}_{pj}, we considered only energy-related commodities (i.e. gasoline, light oil, kerosene, liquefied petroleum gas, city gas, and coal products). The national average direct carbon intensity (Nansai and Moriguchi 2012) was applied due to the limited data availability. For indirect emissions, e^{i}_{pj}, we calculated, for the first time, the 2005 carbon intensities for the 47 prefectures in Japan using the 47MRIO, the domestic energy balance table by prefecture, and the results of a direct survey of each prefectural government. After determining the CF intensity for each prefecture and each commodity, we matched 80 commodities that determine the carbon intensity to 320 items on the NSFIE (table S3). Then, consumption expenditures were transformed from the purchaser price to the producer price to make them consistent with the carbon intensity using the national margin table. Given that the NSFIE is published every five years, we used the NSFIE from 2004, the closest publication year to the 47MRIO, to obtain the specific consumption expenditures by household. The method used to calculate the household CF used in this study is also elaborated (Kanemoto *et al* 2019, 2020).

Next, to examine the relationships between the CF and the household characteristics selected for this study, we used the regression equation formulated in equation (2):

$$\ln(Q_{Ci}) = \beta_0 + \mathbf{x}_i \boldsymbol{\beta} + \epsilon_i, \tag{2}$$

where $Q_{Ci} = \sum_{j \epsilon C} Q_{ij}$ denotes the CF of household i. C indicates a consumption category or a group of commodities. We adopted the following categories and considered the differences among them in terms of the drivers of CFs: (a) food and beverages, (b) electricity, (c) gas, (d) other heating (e.g. kerosene), (e) durable goods, (f) consumable goods, (g) education (e.g. electricity related to school activities), (h) medical (e.g. operation of medical equipment), (i) private transport, (j) public transport, and (k) other services. In this study, these 11 categories ($C = 1, \ldots, 11$) were determined by aggregating 320 commodity sectors ($j = 1, \ldots, 320$) listed in the Japanese NSFIE (MIC 2017) in line with the 'classifications by goods and services' defined in the NSFIE (see table S3). Durable goods cover home electric appliances, furniture, recreational equipment, bicycles, and bags. Note that passenger vehicles and their associated products and fuels are classified as private transport. Consumable goods include nondurable items, except food and beverages, medicines and supplements, and fuels. Other services include non-goods not attributed to (a)–(j) (e.g. commercial laundry, water supply and sewerage, information and communication services). $\mathbf{x}_i = (x_{ik})$ is the vector for the explanatory variables for the attributes of household i. β_0 and $\boldsymbol{\beta}$ are parameters to be estimated, and ϵ_i is an error term. The explanatory variables selected in this study, and the related hypotheses based on the previous studies, are presented by domain in table 2 and in the SI (see sections S1.2 and 1.3). We transformed the values for income, savings, population density, and gross floor area as well as CFs into their logarithmic forms. Note that a value of 1 was added to income, savings, and CF before taking the logarithm because those variables are 0 for some households. This would change the basis of the rate of change from 1 to 0 (Wooldridge 2020).

3. Results and discussion

3.1. Regression analysis of the Japanese household CF

The ordinary least squares (OLS) results obtained by regression analysis are shown in table 3. Additionally, to better clarify the relationship between the CF and household characteristics, we applied the OLS regression method to the household CFs for the 11 consumption categories. The estimation results are presented in table S6. We also applied the seemingly unrelated regression (SUR) for the purposes of comparison; we selected the SUR to consider possible correlations between the error terms in the 11 regression equations (see table S7). For both tables S6 and S7, selected explanatory variables were excluded from the regression equations if they were regarded as irrelevant. For instance, the variables indicating the ownership of vehicles were included only in the equations for private and public services; all of the variables are included in the equation for other services.

Overall, most of the coefficients in the main model shown in table 3 were statistically significant. We examined the robustness of the results obtained using the main model in table 3, by excluding those variables that were not significant (i.e. *Motorbike, Microwave, Fridge*, and *Washer*). The estimated coefficients for the significant variables were not substantially changed and they remained significant, as shown in table S5. We also calculated the variance inflation factor (VIF) and confirmed that there was no serious multicollinearity problem (i.e. VIFs were $\leqslant$2.30). R-squared was approximately 0.385, which is comparable with the adjusted R-squared reported in a previous study (Koide *et al* 2019), which analyzed Japanese CFs using microdata and the global MRIO for Japan. Here, we summarize our most important findings.

