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RESEARCH ARTICLE

Income-based U.S. household carbon footprints (1990–2019) offer new insights on emissions inequality and climate finance

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Abstract

Current policies to reduce greenhouse gas (GHG) emissions and increase adaptation and mitigation funding are insufficient to limit global temperature rise to 1.5˚C. It is clear that further action is needed to avoid the worst impacts of climate change and achieve a just climate future. Here, we offer a new perspective on emissions responsibility and climate finance by conducting an environmentally extended input output analysis that links 30 years (1990–2019) of United States (U.S.) household-level income data to the emissions generated in creating that income. To do this we draw on over 2.8 billion inter-sectoral transfers from the Eora MRIO database to calculate both supplier- and producer-based GHG emissions intensities and connect these with detailed income and demographic data for over 5 million U.S. individuals in the IPUMS Current Population Survey. We find significant and growing emissions inequality that cuts across economic and racial lines. In 2019, fully 40% of total U.S. emissions were associated with income flows to the highest earning 10% of households. Among the highest earning 1% of households (whose income is linked to 15–17% of national emissions) investment holdings account for 38–43% of their emissions. Even when allowing for a considerable range of investment strategies, passive income accruing to this group is a major factor shaping the U.S. emissions distribution. Results suggest an alternative income or shareholder-based carbon tax, focused on investments, may have equity advantages over traditional consumer-facing cap-and-trade or carbon tax options and be a useful policy tool to encourage decarbonization while raising revenue for climate finance.

Introduction

Anthropogenic climate change is an existential threat to all of humanity [1, 2]. Yet, extreme economic inequality, across and within societies, results in a powerful disconnect between those facing the worst climate impacts and those reaping the economic and consumption benefits that drive greenhouse gas (GHG) emissions [3–8]. This disparity in harm and benefits has been a central tension at international climate negotiations, particularly when trying to allocate responsibility and financial compensation between developed and developing countries.

In recognition of such disparities, wealthy nations at the 2009 United Nations Climate Change Conference (UNCCC–COP 15) agreed to mobilize $100 billion a year, by 2020, to fund mitigation and adaptation efforts in poorer developing nations. The creation of a "loss and damage" fund at the recent UNCCC COP 27 marks an additional commitment to address disparities between those disproportionately driving emissions and those disproportionately experiencing the harms they cause. These efforts represent progress, yet there is also some reason for skepticism. Existing climate commitments will not keep global temperature rise within 1.5˚C [9], finance pledges fall about 5-10x short of the need [10], and nations have consistently failed to meet these insufficient emissions and finance pledges [9, 11]. This has made the current moment pivotal to address an increasingly urgent climate crisis and suggests addition perspectives may be useful in motivating such efforts.

Emissions responsibility frameworks and prior work

While existing climate agreements are based on national-level territorial emissions, alternative consumption-based and income-based frameworks have been proposed to account for trade related emissions transfers and to better align responsibility with the flow of benefits. At the national level, consumption-based emissions have been well studied over the last several decades [12–21], while income-based emissions [22–29] have received less attention. Because consumption and income ultimately flow to households, these alternative frameworks also allow emissions responsibility to be quantified sub-nationally at the household-level.

The United States (U.S.) provides an interesting case for consumption- and income-based analysis due to its significant emissions, high levels of consumption, and extreme economic inequality. Since the Industrial Revolution the U.S. has cumulatively emitted more GHGs and captured more wealth (GDP) than any other country. At the same time, the U.S. has significant economic inequality, with the top 10% of income earners capturing 46% of pre-tax national income, in 2021, and the top 1% alone capturing 19% [30].

From a consumption-based standpoint, prior U.S. analyses have been conducted by Weber and Matthews [18], Jones and Kammen [31], Song et al. [17], Sager [32], Feng et al. [16] and others. In a recent paper we fill in a gap in these studies by explicitly addressing the undersampling and underestimation of top 1% and top 0.1% households' emissions in prior work [33]. We find extreme and growing emissions disparities between very high-income households and the rest of U.S. society.

While emissions related to household *consumption* (consumer responsibility) have been well explored for the U.S. and many countries—informing climate equity debates–very little work [34, 35] has been done linking households to the emissions used in generating their *incomes* (income responsibility). This misses a critical connection between climate altering GHG emissions and those households reaping a tangible benefit from these emissions—obscuring alternative policy solutions.

To date, the only research we are familiar with on income-based household GHG footprints are an initial U.S.-based analysis we conducted [34] and recent work by Pottier and Le Truet [35] that report wage-based footprints for households in France. Here we present results for an analysis that links GHG emissions to the full range of U.S. household incomes (wages, investments, retirement, etc.) over a 30 year period (1990–2019). In doing so, we offer a new perspective on emissions responsibility, fill in a key knowledge gap for a major GHG emitting nation, and highlight some alternative tax policies that could help close the climate finance gap [10]–including post-COP 27 loss and damage funds.

Research approach

To link U.S. households with the GHG emissions that enable their income we calculate global GHG emissions intensities (metric tons (t) CO_2e per dollar) of income using a multi-region input-output (MRIO) model (see Materials and Methods) [36, 37]. We calculate emissions intensity using two distinct accounting approaches: direct *producer* emissions and *supplier* emissions. In the producer framework, each industry's direct operational emissions (Scope 1) are allocated to households in proportion to the share of total income they receive from that industry. The supplier framework allocates emissions to households in the same proportional way, but each industry's emissions are calculated as the sum of emissions occurring in all activities which directly and indirectly provide sales revenue to that industry in its role as a supplier. For example, in the producer framework households receiving wage or investment income from a power plant are responsible for the direct emissions it generates, while in the supplier framework households receiving wage or investment income from selling financial services or fossil fuel to that power plant are responsible for the plant's emissions, proportional to their importance as a supplier. The producer approach allocates direct emissions from 429 U.S. industries, while the supplier approach includes the full downstream supply chain emissions of 9,812 industries across 190 countries (about 2.8 billion inter-sectoral transfers or around 96 million per year).

Industry-specific emissions intensities are linked with an individual's wage income from that industry, using the nationally representative Integrated Public Use Microdata Series (IPUMS) harmonized Current Population Survey (CPS), which includes around 5.4 million individuals (~181,000 individuals annually) [38]. Emissions for unearned income, such as investment and retirement (social security, IRA, 401(k), etc.) income, are also included and based on weighted national average multipliers that model a range of diversified investment portfolios. In total, emissions associated with 12 pre-tax income categories are included and aggregated by household (~65,000 annually). The post-tax analysis includes 35 income categories that capture social and government transfers and reduces the household's income responsibility by the amount of taxes paid (see Table E in S1 Text for a comprehensive list of income variables). To compare emissions responsibility across the income distribution, households are then binned into income groups including deciles 1–9, the *next 9%* (90–99.0th percentile), *top 1%* (99.0th - 100th percentile), *next 0.9%* (99.0th—99.9th percentile), and *top 0.1%* (99.9th - 100th percentile) (see Materials and Methods for how we estimate top 1% households, which are under sampled in CPS and S1 Text for additional methodological details).

Results

Below we present results for both supplier and producer frameworks. For brevity, Figures use the supplier framework and all Figures except Fig 1 present pre-tax income footprints. Producer-based Figures generally show similar results. They are included as Supporting information files and referenced in the corresponding Figure legends below. We mainly focus on pre-tax footprints since they provide a clear picture of the raw income-based emissions distribution. Post-tax results are mostly presented to show the impact of tax policy and social transfers on this distribution (see Table 1 and *Tax effects on emissions footprints* in S1 Text).

Income sources and carbon intensity

Across the income distribution, household income sources and GHG intensities are heterogeneous. Social transfers make up a significant share of lower income groups' post-tax footprint,

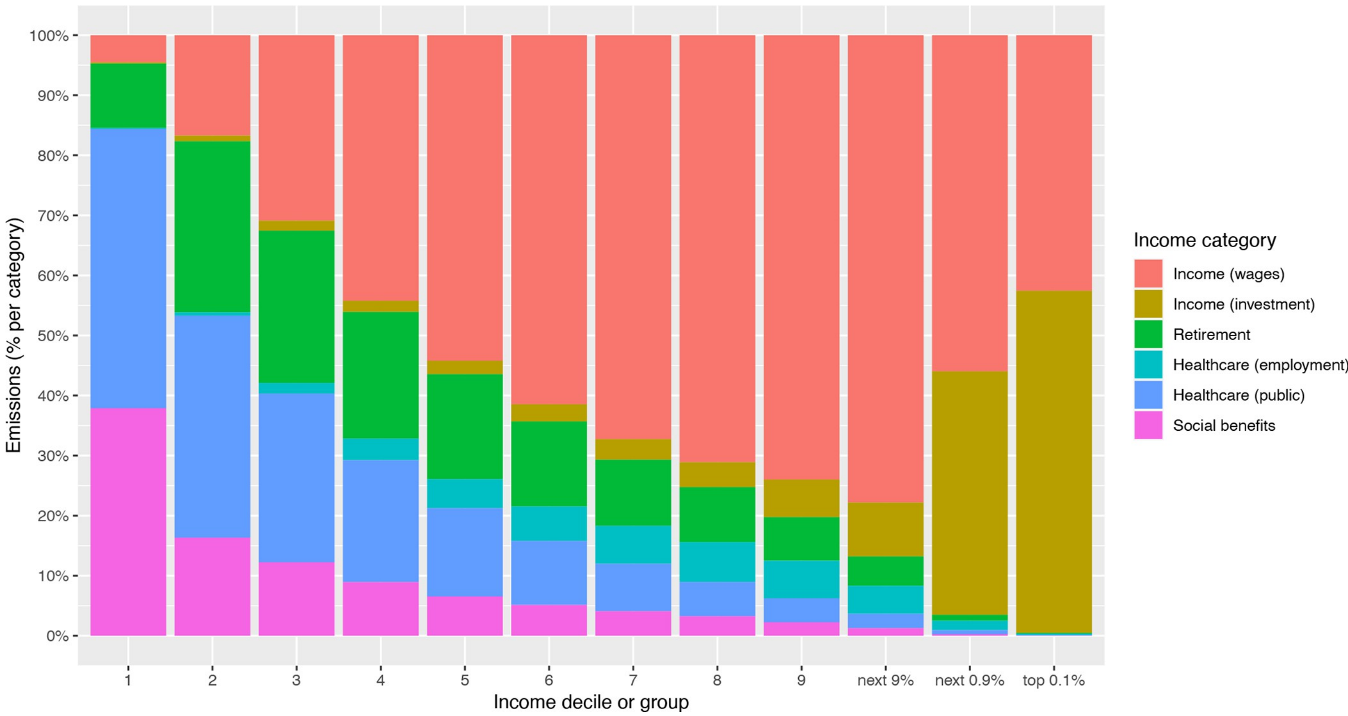

Fig 1. Supplier-based post-tax emissions share per income category, by income group (2018). (Producer-based results are presented in S1 Fig).

