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Household carbon inequality in the U.S.

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ABSTRACT

Household carbon emissions are mainly affected by income and other key demographic factors. Understanding the contribution of these factors can inform climate responsibilities and potential demand-side climate mitigation strategies. By linking US consumer expenditure survey data with a nested national within a global multi-regional input-output model, this study estimates consumption-based GHG emissions for 9 income groups and assesses the carbon inequality in the US for 2015. Our results show that the per capita carbon footprint (CF) of the highest income group (>200 thousand USD per year) with 32.3 tons is about 2.6 times the per capita CF of the lowest income group (<15 thousand USD) with 12.3 tons. This is due to large gap in consumption volume and associated carbon emissions along the entire global production chain. Consumption pattern tends to narrow the gap in household per capita CF between income groups due to the lower carbon intensity per dollar spent by higher income groups. Another important factor influencing carbon footprints is household size and thus sharing of household equipment and other consumption items. The US average per capita CF is 18.1 tons compared to the global average of approximately 5 tons. The high carbon footprint across income groups in the US is largely due to the large contribution of emissions from heating and cooling and private transport, which reflects the settlement structure and lifestyles in the US, relying heavily on cars and living in larger houses.

1. Introduction

Household consumption is an essential component of climate policies, and especially important in countries with high carbon footprints and carbon-intensive lifestyles (Dubois et al., 2019; Moran et al., 2018). Households differ considerably in terms of income, consumption patterns and their contribution to climate change. The gap between rich and poor in terms of carbon footprints as well as other environmental impacts has become part of the discourse on environmental justice and unequal exchange (Feng et al., 2014; Jorgenson et al., 2017; Prell et al., 2014).

Climate justice is an essential component in the climate change discourse, which is to some extent also reflected in the choices of mitigation and policy tools. For example, fairness issues emerge in the potential regressive distributional effects of carbon taxes (Vogt-Schilb et al., 2019), and on how to reallocate the tax income among households and public investment options, especially given households differential contributions of carbon emissions as well as vulnerability to climate change and mitigation policies (Chen and Hafstead, 2019; Goulder et al., 2019; Wang et al., 2016). Inequality in the US is reported as one of the highest amongst developed countries (Norton and Ariely, 2011) and is on the rise again (Mulholland and Shupe, 2018; Stone et al., 2015).

Assessing energy use and emissions associated with household consumption has received considerable attention in environmental sustainability and climate research due to the significant emissions from households and their supply chain effects triggered through consumption choices (Druckman and Jackson, 2009; Girod and Haan, 2010; Tukker et al., 2010). Demand-side management has become increasingly important in the US for its potentialeffects on emission reduction (Dietz et al., 2009), especially given the lack of mitigation efforts and curbing and weakening of existing regulations at the national level (Jotzo et al., 2018). A comprehensive understanding of carbon footprints of different groups of household consumers at the national level is essential to inform policy-makers and to affect top-down demand-side mitigation policies at lower socioeconomic costs (Creutzig et al., 2018; Wolters et al., 2020). A large number of studies are focused on the inequality of

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household consumption, different consumer groups and changing demographics and associated greenhouse gas (GHG) emissions (Kennedy et al., 2014; Liobikienė, 2020; Shittu, 2019). Recent studies have used consumer expenditure surveys (Wiedenhofer et al., 2018), and global trade data to account for emissions along global supply chains (Mach et al., 2018). This is based on the understanding that ignoring the link between household consumption and global production via international trade may significantly underestimate the environmental impacts associated with household consumption, in particular in developed countries such as the US, where a large portion of household consumption is imported from other countries, and this share increases with increasing income (Hubacek et al., 2017).

