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United States Household Carbon Footprints: Quantifying the relationship between household-level income inequality and greenhouse gas emissions (1996-2015)

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United States Household Carbon Footprints:
Quantifying the relationship between household-level income inequality and greenhouse gas emissions (1996-2015)

A Dissertation Presented

by

JARED STARR

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Environmental Conservation

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DEDICATION

I dedicate this work to all those who have come before and all those yet to come who work to preserve nature and make society more equitable.

ACKNOWLEDGMENTS

While the work presented in this dissertation represents countless hours (or perhaps more accurately I'm not sure I wish to count them) of solitary labor reading, thinking, acquiring data, writing code, and interpreting and visualizing results this work would not have been possible without the support of a community of fellow researchers, mentors, friends, and family.

The quantification of U.S. household-level greenhouse gas emissions, in the following pages, were only possible because of the hard work of others toiling away to quantify economic transfers, environmental flows, consumer purchases, income sources, and income inequality and so generously sharing their data with the world. I'm particularly grateful to the Eora MRIO team for making their highly granular global input-output model available to other researchers and particularly Daniel Moran for patiently answering my queries. I'm likewise grateful to the civil servants, particularly at the Census Bureau and Bureau of Labor statistics, whose work collecting data for Consumer Expenditure Surveys (CES) and Current Population Surveys (CPS) both serves the public good and became so crucial to my work. I'm similarly grateful to the IPUMS team at the University of Minnesota who harmonized the CPS data across years: savings me a tremendous amount of time. I'm also extremely grateful to the World Inequality Database team for making their highly granular income and wealth inequality database publically available.

In this vein, I'd like to acknowledge Thomas Piketty, whose book *Capital in the Twenty-First Century* so powerfully illuminated the scale of income and wealth inequality within and across societies. Reading *Capital* is what first got me curious

about how trends in such extreme inequality might relate to and impact concurrent trends around environmental degradation.

In the realm of mentors, I will be forever grateful to my mentor, committee chair, and friend Craig Nicolson for first taking me on as a graduate student, for teaching me how to be a researcher and teacher, and for his friendship along the way. I'm truly grateful for the complete freedom Craig provided in allowing me to follow my interests and for his persistent insights throughout countless discussions, over many cups of coffee, throughout these many years. This work would not have been possible without Craig and I could not have asked for a better guide to have on this PhD adventure.

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As my mentor Craig says, "work fits into life, not the other way around". I'd like to finally thank my family. This whole adventure would not have been possible without the tremendous support of my parents Judith and Michael Starr who always valued and encouraged education. Their love and support provided the space for me to focus on the work. I'm so grateful to my mom, dad, brother, and sister for their love throughout my life and encouragement along this PhD journey. As I neared completion of this dissertation my mom was reminiscing about times in elementary school when I would have my head down on the dining room table, finding it too exhausting to complete an assignment copying words. She would sit with me saying "just write one letter…ok now the next". An assignment that probably should have

taken ten minutes took an hour. But instead of getting frustrated and giving up she stayed and help and eventually I had the stamina to do it on my own. Thanks mom for putting in the time. I'm pleased to say, as you will see in this document, I've developed a significant level of stamina for academic work.

I'd also like to so gratefully acknowledge and thank my parents-in-law Michelle and Henri Cuénoud. From taking us in during the pandemic, to watching the kids, cooking meals, or giving us a break at the pool their support has been so crucial to providing the space to work and the space to take a mental break. Every minute spent working on this research was a minute I wasn't with my kids. I so appreciated knowing Émile and Camille were in such good (French immersion) hands (merci!).

To my wonderful and supportive wife Stéphanie Cuénoud, I could not have done this without you. If not for Stéph's encouragement I don't think I would have ever gone to grad school and if not for her endless support discussing ideas (and patiently listening too me give way to much detail), providing insights on visualizations, caring for our kids, and making life fun outside of work, I would not have been able to produced the research you will find in these pages. Stéph has been the best partner I could ask for on this academic adventure and in the adventure of life. Finally, I thank my children Émile and Camille who joined us part way into this endeavor and whose love I so deeply treasure. It's been such a joy to see Émile go from a newborn to someone that likes to discuss research, talk about data and graphs, and wants to have his paper computer screen have all the same data and figures he sees on mine. It's likewise been such a joy welcoming Camille into our

family these last few months. Thank you Camille for the warm smiles, giggles, and hugs they are always a highlight of my day. It has been such fun seeing them both grow and has provided additional motivation on why this work matters. The decisions we make today are shaping the world they and all the children of the world will live in tomorrow. I hope this research will help make that future brighter.

ABSTRACT

United States Household Carbon Footprints:
Quantifying the relationship between household-level income inequality and greenhouse gas emissions (1996-2015)

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As long as humanity has existed, we have altered our environment to provide goods, services, and (more recently) wealth to people. Over the last several centuries, the scope and pace of this transformation has accelerated with the onset of technological innovation, social and economic reorganization, and an ensuing population boom. Today, humanity's demands on nature have become the dominant force shaping the critical earth systems upon which all life depends. From local land-use change to the global climate many of these anthropogenic pressures pose an existential threat to nature and the dependent social systems that rely on them. Yet, extreme economic and social inequality within and across human societies leads to significant inequality in who reaps the benefits of these transformations, who reaps the harms, and who makes the decisions on that benefit-harm distribution. Here I quantify, at high granularity and over a 20-year period (1996-2015), the GHG emissions footprints of United States households, based on the flow of income, goods and services these emissions enable. I compare the scale and distributions of

household-level GHG emissions across different social groups and responsibility frameworks and provide policy insights related to those findings.

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CHAPTER 1

INTRODUCTION

1.1 Overview

Individual people and society, writ large, are fundamentally dependent on a steady flow of ecosystem goods and services to meet our wants and needs (1).

Over the millennia, the scale and scope of these wants and needs has increased with growing populations and rising living standards. Today, human society is over 7 billion strong and people are living longer, attaining higher levels of education, capturing more wealth, gaining food and energy security, travelling further, and participating in a globally-connected society (2).

Such remarkable gains provide significant human benefits, yet the scale of environmental transformation underpinning these benefits is resulting in increasingly dangerous levels of environmental change (3–5). At scales ranging from local to global, human demands are transforming natural systems in ecologically significant ways that fundamentally reduce their biodiversity (6), resiliency, and ability to provide future ecosystem services (4, 5).

Such changes are not just concerning for those who care about "nature", but also for those who care about people. Our global society depends on stable natural systems: a) from which we produce food, raw materials, and energy; upon which we build our homes, cities, roads, and ports; and to which we send airborne, liquid, and solid waste for processing. As humanity alters the natural systems that produce

value for people, we are reducing their stability, resiliency, dependability, and basic ability to continue producing valuable goods in the future (7).

With the global population projected to swell by 2 billion or more by mid-century, the economy expected to triple (8), and nature already flashing warning signs that human demands are unsustainable, society is drifting down an existentially dangerous path. If we are to welcome billions more people onto the planet and they are to live wealthier lives, then we must find ways to dramatically reduce net environmental impacts: thereby ensuring basic environmental integrity.

To do so, requires thoughtful decision-making in our social, political, and economic systems to balance present and future human wellbeing while maintaining the stable productive ecosystems that underpin this wellbeing. Such decisions, in turn, require a deep empirically-based understanding of the human-nature relationship as it interacts across space, time, and scales.

My work here focuses on one aspect of this relationship: the connection between greenhouse gas (GHG) emissions and the income and consumption benefits these emissions enable. Specifically, I link U.S. households with the global GHG emissions used to generate their income and produce the goods and services they consume. I do this at high granularity, over a 20-year period, and analyze how economic inequality and race shape the distribution of GHG emissions responsibility.

In doing so, this work gives insight into two key trends shaping society's relationship with nature, in recent decades: long globalized supply chains and uneven resource distribution within society. These trends mean that massive

environmental change in one geographic area may be ultimately driven by a small group of consumers (or shareholders) halfway across the globe that reap the benefits of this transformation, while other groups within society are left to face the harms of this transformation. My work reveals these connections and in doing so highlights some policy choices that can help achieve the more ambitious targets of the United Nations 2015 Paris Agreement, to stabilize the global climate.

1.2 Tools for quantifying coupled human-nature systems

People and nature are coupled in complex relationships that span dimensions of organizational levels, time, and space (9). Humanity is a part of nature, fundamentally dependent on our environment for the raw materials and basic conditions that make our lives, societies, and economies possible. Nature is likewise powerfully shaped by people. As humanity's population and consumption have grown, people have become the dominant force driving global environmental change (10). Thus, nature's wellbeing is increasingly determined by humanity's choices.

In recent decades several integrated-system frameworks have emerged to quantify these coupled human-nature connections (11). These include ecosystem services (1, 12), human-nature nexus (11, 13), telecoupling (9, 14), and environmental footprints (15–21).

While ecosystem services are a powerful framework to understand and value the Support, Regulation, Provisioning, and Cultural services nature provides to people, environmental footprints are a way to quantify the flow of such

environmental services through society. These can measure both the quantities of goods and/or services appropriated *from* nature and the quantities of pollution sent back *to* nature. Mathis Wackernagel and William Rees pioneered this field with the development of the Ecological Footprint (EF) in the early 1990s (22, 23). For a given geographical scale, the EF framework defines a concept called "biocapacity" and provides standardized methods for assessing 1) the total biocapacity of that geographic unit at a point in time, and 2) how much of that total available biocapacity people consume in a given time period. By progressively aggregating geographic units up to the ultimate scale of the whole earth, the EF framework allows one to assess whether humanity's demands on natural systems are within nature's constraints, and, if they exceed those constraints, by how much. This framework helps quantify how certain wealthy nations have disproportionately consumed more than their "fair share" of environmental resources while the burdens of environmental change are disproportionately concentrated on those in the developing world (24).

When combined with data on monetary transactions (using input-output (IO) tables), this kind of accounting ties together actors up, down, and across a supply chain by tracking how materials, energy, emissions, or some other environmental indicator of interest flow through different sectors of an economy. This reveals environmental inputs or outputs that are *embodied* in the *production recipe* (25). Comparing these production recipes for different economic sectors within a country, across countries, or analyzing the same sector in different countries reveals

the scale and scope of a sector's environmental demands (i.e. its environmental footprint).

Since the work of Wackernagel and Rees, environmental-extended multi-region input-output (EE-MRIO) tables have been further developed and applied to several resource/topic specific areas like energy (20), nitrogen (17), biodiversity (18, 26), materials (21), and water, land, and carbon (16, 27). Such footprints reveal how resource demands vary across countries and can be normalized to show national level per-capita resources consumption.

In terms of GHG footprints, by tracking individual consumer's purchases from these sectors, final demand consumers can be connected to the full supply chain GHG emissions used to produce the goods and services they purchase (embodied consumption-based GHG responsibility) (Fig. 1.1). Conversely, GHG emissions can also be linked to income they generate by either tracking to whom income flows when GHG emissions occur along the supply chain (direct producer-income GHG responsibility) or to whom income flows when the fossil fuels that enabled downstream emissions enter the economy (supplier-income GHG footprint). The total emissions in all accounting methods are exactly the same, but they differ in terms of how those emissions are distributed across households.