The coefficients for ln(*Income*) and ln(*Income*)^2 were both significant and positive in the main model, suggesting that the CF would increase progressively with income growth. Note that the correlations for the squared values of *Income* and *Savings* were used in the regression equations to examine whether the CF increases nonlinearly with income and might decrease after a certain income threshold (Baiocchi *et al* 2010, Ivanova *et al* 2017). Table 3 shows that the CF increased monotonically with *Income*. Regarding the elasticity of the CF with respect to income, the estimates obtained using the sample mean were significantly positive among all of the columns (See table S2). Moreover, *Savings* showed a similar trend to *Income*, which is associated with an increase in the CF.

Next, the coefficient for ln(*Density*) was significantly negative, which is consistent with the previous studies listed in table 2. An increase in population density, which is a proxy for urbanization, is estimated to generally reduce the household CF. Conversely, looking at the results by consumption category (table S6), population density was associated with an increase in the CFs for food, education, and public transport, which indicates the specific impacts of urbanization on the household CF and identifies targets for mitigation.

The coefficient for *Built III* was also significantly negative, indicating that newer (i.e. more energy efficient) houses are associated with a reduction in the CF. As expected, the coefficient for ln(*Floor*) was significantly positive, which is consistent with previous studies (e.g. Lenzen *et al* 2006). The finding that the coefficient for *House* was significantly negative was surprising as this implies that living in a freestanding house is superior to living in an apartment in terms of the CF. This is a unique, or probably unrealistic, result because a freestanding house should not be superior to an apartment in terms of energy efficiency, particularly in terms of air conditioning (see table 2). Estimating the CF by consumption category (table S6) showed that the coefficient for *House* was significantly positive for other types of heating (e.g. kerosene). This result is consistent with our assumption that a freestanding house is less efficient than an apartment for air conditioning. Conversely, the coefficient for *House* was significantly negative for

Table 2. Selected explanatory variables and expected coefficients used for estimating the household CF.

Domains	Indicator	Predicted effect	Reasoning	References
Economics	*Income*	+	Household income is understood to be a positive determinant of household consumption expenditure because people can spend more on goods and services with a higher income.	(Lenzen *et al* 2006, Baiocchi *et al* 2010, Tukker *et al* 2010, Minx *et al* 2013, Ala-Mantila *et al* 2014, Ala-Mantila *et al* 2016, Jones and Kanmen 2014, Ivanova *et al* 2017, Ivanova *et al* 2018, Fremsted *et al* 2018, Gill and Moeller 2018, Li *et al* 2019, Koide *et al* 2019)
	Savings	+	The amount of savings indicates the degree of allowance for consumption. Higher savings are associated with more purchases of expensive durable goods and services such as leisure travel.	Koide *et al* (2019)
Urbanization	*Density*	±	Population density is a useful proxy for degree of urbanization. Energy requirements for private transport and residence would be reduced while that for public transport increases with higher population density. However, urban areas have higher carbon impacts from food, leisure, and manufactured products.	(Lenzen *et al* 2006, Wiedenhofer *et al* 2013, Minx *et al* 2013, Ala-Mantila *et al* 2014, Ala-Mantila *et al* 2016, Jones and Kammen 2014, Ottelin *et al* 2015, Ottelin *et al* 2018b, Ottelin *et al* 2019, Gudipudi *et al* 2016, Ivanova *et al* 2017, Chen *et al* 2018, Gill and Moeller 2018, Li *et al* 2019, Koide *et al* 2019)
Physical characteristics of dwellings	*House* (dummy)	+	An apartment has better insulation than a solitary house due to fewer outside walls and, generally, smaller rooms, as well as more energy efficient building standards.	(Lenzen *et al* 2006, Tukker *et al* 2010, Ivanova *et al* 2018, Koide *et al* 2019)
	Built I (dummy) *Built II* (dummy) *Built III* (dummy)	±	Newer houses built with higher energy standards for building have better insulation, which is expected to reduce electricity, gas, and heating use.	(Jones and Kammen 2014, Ottelin *et al* 2015)
	Floor	+	Larger floor areas or more rooms would require more home energy use and appliances.	(Lenzen *et al* 2006, Baiocchi *et al* 2010, Jones and Kammen 2014, Fremstad *et al* 2018, Ivanova *et al* 2018, Li *et al* 2019)
Local climate	*CDD*	+	As the monthly CDDs increase, home energy use from gas stoves and other heaters is likely to be higher.	(Mansur *et al* 2008, Zhou and Gurney 2011)
	HDD	+	As the monthly HDDs increase, home energy use from air conditioning is likely to be higher.	(Mansur *et al* 2008, Zhou and Gurney 2011, Wiedenhofer *et al* 2013, Ivanova *et al* 2017)

(Continued.)

Table 2. (Continued.)

