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Scale, distribution and variations of global greenhouse gas emissions driven by U.S. households

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ABSTRACT

The U.S. household consumption, a key engine for the global economy, has significant carbon footprints across the world. Understanding how the U.S. household consumption on specific goods or services drives global greenhouse gas (GHG) emissions is important to guide consumption-side strategies for climate mitigation. Here we examined global GHG emissions driven by the U.S. household consumption from 1995 to 2014 using an environmentally extended multi-regional input-output model and detailed U.S. consumer expenditure survey data. The results show that the annual carbon footprint of the U.S. households ranged from 17.7 to 20.6 tCO_2eq/capita with an expanding proportion occurring overseas. Housing and transportation contributed 53–66% of the domestic carbon footprint. Overseas carbon footprint shows an overall increasing trajectory, from 16.4% of the total carbon footprint in 1995 to the peak of 20.4% in 2006. These findings provide valuable insights on the scale, distribution, and variations of the global GHG emissions driven by the U.S. household consumption for developing consumption-side strategies in the U.S. for climate mitigation.

1. Introduction

Household consumption is an important contributor to greenhouse gas (GHG) emissions. Roughly 20% of global GHG emissions in 2007 were generated directly from household consumption, mostly from fuel use for heating, cooling, cooking, and operating private vehicles (Ivanova et al., 2016). More importantly, a significant amount of GHG emissions are generated in the supply chains of goods and services consumed by households. Because many household consumables have globalized supply chains, emissions driven by household consumption can happen overseas, commonly known as emissions embodied in trade (Peters and Hertwich, 2008). Globally, the carbon footprint of household consumption—GHG emissions both directly generated and indirectly driven by household consumption—is about 72% and 60% of the global GHG emissions in 2001 (Hertwich and Peters, 2009) and 2007 (Ivanova et al., 2016), respectively.

At the national level, household consumption is also frequently reported to contribute significantly to GHG emissions of nations. For example, the carbon footprints of Norwegian household consumption increased by 26% from 1999 to 2012 (Steen-Olsen et al., 2016). Consumption on transport, housing, and food are reported to contribute to 61–65% of household expenditures, responsible for 77–80% of per capita GHG emissions in the Baltic States (Brizga et al., 2017). These studies examining the carbon footprint of household consumption helps develop demand-side strategies for climate mitigation by motivating behavioral changes in household consumption towards less carbon-intensive products and lifestyles.

The quantification of global GHG emissions driven by a nation's consumption is usually done using environmentally extended multi-regional input-output modeling (EE-MRIO) (Liang et al., 2016; Wiedenhofer et al., 2017; Wiedmann, 2009). For example, the U.S. carbon footprint has shown a territorial growth of 23% and a consumption-based growth of 38%, doubled during the last four decades (Kanemoto et al., 2016). Nearly 30% of the carbon footprint of the U.S. household consumption in 2004 occurred outside the U.S. (Weber and Matthews, 2008a). Despite the valuable insights these studies provide, the practical usefulness suffers from the coarse-grained sectoral resolution in EE-MRIO models. To address this issue, consumer expenditure survey (CES) data are increasingly integrated with EE-MRIO models to allocate global GHG emissions to consumption categories at finer categories (Steen-Olsen et al., 2016). Specifically, CES reports data on household purchases at a detailed product level (Fernández-

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Villaverde and Krueger, 2007). Linking CES and EE-MRIO allows the assessment of the complete household environmental footprint without complex bottom-up analyses of every single household expenditure category (Steen-Olsen et al., 2016). For example, (Druckman and Jackson, 2009) linked CES data with EE-MRIO to examine the environmental implications of nine categories of household expenditures in the UK in 1990–2004. (Ivanova et al., 2017) examined emissions from aggregated 14 consumption categories in the EU nations using CES data and EE-MRIO. Additional information of households such as household size and income levels provided by CES are also linked with EE-MRIO to examine their environmental implications (Steen-Olsen et al., 2016; Wiedenhofer et al., 2017).

The U.S. had been the world's largest GHG emitter for a very long time until 2006 when surpassed by China (Guan et al., 2009). Over 20% of the U.S. GHG emissions are directly attributed to household consumption in 2005, more than 80% if considering indirect emissions driven by household consumption (Jones and Kammen, 2011). Worldwide, the U.S. household consumption is estimated to drive approximately 20% of the global GHG emissions in 2001 (Hertwich and Peters, 2009). Given the importance of the U.S. consumers to the world economy, understanding how global GHG emissions have been driven by the U.S. household consumption helps develop demand-side climate mitigation strategies for not only the U.S. itself but also the world. Such demand-side strategies have become particularly important since the U.S. withdrawal from the Paris Agreement which makes non-state actors, whose carbon footprints are largely driven by consumption, the main force for climate actions in the U.S. (Feng et al., 2015; Jacquet and Jamieson, 2016).

To provide better understanding of the carbon footprint of the U.S. household consumption, many studies have incorporated CES data for detailed characterization of consumption categories (Bin and Dowlatabadi, 2005; Jones and Kammen, 2014, 2011; Weber and Matthews, 2008a). However, these studies all focused on linking the U.S. household consumption with GHG emissions within the U.S. To date, little is known how detailed categories of U.S. household consumption drive GHG emissions at the global scale. Here we quantify the GHG emissions driven by the U.S. household consumption at a fine consumption category and the global distribution of these emissions from 1995 to 2014 using the U.S. CES data combined with the EE-MRIO model from World Input-Output Database (WIOD) (Timmer et al., 2016). Our results shed light on the global carbon footprint of the U.S. household consumption and identify key consumption categories that contributed most significantly to global GHG emissions. Further analysis also provides insight to better manage the emissions associated with consumption and lifestyle changes. These findings help develop effective consumption-side policies to reduce the carbon intensity of household consumption in the U.S. for global climate mitigation.