There are a number of studies that have investigated US household carbon emissions by analyzing consumer expenditure from spatial and temporal dimensions, as well as effects of socioeconomic factors. For example, Weber and Matthews (2008) used consumer expenditure survey data and input-output analysis to investigate distributional aspects of the US household carbon footprint (CF) and found that 30% of household GHG emissions occurred outside of the US. They identified a big gap (factor of approximately 10) in per household emissions between the highest and lowest income groups. Some studies also investigated household carbon footprints in spatial detail, from metropolitan areas (Markolf et al., 2017), counties (Tamayao et al., 2014), cities (Ramaswami and Chavez, 2013; Wheeler et al., 2018), to the zipcode level (Jones and Kammen, 2014). Analyzing temporal change, Song et al. (2019), using global MRIO, found that the average US household CF decreased from approximately 70 tCO_2eq per household (tCO_2eq/hh) in 2000 to below 50 tCO_2eq/hh in 2014, with an increasing share of household CF from overseas. In terms of major contributors and potential mitigation, Jones and Kammen (2011) concluded that changes in diet and telecommuting were among the most effective approaches to reduce GHG emissions for households.

Most of the studies analyzing household carbon footprints are quite dated. Our study provides an update of household carbon footprints using the most recent household consumption and input-output data. In addition, prior studies calculated carbon footprints by different metrics and system boundaries; most of them included Scope 1 and Scope 2 emissions (Tamayao et al., 2014), however, ignored the carbon footprints embodied in international trade (Liu et al., 2019), calculated overseas carbon footprints on weighted average level (Druckman and Jackson, 2009), or assumed the imported products have the same carbon coefficients as products manufactured domestically (Jones and Kammen, 2011). This may lead to the underestimation of household carbon footprints ignoring carbon leakage, especially for large net carbon importing countries such as the US. In addition, we quantify the contribution of income, household size and household consumption patterns to explain the CF gaps between different income groups in the US. Furthermore, we constructed a nested US national input-output (IO) table within a global multi-regional input-output (MRIO) table to provide more precise estimates of household carbon footprints accounting for GHG emissions along entire global production chains for different income groups.

In this study, we answer the following questions: What are the per capita carbon footprints of US households with different income levels? What consumption items contribute the most to this variation? How do different factors (e.g. consumption volume, household size and consumption patterns) contribute to the gap in per capita household carbon footprints across income groups? To this end, we assess carbon inequality of US households across 9 income groups in 2015. We analyze their consumption-based CO_2 emissions through connecting US household consumption by income group with a nested national within a global multi-regional input-output model. In addition, we apply index decomposition analysis to identify the main contributors to the gap in per capita carbon footprints of different income groups. This study will enrich our understanding of how household expenditure, consumption patterns and household size affected US household carbon footprints and shed light on potential inequality issues of climate mitigation policies.

2. Materials and method

2.1. Environmental input-output analysis

Environmental input-output analysis (EIO) provides a consistent analytical and modeling framework to link household consumption to global commodity chains and enables us to capture environmental impacts caused in upstream supply chains for the production of household consumption items (Hubacek et al., 2016; Wiedmann and Lenzen, 2018). The environmentally extended input-output approach (EIO) has been frequently used for assessing embodied carbon emissions triggered by final consumption (Liobikienė, 2020; Mi et al., 2020) and international/inter-regional trade (Hubacek et al., 2017; Oswald et al., 2020). Multi-regional input-output (MRIO) Analysis is an accounting and modeling approach relying on regional economic input-output (I—O) tables and inter-regional trade matrices, depicting the flows of money to and from each sector within and between the interlinked economies, and thus revealing each sector's entire supply chain. A MRIO table is a collection of regional transaction tables, T, which connects supplying industries in region r with using industries in region s, plus final demand matrix (Y) and value added vector(v) T consists of diagonal inter-industry blocks (i.e. T^{rr} and T^{ss}, intraregional transactions), and off-diagonal blocks (i.e. T^{rs} and T^{sr}, interregional transactions); Y consists of intraregional (y^{rr} and y^{ss}) and interregional find demand (y^{rs} and y^{sr}); v includes value added of region s and region y (v^r and v^s), international import to processing industries (m^r and m^s) and find demand sectors (m^{yr} and m^{ys}), and international exports of producing sectors (e^r and e^s).

