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Assessing U.S. consumers' carbon footprints reveals outsized impact of the top 1%

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ABSTRACT

Unsustainable environmental degradation and extreme economic inequality are two of humanity's most pressing challenges. They are intimately linked. Climate-altering greenhouse gas (GHG) emissions are disproportionately driven by consumption among wealthy and socially privileged groups, yet poorer and socially marginalized peoples face disproportionate climate harms. Here we use the Eora MRIO database and Consumer Expenditure Surveys to quantify GHG emissions related to goods and services consumed by United States households between 1996 and 2019 - including construction of a synthetic dataset to estimate top 1% and top 0.1% household emissions. Top 1% households are of particular interest because their emissions have been largely missed or simplistically and inaccurately estimated in past analysis, yet they exert disproportionate political power in shaping U.S. climate policy. Results suggest significant GHG inequality across economic class and racial lines. In 2019, we estimate the U.S. top 0.1% had emissions (955 t CO_2e) 57× higher than bottom decile U.S. households and 597× higher than an average low-income country household. White non-Hispanic household emissions were 1.3× higher than Black households. If climate policy does not account for such extreme emissions disparities, it will limit effectiveness, erode public support, and disproportionately harm economic and socially marginalized groups.

1. Introduction

Even if the Nationally Determined Contributions (NDC) of the Paris Agreement are realized, global annual greenhouse gas (GHG) emissions, in 2030, are projected to be 124% higher than what is needed to limit global temperature rise to 1.5 °C (United Nations Environmental Program, 2020). These emissions occur to provide goods, services, and wealth to people around the world (Díaz et al., 2019). Yet significant economic inequality, both within and between countries, results in a powerful disconnect between the groups who reap these benefits and those that are left to deal with the harms caused by excessive GHG emissions, i.e., global climate change. Poorer and socially marginalized peoples tend to be the most impacted by climate change and other environmental degradation (Althor et al., 2016; Ash and Boyce, 2018; Diffenbaugh and Burke, 2019; Hsiang et al., 2017; Intergovernmental Panel on Climate Change, 2014; Islam and Winkel, 2017; King and Harrington, 2018; Leichenko and Silva, 2014) yet environmental change is disproportionately driven by, and for the benefit of, those with the most resources and social privilege (Feng et al., 2021; Hoegh-Guldberg et al., 2019; Moran et al., 2020; Song et al., 2019; Tessum et al., 2019; Wiedmann et al., 2015).

It is widely accepted as a basic principle of fairness that those benefiting from an activity, like the GHG emissions that drive climate change, should bear some responsibility in mitigating the damage caused by those activities. This idea was central to the creation of "loss and damage" funding at the recent United Nations Climate Change Conference (COP27). From the international community's first attempt at collective climate action, the 1992 United Nations Framework Convention on Climate Change (UNFCCC), through the 2015 Paris Agreement and COP27, climate responsibility has largely been

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conceptualized as national-level responsibility for emissions *produced within* a country's territory. However, the continued globalization of supply chains, since the UNFCCC, means that significant emissions may occur in one country to create goods and services that are exported around the globe. To account for this, an alternative *consumer* responsibility framework has been developed over the last few decades (Afionis et al., 2017; Bicknell et al., 1998; Büchs and Schnepf, 2013; Davis and Caldeira, 2010; Feng et al., 2021; Ghertner and Fripp, 2007; Hertwich and Peters, 2009; Jones and Kammen, 2011; Lenzen, 1998; Moran et al., 2020; Song et al., 2019; Weber and Matthews, 2008). This calculates a nation's responsibility based on emissions that occur anywhere in the world to produce the goods and services *consumed* within a country's territory.

Because goods and services ultimately flow to people, consumption-based emissions responsibility can be traced to individual households, including those at the top of the income distribution who have an outsized role in shaping U.S. public policy (Gilens and Page, 2014). If society is to develop effective and just climate policies it is critical to understand how emissions are distributed across the whole of U.S. society, including among those who have disproportionate power to determine climate outcomes.

Below, we present results from a highly granular time series analysis (1996–2019) of consumption-based U.S. household GHG emissions. For each year, we employ an Environmentally-Extended Multi-Region Input-Output Model (EE-MRIO) to calculate the GHG emissions embodied in 10,211 commodities across 190 countries (> 100 million inter-sectoral transfers per year). The embodied emissions in these goods and services are tracked to final-demand household-level purchasing from a mostly nationally representative[1] sample of ~14,500 U.S. households per year. Expenditures for *top 1%* and *0.1%* households, which are under-sampled in the underlying survey data, are also estimated by constructing a synthetic dataset. Direct household emissions, such as vehicle fuel use and home heating, are also accounted for. To reveal how income inequality relates to inequality in emissions footprints, households are binned into income deciles, including a disaggregation of the top decile into the *next 9%* (90.0th - 99th percentile) and *top 1%* (99.0th - 100th percentile), and a further disaggregation of the *top 1%* into the *next 0.9%* (99.0th - 99.9th percentile) and *top 0.1%* (99.9th - 100th percentile) of income earners.

1.1. *Literature review*

The consumption-based GHG emissions of U.S. households, at different income levels, has previously been investigated using bottom-up emissions approaches. Here household-level or decile-level expenditure data is matched with consumption-based GHG emissions, per dollar, across various expenditure categories. Weber and Matthews (2008), Jones and Kammen (2011), Song et al. (2019), Sager (2019), and Feng et al. (2021) respectively report top income groups up to around \$100,000, >\$120,000, >\$150,000, >\$180,000 and > \$200,000. While these capture relatively affluent households, all are far below the minimum needed to count as a *top 1%* U.S. household (\$547,000) and well below the average income of that group (\$1.5 million). A working paper by (Umell, 2014) breaks out top 2% U.S. households. Yet this and all bottom-up studies, to date, rely on Consumer Expenditure Surveys (CEX) that under-sample *top 1%* households and thus have very likely underestimated emissions for the top income groups they report.

In contrast to the bottom-up approach, working papers by Chancel and Piketty (2015) and a report by Oxfam and the Stockholm Environmental Institute (SEI) (Kartha et al., 2020) employ a top-down approach. Using national average income and emissions as a starting point, the studies apply a constant income to CO_2e elasticity across the income distribution. Chancel and Piketty use an elasticity of 0.9 and estimate the *top 1%* of the U.S. income distribution is responsible for 318 t[2] CO_2e, per-person. The Oxfam/SEI report sets a constant elasticity of 1.0, a minimum emissions floor and a maximum emissions ceiling. They estimate the U.S. *top 1%* has a per capita footprint of 192 t CO_2. While top-down studies require far less data their high and constant elasticity and broad assumptions do not accurately capture how carbon intensity varies significantly across the income distribution.

Finally, it is also worth noting work by Otto et al. (2019) and Barros and Wilk (2021) who focus solely on high net worth (HNW) individuals' emissions. Otto et al. interviews three HNW individuals (with investible assets >\$1 million) and a pilot to estimate emissions of 129 t for a two-person HNW household. Barros and Wilk draw on a variety of data sources to estimate dwellings, travel, and superyachts emissions for 20 billionaires. They find average emissions of 8194 t per billionaire. While interesting, both studies have very small sample sizes and are not U.S. focused. The huge range between entry-level millionaire's emissions and billionaires' emissions also suggests more investigation is needed on households between these extremes.

2. Materials and methods

We combine an EE-MRIO, direct emissions data, CEX, and income data to link global GHG emissions with the goods and services consumed by U.S. households.

2.1. *Embodied emissions - background*

IO modeling, including EE-MRIO, is grounded in the work of Wassily Leontief (Leontief, 1970) who formalized calculating the output of an economy as the sum of intermediate (industry to industry transactions) and final demand

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

where x is total output, A is a technical coefficient matrix of the economy's production function, and y is final demand consumption. Using matrix notation this is written as

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

Or in matrix equation form it is

$$x = (I - A)^{-1} y \tag{3}$$

where I is an identity matrix and $(I - A)^{-1}$ is the Leontief inverse matrix (often written as L), which captures all direct and indirect inputs used to create one unit of final demand output.

This is extended to environmental applications by treating them as an input to production. For example, GHG reporting allows for the estimation of t CO_2e directly emitted by each industry. These direct emissions, f, are divided by output per industry to obtain t CO_2e per unit of output

$$e = f \times \widehat{x}^{-1} \tag{4}$$

where e is a vector of the direct environmental intensity (here CO_2e emissions per unit of output), from each sector. The "∧" above x indicates matrix diagonalization. Matrix inversion, −1, is used for division with matrices. This direct intensity is then multiplied by L and y

$$Q = \widehat{e} \times L \times \widehat{y} \tag{5}$$

[1] Note, the underlying survey used in our analysis is considered "nationally representative", but there is a known undercount of high-income households. See *2. Materials and Methods* for how we address this.

[2] (t) denotes metric tons and is used as shorthand for metric tons CO_2e

which yields Q: a matrix of all direct and indirect CO_2e emissions from each sector. Summing each column of Q gives the total consumer-based CO_2e of each industry, summing each row of Q yields the direct producer-based emissions. Finally, by dividing elementwise Q column sums by the row sum of total final demand for that sector, y, one obtains the t CO_2e per dollar of final demand (also referred to as CO_2e intensity) of each global commodity.

2.2. Embodied emissions – data source

To calculate the embodied CO_2e intensity of goods and services consumed by U.S. households, we use the Eora MRIO database (Lenzen et al., 2013; Lenzen et al., 2012) covering 14,839 sectors, across 190 countries, with 1140 final demand and value added categories. For each year, we convert EORA from a heterogeneous classification system to a square 10,211 sector commodity by commodity input-output table, using the Industry Technology Assumption, and convert current year dollars to *constant* 2020 US$. The number of sectors per country varies from a low of 26 for smaller economies to a high of 511 for the United Kingdom. The U.S. has 429 unique sectors in Eora. Direct production-based CO_2e emissions data, from the PRIMAPHIST database (available in Eora), for six Kyoto GHG (Gütschow et al., 2016), are converted to embodied emissions per dollar of final demand using the Leontief inverse (Feng et al., 2021; Lenzen, 1998; Leontief, 1970; Song et al., 2019; Weber and Matthews, 2008; Wiedmann et al., 2015). This captures all *direct* and *indirect* CO_2e emissions, along the whole supply chain ($>$ 100 million inter-sectoral transfers each year), that were used to produce a dollar output to final demand.

2.3. Consumer expenditure surveys

For each year, these supply chain and direct emissions factors are matched with household-level expenditure data from the U.S. Bureau of Labor Statistics (BLS) CEX. CEX is a mostly representative U.S. national sample of about 14,500 unique households (consumer units) each year, capturing about 90–95% of consumer expenditures (United States Bureau of Labor Statistics, 2018). From the full CEX dataset, we extract 83 detailed expenditure categories[3] and 74 variables related to income, geographic location, and demographics. Each year yields a matrix of ~1,200,000 expenditure data points and ~ 2,300,000 total data points. Dollars are converted from current year dollars to *constant* 2020 US$.

2.4. Linking global commodity carbon intensities with U.S. households

For each household, purchases from each of the 83 CEX goods and service sectors are linked to the carbon intensity (t CO_2e per US$ final demand) of that sector, from Eora. This is done via a 10,211 × 83 concordance matrix, where all Eora and CEX commodities are manually coded to the uniform International Standard Industrial Classification (ISIC) system and sectors are matched. The CO_2 intensity of each CEX commodity reflects the unique mix of domestic production and imports that fulfill U.S. household final demand. For each CEX commodity, this is done by first calculating the percent of U.S. household final demand from each Eora commodity row (i.e. the market share). Each row's market share percent is then multiplied by the corresponding carbon intensity of that Eora commodity and the product is summed. Multiplying this market share-adjusted carbon intensity, per CEX category, by each household's expenditure dollars on that category yields each household's total emissions per CEX category. Summing across all categories and adding direct use emissions, yields each household's total consumption-based footprint (t CO_2e) (see *Appendix* for treatment of vehicles).

2.5. Consumer use phase emissions for fuel

While consumption-based EE-MRIO accounting calculates all direct and indirect supply chain emissions, for a commodity, up to the point of sale to the consumer, it does not include emissions from use of that commodity by the consumer. Direct emissions by the consumer, during the use phase, are important for commodities like automotive fuels and home heating fuel that are combusted by the consumer. Combustion CO_2e emissions factors, per physical unit of fuel (units vary by fuel type), were obtained from the U.S. Environmental Protection Agency for gasoline, natural gas, heating oil, propane, and wood (United States Environmental Protection Agency, 2020). CO_2e intensities per physical unit were converted to CO_2e intensity per US$ using annual price data obtained from the Energy Information Administration. Monetary data for gasoline and natural gas were adjusted using state or regional price data per $ of physical unit. Prices for fuel oil, propane and wood were only available at the national level. However, for 2008 onward, these were adjusted based on state and metropolitan status using Price Parity by Portion (PARPP). For each household, the total embodied supply chain emissions plus use phase emissions for a fuel (here gasoline is presented as an example) becomes

$$H_{Gas}\,TOTAL = S_{Gas} \times E_{Gas} + U_{Gas} \times E_{Gas} \tag{6}$$

where $H_{Gas\ Total}$ is total household t CO_2e related to the full supply chain and use phase emissions of that household's gasoline consumption. S_{Gas} is the U.S. market share adjusted CO_2e intensity of all direct and indirect supply chain emissions in creating one dollar of gasoline up to the point of sale to a U.S. consumer. U_{Gas} is the CO_2e intensity when that gasoline is used by the consumer (i.e. when it is combusted in their vehicle). E_{Gas} is consumer gasoline expenditure in dollars.

2.6. Regional price parity adjustments

Prior to 2008, electricity and direct energy use CO_2e intensities per dollar were regionally adjusted, as data allowed, but no regional price adjustments data were available for other expenditure categories. For 2008 onward, all expenditure categories are regionally adjusted using the Bureau of Economic Analysis (BEA) Price Parity by Portion (PARPP). For each household, this makes region-specific price adjustments based on type of expenditure, state, and urban or rural status. For electricity expenditures, the *national* CO_2e intensities are replaced with state-level multipliers that reflect the CO_2e intensity of the local electric grid, in the relevant year (United States Energy Information Administration, 2021; United States Environmental Protection Agency, 2021).

2.7. Estimating top 1% household expenditures

While CEX is the most authoritative source on U.S. household expenditures, it has a known underreporting bias from high-income households (Sabelhaus et al., 2013). For example, in 2019, a CEX *top 1%* household earned at least $399,000 and had an average income of $525,000. Meanwhile, the World Inequality Database (WID) estimates a *top 1%* U.S. household earned at least $554,000 and had an average income of $1,520,000 (World Inequality Database, 2021).[4] This is a $1000,000 difference in the average. To account for this significant under-sampling in CEX, we employ a novel approach where we create synthetic datasets for the *next 0.9%* and *top 0.1%* households with income data from WID and expenditure data from CEX (see the *Appendix* for a detailed methodology and discussion of how under sampling of CEX households in the *next 9%* group is addressed).

For both the *top 0.1%* and *next 0.9%* income groups, we estimate

[3] These are compiled from several hundred lower-level expenditure categories

[4] To better match the household units used in CEX, we convert World Inequality Database estimates from adults to tax units.

expenditures by first creating a distribution of 1000 households, per group, whose mean pre-tax income and upper and lower bounds matches that reported by the WID and whose distribution is right-skewed to reflect the income inequality within these groups. This yields a pre-tax income distribution of 1000 households for each group.

To estimate each household's post-tax income, a distribution of tax rates is derived from *top 1%* households in the Current Population Survey (CPS). CPS rates were used because it has a more robust sampling of *top 1%* U.S. households than CEX. This distribution of tax rates is applied to each of the synthetic distributions and subtracted, yielding post-tax income estimates for each household. Savings rates, the difference between a household's post-tax income and their expenditures, are then applied. To do this, for each year we extract savings rates from CEX households that meet that year's WID *top 1%* threshold (CEX-WID top 1%). We investigated whether the savings rate should increase with income but did not find a statistically significant relationship for that approach. Instead, we use the savings rate mean and standard deviation rates from CEX-WID top 1% households to generate a savings rate distribution for the *next 0.9%* and *top 0.1%* households. We discovered however that under-sampling of these households in CEX resulted in sporadically high year-to year variability in savings rates. To address this, we ran a loess regression on the savings rate time series and assigned these estimated values back to each year. This had limited impact on the average results but reduced wild year to year savings rate swings (see Appendix: *A2.2.3. Savings Rates*).