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wages dominate middle income groups' emissions, and wage and investment income are the key drivers of very high-income groups' emissions (Fig 1). For average top 0.1% households, we find investment income drives >50% of emissions.

The CO_2e intensity of incomes also varies across the income distribution (Fig 2). In the supplier framework, the CO_2e intensity of wages tends to increase with income, though there is significant dispersion within groups. In the producer-based analysis, middle income households have the most CO_2e intensive wages while low- and high-income households, employed

Table 1. The share of pre-tax and post-tax national income and emissions (2019) captured by each income group, for both the supplier and producer frameworks.

		Pre-tax			Post-tax		
		Share of national income (%)	Share of national emissions (NE) (%)		Share of national income (%)	Share of national emissions (NE) (%)	
	Income group		Supplier	Producer		Supplier	Producer
Bottom 99%	Decile 1	0.4	0.4	0.4	2.9	3.1	2.6
	Decile 2	1.8	1.7	1.6	3.8	3.9	3.4
	Decile 3	2.8	2.7	2.7	4.7	4.7	4.4
	Decile 4	4.1	3.9	4.1	5.6	5.6	5.5
	Decile 5	5.5	5.2	5.6	6.6	6.4	6.7
	Decile 6	7.1	6.9	7.5	7.9	7.7	8.1
	Decile 7	9.1	8.9	9.6	9.4	9.2	9.8
	Decile 8	11.8	11.5	12.3	11.5	11.2	12.0
	Decile 9	15.9	15.7	16.5	14.6	14.4	15.3
	Next 9%	25.2	25.9	25.0	21.4	21.9	21.6
Top 1%	Next 0.9%	8.9	9.4	8.2	6.4	6.6	6.0
	Top 0.1%	7.3	7.7	6.6	5.1	5.3	4.7

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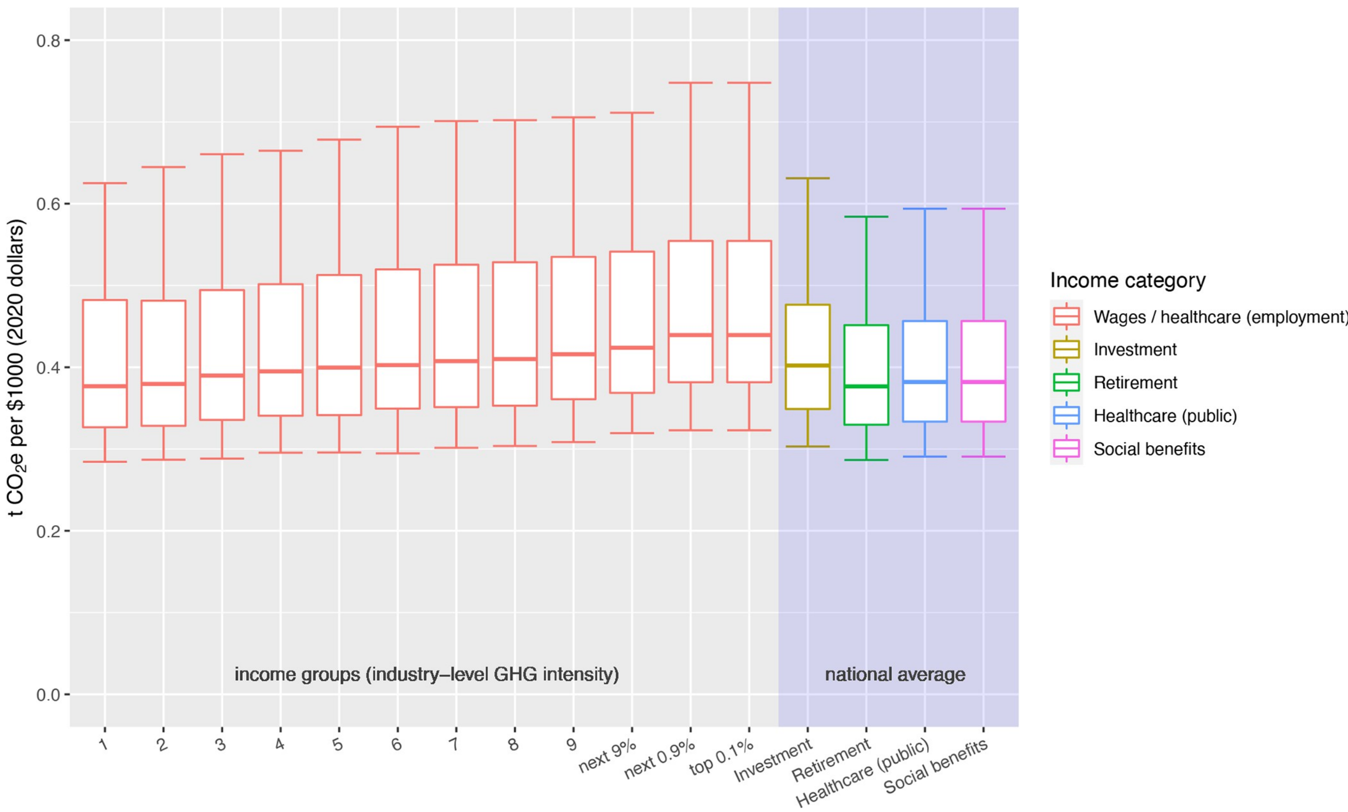

Fig 2. Annual mean CO_2e intensity of supplier-based wages and other income sources (1990–2019). Wages and employer healthcare contributions are industry specific CO_2e multipliers and are presented by income group. The other income categories use weighted national average multipliers (shaded blue area). *(Producer-based results are presented in S2 Fig).*

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in various service sectors, have less emission intensive incomes (see S2 Fig). These differences result in some decoupling of national income and national emissions (NE) shares (Table 1), for some income groups. For example, top 1% households have NE shares that are higher than their income share in the supplier framework and lower in the producer framework. While underlying income inequality is by far the most important factor shaping extreme inequality in emissions footprints, differences in income sources and GHG intensity (see S3 and S4 Figs) cause emissions heterogeneity at a given income level and a divergence between national income shares and emissions shares for some income groups.

Most recent year (2019)

In 2019, we estimate U.S. household income-based emissions range from ~0 to over 8,000 t and follow a strong linear relationship ($R^2 > 0.94$) with an elasticity of 1.0 (Fig 3). We find a highly unequal emissions distribution with Gini coefficients of 0.57 (producer) and 0.58 (supplier) (for Lorenz curves, see S5 and S6 Figs). It is worth noting that at a given income level differences in the GHG intensities of income sources result in emissions variability. For example, we estimate a pre-tax income around $1 million has emissions as low as ~200 t or as high as ~1,300 t depending on the type of profession or investments that are generating that income.

Binning households into income groups, we estimate the highest earning 30% of households are responsible for about 70% of income-based NE while the lowest earning 70% are responsible for only about 30% NE (Fig 4). Depending on the framework, the highest earning