Domains	Indicator	Predicted effect	Reasoning	References
Demographics	*Child* *EmployAdult* *UnemployAdult* *Employ65* *Unemploy65*	+	A larger family size increases household consumption. In particular, more children lead to greater expenditures related to education. The number of unemployed people in a household is expected to raise home energy use because the daytime hours that the house is occupied are longer. Medical expenses are likely to increase in households with people aged more than 65 years.	(Lenzen *et al* 2006, Mansur *et al* 2008, Baiocchi *et al* 2010, Tukker *et al* 2010, Ala-Mantila *et al* 2014, Ala-Mantila *et al* 2016; Ottelin *et al* 2015, Ottelin *et al* 2018b, Ottelin *et al* 2019, Ivanova *et al* 2018, Huang *et al* 2019, Koide *et al* 2019)
Ownership of private vehicles	*VehicleNS* *VehicleK* *Motorbike*	±	The number of private vehicles changes the CF associated with fuel and maintenance. Also, ownership of private vehicles reduces the frequently of public transport use.	(Tukker *et al* 2010, Minx *et al* 2013, Wiedenhofer *et al* 2013, Gill and Moeller 2018, Li *et al* 2019, Koide *et al* 2019)
Ownership of home appliances and electronics	*AirCon* *Microwave* *PC* *Fridge* *TV* *Washer* *Bidet*	+	It is expected that the greater the number of electric appliances and home electronics owned, the more electricity is used. The number of home appliances and electronics would increase with household income.	Koide *et al* (2019)

Table 3. Regression results for total household CF using OLS method.

Domains	Variables	
Economics	ln(*Income*)	-0.299^{***} (0.006)
	ln(*Income*)^2	0.0478^{***} (0.0008)
	ln(*Savings*)	-0.0306^{***} (0.0034)
	ln(*Savings*)^2	0.00525^{***} (0.00036)
Urbanization	ln(*Density*)	-0.00632^{***} (0.00146)
Dwellings	*House*	-0.0821^{***} (0.00651)
	Built I	0.00763^{*} (0.0045)
	Built II	-0.0355^{***} (0.0059)
	Built III	-0.0767^{***} (0.0057)
	ln(*Floor*)	0.0394^{***} (0.0056)
Local climate	*CDD*	0.000693^{**} (0.000345)
	HDD	0.000810^{***} (0.000080)
Demographics	*Child*	0.0332^{***} (0.0019)
	EmployAdult	0.0101^{***} (0.0031)
	UnemployAdult	0.0701^{***} (0.0030)
	Employ65	-0.0514^{***} (0.0059)
	Unemploy65	0.0178^{***} (0.0032)
Ownership of private vehicles	*VehicleNS*	0.0615^{***} (0.0030)
	VehicleK	0.0281^{***} (0.0031)
	Motorbike	0.00545 (0.00363)
Ownership of home appliances and electronics	*AirCon*	0.0176^{***} (0.0014)
	Microwave	0.00738 (0.00631)
	PC	0.0475^{***} (0.0022)
	Fridge	0.00549 (0.00352)
	TV	0.00803^{***} (0.00169)
	Washer	-0.0204^{***} (0.0059)
	Bidet	0.0230^{***} (0.0029)
	Constant	2.253^{***} (0.031)
	Observations	42 257
	R-squared	0.385
	BIC	33 641

Standard errors calculated by the Huber-White method are in parenthesis.
The adjusted R-squared is equal to the R-squared, at least, up to the third decimal place.
BIC is the Schwarz Bayesian information criterion.
$^{***}p < 0.01$.
$^{**}p < 0.05$.
$^{*}p < 0.1$.

electricity. This does not necessarily imply that our assumption is incorrect, because electricity is used for a variety of purposes and not limited to air conditioning, but we were unable to clarify the reasons for this result. It is therefore necessary to explore other factors that affect the coefficient for *House* that reduce the total household CF, such as the building structure and other home equipment, which were not included in this study.

Regarding the demographic factors, *Child, EmployAdult, UnemployAdult*, and *Unemploy65*, were all positively correlated with the household CF, which is expected. The coefficient for *UnemployAdult* was associated with the largest increase in the household CF and was followed by *Child, Unemploy65*, and *EmployAdult*. On the other hand, the coefficient for *Employ65* was negative. Taken together, these differences are expected to reflect the length of time spent at home. More detailed analyses are elaborated in sections S2.1 and S2.2.