For *top 0.1%* households we use a baseline savings rate estimate that is 25% higher than the *next 0.9%* value. We do this to reflect the higher savings that are possible for these extremely wealthy households. This results in *top 0.1%* savings rates between 56 and 69% across the years and a 24-year average of 59%. We tested the sensitivity of our results to savings rate choice by running the model with a mean *top 0.1%* savings rate 25% lower, equal to, 50% higher, and 75% higher than the *next 0.9* savings rate (see *4.3 Limitations and Sensitivity Analysis*). We also tested two linear relationships between income and savings rates (see *A2.2.3. Savings Rates* in the *Appendix*).

Once taxes and savings rates are subtracted, the remaining dollars are considered total expenditures. To allocate these total expenditure dollars across the 83 CEX expenditure categories, we bootstrap CEX-WID top 1% households into a distribution of 1000 households. To simulate a broader range of household spending differences than what is present in the CEX sample, we apply a randomization algorithm that calculates each household's percent of expenditure, per category, while allowing each expenditure category to vary ±50%, from the original bootstrapped value. At the same time, each household's total expenditures are constrained to a sum of 100%. Finally, these estimated percentages, per expenditure category, are multiplied by the synthetic dataset's expenditure dollars. This yields dollars, per expenditure category estimates, for *next 0.9%* and *top 0.1%* groups. *Top 1%* CO_2e estimates come from a weighted average of the *next 0.9%* and *top 0.1%* groups.

While applying a randomization to each expenditure category moves the data away from the original CEX-WID top 1% values, the advantage is it helps account for natural variability in spending across households. Not applying any randomization would assume that all *top 1%* households' expenditures exactly match those of the CEX-WID top 1% sample. To quantify robustness, we tested the effect of various randomization limits (± 0%, 25%, and 50%). The feasibility of very high emissions estimates (our so called "super emitter" group) was also cross checked via a separate estimation of ultra-luxury good emissions and comparison with Barros and Wilk (2021).

3. Results

3.1. Time series: 1996–2019

From 1996 to 2019, national average household emissions declined 16%, from 49.4 to 41.7 t CO_2e (t). Deciles 1–9 show net declines between 16 and 23%. Decile 10 likewise shows an overall decline (6%). However, when decile 10 is broken into the *top 1%* and *next 9%,* we find an interesting divergence. The *next 9%* behaves like deciles 1–9 and declined 14%. Conversely, we estimate the *top 1%* emissions *increased* 23%. This is dominated by the *top 0.1%* increasing emission 50%, while the *next 0.9%* increased 9%. Indeed, across the full 1996–2019 time period, the emissions difference between the *top 1%*, particularly the *top 0.1%*, and everyone else is quite striking (Fig. 1). Our results suggest the *top 0.1%* consistently has annual emissions above 800 t, while bottom 99% household emissions are concentrated between 15 and 100 t.

3.2. Most recent year (2019)

In 2019, the most recent year for which we have data, we estimate U.S. household carbon emissions ranged from ~0 to over 3000 t (Fig. 2). Grouping households into income groups, we see an interesting 30–50 relationship at the top and bottom of the distribution. The top 30% of the population (deciles 8–10) were responsible for 50% of consumption-based U.S. national emissions (NE) while the bottom 50% of the population (deciles 1–5) were responsible for only 31% NE (Fig. 3). We estimate the top decile alone accounted for 24% NE ($\bar{x} = 98$, $\tilde{x} = 77$ t). Within decile 10, results suggest the *next 9%* drove 17% NE ($\bar{x} = 81$, $\tilde{x} = 74$ t) and the t*op 1%* accounted for 6% NE ($\bar{x} = 252$, $\tilde{x} = 169$ t). We estimate the *next 0.9%* accounts for 3.7% NE ($\bar{x} = 174$, $\tilde{x} = 155$ t) and the *top 0.1%* contributes 2.3% NE ($\bar{x} = 955$, $\tilde{x} = 777$ t). Using a bootstrap approach, we find mean 95% confidence intervals of 168–178 t for the *next 0.9%* and 914–996 t for the *top 0.1%* groups. Given inherent uncertainties in income, tax, savings, expenditures, and CO_2e intensities we also calculate a ± 20% error reference point from these CI upper and lower bounds, for each income group (grey bars in Fig. 3, see details and justification in section *4.3. Limitations and Sensitivity Analysis*). This yields a range ± 21–25% from the original group mean. For the *next 0.9%* and *top 0.1%* these larger error references encompass a range from 135 to 214 t to 731–1195 t.

The absolute difference in emissions, between groups, is stark. Yet comparing each groups population share to its income share reveals the scale of inequality. For example, decile 1 accounts for 10% of the U.S. population, yet only 4% of emissions. Their share of emissions is 0.4× lower than one would expect with an equitable distribution. Meanwhile we estimate the *top 0.1%* has an emissions share 23× higher than their population share and 57× higher than a bottom decile household.

These household footprints are critically shaped by the types of goods and services purchased. In 2019, our results indicate purchases from *Transport* and the *Utility and Home Energy* categories accounted for 12% of expenditure dollars, from average *top 1%* households (Fig. 4A); yet contributed 33% to the household's emissions footprint (Fig. 4B). Meanwhile, we estimate expenditures related to the *Finance and Insurance (non-health)* and *Home* categories accounted for 51% of their expenditure dollars, but only 40% of their emissions footprint. Households at a given expenditure level may thus have very different footprints, based on the types of goods and services purchased. Across groups, the CO_2e intensity of low-income household expenditures tends to be higher (1.4×) than upper income households as their consumption is dominated by carbon intensive necessities.

3.3. Relationship to racial inequality

The bottom income decile, which was responsible for 4% NE, in 2019, is 19% Black (the highest share in any decile), 14% Hispanic, and 58% White non-Hispanic (the lowest share in any decile). The top decile, responsible for 24% NE is 4% Black (the lowest share in any decile), 5% Hispanic, and 79% White non-Hispanic (the highest share in any decile). Across all economic groups, we estimate Black households had average footprints of 33.5 t, White Hispanic households averaged 38.6 t, and White non-Hispanic households averaged 43.7 t. The fact that White

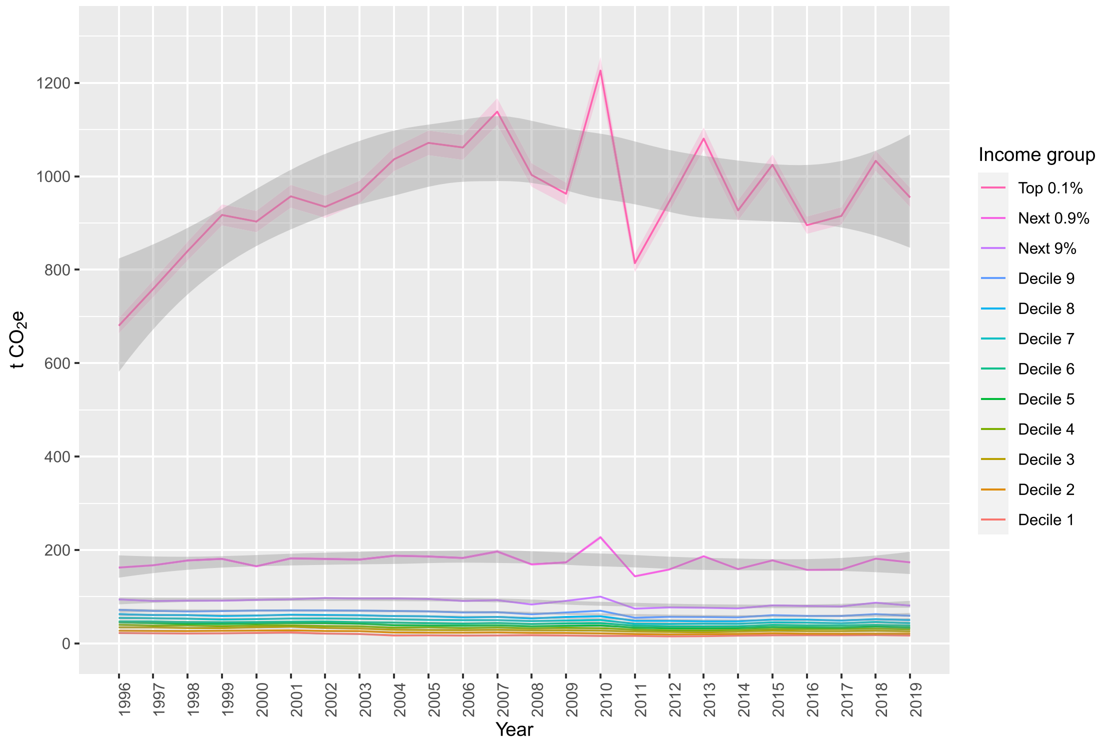

Fig. 1. Mean household carbon footprint (1996–2019) per income group. Colored shading is standard error calculated annually for each income group. Grey shading is 95% confidence interval from loess regression on the time series. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

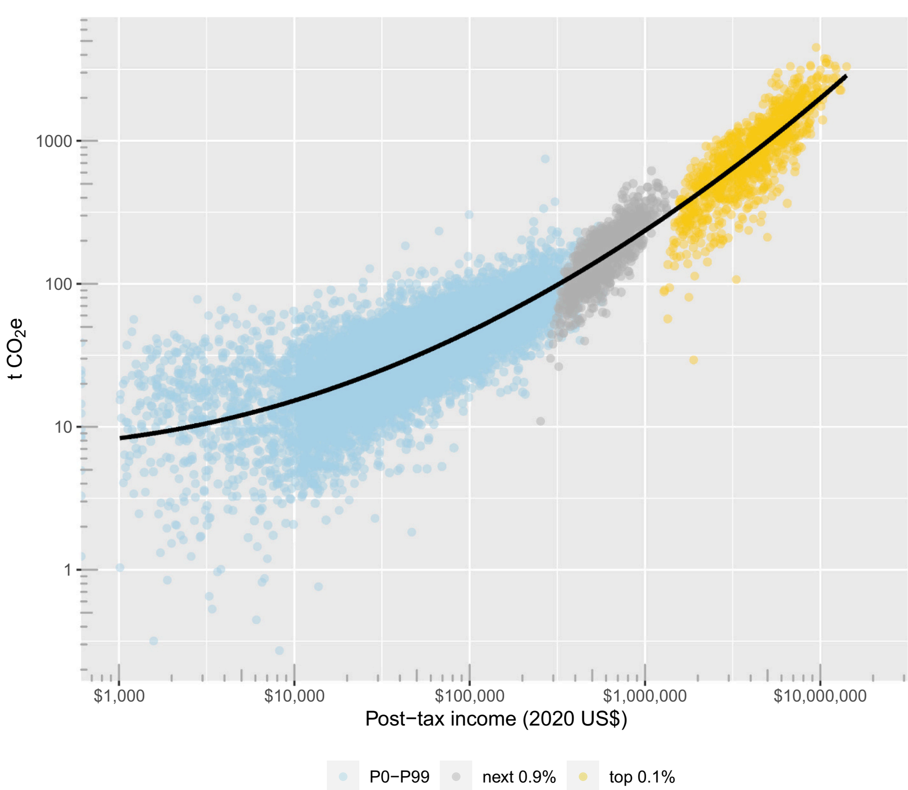

Fig. 2. Post-tax income versus household emissions (2019) with a quadratic polynomial trendline (black). Income percentiles 0–99 (i.e. the bottom 99%) from CEX are presented in blue. The synthetic CEX-WID distributions for the *next 0.9%* and *top 0.1%* are grey and gold. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

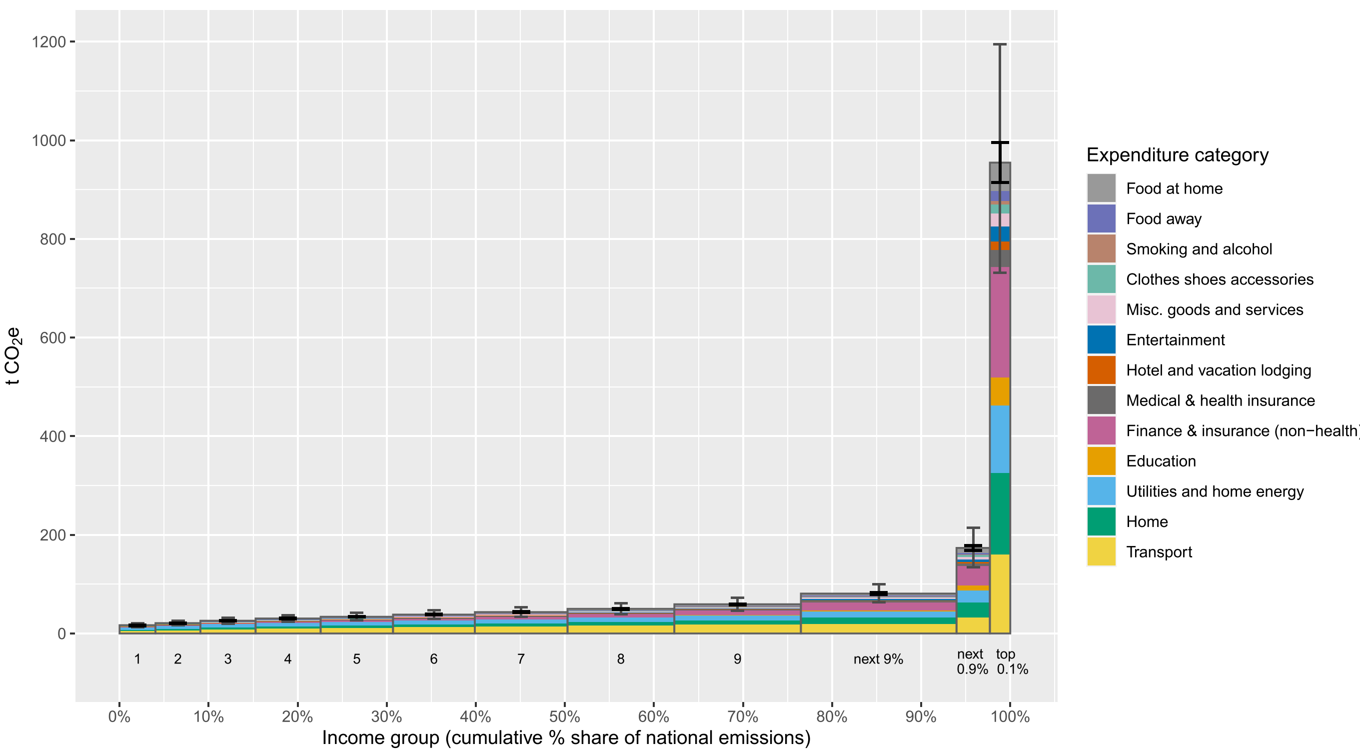

Fig. 3. Mean household emissions (2019) per decile (1–9), *next 9%*, *next 0.9%*, and *top 0.1%*. The width of each income group, on the x-axis, corresponds with its share of consumption-based national emissions. Colors denote mean contribution from each expenditure category. Note: black error bars are bootstrapped 95% confidence intervals for each income group's total mean footprint. Grey bars are ±20% reference point from the upper and lower bootstrapped CIs. Top 1% results are presented in the Appendix (Fig. A11). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

non-Hispanic households had mean emissions 13% higher than Hispanic households and 31% higher than Black households reflects how economic inequality spills over into emissions inequality. This disparity is particularly stark when considering that while poor and racially marginalized communities are least responsible for climate change they are disproportionately vulnerable to the harms caused by it.

3.4. *Super emitters*

For 2019, we estimate 1.5% of the *top 0.1%* households have emissions over 3000 t CO_2e ($\bar{x} = 3443$, $\tilde{x} = 3345$). We term these households "super emitters" and our results indicate about 1900 out of ~130 million U.S. households fall into this super-emitter category. For context, there are over 5000 U.S. households worth >$100 million and over 700 U.S. billionaires.

Even though super emitters make up only a tiny fraction of households and have almost no impact on the *top 0.1%* average, we investigate whether such high estimates are feasible. To cross-check their validity, we independently estimate per household emissions related to luxury goods that are principally or only consumed by *top 1%* households. These include large mansions or multiple large homes, first class air travel, private jets, and superyachts (see *Appendix* for methodology). We also compare our results to Barros and Wilk (2021).

Construction of 40,000 square feet of living space (either in one large home or multiple homes) emits ~1688 t CO_2e. Yet, because these emissions are amortized over an estimated 50 year home lifespan, *annual* emissions, from initial construction, are only about 34 t. Emissions related to home electricity and utilities also add about 95–122 t, per year, for 40,000 square feet of living space. Our estimate is conservative when compared to calculations based on a separate study by Goldstein et al. (2020) which suggest this amount of electricity related emissions is equivalent to about 24,000 square feet of housing. These estimates offer reasonable agreement with our finding that in 2019 *top 0.1%* households had annual emissions related to utilities and home energy of 136 t.