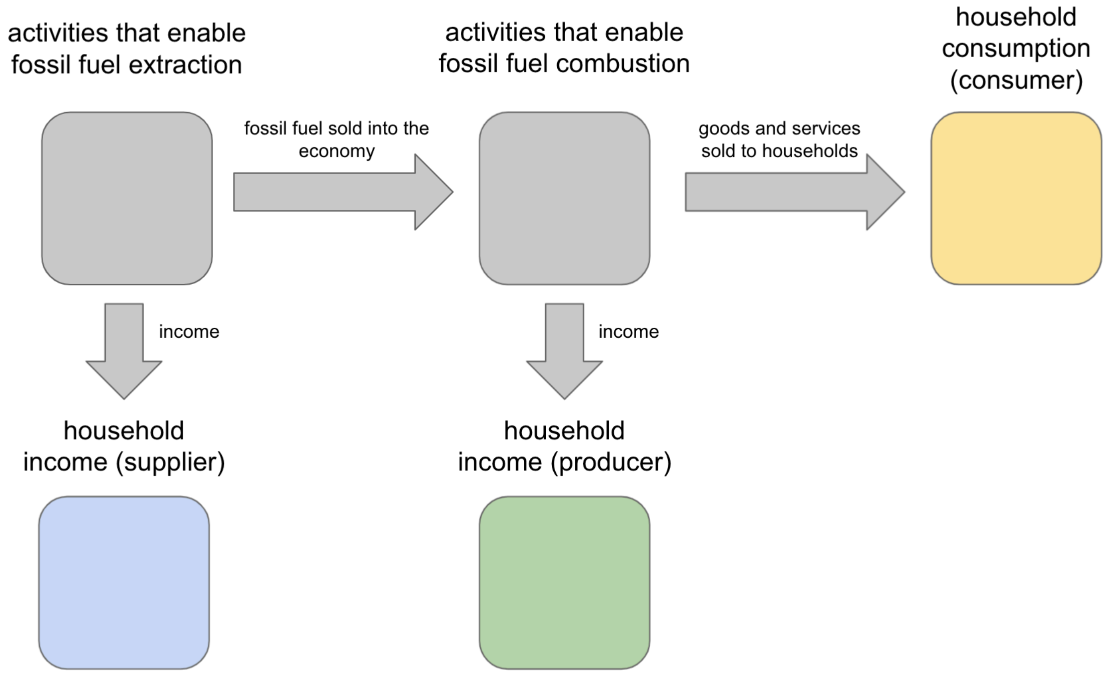

Fig. 1.1: A simplified diagram of responsibility frameworks. In supplier-income responsibility (blue), those who receive income by supplying fossil fuels (this captures direct extraction companies and all those along the entire supply chain who directly or indirectly interact with them: such as machine suppliers, banks, or consulting companies) are assigned full responsibility for all GHG emissions. In a producer-income responsibility (green), those receiving income from an industry are assigned responsibility for emissions directly emitted by that industry. Finally, consumer responsibility (gold) assigns all emissions responsibility to those consuming the goods and services those emissions were used to produce.

In this way, the EE-MRIO footprints can link individual consumers, households, or categories of consumers (e.g. categorized by income level, race, age, region) to their consumption-responsibility (28–39), income-based responsibility (40–46), or a shared / total responsibility that apportions some responsibility to each method (44, 47–50).

1.3 Existing research gaps

Prior work has been done to quantify U.S. national-level GHG emissions based on direct producer emissions (51), consumption-based emissions (52), and supplier income-emissions (43). This has also been explored for U.S. households, for a single time period (28, 35, 38) and more recently for a time series (29). While some prior consumption-based studies investigate differences in footprints related to per capita or household income, no peer-reviewed studies have focused on very high-income households. To date, the maximum group reported is per capita income above $200,000. While this is by no means a paltry amount, it is far below the minimum needed to count as a *top 1%* U.S. household ($535,000) and well below the average income of that group ($1.5 million). This top 1% group is critical to understand because not only does its income allow for disproportionately high consumption levels, but it is this group's preferences that determine U.S. public policy (53).

It is also worth noting two working papers that do make estimates for high-income U.S. groups. Ummel (54) estimates GHG footprints of ~6 million simulated U.S. households (based on expenditures from 23,553 unique households), across 52 consumption categories and specifically makes per capita GHG estimates for the top 2%. He estimates average per capita footprints of 53.5 tons CO_2e for this group. He also finds the share of embodied vs direct emissions increases with income; accounting for 75% of emissions footprint for the highest 2% income group. Yet, this 2% income group is based on survey data that under-samples top income households.

Chancel and Piketty (55) use the Global Trade Analysis Project (GTAP) IO database and the Lakner-Milanovic dataset (56) that provides decile-level average income/consumption. They estimate the top 1% of the U.S. income distribution is responsible for 318 tons CO_2e annually - 50 times the world average and 2,500 times the lowest global emitters. Yet, they are ultimately basing these CO_2e multipliers on estimated income of pre-aggregated decile groups and income to CO_2e elasticity estimated by other studies, using broad expenditure categories, not detailed household level spending data. This lacks the precision of detailed bottom up household-level estimates that assign emissions based on granular expenditure categories and savings rates, before aggregating income groups. Because very top income U.S. households have higher savings rates and purchase less CO_2e intensity goods and services than other groups, the elasticity values they employ will overestimate U.S. top 1% household footprints.

In terms of producer-income or supplier-income responsibility, no prior work at all has examined the distribution of GHG income benefits at the U.S. household level. Nor have there been any shared / total responsibility studies at the U.S. household level. Indeed, I am aware of no existing research, for any country, that links households to the GHG emissions embodied in their income for producer-income, supplier-income, or total responsibility. Furthermore, to my knowledge, no prior study has examined the racial inequality in U.S. consumption emissions under any accounting framework. The lack of knowledge in how GHG responsibility is distributed within U.S. society obscures the truth of who benefits and who is harmed

by climate change and hinders effective policy development that reflects and leverages this distribution of income and consumption benefits.

1.4 Research questions

To fill in these gaps I examine U.S. GHG emissions at a highly granular-level using four accounting frameworks (consumer, producer-income, supplier-income, and total responsibility) over a 20-year period (1996-2015). This is guided by the following research questions:

1) Using a *consumer-responsibility* framework, what is the distribution of GHG responsibility across U.S. households? What is the scale of inequality between different economic and racial groups? Specifically, how do very top income households compare to other economic groups within society? How do the emissions responsibility of these groups compare to households in other countries? And how do these GHG inequities, across economic groups, vary across time?
2) Using a *supplier-responsibility* framework, what is the distribution of GHG responsibility across U.S. households? What is the scale of inequality between different economic and racial groups? Specifically, how do very top income households compare to other economic groups within society? And how do these GHG inequities, across economic groups, vary across time?
3) Using a *producer-responsibility* framework, what is the distribution of GHG responsibility across U.S. households? What is the scale of inequality between different economic and racial groups? Specifically, how do very top

income households compare to other economic groups within society? And how do these GHG inequities, across economic groups, vary across time?

4) Using a *total-responsibility* framework that captures both consumption and income benefits what is the distribution of GHG responsibility, across U.S. households? What is the scale of inequality between different economic and racial groups? Specifically, how do very top income households compare to other economic groups within society? And how do these GHG inequities, across economic groups, vary across time?

By examining U.S. households under these different accounting frameworks, explicitly modeling *top 1%* households (and sub-groups within this), including race, and conducting a time-series analysis my research gives an unprecedentedly clear picture of how economic inequality, race, and GHG responsibility relate and how this changes over time.

1.5 Methods

To conduct this research I pair an EE-MRIO (Fig. 1.2) with consumer expenditure surveys, household income survey data, and additional income data for very high-income households. The GHG intensity of goods and services and income is calculated using the Eora MRIO database (57, 58); a highly granular IO model covering 14,839 sectors, 190 countries, and 1,140 final demand and value added categories. It has 2,720 environmental satellite accounts and 20 years of data tables. Each year tracks about 100 million inter-sectoral interactions, for a total of about 2 billion interactions over the 1996-2015 period.

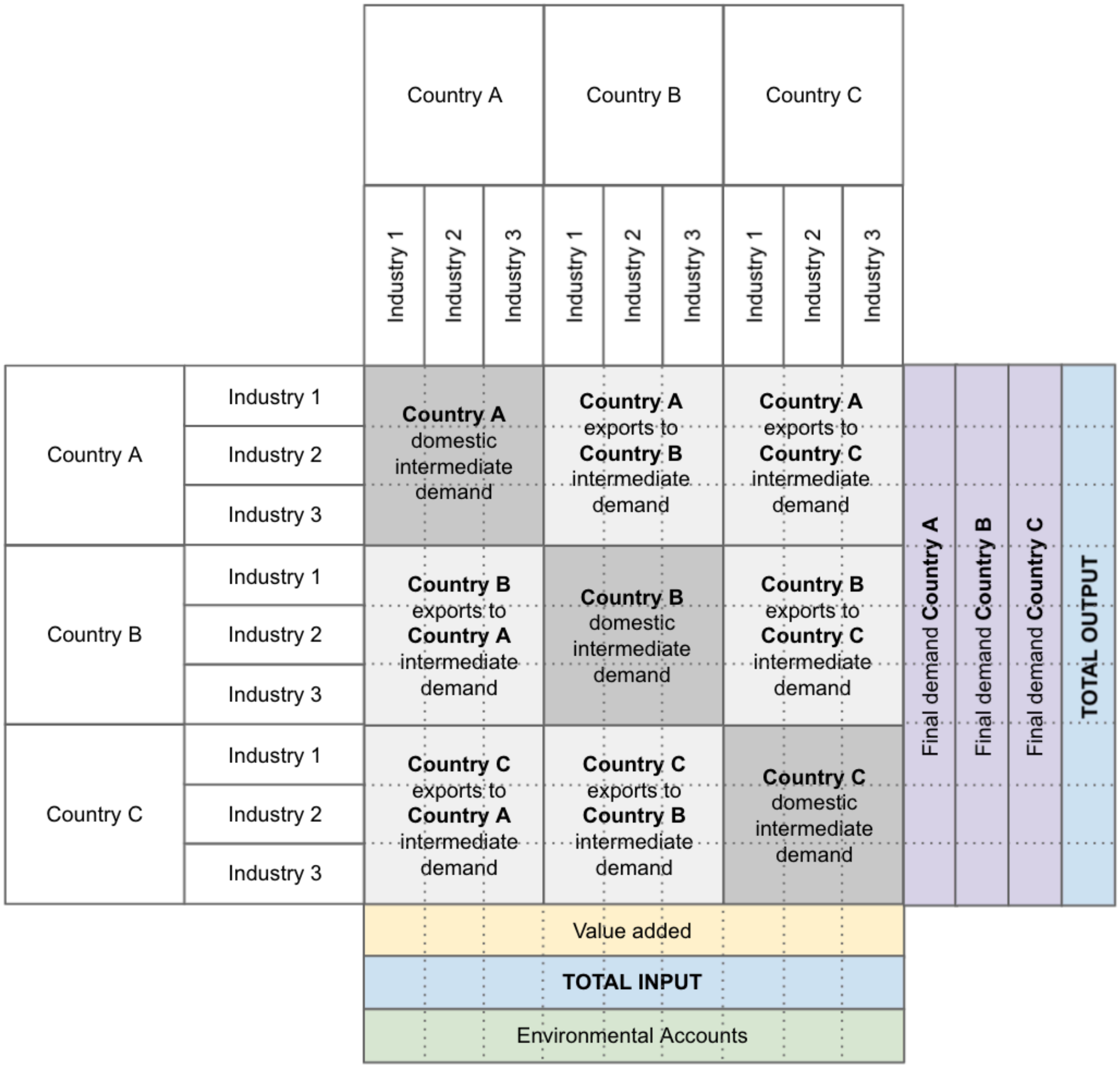

Fig. 1.2: A simplified visual representation of a multi-region input output table for a three-country world. Rows (dotted lines) are output from each industry to intermediate or final demand, columns (dotted lines) are value added, environmental, and intermediate inputs into each industry. Total output and total input are equal (Based on Fig. 2.8 in (59))

1.5.1 Environmentally-Extended Multi-Region Input-Output Model (EE-MRIO)

IO modeling, including EE-MRIO, is grounded in the work of Wassily Leontief (25) who formalized calculating the output of an economy as the sum of intermediate (industry to industry transactions) and final demand

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

In this matrix equation, where x is a vector of total output from each sector, A is a technical coefficient matrix of the economy's production function (the amount of inputs received from each sector divided by total output of that sector), and y is a vector of all final demand consumption for each sector.[1] Using matrix notation this is written as

$$A = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix}; \;\; x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_3 \end{bmatrix}; \;\; y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_3 \end{bmatrix} \tag{2}$$

In matrix equation form it can be written as

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

where I is an identity matrix and $(I - A)^{-1}$ is the Leontief inverse matrix (L)[2], which captures all direct and indirect inputs used to create one unit of final demand output.