3.2. Effective lifestyle choices for carbon reduction

To determine which factors should be prioritized to mitigate climate change in line with lifestyle choice, we estimated the potential CF reduction achieved under typical lifestyle choice scenarios based on the regression results discussed above. For example, the scenario 'living in a more urbanized region' is associated with a change in population density between two regions with other factors being equal. Details of the analysis method are given in section S1.4 in the SI.

Figure 1 summarizes the potential household CF reductions by lifestyle choice or socioeconomic characteristics that were calculated based on the estimation results obtained using the main model shown in table 3.

Note that each of these potential reductions indicate how lifestyle choice affects the decrease in the household CF, under the assumption that all other factors are kept constant. The potential reductions vary across households because our regression is nonlinear. We therefore estimated the potential

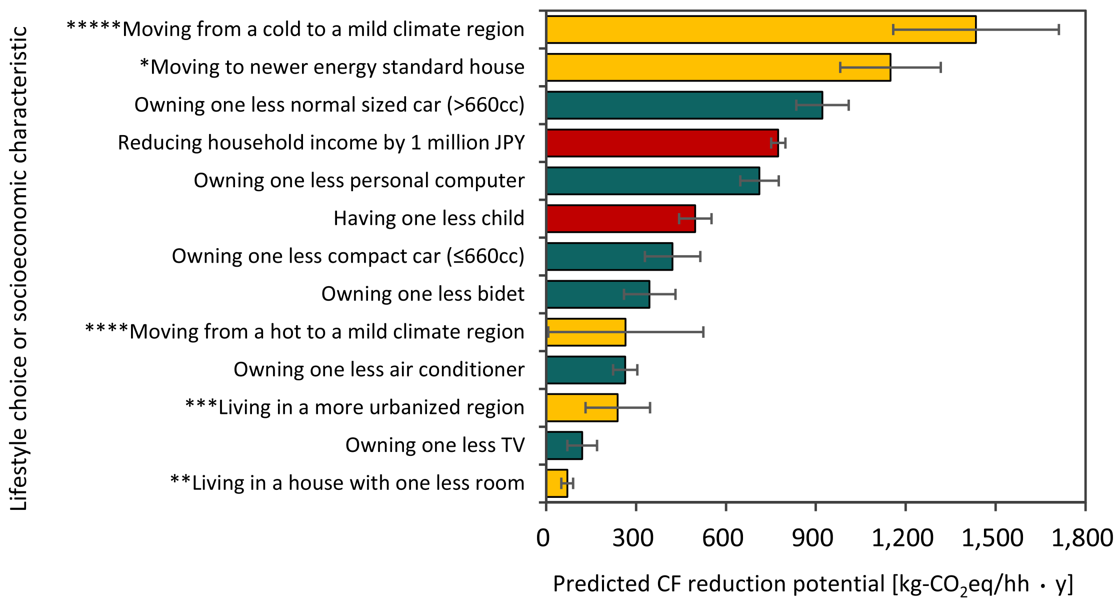

Figure 1. Predicted household CF reduction potential with respect to lifestyle choice and socioeconomic characteristics. Error bars indicate 95% confidence intervals. 'Compact car' is defined as the smallest cars in Japan, with a length <3.4 m, width <1.48 m, height < 2.0 m, and engine displacement ⩽660 cc. 'Normal-sized car' is larger than a compact car, with an engine displacement of >660 cc. *A household living in a house built before 1980 moves to a house built when the 1998 energy standards were in place. **The size of one room is assumed to be 9.72 m^2, which is the standard room size in a typical Japanese house. ***A household moves from a region with the same population density as Nara-shi in Nara to that of Chuo-ku in Tokyo. ****A household moves from a region with the same CDD as Naha-shi in Okinawa to that of Chuo-ku in Tokyo. *****A household moves from a region with the same HDD as Sapporo-shi in Hokkaido to that of Chuo-ku in Tokyo.

reductions using the sample mean (see sectionS1.4). These lifestyle choices were selected based on those examined in previous studies (Wynes and Nicholas 2017, Koide *et al* 2019, Ivanova *et al* 2020) and the statistical significance in this study; for example, 'having one less child' was identified as having the highest impact on carbon reduction by Wynes and Nicholas (2017). We do not recommend implementing these actions without careful consideration of how these actions will affect the other factors than CF.