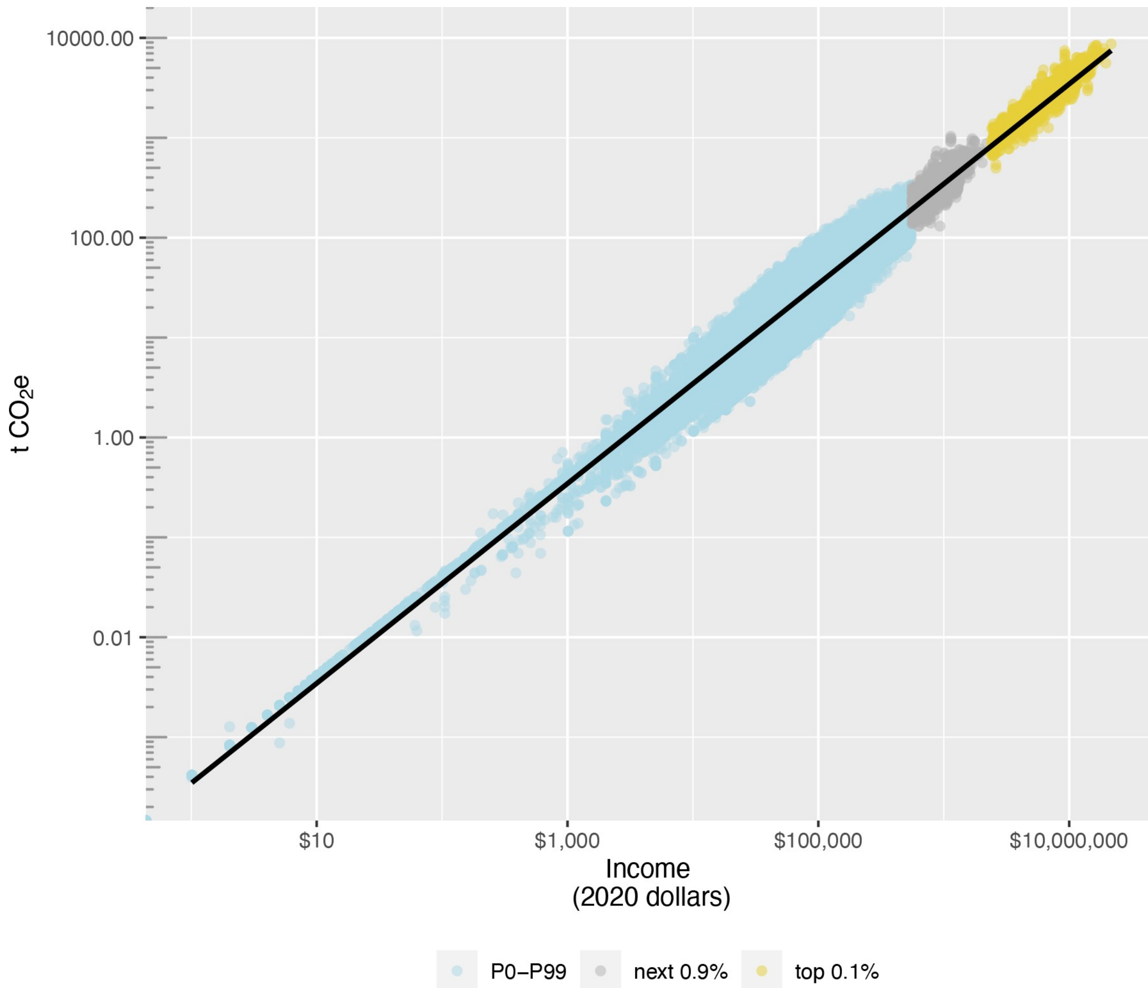

Fig 3. Relationship between pre-tax income and household GHG footprint (log-log) using the supplier income method (2019) (n = 69,483 –includes 2,000 synthetic data points for next 0.9% and top 0.1% households). (Producer-based results are presented in S7 Fig).

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top 10% of households drive 40–43% of NE. At the top of the income distribution, we estimate top 0.1% households account for 7–8% NE and have average absolute emissions > 2,000 t (**producer:** $\bar{x}$ = 2,110; $\tilde{x}$ = 1,870; 95% CI = 2,035 / 2,180 and **supplier:** $\bar{x}$ = 2,670; $\tilde{x}$ = 2,395; 95% CI = 2,585 / 2,765).

Super emitters

We term households with emissions >3,000 t CO_2e per year as "super emitters". For pre-tax income, we estimate about 43,200 U.S. households or 34% of the top 0.1% households are super emitters with the supplier framework ($\bar{x}$ = 4,317 t, $\tilde{x}$ = 4,053). About 26,500 households, or 21% of top 0.1% households surpass this threshold with the producer framework ($\bar{x}$ = 3,906 t, $\tilde{x}$ = 3,583). Post-tax, the percent of *top 0.1%* households classified as super emitters drops to about 9% (supplier) and 3% (producer).

Almost all super emitting households come from the top 0.1% income group. They had average incomes of over $10.6 million (supplier) and $11.5 (producer) (Table 2). Because GHG intensity varies widely across sectors, a household may surpass the 3,000 t threshold with

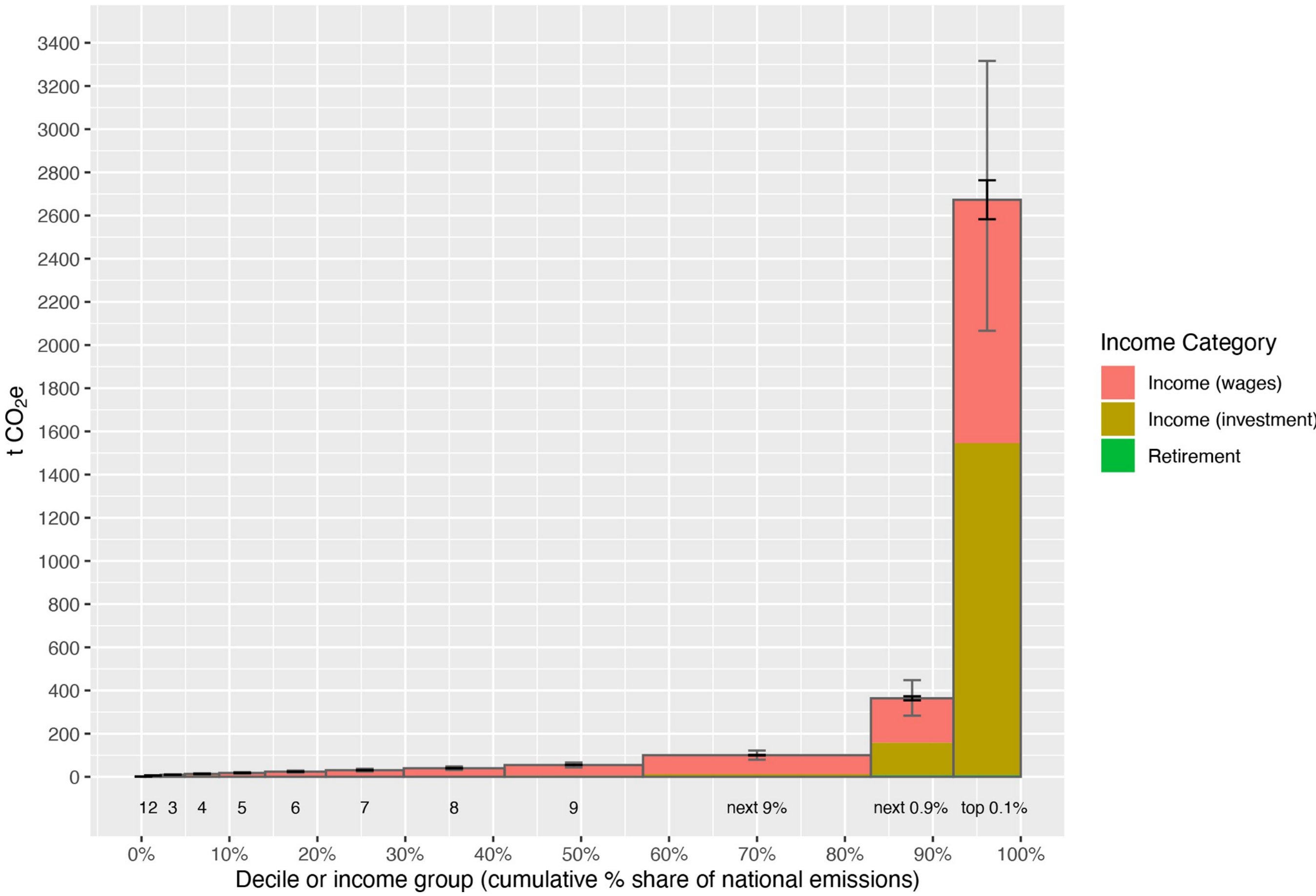

Fig 4. Mean household t CO_2e emissions (2019) per income group under the pre-tax supplier framework. The width of each income group, on the x-axis, corresponds with each group's share of national emissions. Color indicates income category. Black error bars are bootstrapped 95% confidence intervals for *total* t CO_2e from all three sources. Similarly, gray error bars are bootstrapped 95% confidence intervals on the total t CO_2e given an assumed ±20% error in carbon intensity per dollar. *(Producer-based results are presented in S8 Fig).*

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either much lower or much higher income than the average, depending on the GHG intensity of their income source. While super emitting households can also be employed in any sector of the economy (Table 2), they are markedly overrepresented in finance, real estate, and insurance; manufacturing; mining and quarrying; and services (other). Meanwhile, households earning income from accommodations and restaurants; education; retail and wholesale trade; and some other fields are underrepresented among super emitting households. Generally, both producer and supplier frameworks show the same directionality in terms of divergence from U.S. average employment by sector, but there is variability in the scale of this divergence.

Relationship to racial inequality

Black households had mean pre-tax footprints of 19 t CO_2e (supplier and producer) ($\tilde{x}$ = 11 t in both), White Hispanic households had 26 t (supplier) and 25 t (producer) ($\tilde{x}$ = 16 t in both), and White non-Hispanic households had 40 t (supplier) and 36 t (producer) ($\tilde{x}$ = 22 t in both). The fact that White non-Hispanic household emissions were 1.4x - 2.1x higher than other groups partly reflect differences in the CO_2e intensity of employment across groups. For

Table 2. Factors that shape super emitter household footprints (GHG intensity and income) (2019) and a comparison of super emitter employment by sector to that of the overall U.S. economy.