Since $(I - A)^{-1} = L$, this can be simplified to

---

[1] The vector y is the row sum of an m x n matrix, where rows m are all sectors of the global economy and columns n are five categories of final demand (household consumption, non-profits serving households, government final demand, gross fixed capital formation, and changes in inventories), for each country.

[2] For a comprehensive guide to input output analysis see: (61, 95, 106). For a basic introduction see (107)

$$x = Ly \tag{4}$$

An alternative to the Leontief demand-side model was proposed by Ambica Ghosh, in 1958 (60, 61). In this supply-side model gross output is a function of primary inputs, or a unit of value (i.e. value added) entering the economy. In matrix equation form this is

$$x' = v'(I - B)^{-1} \tag{5}$$

where *x* is a vector of total output, ' denotes transposing, *v* is a vector of value added[3], I is an identity matrix, *B* is a direct output-coefficient matrix (output to each industry divided by total output from that industry), and $(I - B)^{-1}$ is the Ghosh inverse matrix (G), which captures all direct and indirect inputs used to create one unit of final demand output.

Matrix notation for *B*, *v*, and *x*, are written as

$$B = \begin{bmatrix} B^{11} & B^{12} & \cdots & B^{1n} \\ B^{21} & B^{22} & \cdots & B^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ B^{n1} & B^{n2} & \cdots & B^{nn} \end{bmatrix}; \ v = \begin{bmatrix} v^1 \\ v^2 \\ \vdots \\ v^n \end{bmatrix}; \ x = \begin{bmatrix} x^1 \\ x^2 \\ \vdots \\ x^n \end{bmatrix} \tag{6}$$

These can also be transposed to

$$x = B'x + v \tag{7}$$

and

$$x = (I - B')^{-1}v \tag{8}$$

or simply

$$x = G'v \tag{9}$$

[3] The vector *v* is the column sum of an *m* x *n* matrix, where rows *m* are five value added categories (compensation of employees, taxes on production, subsidies on production, net operating surplus, net mixed income), for each country, and columns *n* are all sectors of the global economy.

The Ghosh Inverse (G) can also be directly computer from the Leontief inverse (L)

$$G = \hat{x}^{-1} L \hat{x} \tag{10}$$

where ^ denoted a diagonal matrix.

1.5.2 Environmental Extensions

This monetary input-output analysis can be extended to environmental applications by treating environmental inputs (e.g. raw materials) or outputs (e.g. pollution) as an input to production. For example, GHG reporting allows for the estimation of total $mtCO_2e$ directly emitted by each industry. These direct emissions, f, are divided by output per industry to obtain $mtCO_2e$ per unit of output

$$e = f \times \hat{x}^{-1} \tag{11}$$

where e is a vector of the direct environmental intensity, from each sector. The "∧" above x indicates matrix diagonalization. Matrix inversion, -1, is used for division with matrices. This direct intensity is then combined with v and G

$$W = \hat{v} \times G \times \hat{e} \tag{12}$$

which yields W a matrix of all direct and indirect CO_2e emissions from each sector. Summing W, we obtain the total $mtCO_2e$ emissions across the whole economy, which equals the sum of f (direct emissions), but the emissions have now been redistributed based on the supplier-income responsibility principle. Summing each column of W gives the total supplier-based CO_2e of each industry and summing each row of W gives the direct producer-based emissions. Finally, by dividing element-wise W column sums by the column sum of total value added to that sector, v, we obtain the $mtCO_2e$ per dollar of value added (also referred to as CO_2e intensity).

The producer income responsibility is considerably simpler in formulation.

$$P = f \times \hat{v}^{-1} \tag{13}$$

Here P is a vector of direct emissions intensity per dollar of value added, f is direct emissions, and these are divided by value added (v). This yields mt CO_2e per dollar of value added, for the direct producer responsibility framework.

Finally, the original demand-side Leontief model has the form

$$Q = \hat{e} \times L \times \hat{y} \tag{14}$$

Where Q is a matrix of all direct and indirect CO_2e emissions from each sector. Summing Q yields the total mtCO_2e emissions used across the whole economy, which equals the sum of f (direct emissions), but the emissions have now been redistributed based on the consumer-responsibility principle. Summing each column of Q gives the total consumer-based CO_2e of each industry, summing each row of Q gives the direct producer-based emissions. Finally, by dividing element-wise Q column sums by the row sum of total final demand for that sector, y, we obtain the mtCO_2e per dollar of final demand purchase (also referred to as CO_2e intensity).

In theory, while each commodity or industry row of W, P and Q may be different, based on the accounting principle used, summing each one should obtain exactly the same value (here total global GHG emissions). In practice I found total GHG estimates for W, the supply income model, were about 3% off from P (direct producer) and Q (consumer responsibility). This is because total inputs in Eora are

not perfectly balanced with total outputs in Eora. However, at only 3% difference, the effect here is reasonably small.

1.5.3 Pairing GHG intensity with household benefits

To calculate household consumption-based GHG footprints, the GHG intensity of commodities (goods and services) are matched with individual household purchases of those commodities. This is done using U.S. Bureau of Labor Statistics (BLS) Consumer Expenditure Surveys (CES), which reports detailed household consumption data for a mostly representative U.S. national sample[4] of about 14,500 unique households (consumer units) each year. I extract 83 expenditure categories that capture about 90-95% of consumer expenditures (62). In addition I extract 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, totaling about 46,000,000 points over the 20-years. The GHG intensity of income is calculated by linking industry specific GHG multipliers (generated via the Eora IO analysis) with individual-level income data. Income data come from IPUMS CPS, a harmonized dataset drawn from the Census Bureau's Current Population Survey (63). It includes approximately 65,000 U.S. households and about 189,000 individuals per year and reports the industry from which income comes. From CPS, I extract 31 income categories, 3 retirement and employer healthcare variables, and 11 social benefits and 44 other variables related

[4] The CES under-samples high-income households. This is accounted for via a bootstrap and estimation procedure. A detailed methodology is provided in the consumer-responsibility chapter.

to individual or household characteristics. Each year yields 17,000,000 data points, totaling about 350,000,000 data points across the 20-year period.

The total responsibility framework is calculated by first averaging the supplier and producer income footprints then averaging this with consumer footprints. This provides a total responsibility framework in which half a household's responsibility is linked to their source of income and the other half to their consumption.

By quantifying the scale of GHG inequality across U.S. households, exploring the racial and temporal trends in this, and examining households under different responsibility frameworks I hope to reveal a previously unknown insight into U.S. emissions, inform social narratives related to environmental and climate justice, and highlight some policy opportunities these findings might impact. If we are to achieve a stable climate it is critical to understand who is benefitting from GHG emissions so that this group also bears a commensurate responsibility in an effective policy response. My hope is that the research presented here will help contribute to that effort.

1.6 Organization of the Dissertation

Chapter 1 introduced the motivation for this work, research questions, and broad methods. Chapter 2 presents background, results, methods and policy implications for U.S. household consumption-based footprints. Chapter 3 presents background results, methods and policy implications for producer and supplier income based U.S. household GHG footprints. Chapter 4 presents background,

results, methods and policy implications for a producer-supplier shared income responsibility and a total responsibility (based 50% on consumption, 25% on supplier-income, and 25% on producer income). Chapter 5 concludes the work by discussing how the findings of Chapters 2-4 relate to each other and inform policy formation. In addition it proposes future research directions and places this work in a broader context.

CHAPTER 2

CONSUMPTION-BASED U.S. HOUSEHOLD CARBON FOOTPRINTS

2.1 Abstract

Unsustainable environmental degradation and extreme economic inequality are two of humanity's most pressing challenges and they are intimately linked. Climate changing greenhouse gas (GHG) emissions are disproportionately driven by the consumption patterns of wealthy and socially privileged groups, yet poorer and socially marginalized peoples face disproportionate climate harms. Here I quantify GHG emissions related to the goods and services consumed by United States households between 1996 and 2015. Results reveal significant GHG inequality across economic class and racial lines. The top 1% of income earning households captured 18.9% of national income and had emissions 14.8x (1,379%) higher than bottom decile U.S. households and 218x (21,674%) higher than low-income country households. White non-Hispanic household emissions were 42% 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.

2.2 Significance Statement

Over the last several decades, a growing share of U.S. national income has flowed to the top 1% of households. At the same time, U.S. greenhouse gas emissions are well above what is needed to limit global temperature rise to 1.5°C. The link

between income and household-level emissions has previously been investigated, but little work has been done to quantify emissions of those at the very top of the income distribution; this group is of particular interest because it exerts disproportionate political power in shaping climate policy. Here, I report 20 years of U.S. emissions estimates for top income households. I find significant inequality and a meaningful share of national emissions being driven by this small politically powerful group.

2.3 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 (64). These emissions occur to provide goods, services, and wealth to people around the world (65). 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 (66–72) yet environmental change is disproportionately driven by, and for the benefit of, those with the most resources and social privilege (21, 28, 29, 32, 73, 74).

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. 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, this responsibility has been 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 (28–39). 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, this emissions responsibility can be traced to the individual households who consume those goods and services.

Below, I present results from a highly granular time series analysis (1996-2015) of consumption-based U.S. household GHG emissions. For each year, I employ a global multi-region input-output table to track the GHG emissions embodied in 10,211 commodities across 190 countries (> 100 million inter-sectoral transfers per year) (see *Materials and Methods*). The embodied emissions in these goods and services are tracked to final-demand household-level purchasing from a mostly nationally representative[5] 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 (see *Materials and Methods*). Direct

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

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 *top 1%* (99.0th - 100th percentile), *next 9%* (90.0th - 99th percentile), and a further disaggregation of the *top 1%* into the *top 0.1%* (99.9th - 100th percentile) and *next 0.9%* (99.0th - 99.9th percentile) of income earners.

2.4 Results

2.4.1 Time Series: 1996-2015

From 1996 to 2015, national average household emissions declined 14%, from 49.3 to 42.2 metric tons (mt) CO_2e. All deciles show similar net declines (range: -7% to -23%). However, when decile 10 is broken into the *top 1%* and *next 9%,* I find the trends suddenly diverging (Fig. 2.1). The *next 9%,* like all the lower deciles, also shows a net emissions decline (-14%), from 94.1 to 81.3 mt CO_2e. Unlike the lower 99% of households, the *top 1%* saw an *increasing emissions trend* (+19%) from 216 to 256 mt CO_2e.

When I further disaggregate the *top 1%* into the *next 0.9%* and the *top 0.1%,* I find the *next 0.9%* emissions increased 8% in those 20 years (167 to 181 mt CO_2e), while *top 0.1%* households emissions rose 42% (658 to 937 mt CO_2e). These net 20-year rises in estimated household GHG footprint for the *top 1%*, *next 0.9%*, and *top 0.1%* households all stand in stark contrast to the decreasing footprints seen by the bottom 99% of households.