In a MRIO framework, different regions are connected through inter-regional trade, T^{rs} and T^{sr}. The technical coefficient sub-matrix A^{rs} consists of $\{a_{ij}^{rs}\}$ is given by $a_{ij}^{rs} = T_{ij}^{rs}/x_j^s$, in which T_{ij}^{rs} is the inter-sector monetary flow from sector i in region r to sector j in region s; x_j^s is the total output of sector j in region s. The final demand matrix Y is consisting of $\{y_i^{rs}\}$, where y_i^{rs} is the final demand of region s for goods of sector i from region r. Using matrix notation and dropping the subscripts, we have

$$A = \begin{bmatrix} A^{11} & A^{12} & \cdots & A^{1n} \\ A^{21} & A^{22} & \cdots & A^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A^{n1} & A^{n2} & \cdots & A^{nn} \end{bmatrix}; \quad Y = \begin{bmatrix} y^{11} & y^{12} & \cdots & y^{1n} \\ y^{21} & y^{22} & \cdots & y^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y^{n1} & y^{n2} & \cdots & y^{nn} \end{bmatrix}; \quad x = \begin{bmatrix} x^1 \\ x^2 \\ \vdots \\ x^n \end{bmatrix};$$

Consequently, the MRIO framework can be written as:

$$x = Ax + Y \tag{1}$$

By solving x, we have

$$x = (I - A)^{-1} Y \tag{2}$$

where $(I - A)^{-1}$ is the Leontief inverse matrix which captures both direct and indirect economic inputs to satisfy one unit of final demand in monetary value; I is the identity matrix with ones on the diagonal and zeros on the off-diagonal.

In this study, we use global MRIO model to estimate the imported emissions of all the goods and services that consumed by the US households. We first extend the MRIO table with a vector of sectoral $CO_{2\text{-}e}$ emission coefficients for all regions, k:

$$k = [\, k_1 \quad k_2 \quad \cdots \quad k_n \,]$$

The household carbon footprint is comprised of GHG emissions embodied in imports, domestic supply chains and emissions from household direct consumption of fuels. The imported emissions of household goods and services in the US can be calculated using the global MRIO model:

$$CF^{imp} = \tilde{K}(I - A)^{-1} Y^{US} \tag{3}$$

where CF^{imp} is the total imported emissions of goods and services for the US household consumption; $\tilde{K}$ is a matrix with sectoral $CO_{2\text{-}e}$ emission coefficients for all foreign countries and zeros for the sectoral emission coefficients of the US on the diagonal; Y^{US} is a matrix of the US household consumption by income groups.

Since IMPLAN provided very high sectoral resolution input-output table for the US, the domestic carbon footprint of the US households can be calculated using the IMPLAN US input-output model:

$$CF^{dom} = K^{dom}\left(I - A^{dom}\right)^{-1} Y^{US'} \tag{4}$$

where CF^{dom} is a matrix of the embedded domestic emissions of goods and services for US household consumption by income group; K is a matrix with US domestic CO_2 emission coefficients ($CO_{2\text{-}e}$ emissions per unit of economic output) for 536 economic sectors of the US on the diagonal; A^{dom} is a technical coefficient matrix of US production; $Y^{US'}$ is a matrix of US household domestic consumption by income group. Household direct emissions are estimated using total household fuel consumption and the emission conversion factors of different fuels.