2. Methods and data

2.1. Multi-regional input-output (MRIO) model

The Multi-regional input-output (MRIO) model serves to calculate environmental pressures (e.g., GHG emissions) embodied in international trade (Miller and Blair, 2009). It can trace emissions driven by consumers by linking the upstream production and downstream consumption in trade networks (Kitzes, 2013; Xu et al., 2011). In the MRIO framework, sectors are connected by trade between countries and by trade within countries, $T^{rs}(r \neq s)$ and $T^{rs}(r = s)$ respectively (Kanemoto et al., 2016). To calculate the trade flow matrix T_{ij}^{rs}, the technical coefficient matrix (A^{rs}) is introduced, in which each element is given by $a_{ij}^{rs} = t_{ij}^{rs}/x_j^s$. i and j are sectors of origin and destination, and r and s are exporting and importing countries. t_{ij}^{rs} means the money flow from sector r in region i to sector s in region j.

The technical coefficient matrix is $\mathbf{A} = \begin{bmatrix} A^{11} & A^{12} & \dots & A^{1R} \\ A^{21} & A^{22} & \dots & A^{2R} \\ \vdots & \vdots & \ddots & \vdots \\ A^{R1} & A^{R2} & \dots & A^{RR} \end{bmatrix}$.

The final demand matrix is $\mathbf{Y} = \begin{bmatrix} y^{11} & y^{12} & \dots & y^{1F} \\ y^{21} & y^{22} & \dots & y^{2F} \\ \vdots & \vdots & \ddots & \vdots \\ y^{R1} & y^{R2} & \dots & y^{RF} \end{bmatrix}$.

The total output matrix is $\mathbf{X} = \begin{bmatrix} x^1 \\ x^2 \\ \vdots \\ x^R \end{bmatrix}$.

In the equations above, R denotes the total number of countries and F denotes the total number of final demand categories.

The mathematical structure is $\boldsymbol{AX}+\boldsymbol{Y}=\boldsymbol{X}$, rewritten as $\boldsymbol{X}=(\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{Y}$.

where $(\boldsymbol{I}-\boldsymbol{A})^{-1}$ is the Leontief inverse matrix (Leontief, 1986), which captures both direct and indirect effects that one unit of the final demand has on the output (Miller and Blair, 2009). This inverse matrix multiplies a household's consumption vector $\boldsymbol{y}$, so we get a total output vector accounting for all the direct and indirect inputs triggered throughout global supply chains by household's consumption. $\boldsymbol{I}$ is an identity matrix with ones on the main diagonal and zeros everywhere else.

2.2. Environmentally extended MRIO (EE-MRIO) model

For an EE-MRIO model, the total GHG emissions embodied along the supply chain can be calculated by:

$$\boldsymbol{Q_{mrio}} = \boldsymbol{E} \times (\boldsymbol{I}-\boldsymbol{A})^{-1} \times \boldsymbol{W}$$

where $\boldsymbol{E}$ is emission intensity (the amount of emissions generated per unit of output in each sector) and $\boldsymbol{W}$ is the household consumption.

The MRIO data in 1995–2014 are derived from the World Input-Output Database (WIOD) (Timmer et al., 2016). From 1995 to 2011, WIOD covers 35 economic sectors for 40 countries, including all the EU (EU-27) member states and 13 of the world's largest economies. The newly released Input-Output tables for the years of 2012–2014 covers 56 sectors in 44 regions. We aggregated the later version of IOT to be consistent with 35 sectors and 40 countries. The 40 countries together represent over 85% of the world's economy (Dietzenbacher et al., 2013). Other countries are grouped in the Rest of the World (RoW). This table links many single-region input-output tables into one consistent account of intra-regional and inter-regional trade.

To calculate the emissions intensity, total emissions are derived from the Environmental account in the WIOD database. The GHG emissions after 2009 are estimated with fixed emission coefficient in 2009 due to data limitations. Three main GHGs including CO_2, CH_4, and N_2O are quantified in CO_2-equivalent (CO_2eq) per year using Global Warming Potential cumulative forcing over 100 years (GWP100); the GWPs for CO_2, CH_4, and N_2O are 1, 28, 265, respectively (Intergovernmental Panel on Climate Change, 2014).

The double-deflation method was used for many studies in estimation of the value added or GDP in constant prices (Lan et al., 2016; Malik et al., 2016). Referring to this method, this study applies the price index of gross output and the price index of intermediate input to the current price in IOT in the base year 2009 for deflation purposes. The deflation removes the change of emission intensity (CO_2eq tons per unit dollar) due to economic inflation. The price indices for the 40 countries for each sector were derived from WIOD Socio Economic Accounts.

2.3. Direct use of energy

The MRIO method captures the direct and indirect emissions from cradle to gate, i.e., upstream supply chain until the product is ready to be used. However, it does not include the direct emissions from the use

phase in household consumption, such as gasoline burning during car driving and on-site natural gas burning during cooking. The total GHG emissions are calculated by the sum of embodied emissions and direct emissions, as follows:

$$\boldsymbol{Q_{total} = Q_{mrio} + Q_{direct}}$$

The direct emission is calculated by the energy price and CO_2eq coefficients. The gasoline price in the U.S. for each year is derived from the U.S. Department of Energy (U.S. Department of Energy, 2016). The natural gas price for each year is from the U.S. Energy Information Administration (U.S. Energy Information Administration, 2019). The CO_2 coefficients for natural gas and gasoline combustion are from the Environmental Protection Agency (U.S. Environmental Protection Agency, 2018). For consistency purpose, the direct emission coefficients are expressed in the $kgCO_2$-equivalent per dollar in the base year 2009. Direct emissions from household are calculated as follows:

$$\boldsymbol{Q_{direct} = Gas} \times a + \boldsymbol{Petro} \times b$$

where a and b are CO_2 coefficient in $kgCO_2eq/\$(2009)$.