	Overall U.S. economy			Super emitter households (>3000 t CO_2e))			
	t CO_2e / $1000 income		Employment sector (%)			Income (mean in $1000)	
Sector	**Supplier**	**Producer**	**U.S.**	**Supplier**	**Producer**	**Supplier**	**Producer**
Accommodations & restaurants	0.25	0.25	7.5	2.4	2.1	10,314	11,143
Agriculture, forestry, fishing	0.66	0.47	2.9	1.7	1.6	9,813	9,727
Communications	0.41	0.26	0.9	1.0	0.5	9,426	10,946
Construction	0.27	0.41	7.2	7.9	12.6	9,229	9,230
Education	0.20	0.28	9.6	5.2	5.8	11,794	12,721
Entertainment	0.19	0.23	2.7	1.4	0.5	10,701	10,978
Finance, real estate, insurance	0.47	0.31	6.2	14.1	15.7	11,654	12,552
Manufacturing	0.54	0.82	9.5	13.1	17.8	10,236	10,716
Medical services	0.17	0.26	10.6	5.5	6.8	13,897	14,738
Mining and quarrying	0.87	0.48	1.5	2.1	2.6	8,790	9,233
Public administration	0.22	0.33	4.7	5.8	6.8	11,824	12,495
Retail & wholesale trade	0.46	0.28	12.7	5.2	4.2	11,013	13,378
Services (other)	0.38	0.32	18.2	28.2	18.3	9,508	11,083
Transportation & delivery	0.29	0.24	4.7	5.5	3.7	11,092	12,594
Utilities	0.47	0.39	1.2	1.0	1.0	9,991	10,528
AVERAGE	*0.39*	*0.36*				*10,619*	*11,471*

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example, in the supplier footprint White non-Hispanic households had emissions intensity of wages 1.12x higher than Black households. More critical, however, is the extreme racial inequity of the underlying income distribution. In 2019, the *top 1%* of the income distribution was 76% White non-Hispanic, 8% Hispanic, and only 3% Black. Meanwhile, Black households make up a disproportionate share of bottom decile households. Post-tax the racial emissions gap closes somewhat, but White non-Hispanic households still have emissions 1.3–1.7x higher than other groups. An additional observation is that significant emissions inequality exists within each racial group. Comparing the median to the means, shows that the emissions distribution is right skewed, with most of the population having emissions far below the mean and a relatively small percent of the population having emissions much higher than the group mean.

Emissions by age group

In terms of age, average emissions tend to increase with age until peaking within the 45–54 years old head of household age group (Table 3). After this point they tend to decline. This

Table 3. Income and emissions (supplier and producer) by age of "head of household" (2019).

Age Group	Household income ($)		Supplier (t CO_2e)		Producer (t CO_2e)	
	mean	*median*	*mean*	*median*	*mean*	*median*
Less than 35	84,232	58,744	31.2	19.1	29.8	19.2
35–44	119,100	81,075	44.0	26.1	41.0	27.1
45–54	131,239	84,036	48.9	27.6	45.4	28.1
55–64	94,230	60,952	35.3	20.1	32.8	20.0
65–74	65,554	38,474	24.6	13.9	20.9	11.5
75 or older	42,642	24,995	16.4	9.6	13.2	7.3

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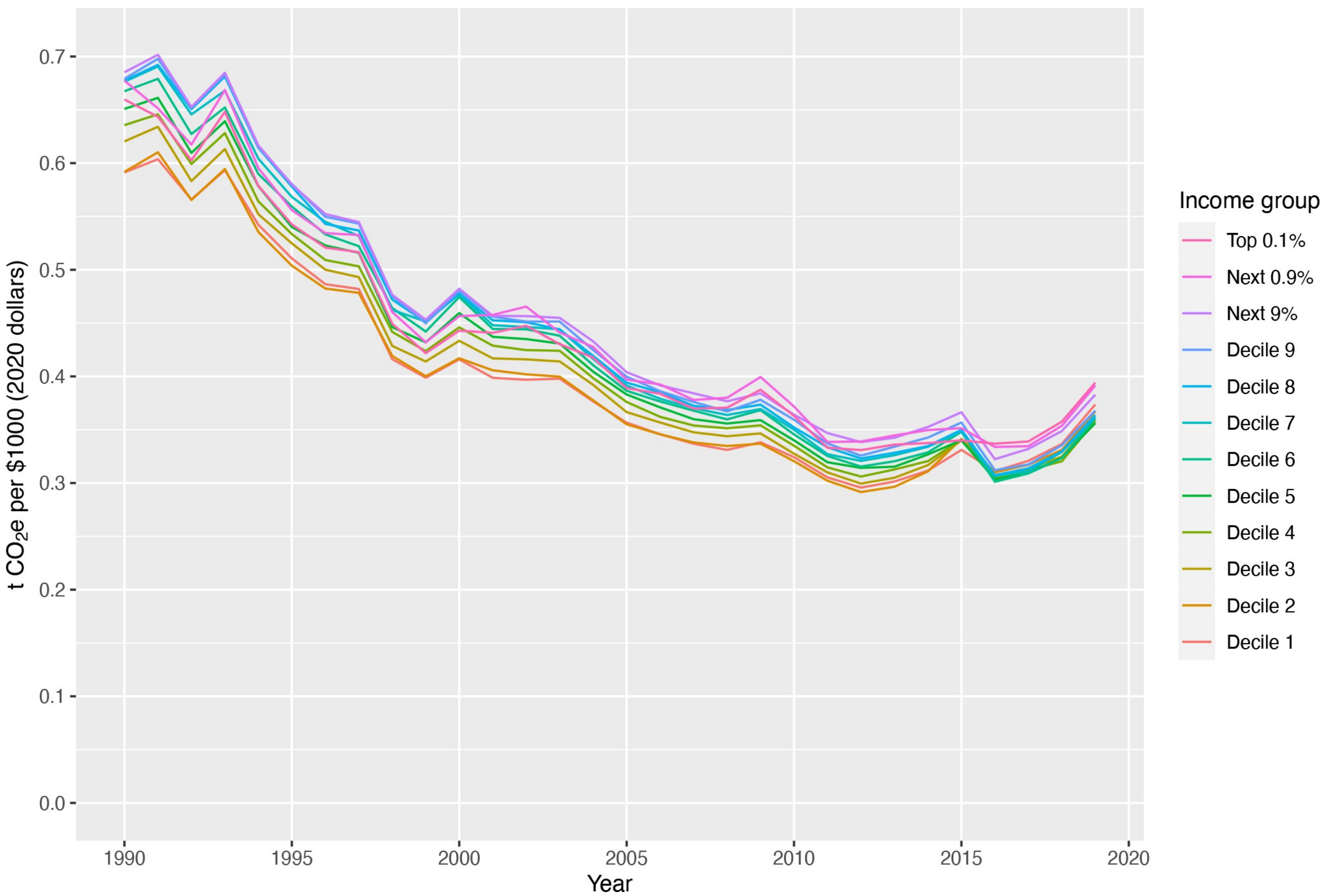

Fig 5. Supplier-based GHG emissions intensity per income group, pre-tax (1990–2019). (Producer-based results are presented in S9 Fig).

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mirrors household incomes, which tend to increase as cohorts gain experience and seniority within the labor force, then decline as they enter early retirement and retirement age.

Time series: (1990–2019)

Looking across 30 years of data a few noteworthy trends emerge. First, *emissions intensities* consistently differ across income groups and have fallen (45–49%) over time (Fig 5). Second, these falling emission intensities have resulted in *decreasing national average* household emissions, despite rising incomes (Fig 6). Yet, this declining national average belies a divergence that has occurred between the bottom 99% of the income distribution and the top 1%. While the bottom 99% have seen rising incomes, their absolute emissions have fallen (Fig 7) due to declining emissions intensities. For the top 1% however, income growth has outpaced falling emission intensities and resulted in flat or rising absolute emissions (Fig 7). Finally, these trends have resulted in a large and increasing *share of national emissions* generating economic benefits for high income households (Fig 8).

Put together, these trends reveal an interesting emissions story: despite falling emissions intensities, declining national average emissions and rising incomes for all groups, unequal income growth has created significant and increasing emissions inequality between extremely high-income households and the rest of U.S. society. This has moved the income-based national emissions Gini coefficient from 0.51 (producer and supplier) in 1990 to 0.57 (producer) and 0.58 (supplier) in 2019.