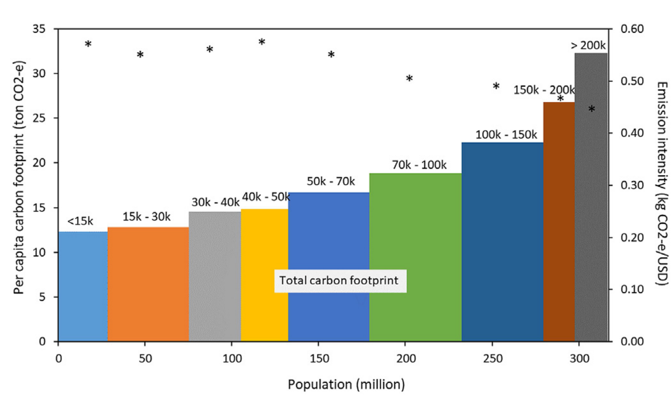

Fig. 1. Carbon footprints and carbon intensity of household consumption for 9 income groups. The size of each box indicates the total carbon footprint for each income group. The star (*) in each category refers to carbon intensity, i.e. emissions per dollar spent (tons/1000 USD).

2.2. Index decomposition analysis

To identify the main contributors to the gap in per capita carbon footprint (CF) between low and high income groups, we apply an index decomposition analysis (IDA) to quantify the contribution of three factors: household size, consumption volume per household, and emission intensity (emission per average dollar spent to reflect household consumption patterns) (Ang et al., 2015; Feng et al., 2015). We chose IDA instead of Structural Decomposition Analysis (SDA) for its flexibility in modelling an aggregate indicator at the sectoral level.

$$\mathrm{CF}_{cap} = \left(\frac{1}{\mathrm{s}}\right) * \ \mathrm{c*e} \tag{5}$$

where CF_{cap} denotes per capita CF; s denotes household size; c represents consumption volume per household, e is emission intensity (consumption patterns).

Any change in per capita CF between two income groups can be captured by equation (6), in which the three factors of household size, emission intensity (representing the changes in household consumption patterns) and consumption volume fully account for the changes in per capita emissions.

$$\varDelta \mathrm{CF}_{cap} = \left(\frac{1}{\varDelta \mathrm{s}}\right) * \ \mathrm{c*e} + \left(\frac{1}{\mathrm{s}}\right) * \ \varDelta \mathrm{c*e} + \left(\frac{1}{\mathrm{s}}\right) * \ \mathrm{c*}\varDelta \mathrm{e} \tag{6}$$

where $\varDelta$ is the difference operator. Equation (6) converts three multiplicative terms in the first term of equation (5) into three additive terms. Each additive term in equation (6) represents the contribution to a change in per capita CF triggered by a factor assuming all other factors are constant. However, there is no unique solution for the decomposition and we use the average of all possible first-order decompositions (Dietzenbacher and Los, 1998; Feng et al., 2015) in this study.

2.3. Data sources

In this study, the US national input-output table was collected from the IMPLAN database (IMPLAN, 2017), which covers 536 US sectors. Global MRIO was used to calculate embodied emissions in US import based on the Eora database (Eora, 2017). Eora is a multi-region input-output database that provides a time series of high-resolution input-output (IO) tables with matching environmental and social satellite accounts including GHG emissions for 186 countries. The harmonized MRIO tables from Eora contain trade flows, production, consumption and intermediate use of commodities and services for 26 sectors, both within and between 186 countries. The framework of nesting national IO table into the global IO table is explained by Tukker and Dietzenbacher (2013) and Wang et al. (2017). Consumer expenditure data for 9 income groups in the US were included in the IMPLAN input-output database based on the consumer expenditure survey from the US Bureau of Labor Statistics (US BLS, 2019). The population of each income group was collected from the US Bureau of Labor Statistics and the population data include average number of adults and children per household in each income group. GHG emissions data were collected from Yang et al. (2017) and the sectoral emission coefficients were inflated from emissions per 2013USD to emissions per 2015USD using the inflation factors provided by IMPLAN. In this study, GHG emissions include all six major Greenhouse Gases (e.g. CO_2, CH4, N_2O, HFCs, PFCs, SF6, and NF3),which are converted to CO_2 equivalent for CF calculation.