Indeed, apart from the consumption-based emissions of these very top households, many emissions-related measures fell during this time: total U.S. territorial producer emissions, national GHG per capita, per household, and per dollar spent (Fig. 2.1). Total consumption-based emissions summed over all U.S. households saw only a modest increase (+5%), in spite of a much larger increase in the U.S. population (+19%) and expenditure dollars per capita (+15%). So why do both subgroups in the *top 1%* of households buck these declining, or only modestly increasing, emissions trends? One factor is the significant income growth that has accrued to this group (Fig. 2.2). The *next 0.9%* saw income growth of 52%, from $595,000 to $903,000. The *top 0.1%* saw average pre tax incomes rise 85% over 20 years, from $3.6 million to $6.7 million (in 2020 US$). Rising incomes result in more dollars available to purchase the goods and services that drive GHG emissions, even though the marginal propensity to consume tends to fall, at higher income levels (75).

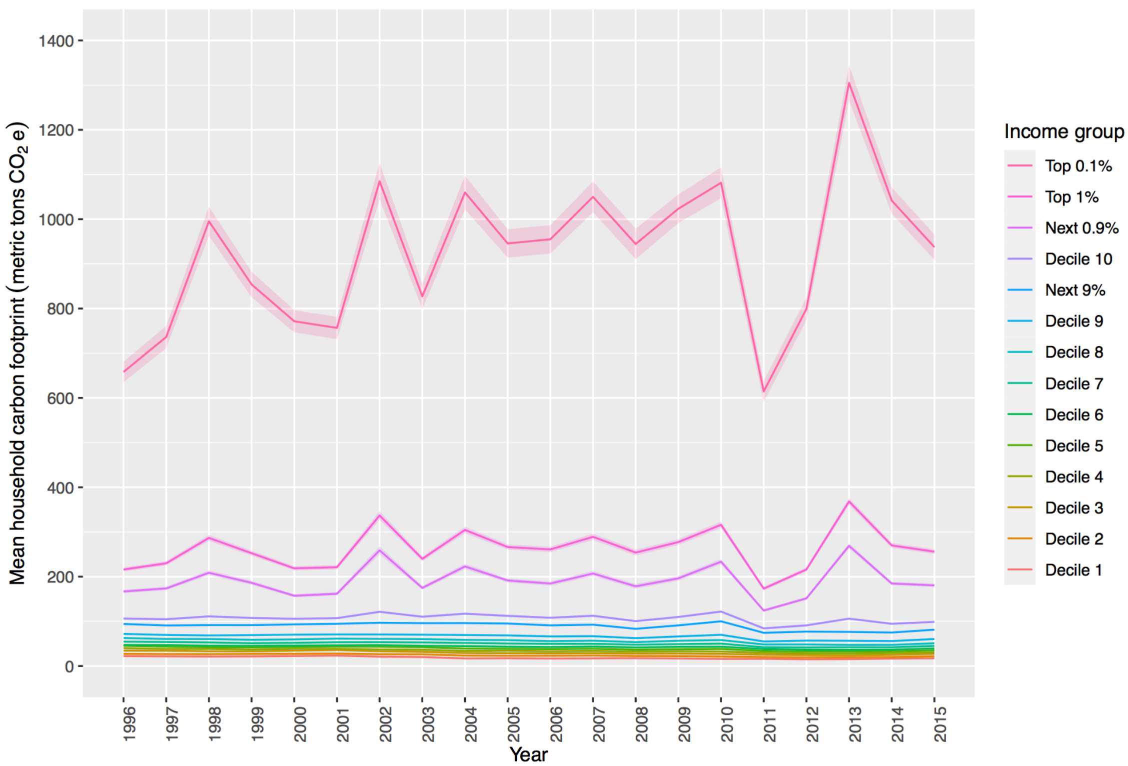

Fig. 2.1: Mean household metric tons CO_2e emissions (1996-2015) per income decile, with Decile 10 broken into *top 0.1%*, *top 1%, next 0.9%* and *next 9%*. Shading is standard error.

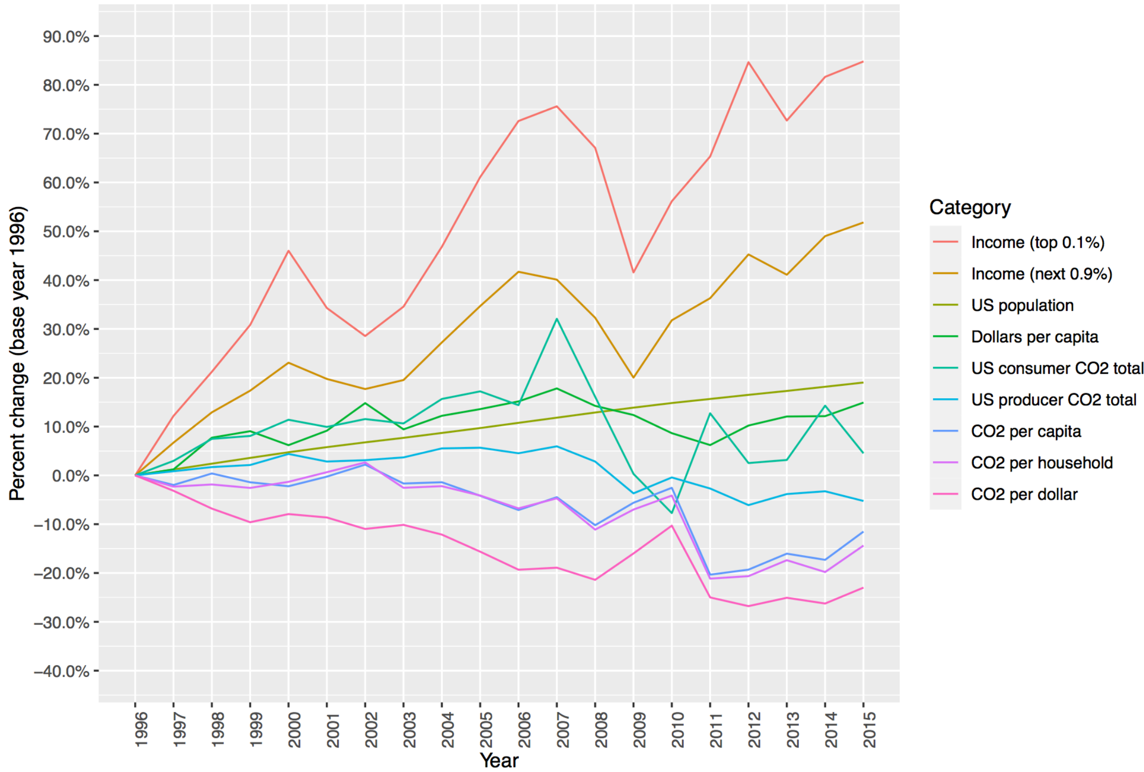

Fig. 2.2: Percent changes (1996-2015) in income, population, spending, total and average U.S. CO_2e emissions, and CO_2e intensity relative to 1996 base year.

2.4.2 Most Recent Year (2015)

In 2015, the most recent year for which I have data, I estimate the top decile had an average emissions footprint of 98.8 mt CO_2e (median ($\tilde{x}$) = 76.1), and collectively accounted for 23% of total U.S. emissions. Within decile 10, the *next 9%* averaged 81.3 mt CO_2e ($\tilde{x}$ = 74.1) and accounted for 17% of total U.S. emissions. *Top 1%* households averaged 255.9 mt CO_2e ($\tilde{x}$ = 165.8, responsible for 6% of total U.S. emissions) (Fig. 2.3); with *next 0.9%* averaging 180.6 mt CO_2e ($\tilde{x}$ = 154.2, 3.8% of U.S. emissions), and *top 0.1%* averaging 937.5 mt CO_2e ($\tilde{x}$ = 567.2, 2.2% of total U.S. emissions) (Fig. 2.4).

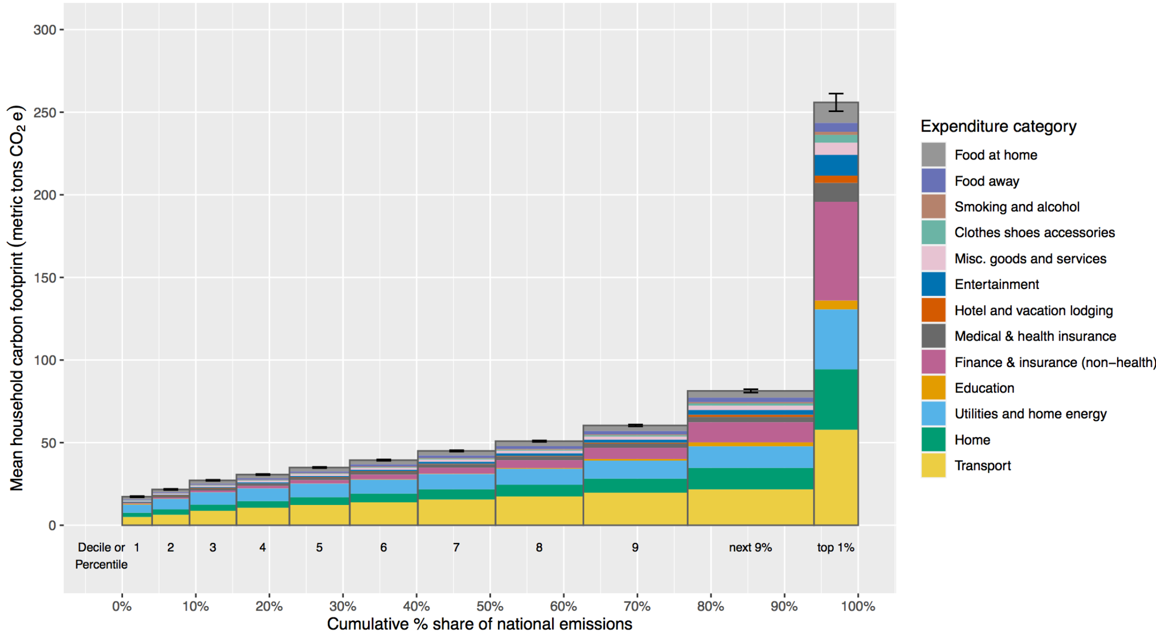

Fig. 2.3: Mean household mt CO_2e emissions (2015) per income decile, with Decile 10 broken into *top 1%* and *next 9%*. The width of each income group, on the x-axis, corresponds with each group's share of total national CO_2e emissions. Colors represent the mt CO_2e from each expenditure category, based on mean contribution from each category, per income group. Note: standard error bars are for each income group's mean footprint.