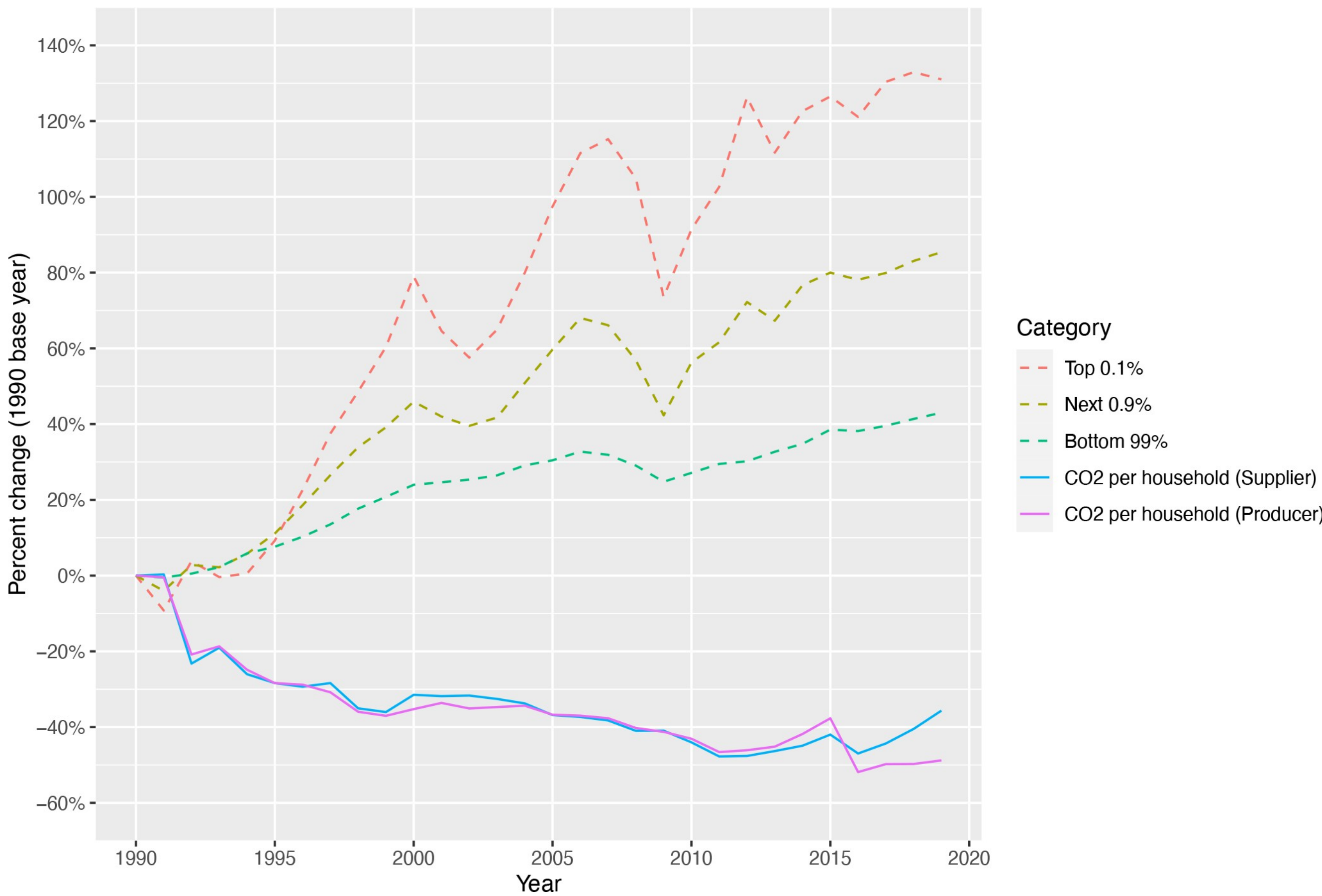

Fig 6. Percent change in income (dashed lines) and national average household emissions (solid lines) for both supplier and producer frameworks, pre-tax.

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Discussion

Limitations and sources of uncertainty

Our study is limited in scope, makes certain assumptions about unearned income that are important for top 1% households, and relies on survey and emissions databases that can introduce errors. First, this study focuses on linking emissions with *income*. Household *wealth* is only considered insofar as it generates realized income as capital gains or dividends. Because wealth is even more unequally distributed than income, a wealth-based emissions analysis would very likely show greater emissions inequality than our results.

In estimating the emissions intensity of *unearned income*, it is not feasible to estimate itemized sources of investment income per household. Instead, we assume that households have a diversified passive investment portfolio generating unearned *investment income* equal to the weighted mean GHG intensity of the U.S. economy. When creating the synthetic dataset for top 1% households, where investments are a key source of income, we allow the GHG intensity of individual household's investment income to vary up to ±25% from the mean. This creates a distribution of households whose average equals the mean but whose individual portfolios can be overweighted to either more or less GHG intensive industries than the national average. While some households may be outside these bounds, we assume extremely overweight portfolios in either GHG intensive or non-intensive industries are somewhat rare, tend to balance

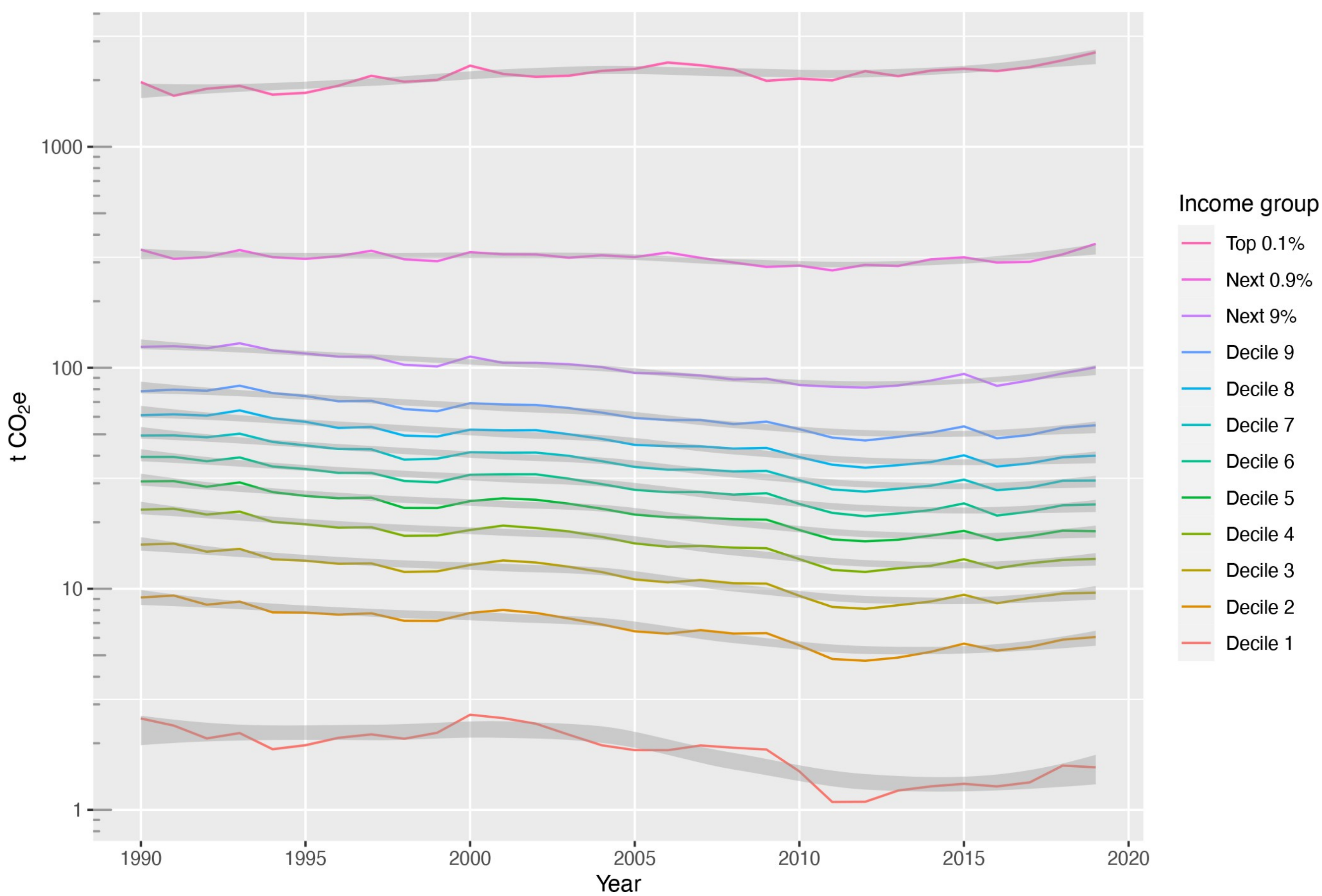

Fig 7. Supplier-based mean absolute household emissions per income group, pre-tax (log-linear scale, grey shading denotes loess fit). (Producer-based results are presented in S10 Fig).

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out and in aggregate do not meaningfully affect the overall group mean. This study assumes that on average, investments are passively managed, though further study of how investors can actively influence the carbon intensity of their investments is an interesting topic for future work.

The emissions per industry for *wage income* are taken from the Eora MRIO (see Materials and Methods). In Eora, import and export data reported across countries may not exactly align and balancing used in Eora to resolve these discrepancies may lead to minor estimation error, though the affect is minimal on large economies like the U.S. In all MRIO models emissions data are taken from IPCC-style inventories which itemize emissions by activity rather than by economic sector. Reallocating from activity-based inventories to sector-based inventories introduces error that could affect the accuracy of estimated emissions per wage income sector. Additionally, converting from symmetrical and non-symmetrical Supply-Use (SUT), Industry-Industry (II), and Commodity-Commodity (CC) tables, in the original Eora, to a symmetrical II intermediate transaction matrix involves the Fixed Product Sales Structure Assumption [39] and again moves away from the original national data reports. While some error is inherent, for a large economy with robust GHG reporting the effect on the final income group GHG estimates is limited.

All surveys, including the IPUMS CPS we use for household income are sensitive to sampling and non-sampling error. Most important to our study, top 1% households are under