In figure 1, our estimates indicate that moving from a cold region to a region with a mild climate has the greatest effect on carbon reduction, with a difference of as much as 1435 kg-CO_2/household·year (hh·yr). Followed by this, the potential footprint reduction that can be achieved by living in a house with the newer energy standards also presented the large potential reduction (figure 1). If a household moves from a house built before 1980 (i.e. a house constructed with no energy standards) to a house built after 1998 (i.e. a house with the most recent energy standards), then the potential footprint reduction would be 1150 kg-CO_2/hh·yr, which represents the second largest CF reduction potential. On the other hand, moving from a hot region to a mild region has a much lesseffect on carbon reduction than moving from a cold region to a mild region (265 kg-CO_2/hh·yr). Note that in estimating the reduction potential of local climate shown in figure 1, regions with cold, hot, and mild climates are those that have CDD and HDD values equal to those in Okinawa (the southernmost prefecture), Hokkaido (the northernmost prefecture), and Tokyo (the capital, located around the center of Japan). These three estimations indicate the importance of energy saving for heating a house.

The third largest potential footprint reduction (922 kg-CO_2/hh·yr) was achieved by owning one less normal-sized car. Owning one less compact car also reduces the CF, but not by as much as one less normal-sized car (421 kg-CO_2/hh·yr). Therefore, reducing the dependence on private transport is essential for reducing the CF. Policy changes to support carbon mitigation by decreasing car ownership could include improvements in public transport infrastructure and implementing carpooling incentives. In addition, encouraging the purchase of smaller vehicles by increasing the tax on larger vehicles, such as the car weight tax implemented in Japan since 1971, would also be effective for reducing the household CF.

Ownership of electric appliances/home electronics also had a positive impact on the CF (figure 1). In particular, owning one less personal computer is expected to reduce the CF by as much as the reduction potential that can be achieved by decreasing the annual household income by 1 million JPY (≃9042 US dollars) (712 and 775 kg-CO_2/hh·yr, respectively). Interestingly, owning one less bidet would reduce the CF of a household by more than one air-conditioner and a TV, perhaps because a bidet is likely to be kept on all the time. It is recommended that people decrease the frequency of use of these appliances by not leaving PCs in sleep mode for extended periods or using bidets only during the winter.

In terms of demographic factors, this study supports the results of previous studies which showed that reducing the number of children in a household is a positive driver for the household CF. As shown in figure 1, the CF reduction potential of having one less child is 498 kg-CO_2/hh·yr. Note that this reduction potential would be offset by a number of potentially simpler lifestyle choices, including owning one less car or owning one less personal computer.

Finally, living in a more urbanized region is defined as a move from a region with the same population density as Nara (a commuter city in a suburban region) to Tokyo (the capital and most populous city in Japan) under the assumption that all of the regional characteristics, except population density, are the same. Such a choice is equivalent to a reduction potential of 239 kg-CO_2/hh·yr. Related to the changes associated with living in a house, a decrease in the number of rooms does not appear to affect CF reduction (we here assume that the floor area of one room is 9.72 m^2, which is the standard room size in Japan) (figure 1). Note that although moving to a freestanding house from an apartment is associated with a CF reduction, as shown in table 3, we did not estimate this reduction potential and present it in figure 1 because this finding warrants further clarification; see also the results for the robustness checks in section S2.2.

3.3. Limitations

There are several limitations associated with calculating household CFs by combining the IOA with the survey-based NSFIE data. First, we assumed that the CF of one Japanese yen's worth of an imported commodity was equivalent to that of the corresponding domestic commodity. Second, the quality of commodities consumed by households could not be considered. For instance, distinguishing between domestic and international air travel would affect the household CF significantly (Czepkiewicz *et al* 2018). Third, government expenditure for public welfare services, such as health care and education, and capital formation were not included in the estimates, resulting in the underestimation of CFs induced by actual consumption (Heinonen *et al* 2020). These are general limitations associated with IOA approaches, and some could be addressed if the relevant data were available (Ottelin *et al* 2018a, Berrill *et al* 2020, Schmidt *et al* 2019); however, it is currently impossible to obtain some of these data for each region. Another limitation related to data availability is that the NSFIE and the 47MRIO datasets are not perfectly matched with each other with respect to geographical resolution (e.g. city versus prefecture) and time scales (e.g. 2004 versus 2005). Further, because the data used in our analysis are from 2005, this study does not consider up-to-date technology, such as solar panels, electric vehicles, and smart phones, that might affect current household energy and CFs. These limitations are associated with MRIO data availability. Future research efforts will focus on addressing the aforementioned limitations and expanding our analysis to factors that drive household CFs in other nations and globally.