While the model we used in this study cannot distinguish the carbon content of specific products within a consumption category, for example, luxury sports cars vs. widely used sedans versus trucks or electric cars for private transport, this method enables us to distinguish the overall carbon content of the same type of consumption at the national level. This study uses the expenditure data from input-output tables by different income groups provided by IMPLAN, which is estimated by combining the benchmark detailed household commodity purchases with annual Personal Consumption Expenditures (PCE) from National Income and Product Accounts (NIPA) and Consumer Expenditure Survey (CES) from Bureau of Economic Analysis (BEA). Detailed CES data were first mapped to the detailed annual NIPA PCE data which gives average purchaser price spending on each PCE item by household income class in purchasing prices. The IMPLAN commodities were then allocated to different income groups, by-PCE-item spending with price conversion by benchmark margins for each sector. This procedure better reflects the household expenditure at the national level and addresses over-estimation and under-estimation issues by starting from the CES data (IMPLAN, 2019).

2.4. Limitations

In this study, we used the Eora MRIO model to capture the overall emissions of US household consumption. However, the Eora MRIO table only includes 26 economic sectors which is more aggregated than the US IO table, thus may lead to aggregation errors (Lenzen, 2011). However, the share of imported emissions in the total US household CF is within the results range of other studies which makes us confident to use the result based on the Eora MRIO model. In addition, oversea emissions were proportionally allocated to different income groups based on their household consumption of goods and service. This assumes the same import ratios for the same categories of goods and services consumed by different income groups. Finally, different income groups may purchase the same category of goods and services at different prices, while in this study, we assume the same category goods and services consumed by different income groups have the same emission coefficients. However, a higher price may not be associated with higher material inputs and higher emissions as for example organic food or higher quality items that are due to aggregation in the same product category. Given that household expenditure survey data is mainly based on monetary spending, this assumption has been broadly accepted in the literature.

3. Results

3.1. Carbon footprints for different income categories

Different income groups have very different lifestyles and thus carbon footprints. When we zoom into the 9 household income groups, we can see a positive correlation between per capita household carbon footprints and income. The per capita carbon footprint (CF) of the highest income group was 2.6 times the footprint of the lowest income group (see Fig. 1). Most of the US population, i.e. 17% fall in the 70-100k income category, and have an average per capita carbon footprint of 18.8 tons, contributing 17% of total emissions. The 100k-150k income group representing 15% of the population, have a CF of 22.3 tons, and contributed the most with more than 18% of total emissions. The highest income group (>200k), with only 6% of the total population, has a CF of 32.3 tons, and contributed about 11% of total emissions, whereas the lowest income group with 9% of the population, and a CF of 12.3 tons, contributed 6% of total emissions.

The carbon intensity of household consumption, which is defined as emissions per dollar of household expenditure, kept flat around 0.55 kg/USD for households earning less than 70k, and then started declining with higher incomes. However, the overall decline in carbon intensity of household consumption is relatively small and 23% lower for households earning more than 200k with 0.44 kg/USD, compared to the 40k-50k income group (0.57 kg/USD), which has the highest carbon intensity of consumption. The lower carbon intensity of high income household consumption is largely due to their higher shares of household spending on services which have relatively low carbon intensity (see Fig. 2 and Fig. 3).

3.2. Composition of household carbon footprints by income group

Fig. 2 shows that consumption of Petroleum Products and Utility (including electricity, natural gas, and water) accounted for the largest share in the household carbon footprint (CF) across all income groups. Emissions from consumption of Petroleum Products, which reflects mainly the contribution of private transport, contributed the most to the per capita CF for households with incomes larger than 40k USD, while for households lower than 40k, the contribution from Utility was the largest. The results reflect that the lifestyle of higher income households is more dependent on private transport with larger size vehicles, while lower income households spend a larger share of their income on basic needs, such as heating and cooling and food. For example, emissions from Utility for the high-income group, i.e., More than 200k only contributed 15% of their total household emissions, while the share is 25% for the lowest income group with 10 percentage points difference. In contrast, emissions from the service sectors for the >200k group is 35% compared with 26% of the 40-50k income group and 28% of the less than 15k income group. This also explains why the emission intensity of low-income household consumption is higher than the emissions intensity of household consumption for high-income groups. The third largest category is food consumption for most low-income households (up to 19% of the household CF) because of the large share of food expenditure in their total consumption.