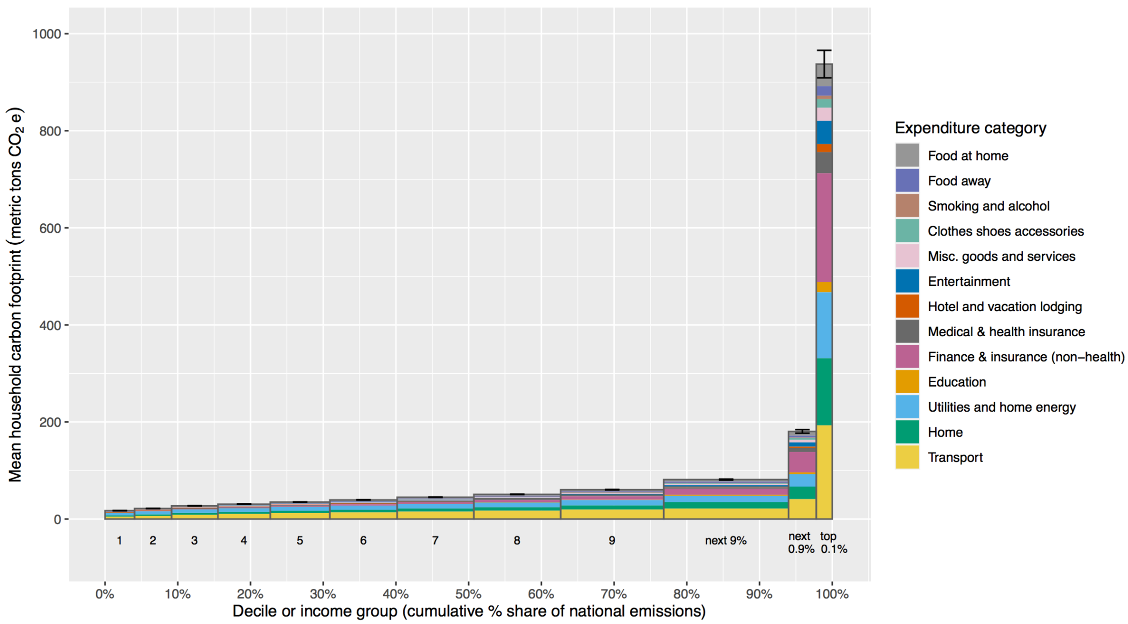

Fig. 2.4: Mean household mt CO_2e emissions (2015) per income decile, with Decile 10 broken into *top 0.1%*, *next 0.9%* and *next 9%*. The width of each income group, on the x-axis, corresponds with each group's share of total national CO2e emissions. Colors represent the mt CO_2e from each expenditure category, based on mean contribution from each category, per income group. Note: standard error bars are for each income group's mean footprint.

The absolute difference in emissions, between groups, is stark. Yet by normalizing each group's share of national emissions by its population share, the results reveal even more significant inequality. The bottom decile's emissions are 60% lower per household, than if emissions were equitably distributed across all U.S. households (Fig. 2.5). Similarly, deciles 2-6 accounts for a smaller emission fraction than their share of total U.S. population. The *top 1%* has emissions 501% (6x) higher than its population share and 1,379% (14.8x) larger than an average bottom decile household. The *top 0.1%* has average emissions 2,099% (22x) higher than its population share and 5,318% (54.2x) larger than an average bottom decile household.

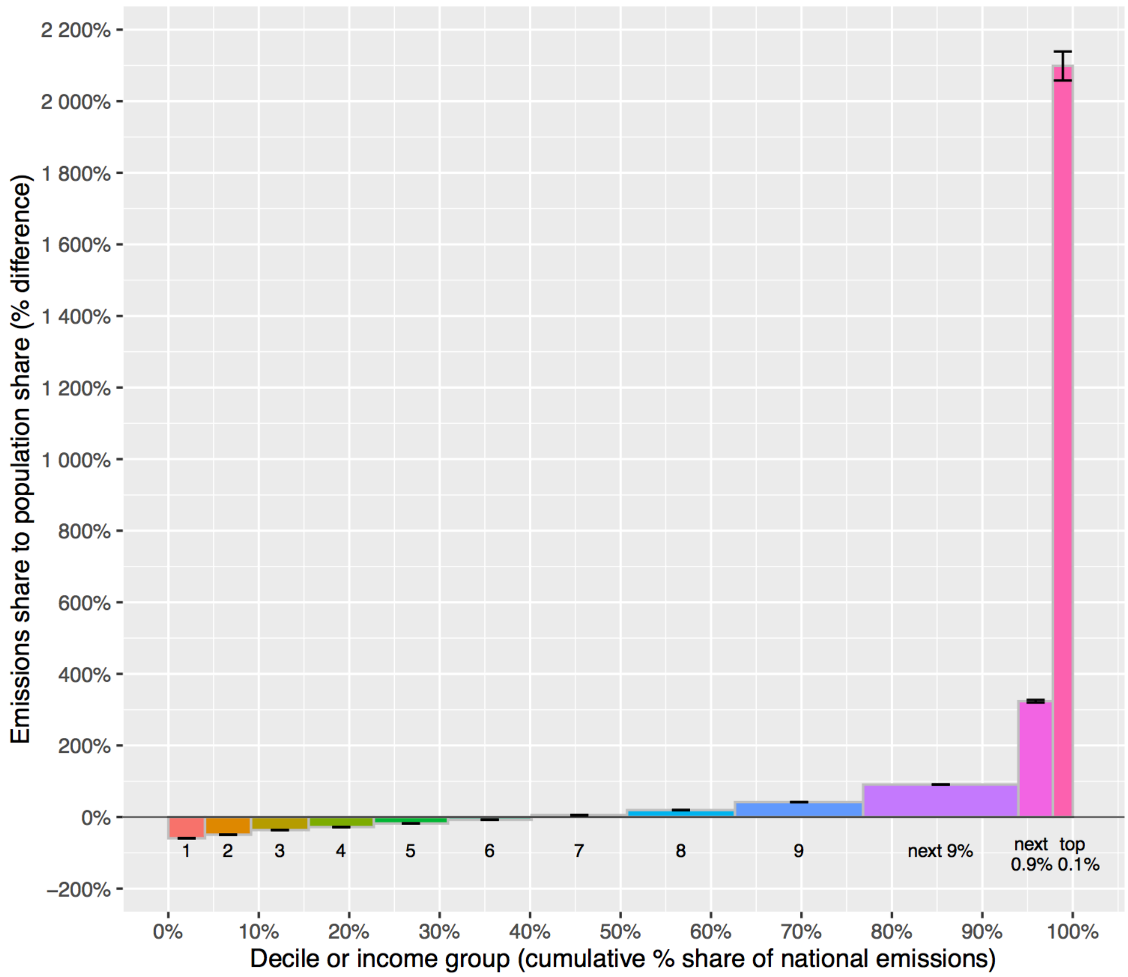

Fig. 2.5: Emissions share relative to population share (% difference) for deciles 1-9, *next 9%*, *next 0.9%* and *top 0.1%* (2015). A zero value on the y-axis indicates an equitable distribution: i.e. the group's share of national emissions equals its population share. The width of each income group, on the x-axis, corresponds with each group's share of total national CO_2e emissions. Note, the negative emissions of deciles 1-6 and extreme inequality of the *next 0.9* and *top 0.1%*.

Household footprints are critically shaped by the types of goods and services purchased. In 2015, purchases from *Transport* and the *Utility and Home Energy* categories accounted for 14.6% of expenditure dollars, from average *top 1%* households (Fig. 2.6); yet contributed 36.7% to the household's emissions footprint (Fig. 2.7). Meanwhile, expenditures related to the *Finance and Insurance (non-*

health) and *Home* categories accounted for 53.0% of their expenditure dollars, but only 37.6% 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 households tends to be higher than upper income households (1.5x higher than the *top 1%*, see Fig. 6.5 in *Appendix A*), as their consumption is dominated by carbon intensive necessities.

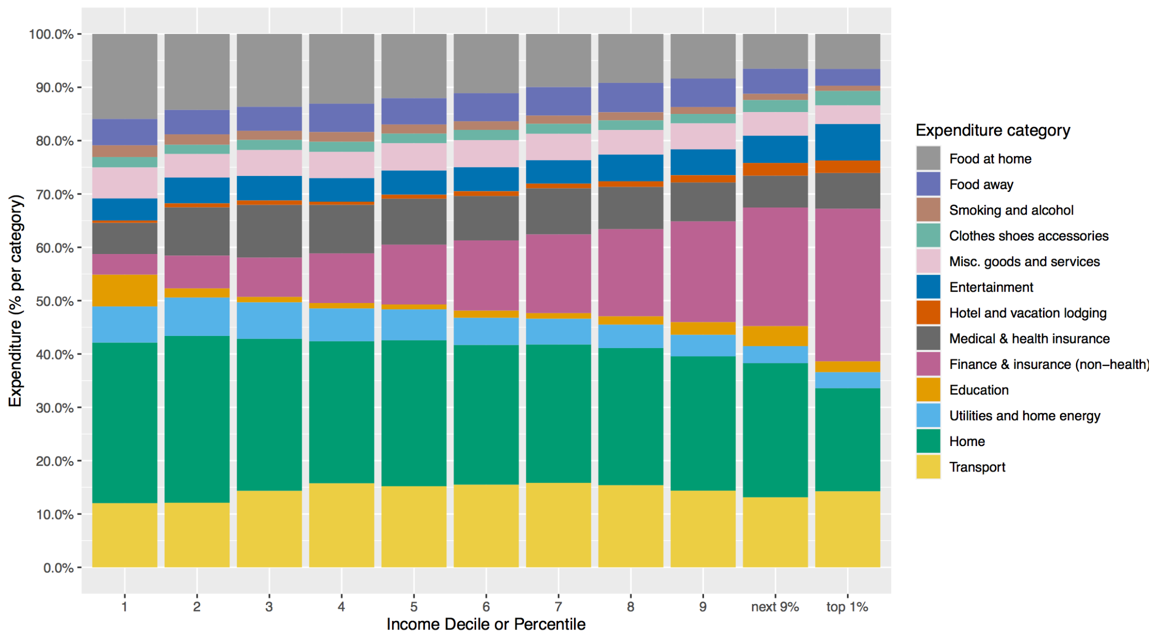

Fig. 2.6: Expenditure percent per expenditure category (2015).

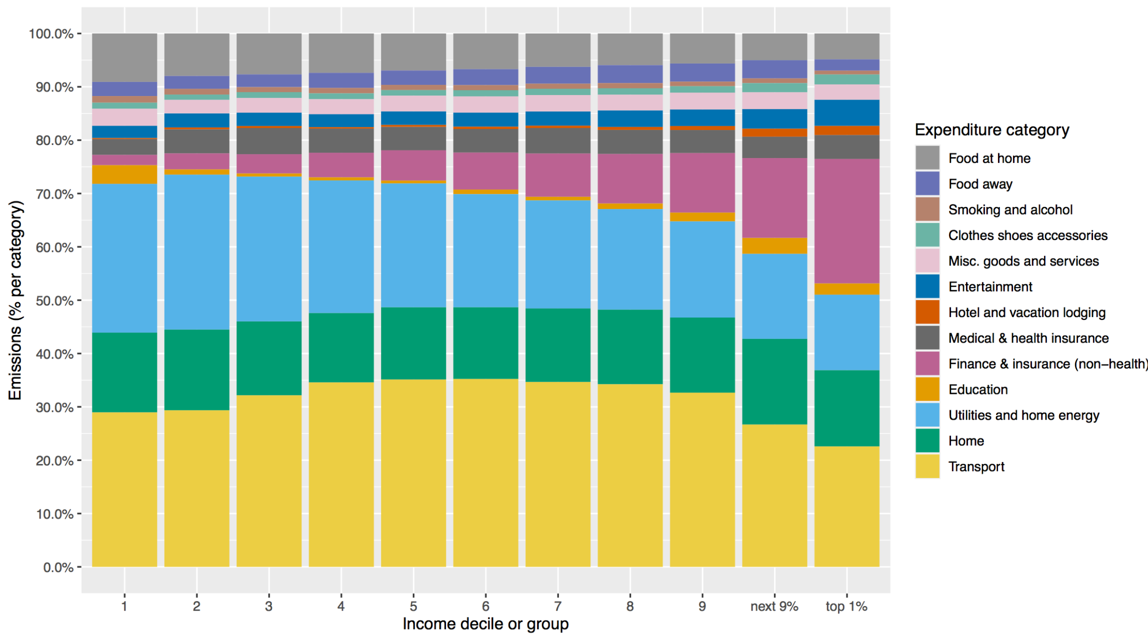

Fig. 2.7: Emissions percent per expenditure category (2015).