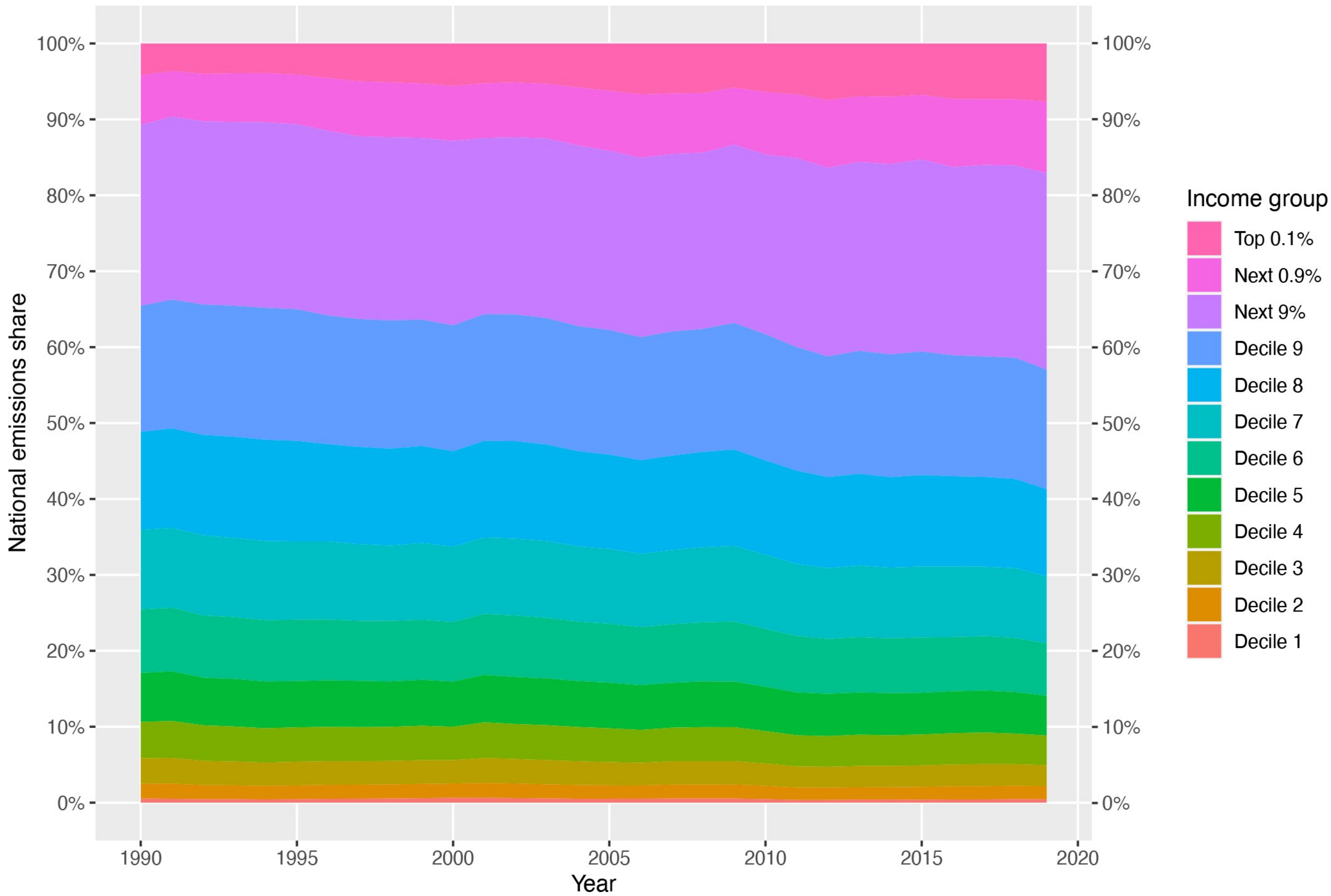

Fig 8. Supplier-based share of national average emissions responsibility for each income group, pre-tax (1990–2019). (Producer-based results are presented in S11 Fig).

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sampled in CPS (See *Undersampling and underestimating top 1% incomes in CPS* and Table A in S1 Text). To address this, we use income data from the World Inequality Database (WID) [30] and Congressional Budget Office (CBO) estimates on capital income shares to estimate incomes for these missing households (see Materials and Methods). Linking household incomes with Eora GHG intensities also requires the use of a concordance matrix. This reduces the number of U.S. industries from 429 to 246 and can impact an individual household's emission estimate if their employer has a much higher or lower emissions intensity than the sector average. Yet, it seems reasonable that over- or under-estimates for individual household emissions intensity tend to balance out at the income group level.

While some degree of measurement error is unavoidably present in any estimate of carbon intensity, ultimately income-based footprints are the direct result of the total income dollars received and the carbon intensity of those dollars. As the U.S. is a large economy with fairly accurate income and emissions data collection, we consider error in overall estimates for these variables is likely small. Considering the limited heterogeneity of emissions intensity across income groups and between capital and wage income, any error in group-level CO_2e intensity is also fairly limited. Nevertheless, to quantify the impact from a quite high level of error, we ran our model with carbon intensity ±20% from the baseline analysis. We then bootstrapped the results for each income group and extract lower 95% bounds from the -20% analysis and upper 95% bounds from the +20% error estimates (gray error bars in Fig 4). In practice this yields lower and upper bounds ±21–24% from the baseline group means. While the ±20% choice is arbitrary and we believe far higher than the actual error, given that the underlying error is unknown, it was chosen as a reasonable starting point. Results show that even when a high degree of error is tested, the absolute emissions and NE share from next 0.9% and top 1% households remains quite high and distinct from the lowest earning 99% of households. (See the S1 Text for additional discussion on uncertainty).

Income and emissions inequality

Across all accounting methods, those at the very top of the income distribution are responsible for striking absolute t CO_2e and disproportionate shares of national emissions. Disparities between these top income groups and the rest of society have also been growing over time. Between 1990 and 2019, Deciles 1–9 all saw declining absolute emissions and NE shares. For the bottom 5 deciles absolute emissions fell an average of 51% (producer) and 38% (supplier), while their NE shares showed average declines of 20% (producer) and 17% (supplier). For top 1% households, trends moved in the opposite direction. The next 0.9% and top 0.1% groups saw their NE shares respectively rise 46% and 82% (producer) and 43% and 83% (supplier). By 2019, the top 1% alone ($\bar{x}$ = 475 t (producer), $\bar{x}$ = 595 t (supplier)) were responsible for more emissions (15–17% NE) than the poorest 50% of U.S. households put together (14% NE). Average top 0.1% households ($\bar{x}$ = 2,110 t (producer), $\bar{x}$ = 2,670 t (supplier)) have emissions 1,650–1,700x higher than an average bottom decile household ($\bar{x}$ = 1.3 t (producer), $\bar{x}$ = 1.6 t CO_2e (supplier)). This divergence between top 1% households and the rest of society has been driven by rising income inequality (Fig 6) and has occurred despite the falling GHG *intensity* of incomes (Fig 5 and S9 Fig).

Income-based emissions responsibility closely correlates with income inequality. We find that in 2019 the poorest 50% of the U.S. population captured just 15% of pre-tax national income and was responsible for 14% of pre-tax NE in both frameworks (Table 1). The top 10%, *top 1%*, and *top 0.1%* captured about 41%, 16%, and 7% of national income. We find they have fairly comparable NE shares of 43%, 17%, and 8% for pre-tax supplier and 40%, 15%, and 7% for pre-tax producer. While limited, the differences between income shares and emission shares are due to variations in GHG-intensity across income sources, income groups, and accounting methods. An interesting recent study by Pottier and Le Treut analyzing wage-based emissions in French households finds the emissions distribution is more unequal than the wage distribution [35]. Here they find large variability in the carbon intensity of wages is driving this difference. They also find an interesting gender gap in emissions, with men tending to earn wages from more carbon intensive activities than women.

While income-based emissions accounting is distinct from consumption-based accounting, it is worth noting that an income-based approach estimates greater inequality. For example, in a related consumption-based study that we conducted, we estimate the top 10%, top 1%, and top 0.1% of U.S. households are responsible for a much lower 24%, 6%, and 2.3% of national emissions [33]. The discrepancy is due to large savings rates among high-income households (which reduces consumption) and significant heterogeneity in GHG intensity across income groups, with low-income households purchasing more GHG intensive goods. In France, Pottier and Le Truet find this same trend of income-based emissions being more unequal than consumption-based emissions [35, 40].

We find that because income-based emissions are the result of both income and the GHG intensity of that income (which varies across industries and producer and supplier accounting principles (Table 2)), households at the same income level can have very different emissions levels. For example, in the producer framework a household earning $980,000 from the petroleum refining industry would be a super emitter (>3,000 t), while the same amount of emissions would require $11 million in income from the hospital industry. In the supplier framework, becoming a super emitting household would take at least $18 million in hospital income, but only $2.7 million in income from the coal industry. Households may also have very different GHG intensities from different income sources. This is particularly true for high income households that have a significant share of income flowing from investments. For example, one might earn wages from a low GHG intensive sector like education but have above average GHG intensity of investment income from a portfolio that is overweight on fossil fuel companies.

In terms of how age relates to emissions, prior consumption-based work by Zheng et al. has shown that seniors (age 60+) in the U.S. had the highest per capita footprint (20 t) of any age group [41]. With our income-based analysis we find the highest household emissions are among the 45–54 years old peak earning group. If our analysis was wealth-based however, rather than income-based, it would likely agree with the findings from Zheng et al. that seniors have the largest emissions footprints. This is because, while incomes tend to decline for cohorts above age 54, household net worth continues rising and peaks within the 65–74 years old cohort [42]. Even the 75 and above group has a higher net worth than the 45–54 peak income group.

While different in methodology, an interesting study by Lucas Chancel looking at global income groups' consumption and investment found that for the global top 1%, emissions related to investments account for a much greater share of their emissions responsibly (70%) than their consumption (30%) [43]. Finally, it is worth noting that household income is shaped by a variety of demographic factors. While we report on emissions disparity by race, ethnicity, and age, we are principally focused on quantifying the emissions distribution in relation to the income distribution as it exists and do not investigate in great detail how demographic factors influence the income distribution.

Policy implications

Carbon pricing, either through cap-and-trade or a carbon tax, are seen by economists as an essential and cost-effective way to help decarbonize the US economy [44, 45]. Prior work has suggested this tax would need to be >$200 per t CO_2e, to achieve even a 5% reduction in oil consumption, and estimates that 70–80% of this cost would be initially passed onto consumers [45]. Another paper we have published looking at consumption-based U.S. emissions suggests that a tax this high would present a significant burden to low-income families, even though they have comparatively small GHG footprints [33]. Meanwhile the tax may not be sufficient to shift behavior of high-income households, who have significant consumption-based emissions, but adequate savings rates to absorb the tax. While a carbon tax-funded dividend has been proposed to reduce financial strain on low income households [46], consumer-facing carbon taxes have not found sufficient political support, despite two decades of development.