2.4. Household consumption

To analyze the GHG emissions from households in more detail, recent studies use CES/IO method to bridge the input-out modeling and consumer expenditures (Steen-Olsen et al., 2016). The current study refers to this method to analyze not only the domestic emissions but also emissions exerted on other countries driven by U.S. household consumptions. The U.S. CES includes 13 parent categories and 74 subcategories (According to *Glossary of Terms*, each sub-category has a detailed description containing several to dozens of items, and over 600 items in total). The classification of CES is based on product level but in alignment Universal Classification Code (UCC). The CES data is linked with sectors of the U.S. in the WIOD database which are based on the Statistical Classification of Economic Activities in the European Community (NACE) that corresponds to the International Standard Industrial Classification of All Economic Activities (ISIC) (Dietzenbacher et al., 2013).

2.4.1. Types of consumption

The first step of this linkage is to aggregate 74 sub-categories in CES into 16 categories that represent the main types of household consumption, as shown in Supporting Information (SI) S1. Manually bridging these two refers to the classification concordance between NAICS and ISIC (U.S. Census Bureau, 2019). The 16 categories are based on the 13 parent categories which exist in the original CES table by aggregating the service sectors and grouping large emission of expenditures within housing with more details. For those types of consumption in CES which correspond to more than one sectors in IOT, they are allocated according to the proportion in the final demand vector in IOT. It assumes that although each household varies from another, the households' consumptions are similar to the national household final demand on the national level.

The second step is to adjust the price in the CES. Consumer Price Index (CPI) (α) is assigned for CES by product to deflate to the price in the base year 2009. CPI for the 74 products is derived from the U.S. Bureau of Labor Statistics. The closest substitution is applied for those categories that have no available data in the corresponding year. The 16 categories of consumption with 35 industries in WIOTs. In the build-up of the concordance matrix, data for wholesale and retail is derived from the Annual Wholesale Trade Survey (AWTS) and Annual Retail Trade Survey (ARTS) (U.S. Census Bureau, 2018a, 2018b). Tax and transportation margins are also subtracted to adjust the purchaser's price to basic price in correspondence with data in WIOD.

Previous studies used one concordance matrix for multiple years; however, this assumption disregards the nuanced structural changes of economies (Brizga et al., 2017). This study builds a concordance matrix for each year with price index adjustment. A country-level final demand matrix by each type of consumption ($\boldsymbol{W_{cons}}$) is expressed as follows:

$$\boldsymbol{W_{cons} = H \times C_{cons}}$$

where $\boldsymbol{H}$ is a vector of final demand on households of the U.S., $\boldsymbol{C_{cons}}$ is the concordance matrix (see Table S2) bridging the categories in IOT and those in CES by types of consumption. The overseas final demand structure is assumed to be the same as the domestic due to data limitation.

2.4.2. Income groups

Following a similar process of building up a concordance matrix and bridging the sectors in IOT and consumption structure, another concordance matrix (see Table S3) is built up to bridge the categories in IOT and different income groups ($\boldsymbol{W_{inc}}$).

$$\boldsymbol{W_{inc} = H \times C_{inc}}$$

Households are divided into 13 groups of different incomes: less than \$5000 (< \$5 k), \$5000–\$9999 (\$5–10 k), \$10,000–\$14,999 (\$10–15 k), \$15,000–19,999 (\$15–20 k), \$20,000–\$29,999 (\$20–30 k), \$30,000–\$39,999 (\$30–40 k), \$40,000–\$49,999 (\$40–50 k), \$50,000–\$69,999 (\$50–70 k), \$70,000–\$79,999 (\$70–80 k), \$80,000–\$99,999 (\$80–100 k), \$100,000–\$119,999 (\$100–120 k), \$120,000–\$149,999 (\$120–150 k), and over \$150,000 (> \$150 k). Data of incomes below \$70,000 are derived from table *Income before tax*, and data of income above \$70,000 are derived from table *Higher income before taxes*. Only the mean values in the census statistics are considered in this study. Data of household size and average persons in a typical household are also from the Consumer Expenditure Survey from 1995 to 2014.

3. Results

3.1. U.S. household carbon footprint in 2009

Our analysis reveals that 5.43 Gigaton of carbon dioxide equivalent ($GtCO_2eq$) GHG emissions (total carbon footprint) were generated worldwide due to the U.S. household consumption in 2009, representing more than 15% of the global GHG emissions. Among the total carbon footprint, 4.47 $GtCO_2eq$ GHG emissions occurred in the U.S. (domestic carbon footprint), equivalent to 82.3% of the total U.S. GHG emissions. The remaining 17.7% total carbon footprint or 0.96 $GtCO_2eq$ GHG emissions were generated outside the U.S. (overseas carbon footprint).

We first assign carbon footprint of the U.S. household consumption to five broad categories including food, housing, clothing, transportation, and services. Each of the five categories is then divided into subcategories to characterize consumption activities in more details (Table S1).

Overall, the U.S. household expenditures on transportation (29.8%) and housing (33.6%) contributed over 60% to the total domestic carbon footprint in 2009 (Fig. 1a). Expenditures in services, food, and clothing contributed 19.3%, 16.7%, and 0.1%, respectively. At the sub-category level, utilities (electricity and onsite natural gas) and fuel use (mostly gasoline and diesel) together contributed nearly 50% to the total domestic carbon footprint. In contrast, expenditures in transportation by the U.S. household contributed only 17% of its overseas carbon footprint, while housing became the most significant driver (34.7%) (Fig. 1b). Among all sub-categories, food at home, furnishing and supplies, and clothing are the three largest drivers, contributing to 40.8% of the total oversea carbon footprint of the U.S. household consumption. Compared to contributions to domestic carbon footprint, the U.S. household consumption on clothing, furnishing and supplies, and electronic and machinery products contributed significantly more to overseas carbon footprint than to domestic carbon footprint. Such difference indicates that the supply chains of those products for the U.S.