Emissions from first class air travel can add up to 100 t for an average sized family travelling on 3–5 long haul flights per year. We estimate annual fuel-related emissions from private jets, whose ownership and use are concentrated within extremely wealthy households, average about 1172 t per jet. On the seas, we estimate average annual emissions from motorized superyachts (30+ meter) to be about 1150 t per vessel. These estimates are based on about 290 flight hours per year and 42 days on the seas. For both jets and super-yachts, individual emissions can of course be even higher if the asset is larger than average or used more frequently. Adding these extreme luxury emissions together with emissions related to home furnishing, travel, food, finance, and all other categories GHG footprints >3000 t per year seem quite rare but feasible.

As a final check, we compare our results to an interesting study on billionaire carbon footprints by Barros and Wilk (2021). They find emissions related to dwellings averaged 189 t per year, superyacht emissions average 7018 t per vessel, and private jet and other transportation emissions average about 2700 t. Overall they estimate total annual footprints averaged 8194 t per billionaire. When considering there are over 700 billionaires in the U.S. *top 0.1%*, their findings suggest that our super emitter results are reasonable and possibly conservative.

4. Discussion

4.1. *Comparison with prior studies*

While our national average results are comparable to prior work (see *Appendix*), our sub-national results are not directly comparable to most prior U.S. bottom-up studies because they either use less granular quintile groups or create groups based on dollar value ranges. It is worth noting though those prior studies using CEX data likely under-report their top income group's emissions since they are relying on a source

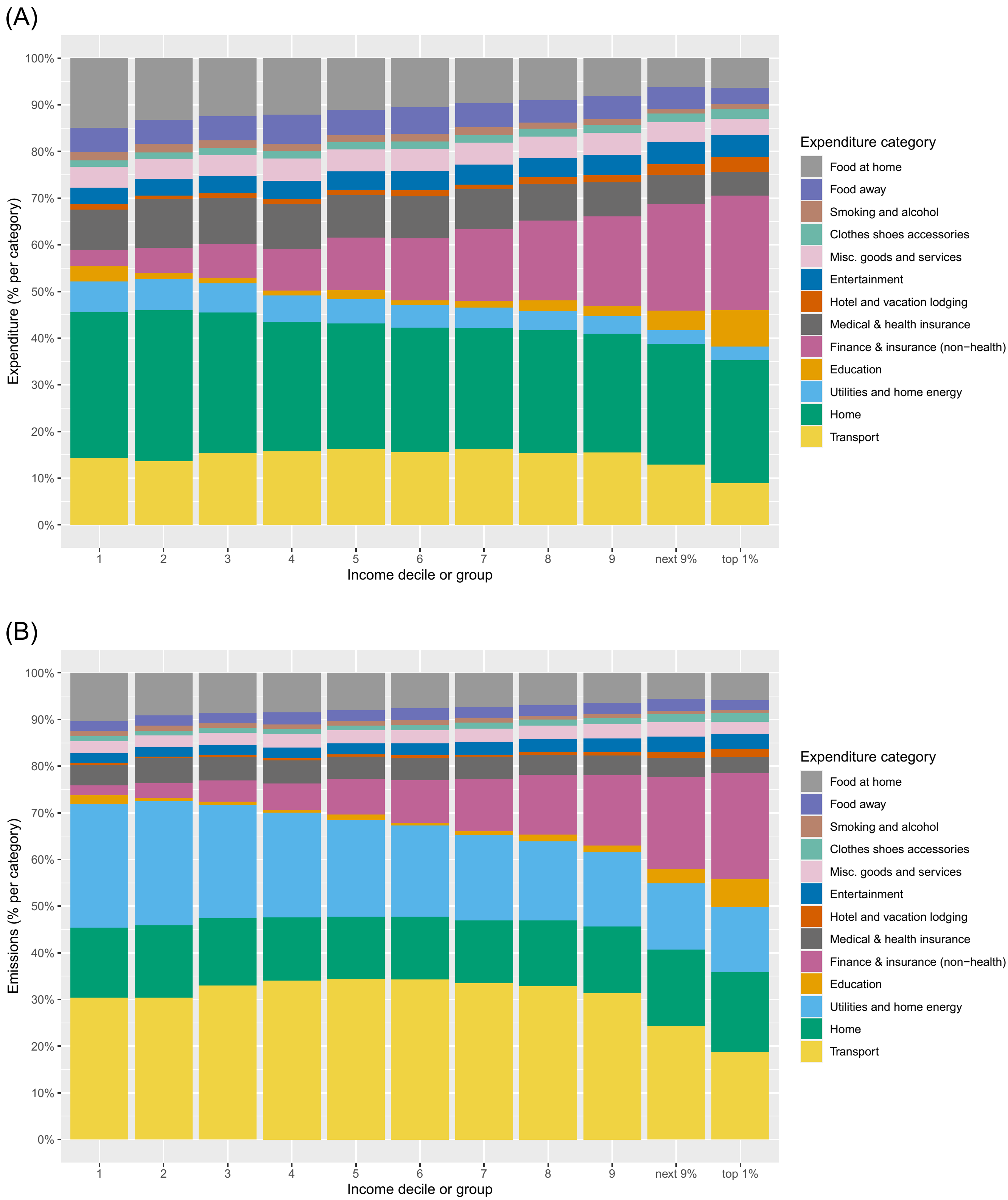

Fig. 4. (A): Expenditure percent per expenditure category, by income group (2019). (B): Emissions percent per expenditure category, by income group (2019). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 1
The share of pre-tax national income, expenditure, and emissions (2019) captured by each income group, when calculated using unadjusted CEX (raw) data and our CEX-WID top 1% adjusted data. WID pre-tax income data is also included for comparison.

	National income (pre-tax) (% share)			National expenditure (% share)		National emissions (% share)	
Income group	**CEX** (raw)	**CEX-WID** (synthetic top 1%)	**WID**	**CEX** (raw)	**CEX-WID** (synthetic top 1%)	**CEX** (raw)	**CEX -WID** (synthetic top 1%)
Decile 1	0.8	0.7	0.3	3.9	3.7	4.2	4.0
Decile 2	2.1	1.8	1.7	4.7	4.5	5.3	5.0
Decile 3	3.3	2.9	2.8	5.8	5.5	6.5	6.2
Decile 4	4.6	4.0	3.8	6.9	6.6	7.6	7.3
Decile 5	6.0	5.3	5.1	7.8	7.5	8.5	8.1
Decile 6	7.8	6.8	6.6	8.9	8.5	9.6	9.2
Decile 7	10.0	8.7	8.3	10.6	10.1	10.8	10.4
Decile 8	13.0	11.4	10.8	12.6	11.9	12.5	12.0
Decile 9	17.9	15.7	15.0	15.1	14.3	14.8	14.2
Next 9%	28.5	27.0	26.6	20.4	20.1	17.6	17.5
Next 0.9%	5.4	8.6	10.6	2.8	4.5	2.3	3.7
Top 0.1%	0.8	7.0	8.5	0.4	2.8	0.3	2.3

that significantly underestimates top income group income and expenditures (Table 1).

For instance, the *top 0.1%* income share reported by WID is 10.3× larger than the CEX raw data value for that group. Running our model with the unadjusted raw CEX values suggest the *top 0.1%* account for 0.3% of NE ($\bar{x}$ = 157 t). Meanwhile, our CEX-WID top 1% adjusted model estimates the *top 0.1%* group is responsible for >6× more emissions (2.3% NE, $\bar{x}$ = 955 t). The CEX-WID adjusted model also shows *top 1%* and top decile results are about 2× and 1.2× higher than the unadjusted model. While these results do not dramatically change our understanding of the U.S. national average, they suggest that previous studies' high income group emissions are likely underestimated. The effect of this underestimation increases the further up the income ladder one looks. They also reveal a scale of emissions disparity within U.S. society that has not previously been well quantified. While an unadjusted CEX analysis suggests the *top 0.1%* has emissions 10× higher than an average bottom decile household we suggest this politically powerful group's emissions are closer to 57× higher.

While no prior bottom-up studies explicitly include U.S. *top 1%* and *top 0.1%* percentiles, there have been some top-down studies of these groups. These studies are notably different from ours in terms of methodology and data sources, but a comparison is useful since these are the works currently informing public debate. For alignment with these studies, here we report our NE and *per-capita* emissions for 2015. We find the bottom 50% was responsible for 31% NE and had a per-capita footprint of 16 t. Oxfam/SEI reports 7 t and 21% NE for this group (Kartha et al., 2020). Meanwhile our decile 10 (23% NE, 37 t) and *top 1%* (6% NE, 93 t) estimates are much lower than their decile 10 (35% NE, 64 t) and *top 1%* (11% NE, 193 t). It is also much lower than the 318 t per capita *top 1%* value reported by (Chancel and Piketty, 2015). Finally, our *top 0.1%* (2% NE, 365 t) agrees well with the 2% NE share reported by Kartha et al. (2020), but is higher than their 300 t estimate, which is their arbitrary emissions cap.

Our top decile and *top 1%* results are much lower, and our bottom 50% estimates are higher than what is suggested by top-down studies because these studies estimate emissions using a constant and relatively high income to emissions elasticity value that is applied across the entire income distribution. As (Pottier, 2022) shows in his review, prior U.S. bottom-up studies estimate mean income to CO_2e elasticity between 0.31 - <0.58, yet the top-down studies use values of 0.9, and 1.0. For comparison, in 2019, we find mean point income to CO_2e elasticity values of 0.32 (pre-tax) and 0.43 (post-tax). A constant income to emissions elasticity also misses variability in this relationship that can distort estimates at the top and bottom of the income distribution. We believe our highly granular household-level approach that explicitly models *top 1%* households and captures variability in carbon intensity across the income distribution offers a significant methodological improvement, over previous efforts.

4.2. Relationship of emissions inequality to income inequality and carbon intensity

Our results show significant emissions inequality within U.S. society. In 2019, the bottom 50% of the population was responsible for 31% NE, while the top 10%, *top 1%*, and *top 0.1%* were respectively responsible for 24%, 6%, and 2.3% NE. Yet, the income that enables consumption-based emissions is even more inequitably distributed (Sommer and Kratena, 2017). In 2019, the bottom 50% of the population captured just 14% of pre-tax national income, while the top 10%, *top 1%*, and *top 0.1%* captured 46%, 19%, and 8.5% of pre-tax national income (World Inequality Database, 2021). The Gini coefficient for the emissions distribution is 0.35. For comparison the U.S. income distribution Gini coefficient is 0.49.

Emissions are less unequal than pre-tax income because progressive taxation, variable savings rates, and social welfare programs decouple income from expenditures (Table 2). Among low-income households, negative tax and savings rates combined with social welfare transfers result in many households having expenditures higher than incomes and an expenditure to pre-tax income ratio above 1. This increases their GHG emissions per dollar of income (See Appendix for calculation and interpretation of negative savings rate). Among high earning households, progressive taxation and high savings rates (as their propensity to consume declines) results in less expenditures per dollar of income. Additionally, the types of goods and services purchased (Fig. 4A) and their respective GHG intensities (Fig. 4B) varies across income groups. Low-income decile expenditures are dominated by GHG intensive necessities while the *top 1%* shifts spending to less GHG-intensive services, resulting in lower GHG intensity per expenditure dollar (Table 2).

4.3. Limitations and sensitivity analysis

While we believe our analysis is a significant improvement over prior attempts to quantify top income group emissions, our approach is not without limitations. Most critically the analysis of *top 1%* households rest on certain assumptions for incomes, taxes, savings, expenditures, and CO_2e intensities for that group. For income and tax rates we rely on WID and CPS. While these sources are considered reliable, some estimation error is always inherent. Savings rates and expenditures per category (with some variability applied to both) are based on actual households in CEX that meet the top 1% WID threshold. However, if these households' savings and expenditures are not representative of the larger *top 1%* population or our variability estimates are off, then emissions could be under- or overestimated. Uncertainties around these estimates increase with income and our confidence in absolute

Table 2
2019 tax rate, savings rate, expenditure to pre-tax income ratio, and CO_2 intensity (t CO_2e per $1000) of pre-tax income, post-tax income, and expenditures.

				CO_2e intensity (t CO_2e per $1000)		
Income group	Tax rate	Savings rate	Expenditure / pre-tax income ratio	Pre-tax income	Post-tax income	Expenditures
Decile 1	−2%	−186%	3.71	2.62	2.63	0.71
Decile 2	−1%	−61%	1.65	1.19	1.18	0.72
Decile 3	−1%	−26%	1.27	0.92	0.91	0.73
Decile 4	1%	−11%	1.09	0.78	0.79	0.71
Decile 5	5%	2%	0.94	0.66	0.70	0.70
Decile 6	7%	12%	0.83	0.58	0.62	0.70
Decile 7	10%	15%	0.77	0.51	0.57	0.66
Decile 8	12%	21%	0.70	0.45	0.51	0.65
Decile 9	14%	28%	0.61	0.39	0.46	0.64
Next 9%	21%	36%	0.49	0.28	0.36	0.56
Next 0.9%	34%	48%	0.35	0.19	0.28	0.54
Top 0.1%	34%	60%	0.27	0.14	0.21	0.52

emissions values decrease with income, as we move further away from households captured in the original survey data.

The CO_2e intensities themselves also have some inherent error as households may purchase goods or services that are more or less GHG intensive than the industry average multipliers. For high income households, that are purchasing luxury goods, dining at the most expensive restaurants, and buying other high-end goods, these differences may be significant for some expenditure categories and result in emissions that are far different from the industry average (Girod and de Haan, 2010). Yet for items that dominate super emitter emissions like electricity for multiple large homes, superyacht diesel and jet fuel, there is no luxury effect. Overall, we believe any effect from non-industry average purchases in sensitive expenditure categories is perhaps a 5–10% reduction in average *top 0.1%* average emissions, though further study on this topic would certainly be useful (Please see *A2.2.5.1 Luxury Goods and Emissions: Quantity* versus *Quality* in the *Appendix* for further discussion).

Given these uncertainties we present our results with both bootstrapped 95% confidence intervals and a ± 20% reference point from CI upper and lower bounds (black and grey bars in Fig. 3). While 95% CIs capture a credible range given our baseline assumptions, the ±20% is provided as a reference point to represent a wider range given uncertainties around those assumptions. While ±20% is a somewhat arbitrary choice, since the level of uncertainty in income, tax, savings, expenditure, and CO_2e intensity estimates is unknown, we provide it as a plausible starting point.

Because expenditures and savings rates are critical factors shaping household footprints and precise uncertainties around these values are unknow, we tested the sensitivity of our results to variability in expenditure and savings rates choices. In the baseline model we allow the percent per expenditure category, in our synthetic dataset, to vary ±50% from the original CEX-WID top 1% households. We tested a ± 25% and 0% change from WID-CEX top 1% expenditure values and found almost no effect on average group emissions. These respectively moved the *top 0.1%* emissions, in 2019, from 955 t to 953 t and 951 t.

In terms of savings rates, we compared our loess time series-adjusted savings rate results to a model run that used unadjusted annual savings rates values from WID-CEX *top 1%* households. Overall, the 24-year *top 0.1%* emissions average changes very little between models: 960 t with loess adjustment versus 954 t for the unadjusted model. The average annual percent change between model results is also only 4%. Yet for certain years (2001, 2011, 2013, 2017) the loess values were helpful in reducing the impact of wild savings rate swings that we believe are the result of under sampling *top 1%* households in CEX. The *top 0.1%* emissions estimate in 2019 (955 t) is also very close to the 24-year average (960 t) - making this year useful as not only the most recent, but also a good representative of *top 0.1%* trends.

We also considered (and tested) whether income and savings rates should follow a linear (or other) functional relationship within the *next 0.9%* and *top 0.1%* income groups. We examined high-income households in CEX and found while there was a lot of variability around the mean savings rate there was not a strong positive or negative relationship between income and savings rates. Given the lack of evidence in the original CEX data, the additional assumptions such a model choice would require, and the lack of effect it would have on the group-level results we did not incorporate it into our model. Rather we use a constant rate for each group with variation across households, based on CEX values (see *A2.2.3. Savings Rates* in the *Appendix* for further discussion).