2.4.3 Relationship to Racial Inequality

The bottom income decile, which was responsible for 4% of U.S. consumption-based emissions, in 2015, 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 23% of national emissions 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, black households had average footprints of 31.8 mt CO_2e, white Hispanic households 35.2 mt CO_2e, and white non-Hispanic households 45.1 mt CO_2e. The fact that white non-Hispanic households had emissions 28% higher than Hispanic households and 42% higher than black households reflects a striking degree of racial inequality in who receives the consumption benefits of GHG emissions.

2.4.4 Super Emitters

For 2015, I estimate 3.9% of the *top 0.1%* households had emissions over 3,000 mt CO_2e (mean = 3,617, $\tilde{x}$ = 3,476) . Even though they make up only a tiny fraction of households, are such high estimates feasible? To cross-check their validity, I independently estimate per household emissions related to luxury goods that are principally or only consumed by *top 1%* households (see *SI* for methodology). This includes large mansions or multiple large homes, first class air travel, private jets, and super yachts.

Construction of 40,000 square feet of living space (either in one large home or multiple homes) emits ~1,688 mt CO_2e. Yet, because these emissions are amortized over an estimated 50 year home lifespan, *annual* emissions, from initial construction, are only about 34 mt CO_2e. Emissions related to electricity and utilities add about 95 - 122 mt CO_2e, per year, for 40,000 square feet of home.

Emissions from first class air travel add up to 100 mt CO_2e or more for an average sized family travelling on 3-5 long haul flights per year. I estimate annual fuel-related emissions from private jets, whose ownership and use are concentrated within extremely wealthy households, average about 1,172 mt CO_2e per jet. On the seas, I estimate average annual emissions from motorized superyachts (30+ meter) to be about 1,150 mt CO_2e per vessel. For both jets and super-yachts, individual emissions can be even higher if the vessels are larger or used more frequently than my estimates. While rare, adding these extreme luxury emissions together with other expenditures, household GHG footprints of 3,000 (or more) mt CO_2e per year, are feasible.

2.4.5 Global Comparison (2010)

While significant emissions inequality exists across U.S. households, even the bottom U.S. decile has relatively high emissions when compared to other countries' consumption-based emissions (Table 2.1) (76). The national average U.S. footprint is 2.9x larger than the high-income country average and 32.6x larger than the low-income country average. An average *top 1%* U.S. household has emissions 19.5x larger than the high-income country average and 218x (21,674%) higher than the low-income country average. At the extremes, the *top 0.1%* U.S. income group is 745x (74,509%) higher than an average household in a low-income country and an average U.S. *super emitter* is 2,582x (258,155%) higher than the low-income country average.

Table 2.1: Comparison (times larger) of mean household emissions, per U.S. income group, including *super emitters* (2010), to per household national averages for low, low-middle, high-middle, and high-income countries (global estimates are 2010 from (76)**.**

	U.S. income groups **(times larger)**								
Global income groups	Decile 1	Decile 5	National household average	Decile 10	Decile 10		*top 1%*		
					next 9%	*top 1%*	*next 0.9%*	*top 0.1%*	*super emitters*
($mtCO_2e$)	*(15.9 mt)*	*(38.3 mt)*	*(47.3 mt)*	*(121.9 mt)*	*(100 mt)*	*(316 mt)*	*(233 mt)*	*(1081 mt)*	*(3747 mt)*
Low *(1.5 mt)*	**11.0**	**26.4**	**32.6**	**84.0**	**68.9**	**217.7**	**160.8**	**745.1**	**2581.6**
Low-middle *(4.4 mt)*	**3.6**	**8.6**	**10.6**	**27.4**	**22.5**	**71.1**	**52.5**	**243.3**	**843.0**
High-middle *(8.9 mt)*	**1.8**	**4.3**	**5.3**	**13.7**	**11.3**	**35.5**	**26.3**	**121.6**	**421.5**
High *(16.2 mt)*	**1.0**	**2.4**	**2.9**	**7.5**	**6.2**	**19.5**	**14.4**	**66.6**	**230.8**

2.5 Discussion

2.5.1 Relationship of Emissions Inequality to Income Inequality

My results show significant emissions inequality within U.S. society. In 2015, the bottom 50% of the population was responsible for 30.9% of national emissions, while the top 10%, *top 1%*, and *top 0.1%* were respectively responsible for 23.2%, 6%, and 2.2% of national emissions. Yet, the income that enables consumption-based emissions is even more inequitably distributed (77). In 2015, the bottom 50% of the population captured just 12.9% of national income, while the top 10%, *top 1%*, and *top 0.1%* captured 45.7%, 18.9%, and 8.5% of national income (78).

Emissions are less unequal than income because social welfare programs, progressive taxation, and variable savings rates decouple income from expenditure. Among low-income households, social welfare programs result in some households having expenditures higher than incomes, thus increasing their GHG emissions per dollar of income. Among high earning households, progressive taxation and high savings rates results in less expenditures per dollar of income. Especially at very high income levels, a high savings rate reflects the diminishing marginal propensity to consume (75). Additionally, the types of goods and services purchased (Fig. 2.6) and their respective GHG intensities (Fig. 2.7) vary across income groups. Low-income decile spending is dominated by GHG intensive necessities while the *top 1%* shifts spending to less GHG-intensive services, resulting in lower GHG intensity per expenditure dollar (see Fig. 6.5 in *Appendix A*).

2.5.2 Factors shaping household footprints

Household footprints are directly determined by the types and quantity of goods and services purchased. As my results show, these household expenditures are strongly tied to household income. Yet even at a given income level, GHG footprints vary due to differences in consumer preferences, geographic, social, economic, and policy factors, cutting across scales (household, community, regional, national, and global) over which individual households have varying degrees of agency (79).

Among the lowest deciles, the ability to shift spending towards less GHG-intensive goods is limited by expenditures principally flowing to carbon intensive

basic necessities and limited access to savings or credit. In contrast, 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. Variations in these factors, particularly tax and savings rates, drive the significant year to year GHG variation we see in *top 0.1%* households (Fig. 2.1).

Household agency is nested within community and regional factors such as local climate, energy efficiency of available housing stock, and transportation and energy infrastructure. The GHG intensity of regional electric grids is a key factor shaping household footprints, and it is one over which they have extremely limited agency. In 2015, the average CO_2e intensity per dollar of electricity production from the ten dirtiest states was 6.7 times higher than that of the ten cleanest states (80, 81). At the state and national-level, differences in tax policy, environmental regulation and clean energy investment also play an important role in shaping household level GHG variations, since they can encourage (or discourage) moves toward less GHG intensity. Finally, the GHG intensity of internationally-produced goods and services is nested within globalized supply chains, and here too, individual consumers cannot exert much influence at all.

2.5.3 Policy Implications

Economists widely agree that carbon pricing, via either a carbon tax or cap-and-trade system, will be essential to decarbonize the US economy in a cost-effective way (82, 83). Both carbon taxes and cap-and-trade have their own unique features, but their ultimate effect is to price in some of the social costs of emissions.

To successfully shift spending, however, it is estimated that the tax rate would need to be set relatively high. For example, Heal and Schlenker (83) have calculated that achieving a 5% impact on oil consumption would require the tax rate to be set at \$200 per ton CO_2e, with 70-80% of this cost initially passed onto consumers.

For a *top 1%* household, a carbon tax of \$200 per mt CO_2e amounts to 3% of pre-tax income (11% of expenditures). In contrast, for deciles 1-3, it equates to 53%, 26%, and 21% of their respective incomes (15-16% of expenditures)[6]. With little discretionary spending or savings to draw on, low-income families would be forced to make painful cutbacks when faced with such a tax, while middle-decile households could pursue a mix of cutbacks and decreased savings. Meanwhile, high-income households enjoy significant savings rates (46% for *top 1%* and 57% for *top 0.1%* groups, in 2015) that allow them to simply absorb the tax. 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 would 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 can make such price increases either cost neutral or even of net benefit to low-income households (84–86). Yet 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 47% more CO_2e

[6] The carbon tax as a share of expenditure is lower and more consistent across these groups, than as a share of income, because social transfers result in expenditures that are higher than incomes and average expenditures between groups are closer than their average incomes.

intensive than *top 1%* households) and thus their GHG emissions. If such transfers made the tax neutral for low-income families and the remainder flowed to clean energy investment and credits or subsidies for low-income households, it may successfully lead to emissions reductions. 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, the high-income households that would pay the most tax are the same households whose preferences dominate policy-making (53), potentially reducing their support for such measures.

2.5.4 Equity, Climate and Environmental Justice

My 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. In order to keep global temperature within 1.5°C, only ~420 GT of additional CO_2e (approximately 10 years of global emissions at current rates) can still be added to the atmosphere (87).[7] How should these emissions be divided among the planet's 7.8 billion inhabitants (and future generations)?

The U.S. accounts for just 4% of the global population, but at current rates, U.S. consumption-based emissions alone would use all of this budget by 2100, with, as my results show, the wealthiest U.S. households capturing a disproportionate share. At the same time, there are currently ~700 million people globally who live in

[7] Note, this is a 66% probability of remaining within 1.5°C. The IPPC estimate was published in 2018, I have updated it to 2020.

extreme poverty (<$1.90 PPP per day). Moving this group to a very modest global middle class[8] (<$2.97 PPP - $8.44 PPP) would also use up the entire remaining CO_2e budget by 2100 (76, 88).

To which group should emissions be allocated? Setting aside for now the thorny question of large disparities between nations' historical emissions, one equity-seeking approach might be to simultaneously set a global emissions target, an individual emissions floor, and an individual emissions cap. The IPCC estimates 30 Gt CO_2e is the upper 2030 limit to keep warming within 1.5°C. Using that as the global emissions target, all people could be allocated a floor of at least 0.9 mt CO_2e and a cap of 8.7 mt CO_2e (89). Currently, even the poorest U.S. decile's emissions per capita are 47% (1.5x) above the cap, while average *top 1%* and *top 0.1%* emissions per capita are 945% (10.5x) and 3,734% (38x) higher.

These emissions disparities highlight the unequal allocation of consumption benefits to higher income countries, and particularly to high-income households *within* such countries. At the same time, the harms of climate change will fall unequally on poorer nations and on poorer households in nearly every country (66, 69).

Humanity is thus faced with stark choices. Should emissions go to the poorest to create a global middle class? Should they go to future generations? Or should they go toward enabling the wealthiest to consume 10, 100, or >1,000 times more than others? If it is to go to the richest, what compensation is owed to society? By

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

quantifying the scale of this inequity, my findings help to inform such discussions and provide the basis for improving policy design.

2.6 Materials and Methods

I combine an Environmentally-Extended Multi-Region Input-Output Model (EE-MRIO) direct emissions data, consumer expenditure surveys (CES), and income data to link global GHG emissions with the goods and services consumed by U.S. households.

To calculate the embodied CO_2e intensity of these goods and services, I use the Eora MRIO database (57, 58) covering 14,839 sectors, across 190 countries, with 1,140 final demand and value added categories. For each year, I 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$. Direct production-based CO_2e emissions data, from the PRIMAPHIST database (available in Eora), for six Kyoto GHG (90), are converted to embodied emissions per dollar of final demand using the Leontief inverse (21, 25, 28–30, 38). 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.

Direct emissions by the consumer, most notably transportation fuels and home heating and cooking fuels, were calculated based on CO_2e emissions factors, per physical unit of fuel (91) and price data per unit of fuel from the U.S. Energy

Information Administration. Where available, regional or state level price adjustments were made.