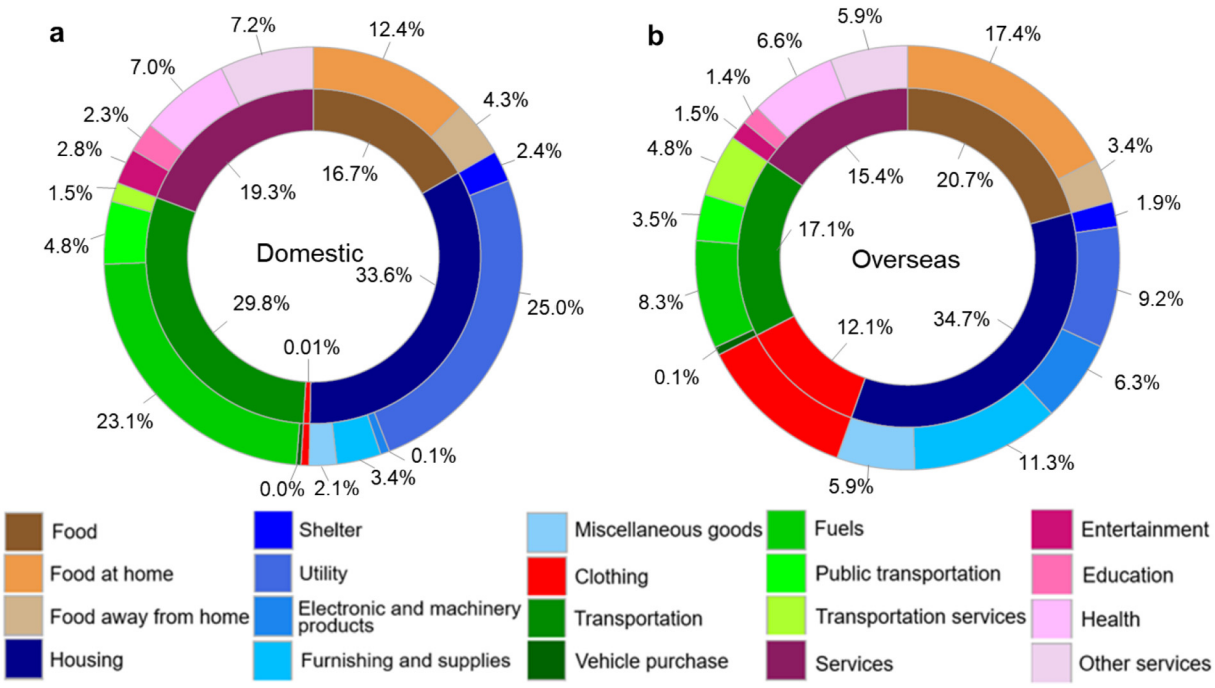


Fig. 1. Shares of domestic (a) and overseas (b) carbon footprint of the U.S. household consumption in 2009 by consumption categories.

household consumption and their GHG emissions spread over large geographic areas outside the U.S.

The overseas carbon footprint driven by the U.S. household consumption distributed unevenly among countries. Fig. 2 shows the GHG emissions in 39 countries/regions driven by the U.S. household consumption in 2009, and the share of those emissions in territorial

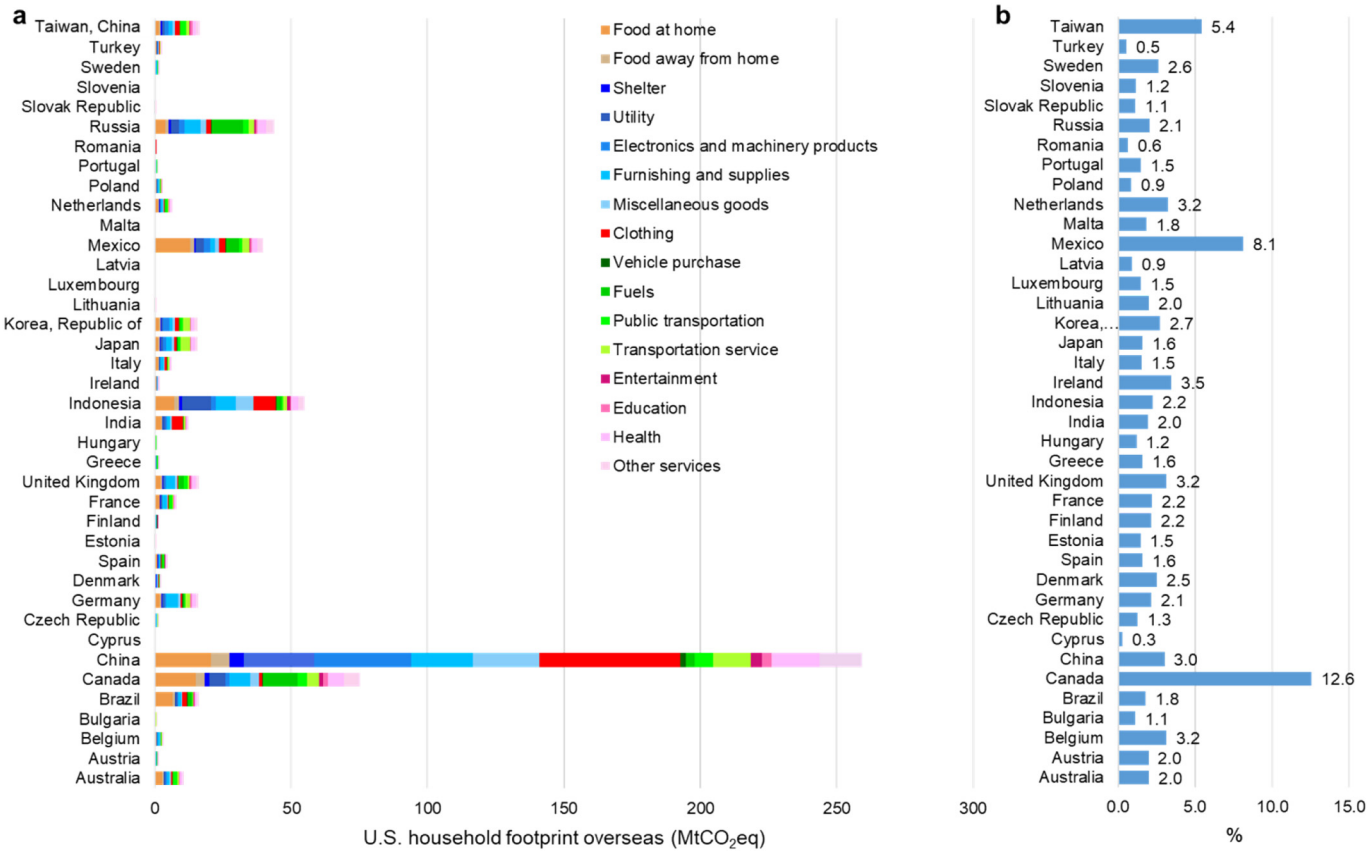


Fig. 2. Overseas carbon footprints of the U.S. household consumption in 2009 by countries of origin (a) and their shares in territory GHG emissions of each country (b) in 2009.
(Note: this figure does not show the emissions in the RoW).