3.3. Domestic and foreign carbon emissions of household spending

Consumption of goods and services in the US not only causes emissions within the US, but also drives emissions outside of the US via international trade. Fig. 3 shows that manufacturing products have a much higher carbon intensity than services, but also have a higher share of emissions from imports. For example, approximate 70% of emissions for the consumption of Textiles and Wearing Apparel is generated outside the US from the US's main trading partners, such as China, India, and Mexico. The shares are even higher for the consumption of Electrical and Machinery (78%) and Other Manufacturing and Recycling Products (76%). Electricity, Gas and Water is the most carbon-intensive household consumption category with about 6 kg CO_2 emissions per dollar and is mainly produced domestically. The same is true for Transport, Post and Telecommunications, which is the most carbon-intensive service sector. Financial Intermediation and Business Activities only cause 0.2 $kgCO_{2\text{-}e}$ emissions per dollars with most emissions from domestic production.

The share of imported emissions in the household per capita carbon footprint tends to increase with income growth, which is largely due to the higher per capita consumption of imported products, such as Textiles and Wearing Apparel, Petroleum

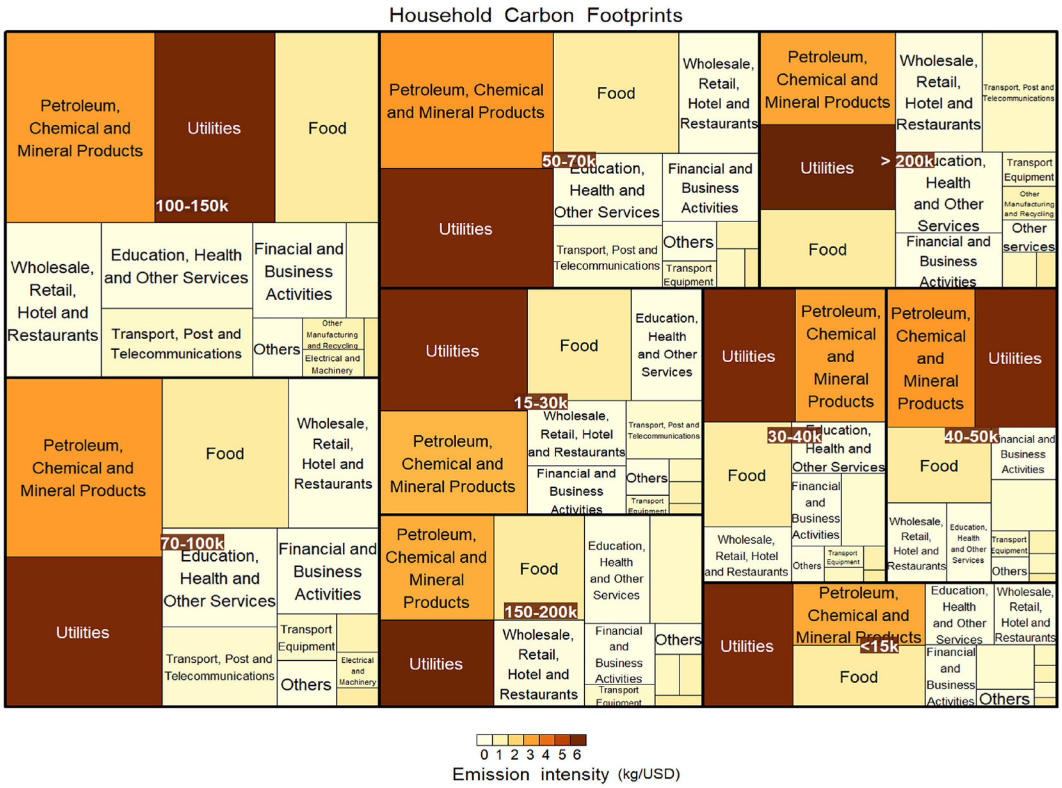

Fig. 2. Visualizing composition of household total carbon footprints for 9 income groups
Notes: Color coding reflects emission intensity. The area of rectangles around each income category and surrounded by a darker lined frame reflects the total household carbon footprints of each income group. See Table S1 for the background data of this figure. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