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) Consumer Expenditure Surveys (CES). The CES 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 (62). From the full CES dataset, I extract 83 detailed expenditure categories[9] 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.

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 (80, 81).

While CES is the most authoritative source on U.S. household expenditures, it has a known underreporting bias from high-income households (92, 93). To account for this, I create a synthetic dataset for the *next 0.9%* and *top 0.1%* households and

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

estimate their expenditures. I do this by first creating a distribution of 1,000 households, per group, whose mean pre-tax income and upper and lower bounds matches that reported by the World Inequality Database (WID), and whose distribution is right-skewed to reflect the income inequality within these groups. I then subtract estimated tax and savings rates, with the difference considered expenditure dollars. To allocate spending across the expenditure categories, I bootstrap CES households that meet the *top 1%* WID threshold. I then apply a randomization algorithm, to simulate household spending differences, 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 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_2 estimates come from a weighted average of the *next 0.9%* and *top 0.1%* groups.

For each household, purchases from each of the 83 CES goods and service sectors are linked to the mt CO_2e per dollar final demand of that sector, from Eora. This is done via a 10,211 x 83 concordance matrix, using the International Standard Industrial Classification (ISIC) system. Multiplying each household's expenditures by this concordance matrix yields emissions per expenditure category. Summing across all categories and adding direct emissions, yields each household's total consumption-based mt CO_2e footprint (see *SI* for more detailed methods, treatment of durable goods, and crosscheck of super-emitter households).

CHAPTER 3

INCOME-BASED U.S. HOUSEHOLD CARBON FOOTPRINTS

3.1 Abstract

Since 1996, the share of national income flowing to the *top 1%* of United States (U.S.) households has increased about a quarter, to over 18% today. At the same time, U.S. greenhouse gas (GHG) emissions remain far above what is possible if humanity is to restrict global temperature rise to 1.5°C. In this chapter I combine environmentally-extended multi-region input-output analysis with nationally representative household surveys and top income group data to examine the GHG emissions responsibility of U.S. households based on the emissions used to generate their income. I do this at high granularity, over the 20-year period 1996-2015, and compare emissions responsibility across income groups. As in Chapter 2, I find significant inequality across groups, with the bottom 50% of households responsible for only 15-24% of national income-based emissions (depending on framework) while the politically powerful *top 1%* of U.S. households is responsible for 11-16%. These results suggest an alternative income-based carbon tax (on wage or investment income) may have equity advantages over traditional consumer-facing cap-and-trade or carbon tax options.

3.2 Significance Statement

Prior work has examined the greenhouse gas (GHG) emissions of nations based on different responsibility principals including: supplier, producer, and

consumer. These have respectively linked GHG emissions to the income it generates and the consumption it enables. While consumption-based footprints have been traced to the household-level, no prior analysis has extended income-based GHG responsibility to households. This misses a critical connection between GHG emissions and the flow of economic benefits. Here, for the first time, I link 20 years of U.S. household-level income data to the GHG emissions that occurred to generate that income, using both supplier and producer responsibility frameworks. I find vast inequality across households and a significant share of national emissions being driven by top income households.

3.3 Introduction

Over the last decade, the average global average temperature was the warmest 10-year period on record and trends in the greenhouse gas (GHG) emissions driving such warming remain stubbornly above Paris Agreement targets (64, 94). At the same time, extreme economic inequality, across and within societies, results in a powerful disconnect between those who reap the economic or consumption benefits these GHG enable and those who face the worst impacts of climate change. Putting aside *intergenerational* equity, this present day disconnect creates a fundamental challenge to effective and equitable policy development, as those most benefitting from GHG emissions also tend to have the most economic and political power while those most at risk of climate harms tend to have the least.

No country on earth has emitted more climate altering greenhouse gases (GHG) or reaped more economic benefit, from the cheap energy driving these

emissions, than the United States (U.S.). It is the largest historical GHG emitter, currently the second largest territorial emitter and has some of the highest per capita incomes and consumption on the planet. At the same time, the U.S. has significant economic inequality, with the top 10% of income earners capturing 46% of national income, in 2019, and the top 1% alone capturing 19% (78). This top income group is not only richer, but also whiter, more educated, and more economically, socially, and politically powerful than any other group in the country. It is the preferences of this group that shape public policy, including climate action (53). Because, prior work linking U.S. households to their consumption or income-based GHG emissions has focused on decile or national-level analysis the GHG emissions responsibility of these politically powerful households have until now been obscured. Here I analyze the income-based GHG emissions of U.S households, including the top 1%, over a 20-year period (1996-2015).

Our income-based approach (40–46) has two distinct accounting regimens: direct-producer emitter and supplier and calculates both pre-tax and post-tax GHG responsibility. In the *direct-producer emitter* approach, households drawing an income from an industry (through wages or return on investment) are held responsible for a share[10] of that industry's direct operational emissions (Scope 1).[11] In the *supplier* approach, households receiving an income (wages or return on

[10] In both accounting schemes the units are metric tons (mt) CO_2e per dollar of income. Each household's share of responsibility is commensurate with their share of income out of total value added (compensation of employees, taxes, subsidies, net operating surplus, and net mixed income) of that industry.
[11] This is similar to current international climate agreements, like Paris, in that emissions are direct emissions from an industry, but distinct in that I link these emissions to *income* that flows to individual households, rather than assigning responsibility at the national or industry-level.

investment) from an industry are responsible for a share of the total downstream emissions enabled by that industry's activities. To make this concrete, in a *direct* approach, income from a fossil fuel extraction company is linked to that company's *direct* operational emissions, whereas in a *supplier* approach, income is linked to the downstream emissions generated when that fossil fuel is ultimately combusted by other industries.

Here I present results for a highly granular time series analysis (1996-2015) that links global GHG emissions to both the direct and supplier based income responsibility of U.S. households. In both responsibility frameworks, global GHG emissions intensity per dollar of income are calculated for 9,812 industries across 190 countries (~ 96 million inter-sectoral transfers per year) using the Eora multi-region input-output (MRIO) model (see *Methods*) (57, 58). Using the nationally representative IPUMS harmonized Current Population Survey (CPS), I link these direct and supplier emissions intensities with industry-specific income received by individuals (annual mean = ~189,000), then aggregate individual emissions into households (annual mean = ~65,000). Households are binned into income groups including 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) and emissions are compared (see *Methods* for how I estimate *top 1%* households, which are under sampled in CPS).

3.4 Results

3.4.1 Time Series: 1996-2015

3.4.1.1 Supplier Income: Pre- and Post-tax

In the supplier income responsibility framework, national average household emissions declined 19% (41.5 – 33.7 mt CO_2e), pre-tax, between 1996 and 2015, and 18% (35.1 to 29.0 mt CO_2e) post-tax. Pre-tax, deciles 1-10 all fell between 9% and 38%. But *within* this top decile, while the *next 9% decreased* 16%, the *top 1%* increased 7% (477 - 510 mt CO_2e), the *next 0.9%* remained essentially flat at -1% (320 - 316 mt CO_2e) and the *top 0.1%* increased 19% (1,888 – 2,254 mt CO_2e) (Fig. 3.1(A)). Post-tax, all deciles declined 7-26%, with the *next 9%* declining 16%, the *top 1%* seeing an almost flat 2% decline (335 - 328 mt CO_2e), the *next 0.9%* declining 9% (226 - 206 mt CO_2e), and the *top 0.1%* increasing 9% (1,319 – 1,434 mt CO_2e) (Fig. 3.1(C)).

3.4.1.2 Producer Income: Pre- and Post-tax

Under the producer income framework, national average household emissions declined 16% (pre-tax) and 12% (post-tax), over the 20-year period, from 47.2 to 39.9 metric tons (mt) CO_2e pre-tax and 39.9 to 35.0 mt CO_2e post-tax. Pre-tax deciles' 1-9 all fell between 22% and 33% and decile 10 declined 3% (Fig. 3.1(B)). The *next 9%* decreased 16% and the *top 1%* increased 26% (498 to 626 mt CO_2e). Within this group, the *next 0.9%* increased 13% (335 - 379 mt CO_2e) and the *top 0.1%* increased 45% (1,966 – 2,849 mt CO_2e). Post-tax, deciles' 1 and 2 show a slight increase (8-10%), while declies' 3-10 all show declines between 3-24%. Here, the

next 9% decreased 16%, the *top 1% increased* 15% (351 to 403 mt CO_2e), the *next 0.9%* increased 4% (237 - 247 mt CO_2e), and the *top 0.1%* increased 32% (1,374 – 1,811 mt CO_2e) (Fig. 3.1 (D)).

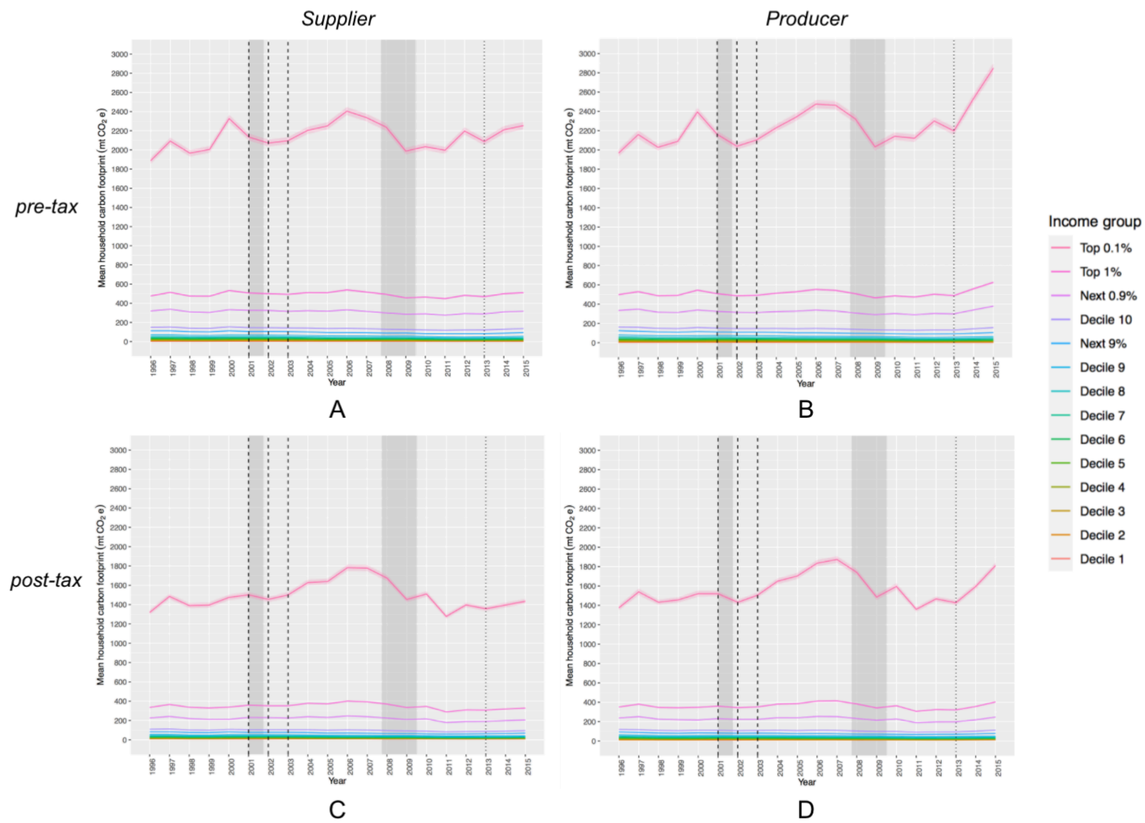

Fig. 3.1: Income-based mean household mt CO_2e emissions (1996-2015) per income group under the Supplier pre-tax (A), post-tax (C) and Producer pre-tax (B) and post-tax (C) accounting methods. Colored shading is standard error, gray box shading indicates recession, vertical dashed lines (2001-2003) and dotted line (2013) respectively indicate tax cuts and tax increase for the highest tax bracket.