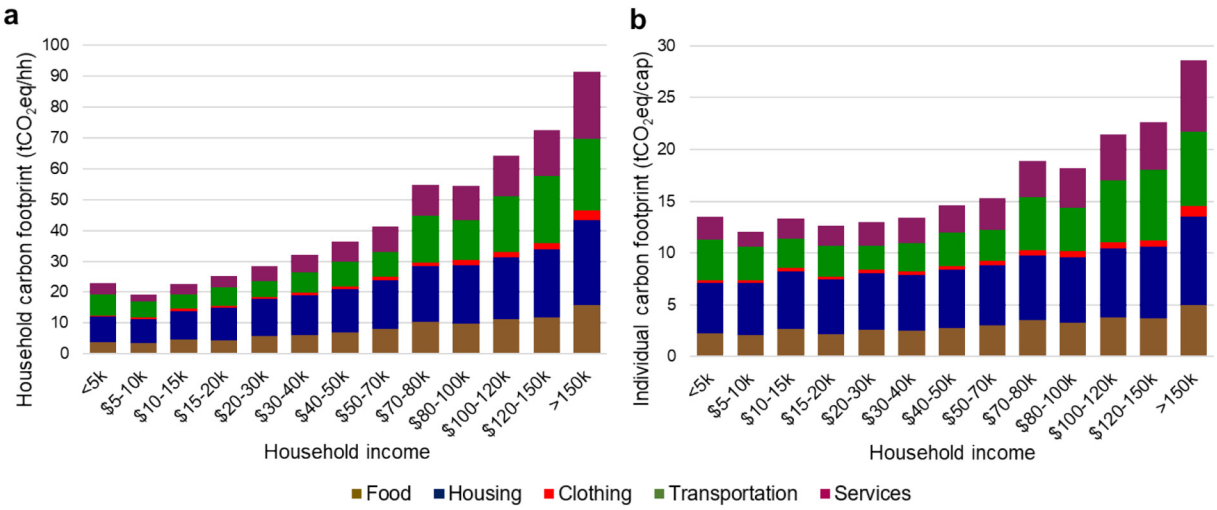


Fig. 3. Household carbon footprints in the U.S. by income level in 2009.

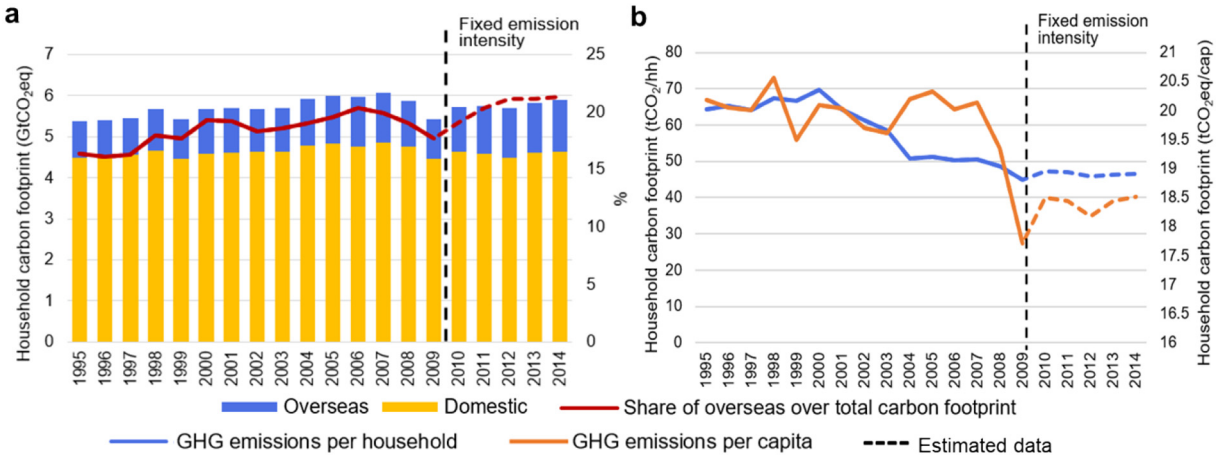


Fig. 4. Domestic and overseas carbon footprints of the U.S. household consumption from 1995 to 2014. Panel a shows the total carbon footprint and the share of overseas carbon footprint, and panel b shows average carbon footprints of households and individuals.

GHG emissions of each country/region. The most considerable portion of overseas carbon footprint of the U.S. household consumption was from China, contributing 27% or over 250 million tCO_2eq, followed by Canada, India, Russia, and Mexico. Specifically, overseas carbon footprint from Mexico was largely driven by food consumption in the U.S., while fuel consumption in the U.S. was the main driver for overseas carbon footprint from Russia and Canada. The GHG emissions driven by the U.S. household consumption were the most significant to Canada, Mexico, and Taiwan among all countries/regions, contributing to 12.6%, 8.1%, and 5.4% of their territorial GHG emissions, respectively, in 2009. Although the most substantial amount of overseas carbon footprint was from China, it was only 3.0% of China's territorial GHG emissions in 2009. The majority of China's GHG emissions were for its domestic consumption and consumption of other countries beyond the U.S. (Davis and Caldeira, 2010; Feng et al., 2013).