4. Conclusion

This study analyzed the drivers of the Japanese household CF with respect to socioeconomics, demographics, urbanization, physical dwelling characteristics, local climate, ownership of passenger vehicles, home appliances and electronics, by combining microdata for more than 42 000 households' consumption and an MRIO model for Japan. We successfully estimated the magnitude of the household CF reduction associated with individual lifestyle choices and socioeconomic factors. We further provided new insights into the lifestyle choices that have the greatest potential for reducing a household's CF by using CFs disaggregated into multiple consumption categories. Identifying these carbon-reducing lifestyle choices has important policy implications. For example, the findings related to demographic factors are relevant to both climate change policy and aging society policy in Japan (Shigetomi *et al* 2014, Prime Minister of Japan and His Cabinet 2016, Shigetomi *et al* 2018). More broadly, our analysis provides quantitative information on potential CF reductions as they relate to policy measures. While having one less child is known to reduce the household CF, we show that other, more feasible, lifestyle choices, such as owning one less car, could more effectively reduce the CF. Policies could be established to support these lifestyle choices by means of subsidies, taxation, and infrastructure improvements.

Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical reasons.

Acknowledgments

This work was supported in part by the Research Institute for Humanity and Nature Project (No. 14200135) and the Japan Society for the Promotion of Science through its Grant-in-Aid for Young Scientists (A) (15H05341) and Young Scientists (18K18231). Microdata of household consumption from the

National Survey of Family Income and Expenditure (NSFIE) is available upon application to the Ministry of Internal Affairs and Communications (MIC). We cannot provide the microdata to third parties as the author are not authorized for secondary distribution.

ORCID iDs

Yosuke Shigetomi https://orcid.org/0000-0003-1384-0992
Keiichiro Kanemoto https://orcid.org/0000-0003-0230-9020
Yuki Yamamoto https://orcid.org/0000-0002-6222-4566
Yasushi Kondo https://orcid.org/0000-0002-6855-2691