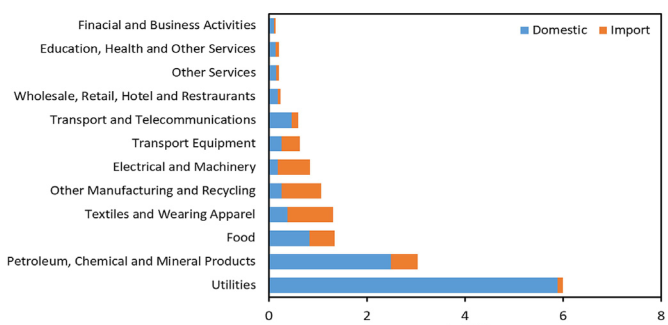

Fig. 3. Average per capita domestic and imported $CO_{2\text{-}e}$ emissions per 1 USD for different consumption categories.

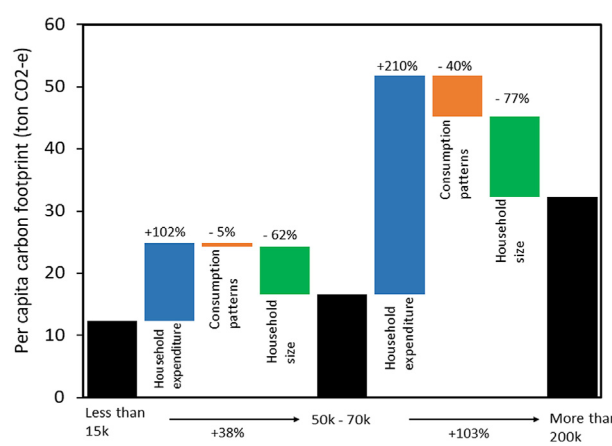

Fig. 4. Percentage contribution explaining the difference of per capita carbon footprint between low, middle and high-income groups
Note: the black bars indicate per capita carbon footprint of different income groups; the colored bars indicate contribution of different factors to the carbon footprint gap between different income groups.

Products, Electrical and Machinery and Transport Equipment. This result is consistent with findings from similar studies (e. g. Duarte et al., 2010; Song et al., 2019; Weber and Matthews, 2008). The share of imported CO_2 emissions increased from about 21% for the lowest income group to 25% for the highest income group.

3.4. Decomposition analysis of the carbon footprint gap between income groups

Figs. 1–3 showed the gap in per capita CF between low and high-income households. To understand the drivers for this gap, we decompose the difference into three factors: household expenditure, household size and household consumption patterns. Fig. 4 shows the results from index decomposition analysis (IDA) quantifying the contributions of three major factors to the differences in per capita CF between different income groups using the lowest (<15k), the middle (50-70k) and the highest (>200k) income group. Our results show that the highest income group is responsible for a larger share of the total US household carbon footprint due to their larger per capita carbon footprint. While the income increases more than 10-fold from the lowest to the highest income category, the per capita carbon footprints less than trebles (162% increase). From the Fig. 4, we can see that the difference in household expenditure is the main contributor to explain the gap in per capita CF across income groups. For example, consumption per household alone would lead to 102% increase in the per capita CF between lowest income group (less than 15k) and the highest income group, if these two groups have the same household size and carbon intensity. And this increase led by per capita consumption would be even further to 210% between the middle income group and the highest income group (more than 200k). However, household size tends to be larger with higher incomes in the US, the larger household size means more people would share the same resources, thus lead to a lower per capita CF. From Fig. 4, we found that the difference in household size alone would lead to a much narrower gap in per capita CF between the lowest income group (1.6 per household) and the middle income (2.6 per household) with a decrease by 62% in per capita CF for the middle income compared with the lowest income group. The effect of difference in household size between middle and highest income groups is even bigger, due to the much larger per capita CF of highest income group. The effect of household consumption patterns on the difference on per capita CF between lowest and middle income groups is almost negligible compared with the effects of the other two factors, but it plays a more important role in the difference between middle and high income group CFs. Per capita CF for the middle income group may decrease by 40% when controlling for household consumption patterns. This result also reflects the small difference in consumption patterns between the lowest and middle income household groups but a much bigger difference between the middle and the highest income groups.