We further group the U.S. household expenditures by 13 income groups and allocate carbon footprint to each income group. As show in Fig. 3a for 2009, carbon footprint generally increases with household income, ranging from 19.3 to 91.5 tCO_2eq per household (hh). The average carbon footprint of the wealthiest households is over five times that of the poorest. Note that the average carbon footprint of the poorest households (less than $5000 annual income) is higher than that of households with $5000–$9999 annual income. This is because the large number of households with annual income lower than $5000 are college students whose expenditures are higher than those of households with annual income between $5000 and $9999. Specifically, expenditures on education in households with less than $5000 annual income are more than twice as much as those for households with annual income between $5000 and $9999.

The per capita carbon footprint also generally increases with household income, ranging from 12.1 to 28.6 tCO_2eq/cap, as shown in Fig. 3b. Consumers with less than $30,000 annual household income consists of 25.7% of the total population but were only responsible for 19.3% of the carbon footprint. On the other hand, wealthy consumers with more than $100,000 annual household income accounted for 22.3% of the total population but were responsible for 31.2% of the total carbon footprint of the U.S. household consumption. As income increases, the share of carbon footprint from “consumption” of services increases. Like what was observed for carbon footprint by households, the carbon footprint of an average consumer from the poorest households (less than $5000 annual income) is larger than that from the slightly more affluent households ($5000–$9999 annual income). The difference was also mainly driven by higher average expenditures from households with the lowest annual income.

3.2. U.S. household carbon footprint from 1995 to 2014

Fig. 4a shows that both domestic and overseas carbon footprint of the U.S. household consumption had been steadily growing since 1995 until reaching a plateau in 2005–2008 at around 6.0 $GtCO_2eq$,

respectively. In 2009, the carbon footprint of the U.S. household consumption dropped by 8.5% compared to that in 2008, mainly due to declined consumption in the Great Recession. The share of overseas carbon footprint in total carbon footprint of the U.S. household consumption had increased from about 16% in 1995 and peaked at around 20% in 2006. After 2006, the share of overseas carbon footprint started to decrease, an indication of slowing down imports before the recession. After 2009, the share of overseas GHG emissions increased to over 20% of the total GHG emissions, under circumstances of fixed emission coefficient, suggesting the dominant role of increase in demand. On the per capita basis, the U.S. household carbon footprint is over five times the world average (3.4 tCO_2eq/cap in 2007 based on (Ivanova et al., 2016)). As show in Fig. 4b, the per-capita carbon footprint of the U.S. household remained stable between 19.5 tCO_2eq/cap to 20.1 tCO_2eq/cap from 1995 to 2007 and then decreased to 17.7 tCO_2eq/cap in 2009. Interestingly, both total household carbon footprint and carbon footprint per capita peaked before the recession. This indicates that the U.S. household carbon footprint has been decreasing already before the recession, and the recession was not the only reason that reduces the U.S. household carbon footprint. Besides, our estimation shows that after 2009, the total amount of GHG emissions increased, with expanding carbon footprints overseas.

Among all consumption categories, consumption in utility and fuels accounted for 30%–40% of the total carbon footprint of the U.S. household during 1995 to 2014. Expenditures on food at home, health, furnishing and supplies, and other services accounted for another 25%–35% of the total carbon footprint (Fig. 5a). Overall, household expenditures in 16 categories are roughly clustered in 6 groups based on their shares of overseas carbon footprint in total carbon footprint (Fig. 5b):

1) Clothing expenditure had the largest share of overseas carbon footprint, ranging from approximately 70% to 85%. In other words, about 70% to 85% of the carbon footprint of for the U.S. household consumption in clothing occurred in other countries from the upper supply chain.
2) Electronics expenditure was ranked second in the shares of overseas carbon footprint, increasing from about 55% to around 65%.
3) Expenditures on transportation service, furnishing and supplies, and miscellaneous goods formed the third group, shares of overseas carbon footprint of which increased from approximately 30% to 40% before 2009, and increased to a share of around 40%–55% mainly due to increase in demand after 2009.
4) Vehicle purchase and food at home had about 20% to 25% of their carbon footprint from overseas.
5) Health, public transportation, shelter, and other services had 10–15% of their carbon footprint from overseas.
6) The shares of overseas carbon footprint for entertainment and utility expenditures were the smallest, ranging from about 5% to 10%.

Fig. 6 shows that the variations of household carbon footprint from 1995 to 2014 were largely driven by the changes of expenditures on housing and transportation. The annual changes allows us to This is true for both domestic and overseas carbon footprint. Expenditures on housing contributed significantly to household carbon footprint given its large share in the total household expenditure, while transportation contributed significantly due to direct GHG emissions from itself. For overseas carbon footprint, expenditures on transportation were the primary driver, including not only direct GHG emissions from fuel use but also emissions from the automotive supply chain in producing vehicles and vehicle parts.

Carbon footprint from each type of consumption changed over time due to the changes in consumption behavior, economic structure, volume of consumption, and fuel mix in energy production. It is noticeable that carbon footprint of expenditures on utility, fuels, and public transportation increased sharply both domestically and overseas (Fig. S1a). This agrees with the literature that GHG emissions from energy consumption in the residential sector have a rebound effect (Brännlund