The fact that income-based footprints are more inequitable than consumption-based footprints [16, 17, 35, 47–49] suggests an alternative income-based approach to carbon pricing schemes, applied to wage earners or investors, could have equity and political advantages over consumer-facing carbon taxes. Such a tax could be calculated based on direct emissions (producer), on the supply of fossil fuels into the economy (supplier), or some split between the two. Tax revenue could be used for climate mitigation or adaptation projects either within the U.S. or to meet and increase international climate finance pledges including loss and damage funding agreed to at COP 27.

While either wage or investment income could be the focus of such a tax, a wage-based tax has some drawbacks. Just like low-income consumers, low-income wage earners would have the least ability to absorb a tax. To address this, a carbon income tax could be applied progressively, to shield low-income workers. Yet the effectiveness of such a tax to shift the economy to lower GHG emissions may be insubstantial as workers generally have limited agency in shifting their industry's emissions behavior. While a tax may generate revenue that could be invested in decarbonization or climate finance, it may be politically unpopular to create a wage-based carbon tax that would impact a wide swath of the public.

Because unearned investment income and asset ownership are heavily concentrated at the top of the income distribution, limiting a carbon tax to either of these items could further focus it on those reaping the most economic benefit from GHG emissions, increase public support, and reduce GHG-intensive economic activity in a more direct way. A consideration here is that while there is some overlap of households in the top 1% or 0.1% of *income earners* and the top 1% or 0.1% of *wealth holders* there is far more annual churn among the top income group [50]. Here, households may see huge profits one year from the sale of a business or stocks, but far less income in subsequent years. In this way, an asset-based shareholder carbon tax may be more desirable than an unearned income tax because it would set a more stable annual tax rate and keep the focus on those with the most economic power. It would also be more equitable in that it accounts for the historical emissions embodied in unrealized capital gains, rather than focusing solely on present day emissions that generate unearned income. Furthermore, it concentrates behavior change incentives on the executives and large shareholders who have the most agency and power to reduce their industries' emissions activities.

At the extreme end of the income distribution, an interesting 2022 study by Oxfam International on 125 global billionaires with assets in excess of $2 trillion, estimates emissions related to their investments were over 3 million t per person annually [51]. If these individuals were incentivized to reduce the GHG intensity of their industries or shift their investments to other industries, in response to a tax, it could meaningfully impact emissions. Indeed, they estimate the overall carbon intensity of billionaires' emissions, in their study, could be reduced fourfold if investments were shifted to funds with stronger environmental and social standards [51]. Work by Lucas Chancel suggests that a progressive carbon tax tied to the carbon intensity of investments could be helpful to accelerate decarbonization, while having limited impact on most households [43]. Further work by Chancel, Bothe, and Voituriez [52] estimate a progressive global wealth tax starting at 1.5% for individuals with net worth's >$100 million (~65,000 individuals or <0.001% of the global population) and going as high as 3% for individuals with assets above $100 billion could raise $300 billion annually for decarbonization, loss and damage, or other climate funding. Even if just the U.S. and European countries adopted such as tax, Chancel and colleagues estimate $175 billion could be raised annually. As they note, because wealth tends to grow 7–9% annually for extremely wealthy individuals, their overall fortunes would still increase, even in the face of these progressive climate-focused taxes [52]. Kapeller, Leitch, and Wildauer also find that a progressive European wealth tax has the potential to raise enough revenue to close the European Union's (E.U.) several hundred billion dollar per year green investment gap [53]. If revenue from capital taxes is reinvested in public infrastructure, such as decarbonization efforts, it can also benefit wealthy countries by increasing social welfare, while reducing extreme economic inequality [54].

While it would increase the complexity of tax administration, basing such a tax on Scope 1 (or full supply chain Scope 1–3) emissions, rather than a tax based solely on net worth, would keep the tax close to the source of the emissions and encourage divestment from high emitting (highly-taxed) industries. In the U.S., new climate disclosure rules proposed by the Securities and Exchange Commission in 2022, which require Scope 1 and 2 reporting (and Scope 3 for companies with Scope 3 emissions targets) would provide company-specific emissions data that could be used for calculating an appropriate tax rate for investments in that company. In

Europe, similar data will become available as the E.U.'s Corporate Sustainability Reporting directive, that came into effect in 2023, requires Scope 3 emissions reporting for E.U. based companies. At the asset manager level, interesting recent work by Zengkai Zhang and colleagues has highlighted the carbon emissions in firms' portfolios in China [55] and emissions associated with investments for multinational enterprises [56].

Finally, while it is impractical to assume large numbers of high-income households could or would easily switch to lower GHG intensive professions, it seems reasonable that in their role as investors high-income households and their asset managers can nimbly shift to lower GHG intensive investments if the market rewards such moves. Linking the shareholder tax rate to the GHG intensity of the industry would also spur fiduciary fund managers to divest from GHG intensive industries in search of higher returns elsewhere. From an industry perspective, such a tax may also encourage firms to decarbonize their operations in order to attract investors with the promise of higher returns, via relatively lower taxes on ownership of the company's shares. It could also encourage executives, who have seen ballooning compensation over the last several decades [57] to decarbonize their operations and supply chains to reduce taxes on the income and shares they receive. If high income households did shift their investments in response to such a tax, we would see further decoupling of the national income shares and national emission shares (Table 1) among high income households.

Conclusion

To avoid the worst impacts of climate change it is imperative that global temperature rise is limited to 1.5˚C [7, 58, 59]. Yet, the window to achieve this goal is rapidly shrinking. By 2030, even if the existing Paris Agreement National Determined Contributions are achieved, global emissions are still projected to overshoot the 1.5˚C pathway by at least 60% [9]. At the same time, climate finance falls well short of what is needed to mitigate and adapt to a warming world. Recent work by Andrew Fanning and Jason Hickel has shown that if nations were each allocated an equality-based fair share of emissions, by 2050 wealthy countries in the global North would owe $192 trillion (or about $6.2 trillion per year) to poorer countries in the global South to compensate for their atmospheric over-appropriations [60]. To date, climate finance flows to developing nations have struggled to reach the $100 billion a year goal set over a decade ago. It is clear that the economy needs to decarbonize faster than its current trajectory and that more money is needed to both fund this transition and equitably adapt societies to a warming world.

By linking GHG emissions with the incomes it enables our work has quantified the scale of emissions inequality in U.S. society and the extreme and growing concentration of emissions among very wealthy households. It also offers some suggestions on how accelerated decarbonization and revenue generation might occur, such as an income or shareholder-based carbon tax that reflects the GHG intensity of one's income sources or financial assets. This is distinct from consumer facing carbon taxes that rely on individuals decarbonizing the economy by shifting their consumption to less GHG intensive goods and services and thereby encouraging companies to respond to their new preferences. A consumer-facing approach assumes individual consumers have the knowledge, financial resources, and agency to shift spending and the power to alter corporate decision making on the GHG intensity of their supply chain and operations. An alternative income or shareholder facing carbon tax puts pressure on executives and large shareholders (i.e. those with the most economic and corporate power) to act in their own self-interest and decarbonize their supply chain and operations in order to reduce taxes on their compensation and investments. Recent work has calculated that a climate inspired wealth tax could indeed be an effective tool to raise revenue for adaptation and mitigation efforts [52, 53].

By thinking of carbon as an outcome of income generation rather than just an outcome of consumption, such alternative policy solutions become possible. While consumer-facing carbon taxes have struggled to move from proposal to law in the U.S. an investment-based carbon tax may be more equitable, politically palatable, and equally justifiable. Of course, any such proposals would likely face significant pushback from the economically advantaged households who dominate policymaking [61]. Finally, given the urgent nature of the climate crisis and the shrinking window in which limiting warming to 1.5˚C is possible, policymakers may be wise to consider adopting multiple approaches (both consumer and income or investor facing carbon taxes) that can simultaneously put pressure on different actors to equitably decarbonize the economy and fund a just transition to a still warming world. We suggest further work quantifying the potential effects of such proposals is warranted.

Materials and methods

For both the producer- and supplier-income approach we link income to GHG emissions using survey data on individual-level income (see Table E in S1 Text for income categories) and an Environmentally-Extended Multi-Region Input-Output Model (EE-MRIO). For earned income, the GHG intensity per dollar of wages, for each industry, is calculated and multiplied by an individual's income from that industry. The GHG intensities of unearned investment income, retirement, and employer contributions to healthcare are also included (12 categories in total) in the pre-tax analysis. In post-tax footprints, emissions responsibilities are increased by 23 categories of social transfers and reduced by the amount of taxes paid. Individuals are aggregated into households and households are ranked into percentiles and deciles, for income group comparisons.

To calculate the CO_2e intensity of income, we use the Eora MRIO database [36, 37] covering 14,839 sectors, 190 countries, and 1,140 final demand and value-added categories. For each of the 30 years, EORA is converted from a 14,839 x 14,839 heterogeneous classification system to a square 9,812 x 9,812 industry by industry input-output table, using the Fixed Product Sales Structure assumption [39]. Current year dollars are adjusted to constant 2020 US$. GHG emissions data come from the PRIMAPHIST database (Version 2.3—available in Eora) [62, 63]. This includes the six Kyoto GHGs and excludes land use, land use change, and forestry (LULUCF).

In a producer-income approach the CO_2e intensity of each industry's direct emissions are calculated by proportionally allocating emissions to each value added category and calculating the GHG intensity per dollar of various income types. In the supplier income emissions framework, we calculate the enabled emissions, in t CO_2e per dollar, using the Ghosh inverse (see S1 Text). This captures all *direct* and *indirect* CO_2e emissions, along the whole downstream global supply chain (~96 million inter-sectoral transfers each year) that were enabled to produce a dollar of value added.