We additionally tested the effect of how increases and decreases in the *top 0.1%* savings rate choice affect the results. In our baseline scenario, we set the *top 0.1%* savings rate 25% higher than the *next 0.9%* group in order to capture more conservative spending patterns that are possible for these extremely high earning households. To test sensitivity of results to this choice, we ran the 2019 model with a mean *top 0.1%* savings rate 25% lower, equal to, 50% higher, and 75% higher than the *next 0.9* savings rate (Table 3). In the highest spending scenario 42% of pre-tax income is used as expenditures, while in the most conservative scenario just 11% of pre-tax income is spent.

We find each 25% change in the savings rate yields a ± 0.5–0.7 percentage point change in the groups' NE. In considering plausibility of each scenario, the number of super emitters is helpful. With over 700 U. S. billionaires, about 13,500 private jets in North America and 1453 super yachts we believe scenarios with less than a few hundred or more than a few thousand super emitters are probably less likely. Yet, it is worth noting that even when the +50% savings rate is tested, where households are spending only 19% of their pre-tax income, the *top 0.1%* group still has mean emissions of 685 t and account for 1.7% NE. Thus, while having firmer data upon which to base the *top 0.1%* savings rate would be helpful, the sensitivity analysis reveals that even when large savings rates are tested these top income groups still have dramatically

Table 3
Savings rate sensitivity analysis (2019), showing how absolute and relative emissions estimates for *top 0.1%* and *top 1%* households change in relation to different *top 0.1%* savings rates. In the baseline scenario, the *top 0.1%* savings rate is 25% higher than the *next 0.9* savings rate. The alternative scenarios set this to 25% lower, equal to, 50% higher, and 75% higher than the *next 0.9%* savings rate.

Top 0.1% savings rate in relation to next 0.9%	Top 0.1%					Top 1%	
	Savings rate	% of pre-tax income spent	t CO2e	% of national emissions	# of super emitters	t CO2e	% of national emissions
- 25%	36%	42%	1494	3.5%	9634	305	7.2%
0%	48%	35%	1232	2.9%	4496	279	6.7%
+ 25% (baseline)	60%	27%	955	2.3%	1927	252	6.0%
+ 50%	72%	19%	685	1.7%	128	225	5.4%
+ 75%	84%	11%	380	1.0%	0	173	4.7%

Table 4
Comparison (times larger) of average emissions, per U.S. income group (2019), to per household national averages for low, low-middle, high-middle, and high-income countries. Global estimates are from Hubacek et al. (2017a).

	U.S. income groups **(times larger)**								
Global income groups	Decile 1	Decile 5	National household average	Decile 10	Decile 10 *next 9%*	*top 1%*	*top 1% next 0.9%*	*top 0.1%*	*super emitters*
(t CO_2e)	*(16.8 t)*	*(33.9 t)*	*(41.7 t)*	*(98.0 t)*	*(80.9 t)*	*(252 t)*	*(173 t)*	*(955 t)*	*(3443 t)*
Low *(1.6 t)*	**10.5**	**21.2**	**26.0**	**61.2**	**50.6**	**157.2**	**108.4**	**596.7**	**2151.8**
Low-middle *(4.9 t)*	**3.4**	**6.9**	**8.5**	**20.0**	**16.5**	**51.3**	**35.4**	**194.8**	**702.6**
High-middle *(9.8 t)*	**1.7**	**3.5**	**4.3**	**10.0**	**8.3**	**25.7**	**17.7**	**97.4**	**351.3**
High *(17.9 t)*	**0.9**	**1.9**	**2.3**	**5.5**	**4.5**	**14.1**	**9.7**	**53.3**	**192.3**

high absolute emissions and account for a meaningful share of NE.

While our baseline estimates are likely inexact and have some error around the mean, the relatively consistent top income group emissions estimates across multiple years (where *top 0.1%* savings rates fluctuate between 56 and 69%), our super emitter crosscheck, and our sensitivity analysis suggest that the baseline estimates are robust, plausible, and a reasonable starting point in quantifying top income group emissions.

4.4. Global comparison

Disparities in GHG emission are a key factor shaping global climate negotiations. Yet much of the current discussion focuses on national-level measures such as total historical emissions or emissions per capita. Our sub-national analysis helps enrich emissions responsibility and compensation conversations by revealing the scale of inequality between key economically and politically powerful groups within the U.S. and global citizens. At the extremes, we estimate the U.S. *top 1%*, *top 0.1%*, and *super-emitters* had emissions 157×, 597× and 2152× higher than the average low-income country household's emissions (Table 4) (Hubacek et al., 2017a). Even relatively poor and modest income U.S. deciles have emissions several times higher than average emissions in most other countries. The scale of these disparities highlights a critical challenge to climate equity, particularly since poorer nations, who are least responsible for driving climate change, will suffer disproportionate harm from it.

4.5. Factors shaping household footprints

Household footprints are directly determined by the types and quantity of goods and services purchased. As our results show, these household expenditures are strongly tied to household income. Indeed the key factor shaping rising emissions for the *top 1%* group over the 1996–2019 period is significant income growth. While national average CO_2e intensity per capita, per household, and per dollar all fell between 10 and 30% during that time, these moderating trends were outpaced by income growth of 56 and 88% for the *next 0.9%* and *top 0.1%* income groups. For the bottom 99% this trend was reversed. Here the effect of efficiency gains outpaced income growth.

Yet even at a given income level, GHG footprints vary due to differences in consumer preferences and geographic, social, economic, and policy factors cutting across scales (household, community, regional, national, and global) and over which individual households have varying degrees of agency (Pacala and Socolow, 2004). Among the lowest deciles, this agency is constrained by expenditures principally flowing to carbon intensive basic necessities and limited access to savings or credit. High-income households have significant agency, discretionary spending, saving rates, wealth, and credit that results in consequential emissions differences, even at a given income level.

4.6. Policy implications

Economists widely agree that carbon pricing, via either a carbon tax or cap-and-trade system, is essential to decarbonize the US economy in a cost-effective way (Heal and Schlenker, 2019; Stavins, 2020). Yet, to shift spending the cost of carbon would need to be set fairly high. Heal and Schlenker (2019), for example, estimate that reducing oil consumption 5% would require a \$200 t CO_2e tax. For a *top 1%* household, a carbon tax of \$200 t amounts to 3% of pre-tax income (11% of expenditures). For deciles 1–3, it equates to 52%, 24%, and 18% of their respective incomes (14–15% of expenditures). This raises a significant equity concern that high-emitting wealthy families would be free to make no meaningful lifestyle changes, while low-emitting poor families could face a crushing burden.

To address this, any revenue generated from tax or emissions permit sales could be used to reduce general sales tax or even make lump sum dividend payments to households. This could make price increases either cost neutral or even of net benefit to low-income households (Boyce, 2018; Wang et al., 2016; Yusuf and Resosudarmo, 2015). Yet, like Sager (2019), our results suggests that if high-income households largely absorb the tax, and low-income households see a net benefit, it could have the result of boosting their expenditures (which are 1.4× more CO_2e intensive than *top 0.1%* households) and thus their GHG emissions. If transfers were neutral for low-income families and the remainder flowed to clean energy investment or subsidies for low-income households, it may reduce overall emissions. Yet, a significant political challenge with any such proposal is that setting rates high enough to shift behavior may stimulate public backlash. While a redistribution plan could increase public support, high-income households that would pay the most tax are the same households whose preferences dominate policymaking (Gilens and Page, 2014), potentially reducing their support for such measures.

4.7. Conclusion

Our results show significant emissions inequality, within U.S. society, that cuts across economic class and race. They also show this inequality is even more significant when compared to global income groups. Indeed, our findings indicate some U.S. households generate more emissions in a week than a developing nation household generates in a lifetime.

In order to keep global temperature within 1.5 °C, <400 Gt of additional CO_2e can still be added to the atmosphere (Intergovernmental Panel on Climate Change, 2019).[5] At current rates, U.S. consumption-based emissions alone would use all of this budget by 2100, with, as our results show, the wealthiest U.S. households driving a disproportionate share. At the same time, there are ~700 million people globally living in extreme poverty (<$1.90 PPP per day). Moving this group to a very modest global middle class[6] (<$2.97 PPP - $8.44 PPP) would also use up the entire remaining CO_2e budget by 2100 (Hubacek et al., 2017b; Hubacek et al., 2017a).

To whom should emissions be allocated? Should emissions go to the poorest to create a global middle class? Should they go to future generations? Or should they go towards enabling the wealthiest to consume 10, 100, or > 1000× more than others? If it is to go to the richest, what compensation is owed to society and from whom? Currently, developed and developing nations have agreed that $100 billion a year in climate financing is the amount owed; though actual finance, particularly from the U.S., has consistently fallen short. Recent agreement on a "loss and damage" fund at COP27 indicates an increasing willingness to further link finance with climate responsibility. By quantifying the scale of emissions disparity within the U.S. and globally, our work can inform discourse and policy making around these topics, for example, by better linking climate finance responsibility to those most responsible for driving climate change.

Author contributions

Conceptualization: JS; Data curation: JS; Formal Analysis: JS; Investigation: JS; Methodology: JS; Software: JS; Supervision: CN, MA, EMM; Visualization: JS, CN, MA, EMM; Data Sourcing: JS, DM; Writing – original draft: JS; Writing – review & editing: JS, CN, MA, EMM, DM.

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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.

Data availability

Data requests will be considered by the authors.

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Appendix A. Additional Methodological Details

A.1. Eora MRIO

A.1.1. Price Conversions

Because the CO_2e intensity of each product is being matched with consumer purchases, Basic Price is converted to Purchaser Price, by adding four margin sheets (Trade, Transport, Taxes, Subsidies) to the Basic Price sheet. For comparison across time, we convert currency from *current* year US$ to *constant* 2020 US$, using the Bureau of Labor Statistics (BLS) Consumer Price Index (CPI). Note that Eora currencies are already compatible across countries because Eora converts all currencies into current year US$,[7] principally using International Monetary Fund (IMF) Official Exchange Rates. Price adjusted rates of exchange and UN Operational Rates are used if IMF data are not available (Lenzen et al., 2013).

[5] Note, this is a 66% probability of remaining within 1.5 °C. The IPPC estimate was published in 2018, we have updated it to 2022.

[6] Note, this is the *global middle class*, which is well below middle class living standards in developed countries. *Global* middle class falls below the poverty line in a developed nation.

[7] Eora monetary units are in '000 (thousand) US$. We convert them to a 1 US$ unit to match household expenditure data.

A.1.2. Negative Values at Purchaser Prices

Eora notes that values in the margin sheets are poorly constrained during optimization and can erroneously become negative. If values in these margin sheets are large enough, a commodity's CO_2e intensity, at Basic Price, can become negative at Purchaser Price. We found large negative Transport Margin sheet values were causing seven U.S. transport sectors to have negative CO_2e intensities in Purchaser Price, i.e. the more a household purchased from those sectors (such as Air Transport), the *lower* their emissions would be. Indeed households, with large airline expenditures, were erroneously generating negative total household emissions footprints. To address this, we followed the EORA recommendation to set these seven negative Transport Sheet values to zero before adding to the other four sheets.

We discovered a very small number of other commodities occasionally had negative values at Purchaser Price. This was quite infrequent (between 6 and 34, per year, out of 10,211 sectors). When present we either replaced it with the CO_2e intensity multiplier of a fairly comparable U.S. commodity; for example replacing a negative Canadian air transport intensity with the U.S. air transport sector multiplier. Or when a suitable replacement was not possible, we set that commodity's intensity to zero. The first approach assumes U.S. emissions intensities are comparable to the non-U.S. sector. The second seeks to eliminate the effect of negative values by removing them altogether. While neither approach is completely satisfactory, both are preferable to including negative values that would erroneously reduce emissions estimates per dollar of purchase of that commodity. The actual effect of either treatment choice, on household footprint estimates, is almost nonexistent as so few categories are affected and they account for an *exceedingly* small amount of the final CO_2e intensity, of the final 83 expenditure categories for U.S. consumers.

A.2. Methodological Limitations and Challenges

A.2.1. MRIO and CEX

A variety of estimation errors are possible with the methods employed here. MRIO trade data is imperfect and import and export data reported across countries may not exactly align. Eora makes estimations to balance such conflicts, but it is not possible to achieve both balanced tables and be true to conflicting national reports. The conversion from Basic Price to Purchaser Price also introduces estimation error. Indeed, estimation errors, in the transport margin sheet, for seven U.S. transport sectors needed to be set from negative to zero values. Additionally, converting from symmetrical and non-symmetrical SUT, II, and CC tables, in the original Eora, to a symmetrical CC intermediate transaction matrix involves an Industry Technology Assumption and again moves away from the original national data reports. The GHG data may also contain reporting or estimation errors.

Expenditures are estimated using survey data. This excludes data on foreign purchases. It also does not include capital formation or nonprofit expenditures that benefit household in different ways. Some government expenditures that are directly transferred to households, like Supplemental Nutrition Assistance Program, are included in CEX and our analysis. But general government expenditures like infrastructure, science and research investment, or national defense are not captured. Some studies allocate these non-household expenditures to final demand consumers, based on the idea that all expenditures within a society ultimately occur to benefit the people within that society. Therefore emissions associated with those expenditures should also be allocated to final demand consumers. One approach is to allocate an equal emissions share to each household. Another approach might allocate these general emissions based on share of income received, with the idea that those most benefitting economically from the current system should bear a commensurate responsibility for emissions related to supporting this system.

We do not include these emissions in our analysis because doing so obscures the individual household agency around purchasing decisions. Our focus here is on spending and emissions that households have direct control over. If these emissions were allocated to households, national average emissions would likely be ~30% higher, since consumer expenditure makes up ~70% of U.S. GDP. If an equal absolute emissions allocation was done, the lowest income households would see the largest relative increase in their absolute emissions. If emissions allocation was linked to economic benefit than wealthier households would see a larger increase in their absolute emissions.

A.2.2. Limitations and Challenges - Top Income Groups

A.2.2.1. Under-Sampling. As prior work has shown, the CEX database we use for household consumer expenditures under-samples high income households (Sabelhaus et al., 2013). The problem is most acute for *top 1%* households, but it also impacts households in the *next 9%* group. We address the under sampling of the *next 9%* income group by reclassifying CEX top 1% households that fall below the World Inequality Database (WID) *top 1%* threshold as members of the *next 9%* (World Inequality Database, 2021). By moving these households from P99 to P98 it increases the average income of that group and helps capture higher end spending patterns within it.

While CEX under-sampling exists within the *next 9%*, it is most problematic within the *top 1%*, where a disproportionate share of national income is captured and the differences between average incomes reported by CEX and that reported by WID are greatest. To account for the under sampling and under estimation on income, we estimate *top 0.1%* and *next 0.9%* expenditures by creating synthetic datasets of households, whose mean income matches WID estimates and whose distribution is right skewed (to capture the significant inequality even within these groups) (Fig. A1). The first challenge is that WID average and threshold income data is for adults, while CEX data is in consumer units (i.e. households). To better match the WID and units we convert WID estimates from adults to tax units (which combines incomes of married couples). This is done by calculating the percent difference of national income captured by each group and increasing the tax unit income proportionally (Piketty et al., 2016). In practice, we estimate pre- and post-tax income of tax units are respectively about 6–8% and 7–9% higher than adult (equal-split) unit incomes. After making those adjustments to the CEX data, the share of national income captured by each income group agrees quite well with that reported by WID while the raw CEX data (that has not been adjusted for top 1% under-reporting) shows a significantly smaller income share for the *top 1%* group (Table 2 in main text).