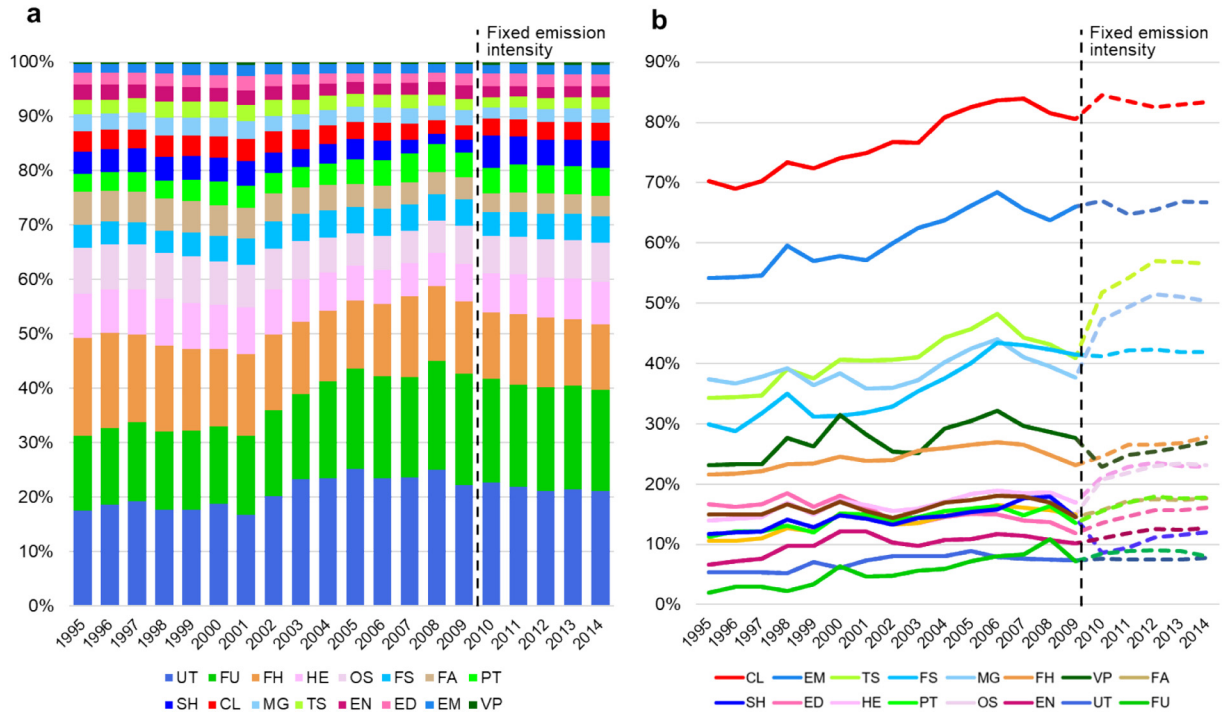


Fig. 5. Shares of carbon footprint of the U.S. households by consumption categories from 1995 to 2014. Panel a shows the shares of carbon footprint from 16 types of U.S. household consumption, and panel b shows the shares of overseas carbon footprint in total carbon footprint of the U.S. households for each type of consumption (Note: FH = Food at home, FA = Food away from home, SH = Shelter, UT = Utility, EM = Electronic and Machinery products, FS = Furnishing and supplies, MG = Miscellaneous goods, CL = Clothing, VP = Vehicle purchase, FU = Fuels, PT = Public transportation, TS = Transportation service, EN = Entertainment, ED = Education, HE = Health, OS = Other services).

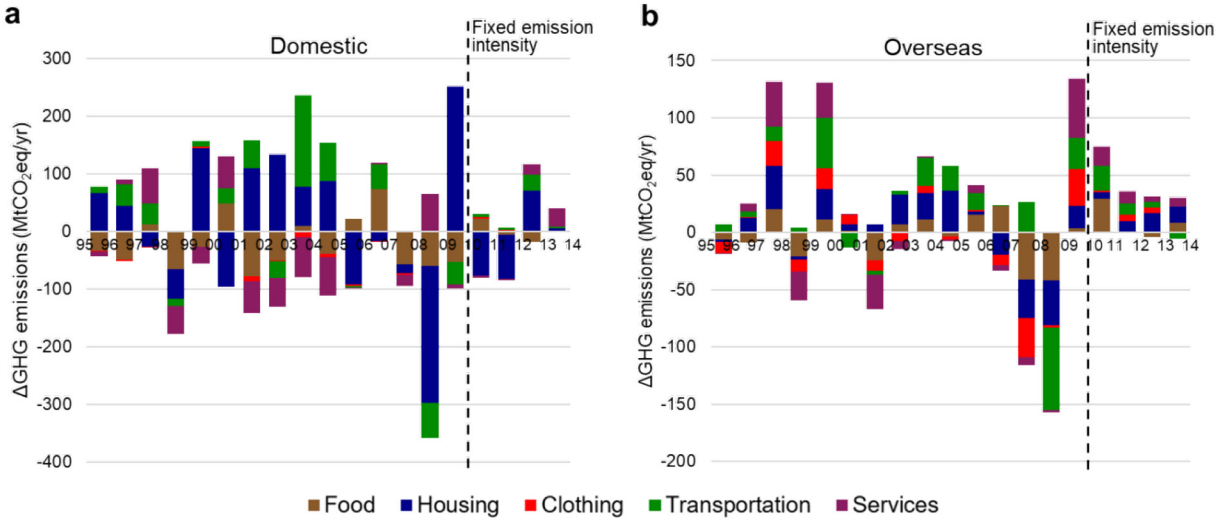


Fig. 6. Annual changes in domestic and overseas carbon footprint of the U.S. household consumption from 1995 to 2014.

et al., 2007; Hertwich, 2005; Taiebat et al., 2019; Thomas and Azevedo, 2013). For expenditures on food away from home, electronics, furnishing and supplies, clothing, vehicle purchase, transportation service, and health, the decreases in domestic carbon footprint are generally accompanied by increases in overseas carbon footprint.

The carbon intensity of household consumption—carbon footprint of unitary consumption—had varied significantly by consumption categories (Fig. S1b). Overall, carbon intensity for most types of expenditures had decreased from 1995 to 2014. It means that carbon footprint decreased for the consumption of the same amount of products or services measured in constant price, indicating the overall improvement of production efficiency and reduction of carbon intensity in production. Domestic carbon intensity (only accounting for domestic carbon footprint) decreased faster than overseas carbon intensity, demonstrating the faster improvement in the U.S. (Liang et al., 2016) At the consumption category level, housing and services, such as shelter, transportation services, health, and education had carbon intensities much lower than that of energy-related consumption such as utility and fuels. For example, the carbon intensity of expenditures on health products and services ranged from 0.15 to 0.40 $kgCO_2eq/$(2009)$ domestically and 0.03 to 0.05 $kgCO_2eq/$(2009)$ overseas, while the carbon intensity of consumption on fuels was as high as 5.0–10.0 $kgCO_2eq/$(2009).