References

Agency for Natural Resources and Energy 2018 Energy Balance Table, Japan (https://www.enecho.meti.go.jp/statistics/total_energy/results.html#headline2)
Ala-Mantila S, Heinonen J and Junnila S 2014 Relationship between urbanization, direct and indirect greenhouse gas emissions, and expenditures: a multivariate analysis *Ecol. Econ.* **104** 129–39
Ala-Mantila S, Ottelin J, Heinonen J and Junnila S 2016 To each their own? The greenhouse gas impacts of intra-household sharing in different urban zones *J. Clean. Prod.* **135** 356–67
Baiocchi G, Creutzig F, Minx J and Pichler P-P 2015 A spatial typology of human settlements and their CO_2 emissions in England *Glob. Environ. Change* **34** 13–21
Baiocchi G, Minx J and Hubacek K 2010 The impact of social factors and consumer behavior on carbon dioxide emissions in the United Kingdom *J. Ind. Ecol.* **14** 50–72
Berrill P, Miller T R, Kondo Y and Hertwich E G 2020 Capital in the American carbon, energy, and material footprint *J. Ind. Ecol.* **24** 589–600
Chen G, Hadjikakou M, Wiedmann T and Shi L 2018 Global warming impact of suburbanization: The case of Sydney *J. Clean. Prod.* **172** 287–301
Clark W A and Avery K L 1976 The effects of data aggregation in statistical analysis *Geogr. Anal.* **8** 428–38
Creutzig F *et al* 2018 Towards demand-side solutions for mitigating climate change *Nat. Clim. Change* **8** 268–71
Czepkiewicz M, Heinonen J and Ottelin J 2018 Why do urbanites travel more than do others? A review of associations between urban form and long-distance leisure travel *Environ. Res. Lett.* **13** 073001
Fremstad A, Underwood A and Zahran S 2018 The environmental impact of sharing: household and urban economies in CO_2 emissions *Ecol. Econ.* **145** 137–47
Gill B and Moeller S 2018 GHG emissions and the rural-urban divide. A carbon footprint analysis based on the German official income and expenditure survey *Ecol. Econ.* **145** 160–9
Gudipudi R, Fluschnik T, Ros A G, Walther C and Kropp J P 2016 City density and CO2 efficiency *Energy Policy* **91** 352–61
Hasegawa R, Kagawa S and Tsukui M 2015 Carbon footprint analysis through constructing a multi-region input–output table: a case study of Japan *J. Econ. Struct.* **4** 5
Heinonen J, Ottelin J, Ala-Mantila S, Wiedmann T, Clarke J and Junnila S 2020 Spatial consumption-based carbon footprint assessments—a review of recent developments in the field *J. Clean. Prod.* **256** 120335
Hertwich E G 2005 Life cycle approaches to sustainable consumption: a critical review *Environ. Sci. Technol.* **39** 4673–84
Hertwich E G 2011 The life cycle environmental impacts of consumption *Econ. Syst. Res.* **23** 27–47
Huang Y, Shigetomi Y, Chapman A and Matsumoto K 2019 Uncovering household carbon footprint drivers in an aging, shrinking society *Energies* **12** 3745
Huppes G 2006 Environmental impacts of consumption in the European Union *J. Ind. Ecol.* **10** 129–46
Inomata S and Owen A 2014 Comparative evaluation of MIRO databases *Econ. Syst. Res.* **26** 239–44
Ivanova D, Barrett J, Wiedenhofer D, Macura B, Callaghan M and Creutzig F 2020 Quantifying the potential for climate change mitigation of consumption options *Environ. Res. Lett.* **15** 093001
Ivanova D, Stadler K, Steen-Olsen K, Wood R, Vita G, Tukker A and Hertwich E G 2016 Environmental impact assessment of household consumption *J. Ind. Ecol.* **20** 526–36
Ivanova D, Vita G, Steen-Olsen K, Stadler K, Melo P C, Wood R and Hertwich E G 2017 Mapping the carbon footprint of EU regions *Environ. Res. Lett.* **12** 054013
Ivanova D, Vita G, Wood R, Lausselet C, Dumitru A, Krause K, Macsinga I and Hertwich E G 2018 Carbon mitigation in domains of high consumer lock-in *Glob. Environ. Chang.* **52** 117–30
Japan Meteorological Agency 2017 Download historical weather data (available at: http://www.data.jma.go.jp/gmd/risk/obsdl/index.php)
Japan Meteorological Agency 2017 Download historical weather data (available at: http://www.data.jma.go.jp/gmd/risk/obsdl/index.php)
Jiang Y, Long Y, Liu Q, Dowaki K and Ihara T 2020 Carbon emission quantification and decarbonization policy exploration for the household sector—evidence from 51 Japanese cities *Energy Policy* **140** 111438
Jones C and Kammen D M 2014 Spatial distribution of U.S. household carbon footprints reveals suburbanization undermines greenhouse gas benefits of urban population density *Environ. Sci. Technol.* **48** 895–902
Kanemoto K, Moran D, Shigetomi Y, Reynolds C and Kondo Y 2019 Meat consumption does not explain differences in household food carbon footprints in Japan *One Earth* **1** 464–71
Kanemoto K, Shigetomi Y, Hoang N T, Okuoka K and Moran D 2020 Spatial variation in household consumption-based carbon emission inventories for 1200 Japanese cities *Environ. Res. Lett.* **15** 114053
Koide R, Lettenmeier M, Kojima S, Toivio V, Amellina A and Akenji L 2019 Carbon footprints and consumer lifestyles: an analysis of lifestyle factors and gap analysis by consumer segment in Japan *Sustain.* **11** 1–25
Lenzen M *et al* 2017 The global MRIO lab—charting the world economy *Econ. Syst. Res.* **29** 158–86
Lenzen M, Wier M, Cohen C, Hayami H, Pachauri S and Schaeffer R 2006 A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan *Energy* **31** 181–207
Li J, Zhang D and Su B 2019 The impact of social awareness and lifestyles on household carbon emissions in China *Ecol. Econ.* **160** 145–55
Mansur E T, Mendelsohn R and Morrison W 2008 Climate change adaptation: A study of fuel choice and consumption in the US energy sector *J. Environ. Econ. Manag.* **55** 175–93
Mi Z, Meng J, Zheng H, Shan Y, Wei Y-M and Guan D 2018 A multi-regional input-output table mapping China's economic outputs and interdependencies in 2012 *Sci. Data* **5** 180155
MIC 2011 Basic Resident Registration (available at: www.e-stat.go.jp/stat-search/files?page=1&layout=datalist&toukei=00200241&tstat=000001039591&cycle=7&year=20040&month=0&tclass1=000001039601&result_back=1)
MIC 2017 NSFIE; National Survey of Family Income and Expenditure (available at: https://www.stat.go.jp/english/data/zensho/)

Miller R E and Blair P D 2009 *Input–Output Analysis* (Cambridge: Cambridge University Press) (http://ebooks.cambridge.org/ref/id/CBO9780511626982)

Minx J, Baiocchi G, Wiedmann T, Barett J, Creutzig F, Feng K, Förster M, Pichler P, Weisz H and Hubacek K 2013 Carbon footprints of cities and other human settlements in the UK *Environ. Res. Lett.* **8** 035039

MLIT 2020 National land numerical information download service (available at: https://nlftp.mlit.go.jp/ksj/)

Naegele H and Zaklan A 2019 Does the EU ETS cause carbon leakage in European manufacturing? *J. Environ. Econ. Manage.* **93** 125–47