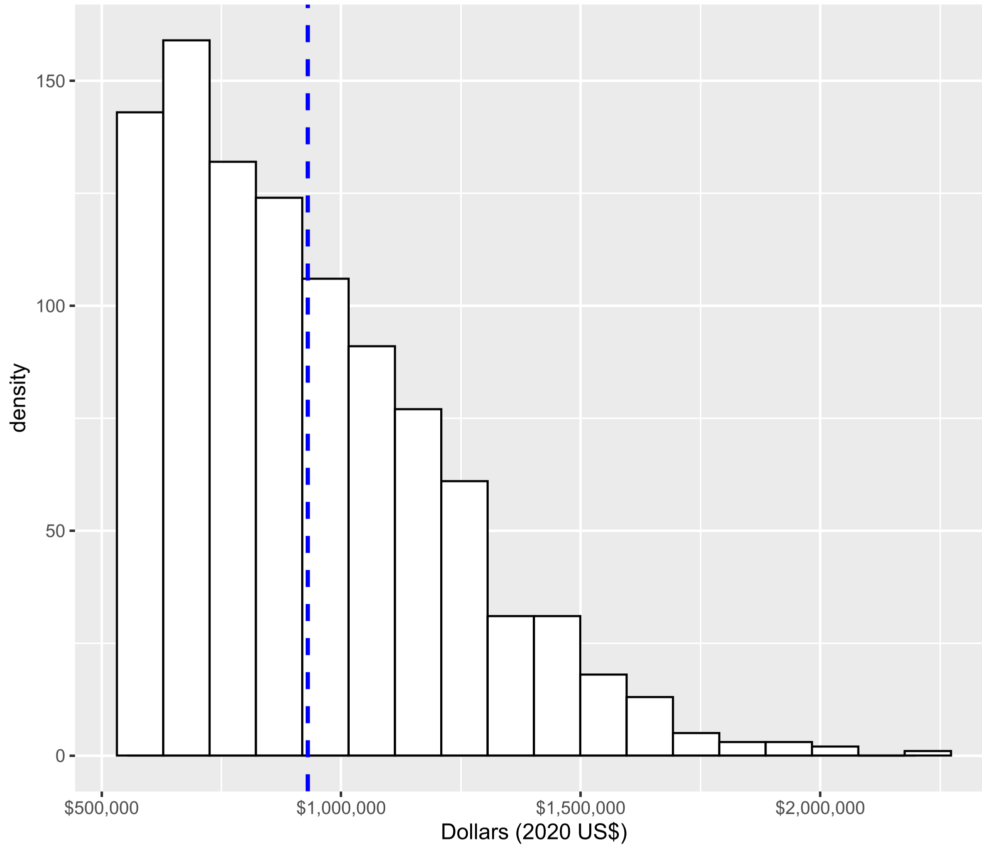

Fig. A1. The right-skewed synthetic household income distribution ($n = 1000$) for the *next 0.9%* income group (2019) bounded within WID lower and upper income thresholds. The dashed blue line represents the group mean: $930,000. The *top 0.1%* distribution has a similar form. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

A.2.2.2. Tax Rates. To this synthetic distribution of top income households, we then estimate and apply tax rates to each household. *Top 1%* tax rates are derived from the Current Population Survey (CPS), which has better sampling of high-income households than CEX. From the CPS, we sample households that meet the WID *top 1%* income threshold. The mean ($\bar{x}$) and standard deviation (s) tax rate from this group is used to generate a distribution of tax rates that is subtracted from household income in our synthetic income distribution.

A.2.2.3. Savings Rates. Savings rates are estimated by subtracting total expenditure dollars from total post-tax income, for CEX households that meet the WID *top 1*% threshold, generating $\bar{x}$ and s, and creating a distribution of savings rates. Because CEX under-samples *top 1%* households, a small number of high or low values can artificially create large standard deviations. For some years this resulted in a significant number of *next 0.9%* households (>10%) having savings rates below 0% or above 100% of their post-tax income. The problem was even more acute for the *top 0.1%* group. In 2011 for instance, 20% of households had savings rates above 100% of their post-tax income. While values below 0% or above 100% are certainly possible, having a significant number of households below or above those limits is unrealistic and not consistent with the minimum and maximum values in the original CEX data. To address this, we make three adjustments to the raw $\bar{x}$ and s values from CEX.

First, we create a distribution whose mean matches that of the raw CEX data, but we multiply the standard deviation by 0.5 to reduce spread around the mean. We tested different standard deviation adjustment values and found a 50% reduction from the raw CEX standard deviation yielded a normal distribution with the CEX mean and a realistic number of values outside the 0% - 100% saving rate range.

Second, we set a minimum savings rate value of −50% and maximum savings rate value equal to the maximum value in the CEX data. The maximum value in the original CEX data was generally quite high: 75–85%. Values below or above these thresholds are redistributed within those bounds. For most years, this affects very few households and has a minimal effect on the distribution average. In 2019, for example, these adjustments only shifted the *next 0.9%* savings rate from 50.7% to 50.5%. This distribution is directly used to assign savings rates to the *next 0.9%* group.

Mean savings rates for the *top 0.1%* are estimated to be 25% higher than the *next 0.9%* group, to reflect the higher savings that are possible for these extremely wealthy households. The standard deviation is the same as what is used for the *next 0.9%* group. These values are used to generate a *top 0.1%* savings rate distribution. We then set a lower bound of 0% and an upper bound savings rate of 98% to ensure households do not have savings rates below 0% or higher than 100% of their post-tax income. Values below or above these limits are randomly assigned a value between 0% and 98%. In practice, these adjustments affect very few households. For example, in 2019 no households had a value below 0% and just 1 household (out of the 1000 households in the synthetic distribution) had a value above 98%.

The third adjustment we make is to smooth out the high annual variability in mean *top 1%* savings rates (see the ***A.3. Volatility in top 1% time series (1996–2019)*** section for a full description). Because the CEX data under-samples *top 1%* households the savings rate for a given year is based on a relatively small number of *top 1%* households. This leads to wild swings from one year to the next. While swings are possible, the large oscillations back and forth suggests this is more likely the result of small sample sizes rather than actual trends. To address this, after creating the savings rate distribution for each year we run a loess model on the savings rate time series data (Fig. A2). In effect, by using multiple years of data this creates a larger *top 1%* dataset from which we can draw savings rates. By using a loess model it also allows for dynamic changes to this rate over time. From this model, we extract the fitted values for each year and impute these back into the original model as the mean *next 0.9%* savings rate for that year. The savings rate distribution is then regenerated via steps one and two described above. While the ultimate effect on GHG estimates is minimal for most years (including 2019, which we spend the most time presenting) it does help to reduce some of the more extreme swings in *top 1%* GHG estimates for a couple of years (2001, 2011, 2013, 2017). While not making such an adjustment is also a reasonable approach, in our view using the time series-derived estimates likely does a better job approximating the actual mean savings rates for a given year.

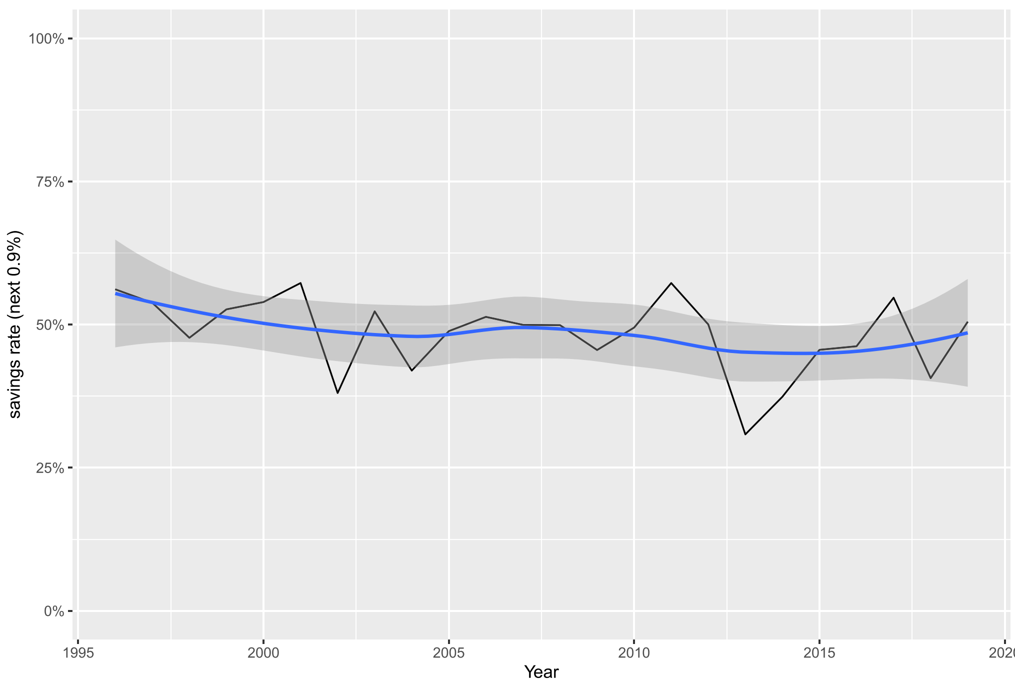

Fig. A2. Next 0.9% savings rate (2019), with loess regression line.

Because CEX households that meet the WID top 1% threshold have a mean income significantly lower than that reported by WID, we also investigated the relationship between high-income CEX household incomes and savings rates to see whether a linear, sigmoidal, or other functional relationship between these variables would be more appropriate. One might imagine that savings rates increase with income as a person with a very high income can live quite comfortably while spending only a small share of that income. One could also imagine living standard increasing in step with income and savings rates remaining flat. One can further imagine savings rates decreasing past a certain point of income as spending flows to new ultra-luxury items like multiple mansions, superyachts and private jets. Looking at CEX households with pre-tax income above $400,000, we found savings rates above this threshold have a generally normal distribution (Fig. A3). We also found when a linear relationship was tested, savings rates sometimes appear slightly increasing (2019) or slightly decreasing (2013) with income. But this relationship is generally rather flat (2014) (Fig. A4) and for almost all years there was no statistically significant relationship between income and savings rates among high earning households. Despite this, we tested and decided that a slight increase in mean savings rate for the *top 0.1%* group (25% higher than the *next 0.9%* group) was reasonable. In 2019, this yields a 60% saving rate. For both the *next 0.9%* and *top 0.1%* a random distribution of savings rates were created around the means. We also conducted a sensitivity analysis of *top 0.1%* savings rates to quantify the effect on emissions estimates (see ***4.3 Limitations and Sensitivity Analysis*** in the main text).

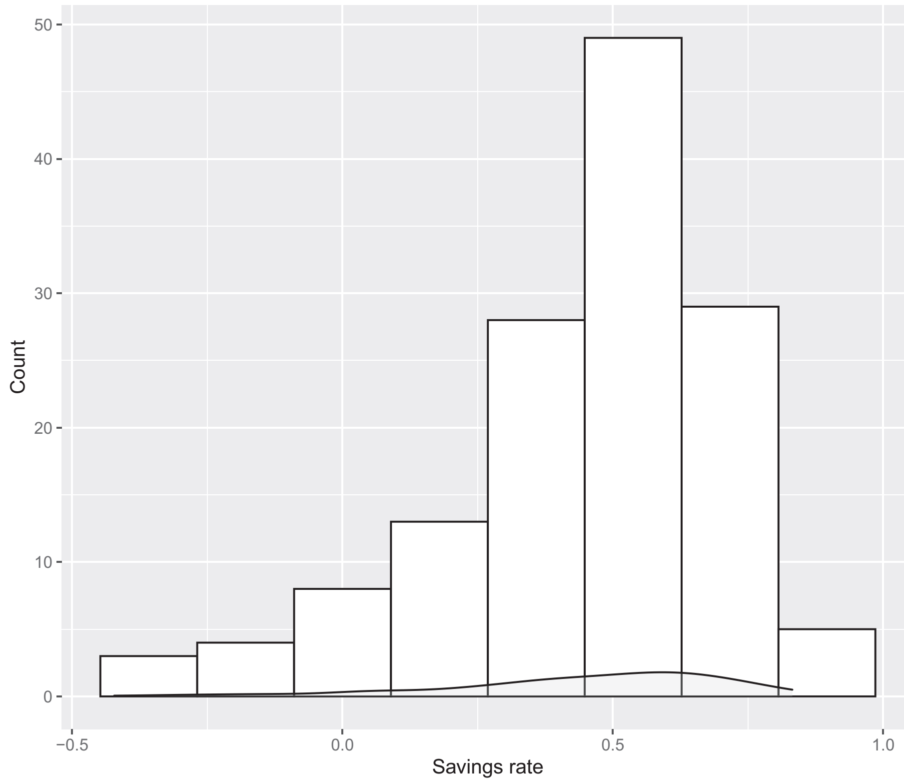

Fig. A3. Savings rate distribution (2019), for CEX households with pre-tax income >$400,000.

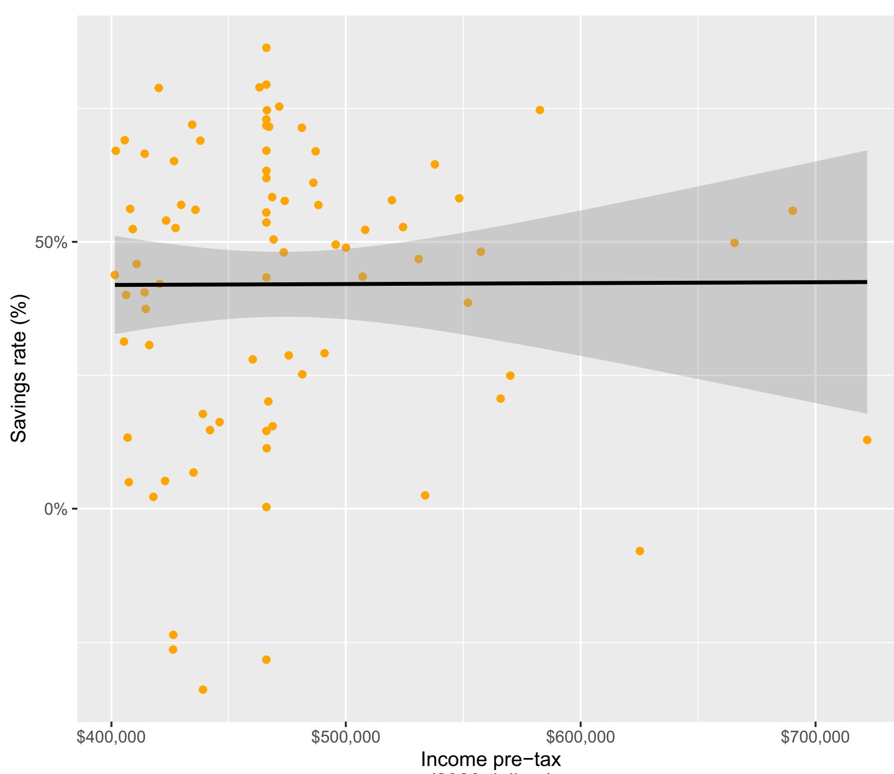

Fig. A4. Income versus savings rates (2014), for CEX households with pre-tax income >$400,000.

Since, CEX under samples *top 1%* households and those households that are present tend to be on the lower end of the income distribution it is certainty possible that unsampled households could have different savings rates than those present in CEX and there is some relationship between income and savings rates within these groups. Yet, including such a relationship in our model requires additional assumptions about what the start and end rates are in the distribution and what functional form such a relationship should take (e.g. linear, sigmoidal, stepwise, etc.…). While we do not have strong data upon which to base these assumptions we considered and tested two alternative savings rate models that use a linear relationship between income and savings (Table A1).

Table A1
Comparison of a static group-level savings rate with random variability (our baseline used in the main text), a linear income to savings rate relationship, and a linear income to savings rate relationship with random variability around the mean (2019).

	top 0.1%			next 0.9%	
Savings Rates	t CO2e	national emissions share	# of super emitters	t CO2e	national emissions share
Static group-level savings rate (with random variation) (baseline scenario)	955	2.3%	1927	173	3.7%
Linear increase	907	2.2%	0	167	3.6%
Linear increase (random variation)	907	2.2%	899	167	3.6%

Both approaches have mean savings rates equal to those used in our main model: 48% for the *next 0.9%* and 60% for the *top 0.1%*. But instead of applying random variability around this mean within each group (as we do in our baseline model) we model a linear relationship where savings rates increase in step with income. In one version, savings rates linearly increase from 44 to 58% for the *next 0.9%* and 58–68% for the top 0.1%. In the second version, rates increase in the same linear way and across the same savings rate range, but we add normally distributed random variability around these linearly estimated values. This captures more natural variability in savings rates that occur among households at the same income level.

Using the linear increase with random variation makes a smoother transition between the *next 0.9%* and *top 0.1%* household footprints as high earning *next 0.9%* household savings rates are closer to lower earning *top 0.1%* rates (Fig. A5 – compare to Fig. 2 in the main text). This results in decreased emissions for higher-income *next 0.9%* households and increased emissions (due to lower savings rates) for lower-income *next 0.9%* households. When looking at the group-level effect however the difference between approaches is quite minor (Table A1). The absolute emissions for *next 0.9%* and *top 0.1%* households are 4 and 5% lower than what we estimate using the static group-level savings rates and the impact on the national emissions share is minute (0.1%).