4. Discussion

This study investigates the U.S. household carbon footprint from 1995 to 2014. The average household carbon footprint was between 17.7 tCO_2eq/cap and 20.6 tCO_2eq/cap, which agrees reasonably with the previous study of 18.6 tCO_2eq/cap in 2007 (Ivanova et al., 2016). A similar study also indicates that the per capita carbon footprint for the U.S. household consumption is roughly 20 tCO_2eq/cap (Jones and Kammen, 2011). A spatial analysis of the U.S. household carbon footprint indicates that per capita carbon footprint of Metropolitan Statistical Areas (MSAs) ranges from 17.2 to 19.5 tCO_2/cap with a weighted average of 18.6 tCO_2/cap (Jones and Kammen, 2014). Our study also shows that overseas carbon footprint is approximately 20% of the total carbon footprint, which corresponds with the results in (Kanemoto et al., 2016), but is less than the results from (Weber and Matthews, 2008a). This difference is likely because, while both our study and (Kanemoto et al., 2016) cover most countries in the world, (Weber and Matthews, 2008a) only examined carbon footprint from the U.S. trades with seven other countries. The food carbon footprints in a U.S. household averaged around 7.8 tCO_2eq/hh and 3.1 tCO_2eq/cap in 2009, which conforms to food impact assessment from (Weber and Matthews, 2008b) which is 8.1 tCO_2/hh in 1997 and from (Mohareb et al., 2018) which is 3.8 tCO_2eq/cap in 2010. (Weber and Matthews, 2008b) used an IO-LCA method and (Mohareb et al., 2018) used a process-based LCA quantification. This implies that our method of bridging input-output data and consumer expenditure survey data could capture the life-cycle emissions thus potentially serve as an improved method to provide more details about emissions associated with household consumption.

Trade policies can significantly reshape the GHG implications of household consumption in a globalized market. We observed reduction of carbon intensities for most of the household consumption categories in the U.S. from 1995 to 2009. However, the overseas carbon intensity does not decrease as fast as that in the U.S., even increases for some categories such as furnishing and supplies and fuels. Global climate mitigation requires the reduction of carbon intensity for all countries; otherwise the domestic effort in one country will be diminished by importing carbon-intensive products and services from other countries. Consumers should also be aware of carbon footprints of their consumption and make informed purchase decisions. Specifically, wealthier consumers should take more climate responsibilities given larger carbon footprint of their consumption.

Our analysis also shows that long-term sustainable development relies on the energy system transition away from fossil fuels. About half of the carbon footprint of the U.S. household consumption comes from utilities and fuels. A significant portion of GHG emissions from upstream supply chain of household consumption are from electricity generation. To reduce carbon footprint of consumption without significant welfare sacrifice (i.e., no reduction of consumption volumes), replacing fossil fuels with renewable energy in power and transportation sectors is the ultimate solution.

Limitations exist in our study. We build a concordance matrix to address the challenge of different classification schemes as described in Methods and Data. Prices are also adjusted to be constant and comparable in different years. We also include direct GHG emissions from household consumption such as fuel use. However, this study covers the period from 1995 to 2014, due to the lack of more recent EE-MRIO data in WIOD. Other available EE-MRIO databases include GTAP, EXIOBASE, and Eora (Athanassiadis et al., 2018). While each offers global trade flows with environmental accounts, we choose to use WIOD because its sector classification scheme is the closest to that of the U.S. CES data. Despite EXIOBASE and Eora provide finer classification of sectors and more recent data, their sector classification schemes (COICOP for EXIOBASE and mixed classification for the full Eora

database) can introduce additional uncertainties when bridging to the U.S. CES data. 1). Admittedly, the up-to-date U.S. Input-Output data can provide information about the current carbon footprints of households in the U.S. However, understanding the carbon footprints of U.S. households around the world requires the Multi-regional Input-Output data. The environmental account of WIOD is updated to 2009, which provides the latest detailed information to quantify the U.S. carbon footprints around the world. It is limited by the update of MRIO databases and their sector details for concordance purpose; on the other, the household expenditure patterns did not change significantly within several years. Our analysis based on 20-year historical data quantifies either subtle or dramatic changes in household consumption patterns and associated GHG emissions. Such quantification could offer insights to the lifestyle changes, which plays an essential role in demand-side emission management, and shed lights on the emission reduction potentials for further climate actions that both decisionmakers and individuals can take.

In addition to inherent uncertainties associated with the EE-MRIO methodology and underlying data (Athanassiadis et al., 2018), additional uncertainties come from CES survey reports and the reconciliation of CES data. For example, the over-report of food and under-report of alcohol and other less frequently-used goods are well-documented in previous studies (Ivanova et al., 2016; Weber and Matthews, 2008a).

5. Conclusions

This paper analyzed GHG emissions from U.S. household consumption from the angles of scale, distribution and variation. Our 20-year coverage analysis from 1995 to 2014 found that the annual U.S. household footprint averaged between 17.7 tCO_2eq/cap (in 1998) and 20.6 tCO_2eq/cap (in 2009), in which housing and transportation are the two major contributors. The household footprint has increasingly extended globally, especially for manufacturing products such as clothing and electronic and machinery products, half of whose emissions occurred overseas. Among the countries, China and Canada are the top two countries that U.S. households outsource emissions from. Within the country, carbon inequity still exists in that per capita carbon footprint generally increases with household income, ranging from 12.1 to 28.6 tCO_2eq/cap. This study highlighted the household consumption that contributes most to the total GHG emissions and has most spillover effects overseas. Given these facts, effective climate mitigation policies should target emission-intensive expenditure and high emission consumer groups. Further attention should be paid to the lifestyle shifts from the demand-side.

Declaration of competing interest

The authors state no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2019.105137.

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