For each year, these supply chain and direct emissions factors are matched with individual-level IPUMS CPS income data. IPUMS CPS is a harmonized dataset drawn from the Census Bureau's Current Population Survey [38]. It includes approximately 65,000 U.S. households and about 181,000 individuals per year. From CPS, we extract 58 variables related to income, healthcare, social benefits, industry from which wages are earned, and individual or household characteristics. Each year yields approximately 10,500,000 data points, totaling about 315,000,000 data points across the 30-year period. Individual-level emissions and income matching is done by applying a concordance matrix to convert emissions factors from the 429 U.S. industries in Eora to the 246 U.S. industries reported by CPS, using International Standard Industrial Classification (ISIC) system coding (For more details see *Converting Eora* *industries into CPS industries* in S1 Text and S12 Data). Individual-level wage data in CPS includes both the amount (in dollars) and the industry from which income is earned (IND90LY). Individual-level wage data are then multiplied by the corresponding CO_2e intensity for that industry. The income value of employer healthcare contributions is added, based on the employing industry's CO_2e multiplier. This is included for all years except 1990–1992 and 2019, where data is not reported in CPS.

The GHG responsibility of social security, retirement, capital gains, interest and dividends, and social benefits are also accounted for using weighted average income-based emissions intensities of the U.S. economy. These national average intensities are calculated to reflect each industry's share of emissions from the relevant value added category/ies (see *Converting Eora industries into CPS industries* and *Calculating CO_2e intensities of income sources from value added* in S1 Text). For example, because Social Security comes out of employee compensation, an industry specific weight is calculated based on each industry's share of total employee compensation. Each industry's weight is then multiplied by its CO_2e intensity. All the weighted CO_2e intensities are then summed into the weighted national average CO_2e intensity per dollar Social Security. Interests and dividends multipliers are calculated the same way but based on each industry's share of Net Operating Surplus. Social benefits are also calculated in this way but based on each industry's share out of all value added categories. In practice, the difference between these three different national average CO_2e intensities is generally quite small (a few percentage points).

For each individual in CPS, income dollars from wages, investments, retirement, and employer healthcare contributions are multiplied by the corresponding CO_2e intensity of that income source. Individuals are then merged into their respective households and t CO_2e are summed. This yields the pre-tax emissions footprint of each household. Households are then binned into income groups.

To calculate the post-tax and transfer footprint, the value of social transfers such as monetary gifts and publicly provided benefits such as veterans benefits, unemployment, home heating, rental, and educational assistance are multiplied by the social benefit CO_2e intensity. Tons CO_2e are summed and added to the pre-tax footprint. Finally, post-tax footprints are reduced by subtracting emissions equivalent to the percentage of taxes paid. For example, a household with a 20% tax rate would have its t CO_2e pre-tax plus benefits footprint reduced by 20%.

Top 1% households

While CPS is the most authoritative source on U.S. household income, top 1% households are under sampled, average incomes are underestimated (see S1 Text), and top-coding affects some income categories. To address this, we create an over-sampled synthetic dataset for the next 0.9% and top 0.1% households and estimate their income, income sources, and CO_2e intensity. This is done by creating a distribution of 1,000 households, for each group, whose mean pre-tax income and upper and lower thresholds come from WID and whose distributions is right-skewed to reflect within-group income inequality (see S1 Text for detailed methodology).

We then extract the IPUMS CPS households that meet the WID top 1% threshold and bootstrap these into two 1,000 row datasets that are matched with the next 0.9% and top 0.1% WID synthetic income distributions. In this merged synthetic distribution, total household income from WID is then distributed to wage, investment, retirement, and employer healthcare income categories, based on values from the bootstrapped CPS households. Income related to retirement and employer healthcare, which makes up an exceedingly small share of total income (and emissions) for *top 1%* households, are directly extracted from the CPS households and subtracted from the household's total income.

The remaining income is divided among wages and investment income. Due to limited reporting on capital gains and investment income in CPS we do not directly apply the raw income share allocation from the CPS bootstrapped households. Instead, we use CBO estimates on the share of capital income versus wage income for next 0.9% and top 0.1% households [64]. To do this we use CBO values for each group's mean capital income share and create a normal distribution (s = 15%) of capital share values around this mean. In so doing we simulate variations in household income streams for each group. For each household, this wage and capital share (which sum to 100) are multiplied by the remaining household total income dollars. This yields dollars per wage and investment income category (see *Investment CO_2e intensity* and *Investments and capital gains* in S1 Text for more details on the investment income approach).

Each income category total dollars are then multiplied by the corresponding CO_2e intensities for that category. These intensities come from the bootstrapped dataset but are allowed to randomly vary up ±25% from the original value. This is done to reflect the natural variation in GHG intensity that exists between top 1% households due to differences in employment and investment choices. Summing all categories yields pre-tax income based GHG footprints for the next 0.9% and top 0.1% groups. Post-tax footprints are calculated by adding the emissions value of social benefits (which are exceeding small as a portion of total income for these groups) and reducing these footprints in proportion to the household's tax rate.

Supporting information

S1 Text. Supplementary text with additional methodological details and discussion, figures, and tables.
(PDF)

S1 Fig. Producer-based post-tax emissions share per income category, by income group (2018). *Note, we present 2018 results here because "Healthcare (employment)" is not available for 2019. The 2019 results are otherwise similar.* (Supplier-based results are presented in Fig 1).
(TIF)

S2 Fig. Annual mean CO_2e intensity of producer-based wages and other income sources (1990–2019). Wages and employer healthcare contributions are industry specific CO_2e multipliers and are presented by income group. The other income categories use weighted national average multipliers (shaded blue area). *Note: Healthcare (employment) has the same intensity as wage income and Healthcare (public) has the same intensity as social benefits.* (Supplier-based results are presented in Fig 2).
(TIF)

S3 Fig. Supplier-based CO_2e intensity of wages per individual (n = 141,159), by sector (2019). The blue diamond denotes the mean. Note, means here are calculated based on individual-level wage data and the CO_2e intensity of their primary employment industry. This leads to some minor differences from the industry-level (n = 246) CO_2e intensities used to calculate sectoral means in Table 2. See *Carbon intensity by sector* in S1 Text for further discussion.
(TIF)

S4 Fig. Producer-based CO_2e intensity by sector (2019) (n = 141,031). The blue diamond denotes the mean. Note, to make differences between sectors clearer, 128 outlier observations related to Manufacturing are not displayed. The max value of those observations is 3.03 t CO_2e per $1000. Note, means here are calculated based on individual-level wage data and the CO_2e

intensity of their primary employment industry. This leads to some minor differences from the industry-level (n = 246) CO_2e intensities used to calculate sectoral means in Table 2. See *Carbon intensity by sector* in S1 Text for further discussion.
(TIF)

S5 Fig. Supplier-based emissions Lorenz curve (2019). Note, the population on the x axis is ranked by emissions, rather than income. While emissions strongly correlate with income there is some emissions variability at any given income level. Therefore, there is some minor discrepancy between the national emissions shares here and those seen in Fig 4.
(TIF)

S6 Fig. Producer-based emissions Lorenz curve (2019). Note, the population on the x axis is ranked by emissions, rather than income. While emissions strongly correlate with income there is some emissions variability at any given income level. Therefore, there is some minor discrepancy between the national emissions shares here and those seen in S8 Fig.
(TIF)

S7 Fig. Relationship between pre-tax income and household GHG footprint (log-log) using the producer income method (2019) (n = 69,483 –includes 2,000 synthetic data points for next 0.9% and top 0.1% households). (Supplier-based results are presented in Fig 3).
(TIF)

S8 Fig. Mean household t CO_2e emissions (2019) per income group under the pre-tax producer framework. The width of each income group, on the x-axis, corresponds with each group's share of national emissions. Color indicates income category. Black error bars are bootstrapped 95% confidence intervals. Gray error bars are bootstrapped 95% confidence intervals when assuming ±20% error in carbon intensity per dollar. (Supplier-based results are presented in Fig 4).
(TIF)

S9 Fig. Producer-based GHG emissions intensity per income group, pre-tax (1990–2019). *Note, we believe the convergence of CO_2e intensities in 2015 is the result of some error in the dataset. As this single year is not critical to the overall results, we do not attempt to impute alternative values.* (Supplier-based results are presented in Fig 5).
(TIF)

S10 Fig. Producer-based mean absolute household emissions per income group, pre-tax (log-linear scale, grey shading denotes loess fit) (1990–2019). (Supplier-based results are presented in Fig 7).
(TIF)

S11 Fig. Producer-based share of national average emissions, by income group, pre-tax (1990–2019). (Supplier-based results are presented in Fig 8).
(TIF)

S1 Data. Supplier-based household-level demographic, income, and emissions data (2019) that supports Figs 3 and 4, Tables 1–3 in the main text; Tables A-C in S1 Text; and S3 and S5 Figs in Supporting information.
(XLSX)

S2 Data. Producer-based household-level demographic, income, and emissions data (2019) that supports S3, S4, S7, and S8 Figs in Supporting information; Tables 1–3 in the main text; and Tables A-C in S1 Text.
(XLSX)

S3 Data. Data supporting Fig 1 (supplier).
(XLSX)

S4 Data. Data supporting S1 Fig (producer).
(XLSX)

S5 Data. Data supporting Fig 2 (supplier).
(XLSX)

S6 Data. Data supporting S2 Fig (producer).
(XLSX)

S7 Data. Data supporting Fig 5 (supplier).
(XLSX)

S8 Data. Data supporting S9 Fig (producer).
(XLSX)

S9 Data. Data supporting Fig 6.
(XLSX)

S10 Data. Data supporting Figs 7 & 8 (supplier).
(XLSX)

S11 Data. Data supporting S10 & S11 Figs (producer).
(XLSX)

S12 Data. Eora to IPUMS CPS industry concordance matrix.
(XLSX)

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