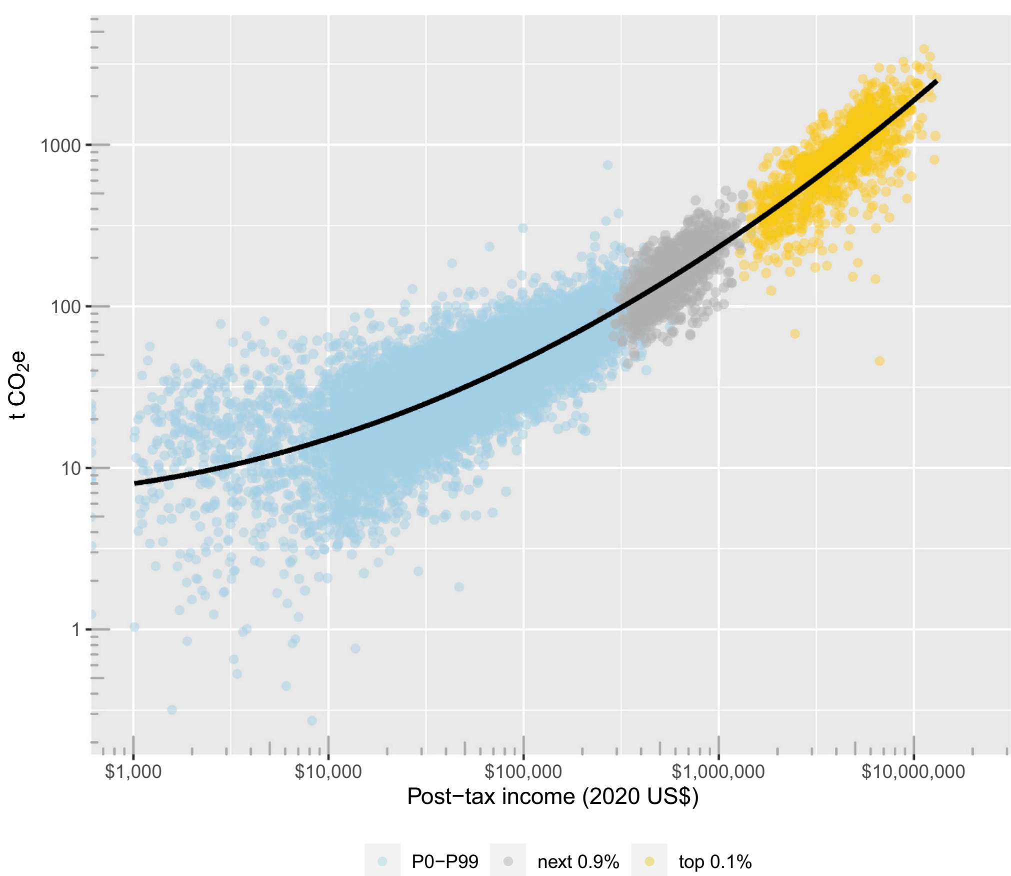

Fig. A5. Post-tax income versus household emissions (2019) with a quadratic polynomial trendline (black). Income percentiles 0–99 (i.e. the bottom 99%) from CEX are presented in blue. The synthetic CEX-WID distributions for the *next 0.9%* and *top 0.1%* are grey and gold. Note the smoother transition here between *next 0.9%* and *top 0.1%* households than what is present in Fig. 2 in the main text. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Indeed, the 4–5% difference we find is likely the result of random chance in how households were assigned expenditure profiles. While expenditures vary across households within each income group, in our synthetic dataset these variations in expenditures are not tied to changes in income within the *next 0.9%* or *top 0.1%*. Therefore, while a linear (or other) relationship between income and savings will alter the emissions distribution within a group - increasing emissions at the bottom and decreasing them at the top – it should not change the group-level results. This is because, if all households within a group have the same expenditure profiles, then total expenditures per category, summed across all households, does not change from what it would be if the same mean savings rate was applied as a constant to all households within the group. Consequently, average emissions per households likewise do not change. We believe random variation that were applied to household expenditure profiles in our dataset are creating slight differences in the final CO_2e estimates.

One area where the choice between a linear or static savings rate does make a meaningful difference is in the number of super emitters. If savings rates fall with income the number of super emitters drops. For the linear model with no random variation zero super emitters are estimated. When random variation is applied to the linear model, we estimate there are about 900 super emitter households. This number seems plausible, but perhaps low given the number of U.S. superyachts, private jets, and billionaires.

While a linear or other income to savings rate relationship is reasonable, we have no data upon which to base it. Incorporating one despite this fact could certainly be justified but would perhaps suggest a higher level of insight into high-income households than we currently have. Given the limited effect on group-level results (which we believe is largely due to random differences in expenditure profiles), the fact that the number of super emitters seems reasonable in our baseline scenario (given our crosscheck), and the additional assumption required in including a linear relationship (without having strong data on which to base it), we do not have savings rates vary as income increases within the *next 0.9%* and *top 0.1%* groups, in the main text.

It is worth noting that expenditures per category could vary within each income group if higher and lower income households within these groups are purchasing a very different mix of goods and services. If these expenditure proportions do vary with income, within a group, identifying a precise functional relationship between income and savings rate would have some effect on the group-level results. The scale of this effect would be tied to how different the CO_2e intensity of these expenditure differences was. One can certainly imagine proportional expenditure differences. For example, once one passes a certain income threshold perhaps absolute dollars spent on food and clothing remain fairly flat. Therefore, a higher expenditure household past the threshold would have a smaller *share* of expenditures devoted to these categories than a household just past this threshold. However, for big ticket items that have a larger impact on household carbon emissions one can also imagine similar expenditure shares across high- and low-income households within the group. For example, an extremely high income *top 0.1%* household may spend the same *proportion* of their expenditures on a 40-m superyacht, large private jet, and 5 vacation homes that a lower income *top 0.1%* household spends on a more modest 15-m yacht, smaller private plane, and 2 vacation homes. As long as the proportion of expenditures per category is the same (or quite similar) across high- and low-income households within an income group, then there will not be a meaningful difference in average emissions per household between a constant group savings rate and one that varies in relation to income.

While we believe our approach is reasonable, a lack of definitive savings rate data for extremely wealthy households is certainly an acute challenge. More research on very-high income savings rates would certainly be useful in helping to refine future emissions estimates.

A.2.2.4. Expenditures. Once the tax and savings rates are applied to each household in the synthetic income distribution, the remaining post-tax post-savings income is considered expenditure dollars.

To apply these total expenditure dollars across the 83 expenditure categories we extract the percent expenditure per category, from households that meet the WID *top 1%* income threshold. These are bootstrapped, with replacement, into 1000 households, with percent spending per category allowed to vary $\pm$ 50% from the original value, while constraining total expenditures across all categories to 100%. This allows us to capture natural variation in spending across households. We again conducted a sensitivity analysis where we tested various randomization limits ($\pm$ 0%, 25%, and 50%). The results were fairly insensitive to threshold choice. For example, in 2015, we find only a $<$ 1% difference in the mean and median emissions, for the *0.1%* income group, when comparing $\pm$ 0% randomization limit to $\pm$ 50%. These expenditure percentages per category are converted to dollar terms by multiplying them by the total expenditure dollars per household, from our synthetic distribution. This is multiplied by the CO_2e intensity per dollar for each category, consumer use emissions estimates for fuel are then added, and this yields a distribution of households with GHG estimates per category. Summing all categories yields total GHG footprint per household.

A.2.2.5. Extreme Emissions and Assumptions. Each estimation we make introduces some inherent error. Most notably we model *next 0.9%*, *top 1%* and *top 0.1%* spending patterns, with some introduced variability, based on the CEX households that meet the WID *top 1%* threshold. If these estimates are not representative of other *1%* and *0.1%* households, the corresponding CO_2e emissions footprints we calculate could be correspondingly over- or under-estimated.

Our crosscheck of super-emitter households suggests it is quite rare for households to have emissions in excess of 4000–5000 t. To control the effect of such outliers, we drop emissions estimates higher than 5000 t. In practice, this limit has no meaningful effect on our results as values $>$3000 t are quite rare (Fig. A6). Across the 24 years $<$30 households out of 24,000 were dropped. In 2019, no households surpassed the threshold.

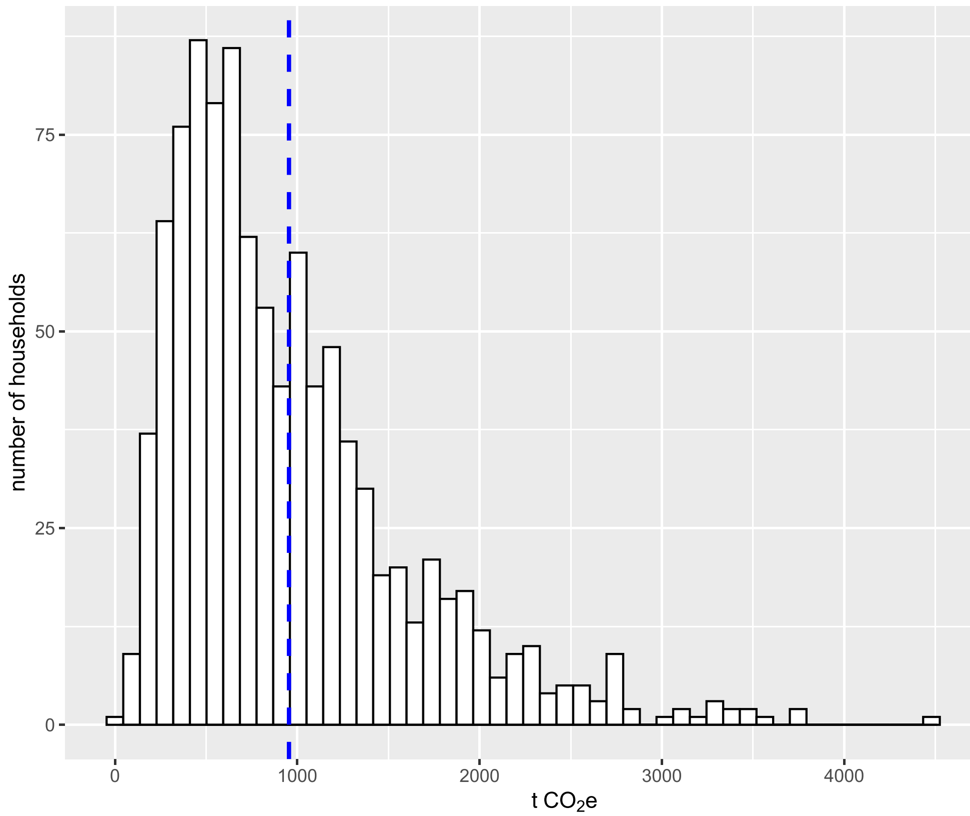

Fig. A6. Histogram of *top 0.1%* households by their emissions (2019). The dashed blue line denotes the group mean. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

A.2.2.5.1. Luxury Goods and Emissions: Quantity Versus Quality. The Leontief method we employ has an inherent assumption that CO_2e per US$ intensity is an appropriate measure of embodied CO_2e. But, quality of goods is an important factor determining price, so a luxury good may have the same CO_2e emissions as a cheaper good in volume terms but using a price term will yield a higher CO_2e emissions for a luxury good. This could be addressed by estimating a quality adjustment factor. For example, this could be achieved by either reducing the CO_2e intensity per dollar multiplier applied to spending of top income groups, or perhaps simply reducing the estimated dollars expenditures, by some luxury estimation percent, to account for this decoupling of dollars and CO_2e intensity.

An extensive review of over 100 consumption-based carbon footprints (Heinonen et al., 2020) found only one paper (Girod and de Haan, 2010) that attempted to adjust emissions based on quality of goods. They found a 21% increase in price per functional unit (e.g. a bottle of wine or a dishwasher are functional units) between lower and higher income groups. For food consumption they find a carbon footprint based on functional unit is 8% lower than when direct expenditures are used. For durable goods they find the difference between functional unit and expenditure models is 50%. They do not make estimates for how emissions would change related to electricity or services. Homes are also not addressed, but prior study from Weber and Matthews (2008), found an insignificant difference on their results when square footage versus expenditure was used (see ***A8.3. Homes*** for a fuller discussion). While the Girod and Haan study is intriguing for its handling of quality and price increases, we did not feel there was sufficient data to adjust our emissions intensity estimates for higher income households. First, the Girod and Haan study only analyzed Swiss households and estimates are based on comparing two somewhat coarse groups: low income and high income. Second, while they find differences between the models, the two categories they look at in depth, food and durable goods, make up a relatively small share of U.S. *top 1%* spending and emissions (Fig. 4**(A)** and 4**(B)** in main text). If we reduced emissions intensity 25–50% in these categories, the overall impact on our results would be perhaps a 5–10% reduction in the average footprint. For super emitter group, emissions are dominated by private jet and superyacht fuel emissions, for which no “luxury fuel” adjustment is needed. More studies on this topic would certainly be beneficial. Yet, the uncertainty in reduction amount, the relatively small impact we expect an adjustment would have, and for consistency with prior studies we maintain a constant CO_2e intensity per dollar expenditure.

A.3. Volatility in Top 1% Time Series (1996–2019)

Initially when running our model, the savings rates for each year were calculated from CEX households, from that year, that meet the WID *top 1%* threshold. While there was a clear slightly increasing trend in *top 1%* GHG emissions over time, there was also a fair amount of year-to-year volatility (Fig. A7). A few years (2011, 2013, 2017) stood out for having particularly low or high GHG estimates. We investigated the key factors shaping such volatility: pre-tax income, taxes, savings, and CO_2e intensity. Expenditures are the result of the first three of these factors (expenditures = income – taxes – savings).

To compare the four factors, we normalize them by calculating the percent difference of each years' estimated value from a fitted loess model trend (Fig. A8). We found that income, taxes, and CO_2e were fairly stable. Savings rates however had significant annual variability including 10 years where variability was >10% from the loess fitted value. In two years with sharp drops in CO_2e estimates (2011 and 2017) we find above average savings rates and below average CO_2e intensities combine to sharply decrease those years' *top 0.1%* GHG estimates. The abnormally high GHG estimate for this group in 2013 results from the opposite trend: higher than trend savings rates and CO_2e intensities. Having higher volatility for income and CO_2e intensity makes sense, since each year these are based on CEX households that meet the WID top 1% threshold. Since CEX under-samples these households, the relatively small sample size introduces savings rate volatility. Meanwhile, income and taxes are based on much larger sample sizes from WID and CPS estimates, thus reducing volatility. We address the savings rate volatility by using savings rate time series to calculate a loess fit, which we then input back into the model (see **A2.2.3. Savings Rates**).