Nansai K and Moriguchi Y 2012 Embodied energy and emission intensity data for Japan using input-output tables (3EID): For 2005 IO table, CGER, National Institute for Environmental Studies, Japan (available at: www.cger.nies.go.jp/publications/report/d031/jpn/datafile/embodied/2005/403.htm)

Orcutt G H, Watts H W and Edwards J B 1968 Data aggregation and information loss *Am. Econ. Rev.* **58** 773–87

Ottelin J, Heinonen J and Junnila S 2015 New energy efficient housing has reduced carbon footprints in outer but not in inner urban areas *Environ. Sci. Technol.* **49** 9574–83

Ottelin J, Heinonen J and Junnila S 2018a Carbon and material footprints of a welfare state: why and how governments should enhance green investments *Environ. Sci. Policy* **86** 1–10

Ottelin J, Heinonen J and Junnila S 2018b Carbon footprint trends of metropolitan residents in Finland: How strong mitigation policies affect different urban zones *J. Clean. Prod.* **170** 1523–35

Ottelin J, Heinonen J, Nässén J and Junnila S 2019 Household carbon footprint patterns by the degree of urbanisation in Europe *Environ. Res. Lett.* **14** 114016

Prime Minister of Japan and His Cabinet 2016 The Japan's plan for dynamic engagement of all citizens (provisional)

Schmidt S, Södersten C-J, Wiebe K, Simas M, Palm V and Wood R 2019 Understanding GHG emissions from Swedish consumption—current challenges in reaching the generational goal *J. Clean. Prod.* **212** 428–37

Seto K C, Davis S J, Mitchell R B, Stokes E C, Unruh G and Ürge-Vorsatz D 2016 Carbon lock-in: types, causes, and policy implications *Annu. Rev. Environ. Resour.* **41** 425–52

Shigetomi Y, Nansai K, Kagawa S and Tohno S 2014 Changes in the Carbon Footprint of Japanese Households in an Aging Society *Environ. Sci. Techonol.* **48** 6069–80

Shigetomi Y, Nansai K, Kagawa S and Tohno S 2018 Fertility-rate recovery and double-income policies require solving the carbon gap under the Paris Agreement *Resour. Conserv. Recycl.* **133** 385–94

Shigetomi Y, Nansai K, Shironitta K and Kagawa S 2017 Revisiting Japanese carbon footprint studies *Environmental and Economic Impacts of Decarbonization: Input–Output Studies on the Consequences of the 2015 Paris Agreements* ed L M Ó Dejuán, M Lenzen and Cadarso M-Á (New York: Routledge) pp 335–50

Theil H 1954 *Linear Aggregation of Economic Relations* Contributions to economic analysis **7** (Amsterdam: North-Holland Publishing Company)

Tukker A, Cohen M J, Hubacek K and Mont O 2010 The impacts of household consumption and options for change *J. Ind. Ecol.* **14** 13–30

Tukker A and Jansen B 2006 Environmental impacts of products: a detailed review of studies *J. Ind. Ecol.* **10** 159–82

Vita G, Lundström J R, Hertwich E G, Quist J, Ivanova D, Stadler K and Wood R 2019 The environmental impact of green consumption and sufficiency lifestyles scenarios in Europe: connecting local sustainability visions to global consequences *Ecol. Econ.* **164** 106322

Weber C L and Matthews H S 2008 Quantifying the global and distributional aspects of American household carbon footprint *Ecol. Econ.* **66** 379–91

Wiedenhofer D, Lenzen M and Steinberger J K 2013 Energy requirements of consumption: urban form, climatic and socio-economic factors, rebounds and their policy implications *Energy Policy* **63** 696–707

Wiedenhofer D, Smetschka B, Akenji L, Jalas M and Haberl H 2018 Household time use, carbon footprints, and urban form: a review of the potential contributions of everyday living to the 1.5 °C climate target *Curr. Opin. Environ. Sustain.* **30** 7–17

Wiedmann T and Lenzen M 2018 Environmental and social footprints of international trade *Nat. Geosci.* **11** 314–21

Wiedmann T, Wilting H C, Lenzen M, Lutter S and Palm V 2011 Quo vadis MRIO? Methodological, data and institutional requirements for multi-region input-output analysis *Ecol. Econ.* **70** 1937–45

Wooldridge J M 2020 Introductory Econometrics: A Modern Approach 7 (Boston: Cengage)

Wynes S and Nicholas K A 2017 The climate mitigation gap: education and government recommendations miss the most effective individual actions *Environ. Res. Lett.* **12** 074024

Zhou Y and Gurney K R 2011 Spatial relationships of sector-specific fossil fuel CO_2 emissions in the United States *Glob. Biogeochem. Cycles* **25** GB3002