4. Discussion and conclusions

To tackle global climate change, it is desirable to reduce GHG emissions associated with household consumption of high carbon footprint households in both developing and developed countries (Hubacek et al., 2017). In developed countries, even lower-income households fall into the global category of high carbon footprint households. Per capita consumption-based emissions of a US household is about 18.1 tons on average, which is higher than for most other countries in the world (Davis and Caldeira, 2010; Feng et al., 2015). Even if we only look at the lowest income group in the US, their per capita carbon footprint is more than 10 tons, which is much higher than the global average of 5 tons per capita (World Bank, 2019). Per capita CF across income groups in the US is also higher when compared with per capita CF in other rich countries, largely due to their higher dependency on Utilities and Petroleum products for heating and cooling and driving.

For the carbon inequality across different income groups within the US, this study reveals that the per capita carbon footprint (CF) of the highest income group (More than 200k) with 32.3 tons is about 2.6 times the per capita CF of the lowest income group (Less than 15k) with 12.3 tons in 2015. This finding is similar to Song et al. (2019) which showed that US household carbon footprint ranged from 12.1 (5–10 thousand USD) to 28.6 (>150 thousand USD) tCO_2eq per capita (tCO_2e/cap) in 2009, and Jones and Kammen (2014) with a range of 16.2–19.5 tCO_2/cap for Metropolitan Statistical Areas. The differences are due to a range of factors such as the use of different databases, different income group categories, different study periods, and the types of emissions included in these studies. Our results show 23% of variation in carbon intensity of consumption across income groups, much less than the variation in income. Our results reflect that the lifestyle of higher income households is more dependent on private transport, while lower income households spend a larger share of their income on basic needs, such as heating and cooling and food.

At the global level, US household consumption across income categories is very carbon-intensive, given that even the lowest income group (<15k) has a carbon footprint of 2.3 times the world average. While higher income households tend to consume more low-emission intensive service products such as Education and Leisure activities, our index decomposition shows that a larger share of expenditure on services contributed little to narrow the gap between low and high-income groups. The large gap in per capita CFs between low and high-income groups is largely due to the difference in the overall level of consumption. Higher income households tend to spend more on everything.

For carbon taxes and cap and trade systems it is important to know who causes emissions and why. Our results show that more than 20% of the household carbon footprint occurred outside the US. As higher income groups tend to cause a higher share of their carbon footprint in foreign countries, without carbon tax adjustments for imported goods, a significant portion of the carbon emissions for US household consumption would be excluded and thus higher income group would pay less for their emissions than their fair share, given their consumption structure and volume. In addition, lower income households spending a larger share of their income on carbon-intensive necessities of daily living would be hit harder by carbon mitigation policies. Therefore, climate mitigation policies need to take into account distributional effects on different income groups (Feng et al., 2018; Vogt-Schilb et al., 2019).

CRediT authorship contribution statement

Kuishuang Feng: Conceptualization, Methodology, Data curation, Investigation, Formal analysis, Writing - original draft, Writing - review & editing. **Klaus Hubacek:** Supervision, Formal analysis, Writing - original draft, Writing - review & editing. **Kaihui Song:** Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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