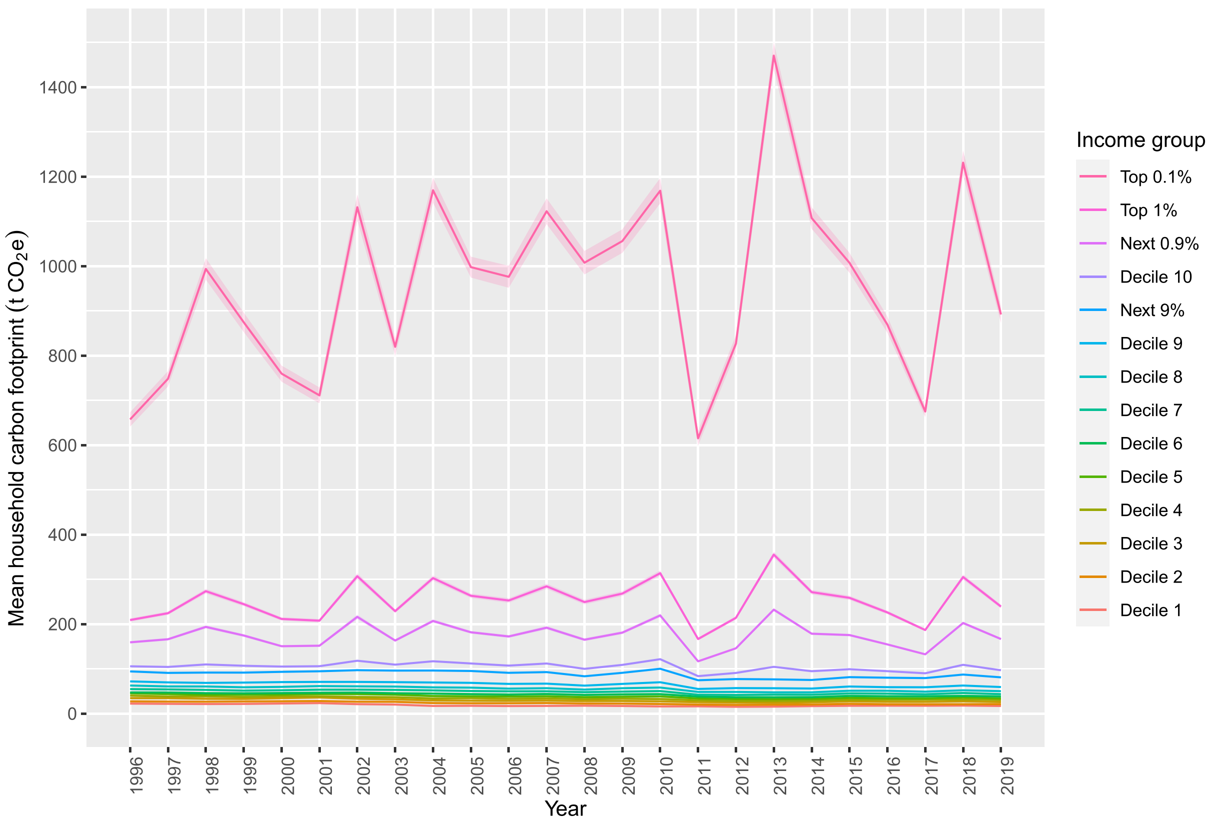

Fig. A7. Mean household carbon footprint (1996–2019) per income group when savings rates are not adjusted using loess regression values. Colored shading is standard error calculated annually for each income group. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

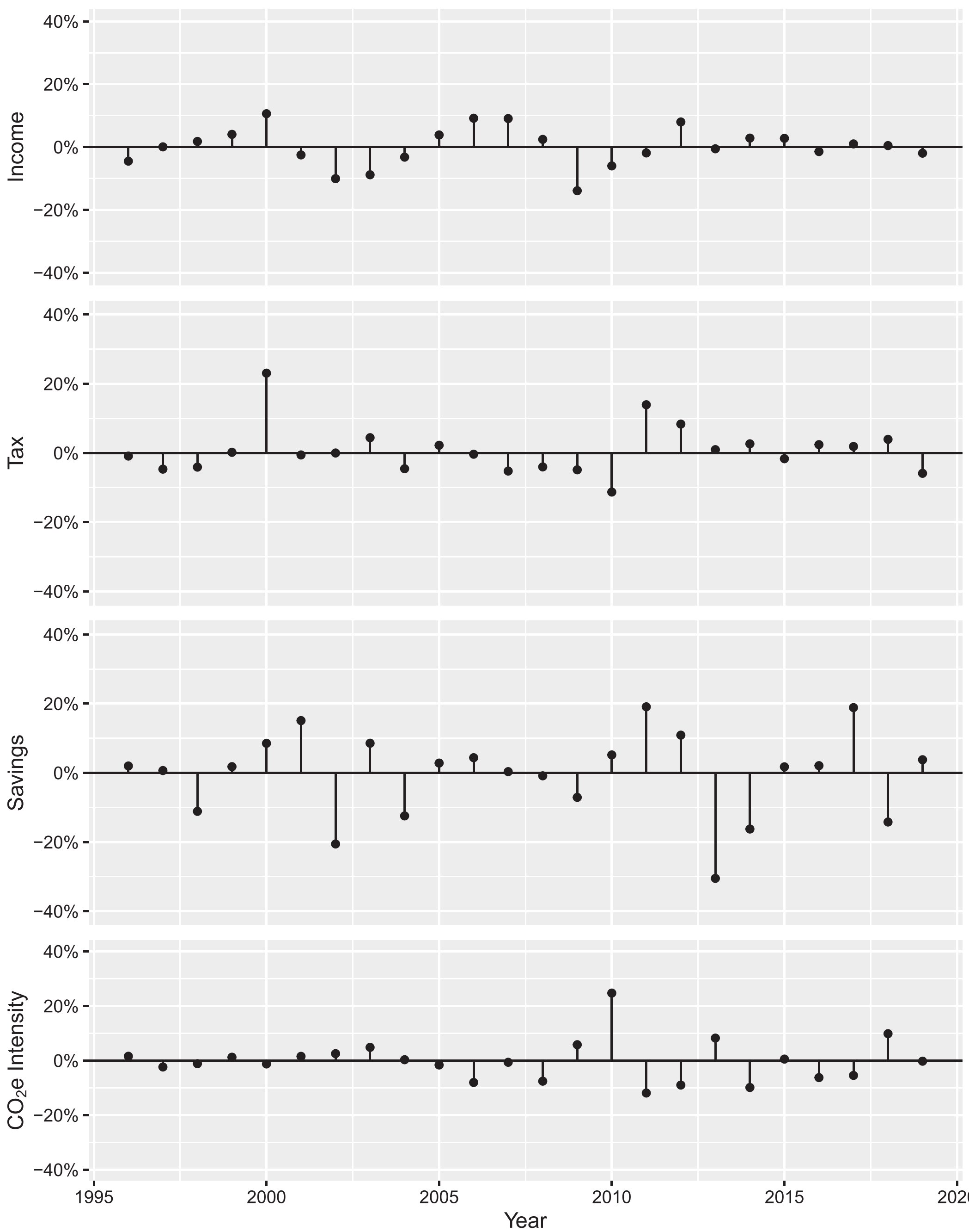

Fig. A8. Volatility in four key variables determining household GHG footprints: income, taxes, savings, and CO_2e intensity (2019) for the top 0.1% income group. The y axis show % change between the actual value and a loess fitted regression for each variable.

A.4. Comparing Income Growth in CEX and WID

In the main text we estimate that, between 1996 and 2019 the *top 1%* income group saw rising absolute GHG emissions while the bottom 99% saw decreasing emissions. This *top 1%* emissions increase occurred despite an almost 30% decrease in national carbon intensity per expenditure dollar, during that time. In the text we discuss how these divergent emissions are shaped by the disproportionate income growth that has flowed to the *top 1%* group. To confirm that these emissions disparities were not artificially inflated by differences in income growth rates between CEX and WID we investigated the percent change of income groups in both databases, between 1996 and 2019. For the *next 0.9* and *top 0.1%*, we just use WID income values in our synthetic distribution, due to under-sampling of these groups in CEX. These groups respectively experienced income growth of 56% and 88% during that time. For the bottom 99%, we found CEX and WID had remarkably close income growth rates. The bottom 99% in CEX had income growth of 32%, while WID showed 30% growth for this group. This close alignment between CEX and WID suggests that income differences between these databases are not artificially inflating the top 1% bottom 99% emissions divergence we report.

A.5. Savings Rates and Expenditure to Post-Tax Income Ratio

Table 2 in the main text provides income group estimates on savings rates and the ratio of expenditures to post-tax income. Savings rates are not strictly the percent of post-tax income saved rather they are calculated as 1 minus expenditure dollars divided by post-tax income. For high-income households this distinction is negligible, but for low-income households this distinction can have a significant effect. Because social transfers are included in expenditure dollars, low-income households may have high negative savings rate values. Negative values should not be interpreted directly as a debt or savings fueled spending, since they include the value of social transfers that are not eligible to be saved. Low-income household savings of post-tax income are likely around zero or slightly negative (debt-enabled spending) but are not as high as our decile 1 estimates, which include social transfers. The calculation we make highlights the scale of difference between expenditures and post-tax income that are particularly interesting at the extremes of the income distribution. For the expenditure divided by post-tax income column (Table 2), values >1.0 indicate expenditure spending is higher than post-tax income. This can be the result of savings drawdown, debt-fueled spending, or public or private social transfers. Social transfers being much larger than income explains why decile 1 pre-tax income and post-tax income have very high CO_2e intensities per dollar income.

A.6. Income and Emissions Trends

In the main text we discuss how income growth within the *top 1%* has outpaced declines in emissions intensity. This results in the *top 1%* seeing rising emissions during the 1996–2019 period, despite the bottom 99% experiencing declining emissions. Fig. A9 helps highlight what is driving these trends. While national average CO_2e intensity per capita, per household, and per dollar all fell between 10 and 30% it was outpaced by 56 and 88% income growth for the *top 1%* income groups.

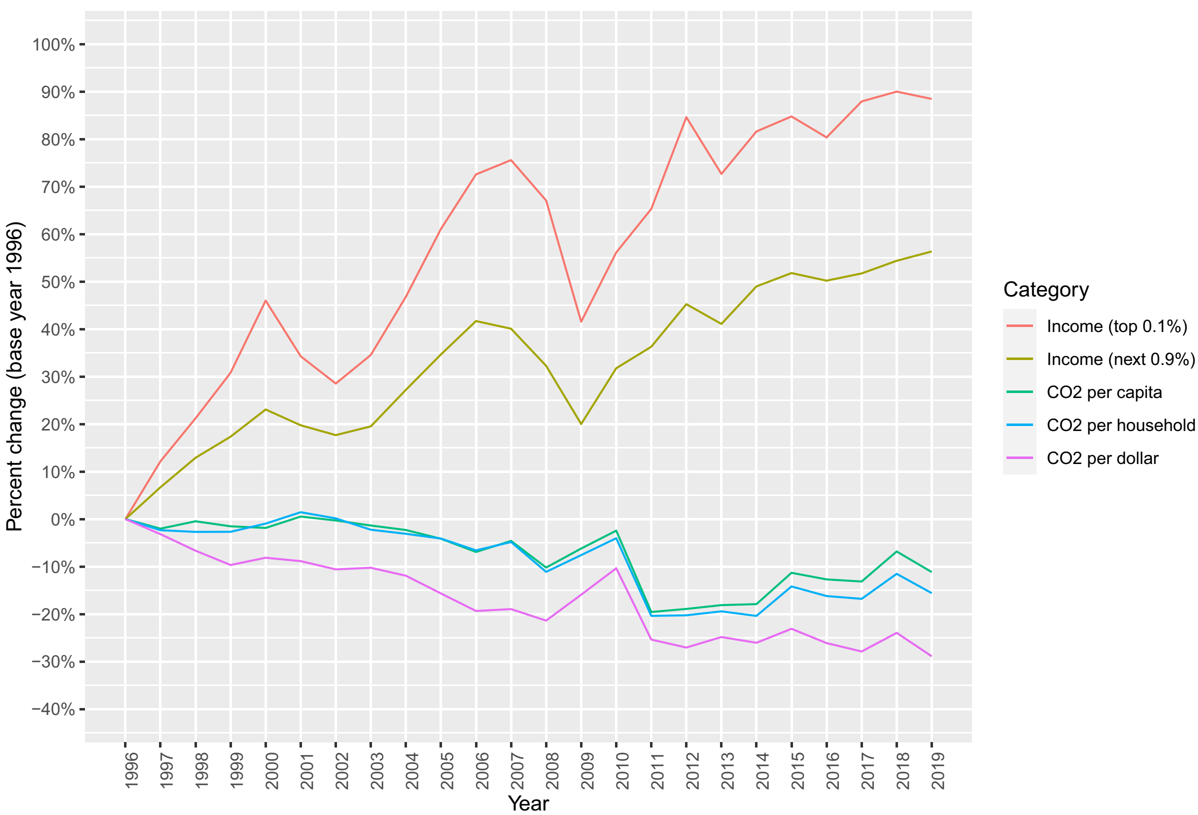

Fig. A9. Percent change in national average U.S. per capita, per households, and per dollar CO_2e intensity (relative to base year 1996) and change in income for the top 0.1% and next 0.9% groups during that time. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

A.7. Super Emitters

For a crosscheck of our super-emitter results we acquire single family home square footage estimates from the U.S. Census Bureau. In 2019, 0.6% of new single family homes completed were a minimum of 8000 square feet. (United States Census Bureau, 2020). Our t per square foot estimates of initial construction are based on the average of Jones and Kammen (2011) and Monahan and Powell (2011). We calculate electricity and utility emissions per square foot using EPA, EIA, and Census data on emissions per dollar, electricity costs, and average home sizes. Our results are more conservative than calculations derived from Goldstein et al. (2020), which suggest emissions related to home electricity might be almost twice as high per square foot. Of course, if a household's total square footage is spread out over multiple homes there can be variability in electricity emissions based on occupancy of each property, though as Barros and Wilk (2021) point out these properties are often used by friends or maintained by staff, so electricity is still being used. Emissions from first class commercial aviation (Atmosfair, n.d.), number of private jets and miles travelled (Argus, 2017; Knight Frank, 2019; Wealth-X and Vista Jet, 2017), number of private yachts (Superyacht News, n.d.), fuel use, and t CO_2e per unit of fuel (United States Environmental Protection Agency, 2020) were acquired from a mix of non-profit, research reports, and government sources.

For context, there are over 13,500 private jets in North America, approximately 1453 North American-owned motorized superyachts (30+ meter) and about 124,000 *top 0.1%* households. Private jet ownership, fractional ownership, charters and super yacht ownership is overwhelmingly concentrated within *top 0.1%* households. For both jets and super-yachts, annual emissions estimates can be even higher if it is larger than average or used more frequently than our estimates of 293 flight hours per year per jet (~12 full days of flight per year) and 1009 h of super-yacht operation per year (~42 full days of use) with an average size of 65 m. As a general note, precise expenditure data from *top 0.1%* U.S. households is notoriously difficult to acquire as extremely wealthy households have complex finance and spending habits, top coding in surveys limits high-income household data, these households are generally far less willing to participate in government surveys, and there are simply far less of these households to survey. While different assumptions on very top income household expenditures would change the estimated emissions results, we think our highly granular approach that is cross-checked against extreme luxury expenditures yields reasonable estimates for this group.

A.8. Handling Special Expenditure Categories

A.8.1. Food

CEX is made up of an interview and a diary tool. While the interview captures detailed data for about ~60–70% of total household expenditure it only collects broad categories for food expenditures (food at home and food away). The diary contains 18 detailed at home food categories. To take advantage of the high category granularity of each instrument the data from each needs to be combined. To do this, the detailed food expenditures, from the diary, are assigned to similar households in the interview sample. Following the approach of Weber and Matthews (2008) we minimize Euclidean distance across three normalized variables common to both datasets: food at home, family size, and total income. The detailed food expenditures, from the diary, are then matched to comparable households with minimal Euclidean distance estimates, from the interview. Unlike Weber and Matthews, instead of simply allocating the diary derived dollar amounts to the Euclidean matched interview households, we instead calculate the percent expenditure per food category in the diary and multiply this by the total food at home reported in the interview. The advantage to this approach is it proportionally assigns food expenditure to the more granular food categories used in the diary but uses the more accurate annualized total food at home amount reported in the interview. Because the interview measures expenditures over the previous quarter, rather than the previous week (as is the case for the diary), the total food at home dollars reported in the interview is a better estimate of actual annual total food at home expenditures. As Weber and Matthews note, their approach (and ours) introduces uncertainty as households of similar size, income, and home food expenditures may actually purchase different kinds of food. However, these differences are likely quite small and not critical to overall footprint estimation, since food at home tends to account for a relatively small share of CO_2e (< 6% in 2015).

A.8.2. Durable Goods

Durable goods present a challenge with EE-MRIO analysis. Durable goods may be purchased in one year but last many years. Many prior studies have either ignored durable good purchases (Weber and Matthews, 2008) or assigned all emissions to a single year (Feng et al., 2021; Song et al., 2019). For relatively inexpensive items like a kitchen sink or chair, the method choice will not have a dramatic effect on a household's CO_2e footprint. But as the cost of an item increases, the above methods can distort a household's carbon responsibility by underestimating, overestimating, or double counting the CO_2e emissions. For example, imagine a vehicle is purchased in one year, but driven for 15 years. All CO_2e emissions are assigned for that purchasing year, even though the utility of the vehicle is spread out over 15 years. Beyond spiking emissions estimates in the first year, this presents a problem if the vehicle is then sold. At the time of sale, emissions would be calculated again, based on the purchase price - thus the original production emissions would be double counted. Buying a used car would also treat the vehicle as though it was manufactured in that year. If automobile production has become more (or less) energy efficient than at the time of actual manufacture, there may be an over or under estimation.

Vehicles present a second challenge in that the price of the vehicle may not be well tied to the actual CO_2e emissions associated with its production. Producing a $200,000 sports car, for example, likely does not generate 10 times more CO_2e than a $20,000 economy vehicle. But using the standard CO_2e/$ multiplier of EE-MRIO would treat it as such. This luxury-inflation problem can be present in any class of goods.

A.8.2.1. Vehicles. We address the vehicle issue in a novel way. Instead of multiplying the vehicle purchase price by the Leontief derived t CO_2e/$ final demand, we take the total consumer-based t CO_2e emitted by the auto industry and divide this by the *number* of vehicles produced.[8] Going from a price to volume measure accounts for the luxury-inflation problem. I do this for the U.S., Japan, South Korea, and Germany. Together these four countries captured between 97% - 98% of automobile market share in the U.S., each year between 1990 and 2016. Domestic and Foreign auto production data is from the Bureau of Transportation Statistics. For each country, this yields t of CO_2e *per vehicle* produced.

The next calculation produces an average vehicle CO_2e footprint that reflects the unique mix of foreign and domestically produced vehicles for sale in the U.S., in a given year. This is done by scaling each country's CO_2e footprint per vehicle, in relation to their U.S. market share, and then summing to acquire a national average.[9] We do this for each year in the study, 1996–2019, creating a 1×19 vector. But for each year, this assigns emissions to a household based on CO_2e estimate from the current year's production and domestic/foreign mix. In other words it assumes everyone has a brand new car each year.

To address this, we use data on miles driven per year of vehicle life to make the CO_2e per vehicle estimate proportional to the miles driven by a vehicle each year.[10] Data are acquired from the National Highway Traffic Safety Administration. This is used as a proxy for the number of vehicles from a given year that are in the current year U.S. fleet. We use this to estimate the total t CO_2e of a vehicle in the U.S. fleet, in a given year.

The final step is to depreciate the total t CO_2e of a vehicle over its lifetime. Here, 15 years was chosen because about 95% of miles have been put on

8 Number of vehicles owned or leased are acquired from the CEX database (United States Bureau of Labor Statistics, 2021)

9 For example, in 2015 a vehicle produced in the U.S. had a 39 t footprint, while a vehicle produced in Germany had a 16 t footprint. Domestic vehicles captured 45% of sales in the U.S.A, while German vehicles captured 9% of the market. Thus the CO_2e per U.S. vehicle (39 t) is multiplied by U.S. producers market share (0.45), the German CO_2e footprint per vehicle (16 t) is multiplied by German market share (0.09). Japan and South Korea are calculated in the same way, and the remaining 2–3% captured by other countries are treated as though they have German CO_2e footprints. These scaled values are then summed to equal the average CO_2e footprint of a vehicle.

10 In 2015 for example, we estimate about 9% of the cars are from 2015, 9% from, 2014, about 5% from 2005, about 1.5% from 2000, etc…

an average car by this time, even though a diminishing proportion of cars will remain on the road for another 10 years.[11] That long tail would distort the fact that the majority of cars do not go beyond 15 years of useful life. And, about 77% of vehicles will not survive past 15 years (National Highway Traffic Safety Administration, 2006). This yields an annual depreciated CO_2e per vehicle that reflects each years' unique mix of foreign and domestic vehicles and vehicle ages in the U.S. fleet. Each vehicle in a household is then multiplied by this amount.

A.8.3. Homes

Home down payments and mortgage outlays present a similar challenge to vehicles, in that houses have long depreciation periods, current year emissions estimates from the home building sector do not necessarily reflect CO_2e emissions used in an older house, and prices may not correlate well with CO_2e emissions. Prior studies have addressed this by using CO_2e per square foot (Jones and Kammen, 2011). But existing estimates on this are somewhat out of date now. Additionally, while data reports the number of rooms in the primary home, which could be used for square footage estimates, it does not report the number of rooms in secondary or tertiary homes. Since we are particularly interested in those at the top of the income distribution, missing expenditures on these additional homes would be a critical category to omit. Instead, we do the traditional multiplication of home expenses by the CO_2e/$ intensity calculated for the home commodity category. The last two studies on the U.S., Feng et al. (2021) and Song et al. (2019) use this same approach. Weber and Matthews (2008) explored both methods and found their results were insensitive to model choice.

A.9. Comparison with Prior Studies

While our approach to top income groups is novel, to check the general robustness of our results we compared our per capita and national average results to other U.S. household consumption-based emissions studies. For 2004, Weber and Matthews (2008) estimated average U.S. household emissions between 48 and 67 t. Our 2004 estimate is in this range, at 48 t. Jones and Kammen (2011) find household emissions of about 48 t, for 2005, quite close to our findings of 47 t. For 2007, Ivanova et al., (2016) estimated U.S. per capita emissions were 18.6 t, which matches exactly our per capita finding for that year. Feng et al. (2021) estimate 2015 per capita emissions at 18.1 t, while we estimate 16.7 t. Finally, the only time series analyses we are familiar with, for U.S. households, are Sager (2019) and Song et al. (2019). Sager estimates average U.S. household emissions of 37.8 and 33.9 t for 1996 and 2009 and average top decile emissions of 56 t in 2009. We respectively estimate higher emissions of 51, 46, and 106 t for these years and groups. Sager's household and per capita estimates tend to be on the lower side, when compared to other studies. The difference with our results, particularly for the top decile are at least partly due to the fact that Sager does not adjust incomes to account for the under-sampling of high-income households in CEX. In Sager's analysis, the top decile in 2009 has an average income around $215 k (adjusted to 2020 dollars), while our top decile that year has an average income around $321 k (1.5× higher). Song et al. find per capita emissions between 1995 and 2014 averaged between 17.7 and 20.6 t. We find 1996–2014 emissions averaged between 15.5 and 19.7 t. While these studies differ in their methodology and exactly which GHGs are included, we find our per household and per capita emissions estimates generally align well with previous work.

In the main text we report comparisons with two top down studies (Chancel and Piketty, 2015; Kartha et al., 2020). There is also a study by Chancel (2022) that is worth noting. We do not discuss it in the main text because it combines consumption and investment income into one footprint. While this is methodologically distinct in a critical way, it is worth comparing it with our work, since so few studies investigate these top income groups. While Chancel's paper reports mostly at the global and regional level, the World Inequality Database - Carbon Inequality Indicator offers country-level data using almost the same methodology as the paper (World Inequality Database, 2022). Here we compare 2019 estimates from our study to those provided at WID and convert from per capita to per household t CO_2e. Our bottom 50% estimate (26 t) is equivalent to the 27 t estimate we derive from the Chancel / WID dataset. Our top decile (98 t) and top 1% (252 t) is far lower than what we calculate from Chancel / WID's estimate (174 and 577 t). WID does not report top 0.1% estimates or national emissions shares. We believe the divergence with Chancel / WID for high income groups is the result of investment income, which is concentrated at the top of the income distribution, counting towards emissions footprints in that analysis. In our approach only purchases of goods and services are counted towards the consumption-based footprint – asset ownership is not included.

While the main methodological differences between the top-down works and our approach are explored in the main text, here we present some of the differences in source data and the effect those might have on comparability across studies. To start, our consumption-based GHG emissions calculations are derived from the Eora database using six Kyoto GHGs included in the Eora satellite accounts. Meanwhile Kartha et al. (2020) uses just CO_2 data from the Global Carbon Project (GCP) and the Carbon Atlas, (Chancel, 2022) uses GCP and Eora to calculate CO_2e GHGs, and Chancel and Piketty use the Global Trade Analysis Project (GTAP) for calculating CO_2e GHGs. Differences exist across these databases, though for developed countries the differences in consumption-based CO_2 estimates are generally small (<10%) (Moran and Wood, 2014).

While most of the studies use CO_2e, like we do, Kartha et al., 2020 uses just CO_2 emissions. In the U.S., CO_2 makes up about 79% of GHGs (when converting GHGs to CO_2e). Therefore, based on this, one might expect Kartha et al. estimates to be consistently lower than our work. Working in the other direction, while our household footprints are based on just household consumption, Kartha et al. allocates government expenditures and capital formation to individual carbon footprints. In the U.S., household consumption accounts for about 70% of GDP, so looking at this factor, one might expect our absolute values to be consistently lower than Kartha et al. Putting these two factors together, our larger GHG scope and smaller spending scope work somewhat to cancel each other when comparing our work to Kartha et al.

[11] For example, in 2015, a vehicle in the U.S. fleet (which now includes foreign and domestic mix and vehicles produced in different years) is estimated to have required 26.8 t in its production. This is divided by 15 years to yield 1.79 t per vehicle in 2015. Each vehicle a household has in 2015 is multiplied by this amount.

While one might expect our study would consistently show somewhat higher results than Kartha et al., across all income groups, because we use more GHGs or it would show somewhat lower footprints because we only count direct household spending, we find results are inconsistent across income groups. Our absolute and relative (national emission share) bottom 50% values are higher, our top 10% and *top 1%* absolute and relative shares are much lower, and our *top 0.1%* relative value is equivalent while the absolute value is higher. As we discuss in the main text, this inconsistency is being driven less by differences in datasets or scope and more by the bottom-up vs top-down approach. The top-down income-elasticity approach and ceiling on very top income household footprints tends to artificially underestimate bottom income households, over-estimate high income households, and under-estimate very top income households.

Our attention has mostly been devoted to comparison with Kartha et al. (2020) since they provide both absolute and relative shares of national emissions per income group. While Chancel and Piketty (2015) and Chancel (2022) do not provide relative shares, we include a comparison with their absolute values in the main text. Like Kartha et al., both of those studies also allocate government expenditures and investments to their individual footprint calculations, while we do not. If we were to include this, all our income group footprints would be perhaps ~30% higher. Even if we were to make this adjustment, for the *top 1%*, our absolute values would still be significantly lower than those reported by these other studies.

A.10. A Closer Look at the Bottom 99%

In the main text time series (Fig. 1) we present all deciles together with *top 1%*, *top 0.1%*, *next 0.9%* and *next 9%* households. Because the scale of GHG disparity is so high, the decile-level results are difficult to distinguish. Here we present just deciles from 1996 to 2019, to better visualize the decile-level differences (Fig. A10). Note all deciles saw emissions decline across the 24-year period.

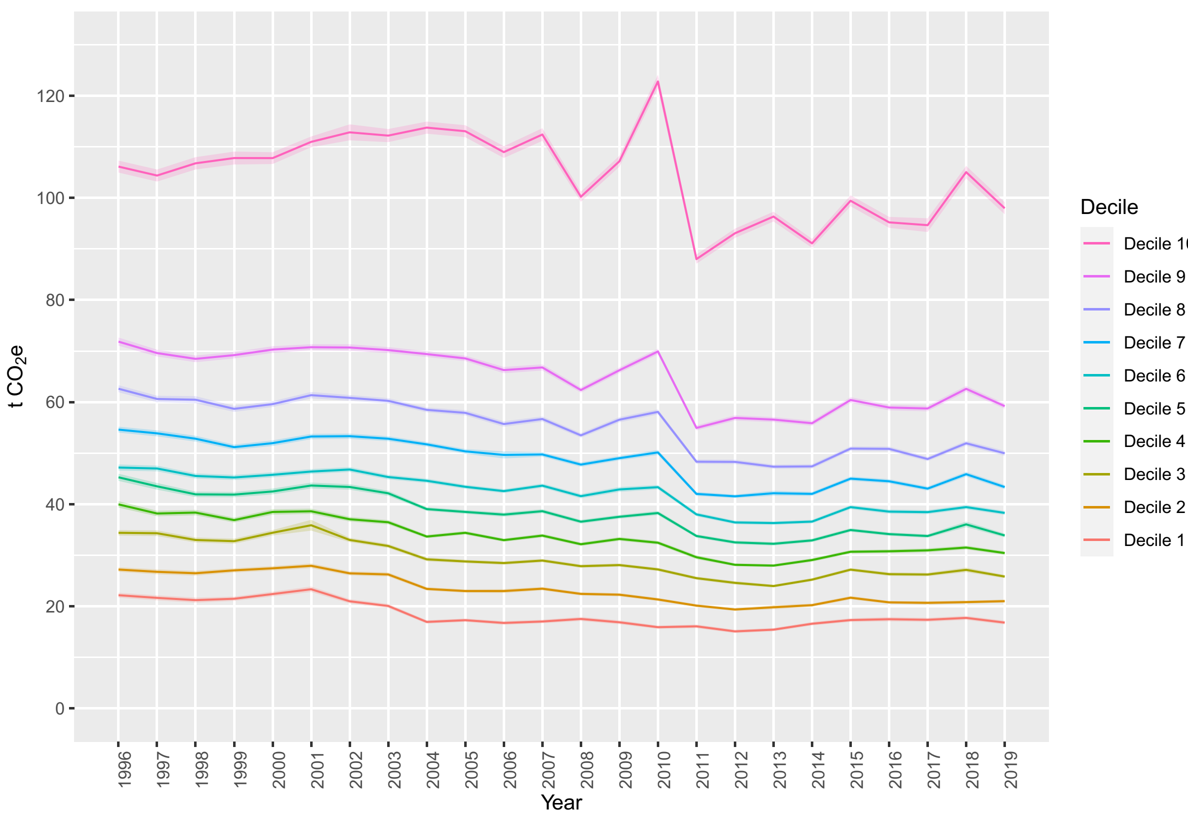

Fig. A10. Mean household emissions (1996–2019) for each income decile. Shading is standard error. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Fig. 3 in the main shows the 2019 emissions with a thirteen-expenditure category breakdown for declines 1–9, the *next 9%*, the *next 0.9%*, and the *top 0.1%*. Because the *top 0.1%* emissions are so high it again makes the lower 99% emissions difficult to differentiate. Here we present the 2019 thirteen category emission breakdown for deciles 1–9, next 9% and the *top 1%* (Fig. A11).

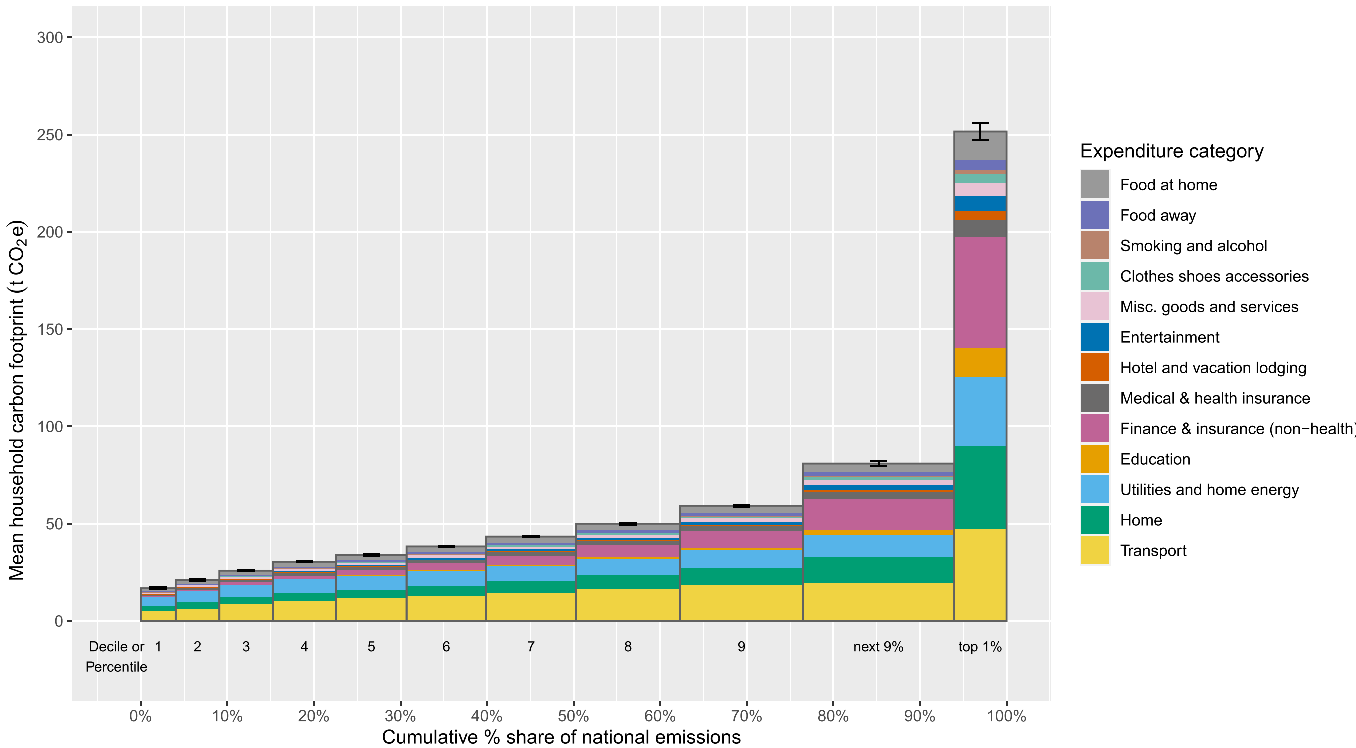

Fig. A11. Mean household t CO_2e emissions (2019) per decile (1–9) *next 9%*, and *top 1%*. The width of each income group, on the x-axis, corresponds with its share of consumption-based national emissions. Colors denote mean contribution from each expenditure category. Note: standard error bars are from each income group's total mean footprint. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Appendix B. Appendix References

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