3.4.2 Income, Population and Emissions Trends

The U.S. population grew 19% during this 20-year period and dollars per household[12] increased 26% (Fig. 3.2). At the same time that the nation's population and wealth increased, its total national Supplier and Producer emissions,

[12] All dollar units, in this paper, are inflation adjusted from current year to constant 2020 dollars.

respectively fell 15% and 5%. With both frameworks, per household emissions fell between 12-18% and GHG intensity (mt CO_2e per dollar) fell 30-34%, likely reflecting the effect of technological efficiency gains in the broader U.S. economy and the gradual decrease in GHG intensity of the U.S. energy sector. Yet, income flowing to the *top 1%* of households increased significantly, 52% for the *next 0.9%* group (from $595,000 to $903,000) and 85% (from $3.6 million to $6.7 million) for the *top 0.1%*. This income growth outpaced the declining GHG intensity per dollar and helps explain why, unlike the bottom 99% of the population, *top 1%* households saw increasing income-based emissions footprints between 1996 and 2015.

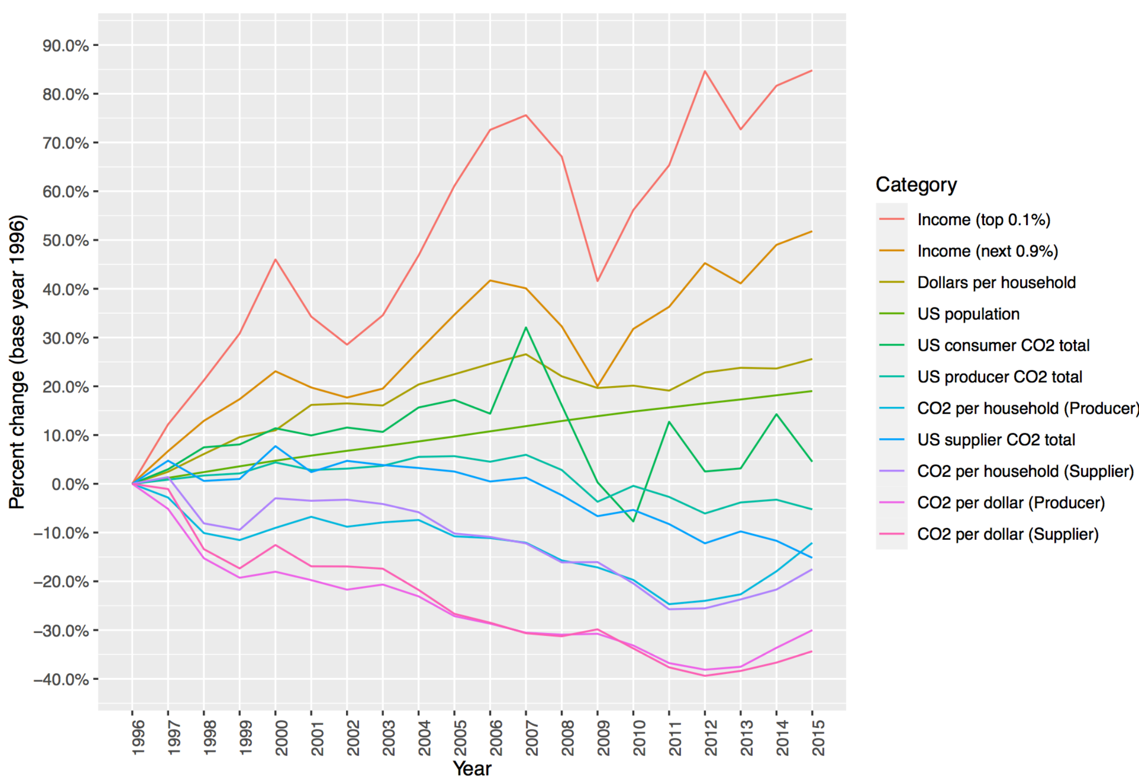

Fig. 3.2: Percent changes (1996-2015) in income, population, spending, total and average U.S. CO_2e emissions, and CO_2e intensity for both Producer and Supplier frameworks (post-tax), relative to 1996 base year.

3.4.3 Most Recent Year (2015)

3.4.3.1 Supplier Income

Pre-tax, the top decile, in 2015, was responsible for 41% of U.S. emissions (mean ($\bar{x}$) = 135.4 mt CO_2e, (median ($\tilde{x}$) = 86.6) (Fig. 3.3(A)). The *top 1%* averaged 510 mt CO_2e ($\tilde{x}$ = 306) and accounted for 15% of national emissions. With the *next 0.9%* driving 9% of emissions ($\bar{x}$ = 316, $\tilde{x}$ = 291 mt CO_2e) and the *top 0.1%* alone was responsible for 7% of emissions, with a significant 2,254 mt CO_2e average footprint ($\tilde{x}$ = 1,990). By comparison, the bottom 50% of households were responsible for less than 15% of national emissions. Post-tax, the bottom 50% increased its share to 23% of national emission. The top decile was responsible for 33% of emissions ($\bar{x}$ = 95.7, $\tilde{x}$ = 65.2 mt CO_2e), the *top 1%* drove 11% of national emissions ($\bar{x}$ = 329, $\tilde{x}$ = 202 mt CO_2e), the *next 0.9%* was responsible for 6% of emissions ($\bar{x}$ = 205, $\tilde{x}$ = 192 mt CO_2e), and the *top 0.1%* was responsible for 5% ($\bar{x}$ = 1,299, $\tilde{x}$ = 711 mt CO_2e) (Fig. 3.3(C)).

3.4.3.2 Producer Income

Producer-based income results for 2015 are generally similar, with the pre-tax top decile responsible for 40% of U.S. emissions ($\bar{x}$ = 157.1 mt CO_2e, $\tilde{x}$ = 94.8) (Fig. 3.3(B)). The *top 1%* accounted for 16% of national emissions ($\bar{x}$ = 626 mt CO_2e, $\tilde{x}$ = 360). The *next 0.9%* bore responsibility for 9%, ($\bar{x}$ = 379, $\tilde{x}$ = 342 mt CO_2e). While the *top 0.1%* bore responsibility for 7% of emissions, averaging 2,849 mt CO_2e ($\tilde{x}$ = 2,481). Similar to the pre-tax supplier emissions responsibility, the bottom 5 deciles account for just under 15% of national emissions. Post-tax the bottom 50%

increased their share to 24% and the top decile dropped to 32% ($\bar{x}$ = 111.2, $\tilde{x}$ = 72.7 mt CO_2e). The *top 1%* drove 12% of national emissions ($\bar{x}$ = 403, $\tilde{x}$ = 238 mt CO_2e), the *next 0.9%* drove 6% ($\bar{x}$ = 247, $\tilde{x}$ = 227 mt CO_2e) and the *top 0.1%* was responsible for 5% ($\bar{x}$ = 1,811, $\tilde{x}$ = 1,624 mt CO_2e) (Fig. 3.3(D)).

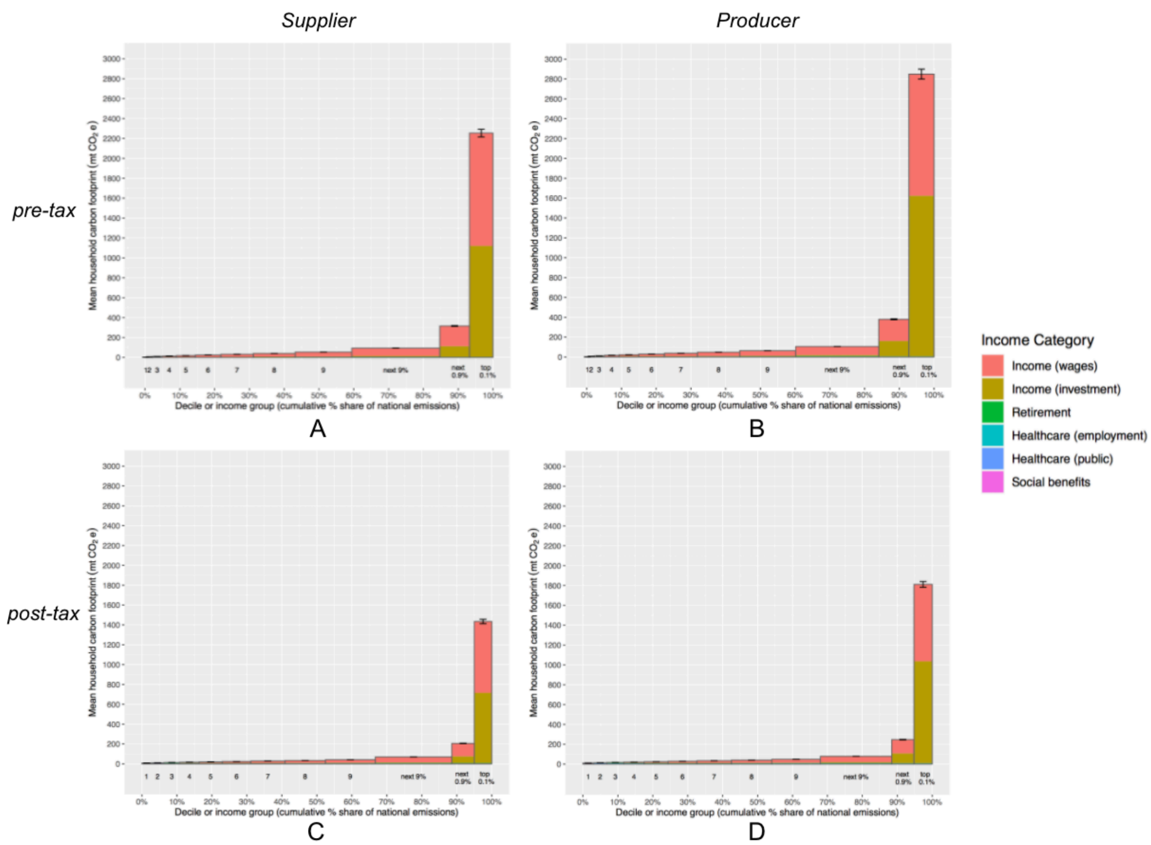

Fig. 3.3: Mean household mt CO_2e emissions (2015) per income group under the Supplier pre-tax (A), post-tax (C) and Producer pre-tax (C) and post-tax (D) frameworks. The width of each income group, on the x-axis, corresponds with each group's share of total national CO_2e emissions. Color indicates income category and bars are standard error.

With both accounting methods and for pre-tax and post-tax there are stark differences between income groups; with those at the very top responsible for large absolute values (mt CO_2e) and driving a significant share of national emissions. But

by normalizing each group's share of national emissions by its population share, I produce an even clearer picture of inequality across groups. In a supplier income framework the bottom decile's emissions are 96% lower per household (pre-tax, 73% post-tax), than if emissions were equitably distributed across all U.S. households (Fig. 3.4). Deciles 2-7 also account for a smaller emission fraction than their population share. Pre-tax the *top 1%* has emissions 1,428% (15.3x) higher than its population share and 38,791% (389x) larger than an average bottom decile household. The *top 0.1%* has average emissions 6,657% (68x) higher than its population share and 171,800% (1,719x) larger than an average bottom decile household. The producer responsibility framework shows similar trends with the first 7 deciles all negative and the *top 1%* and *0.1%* having emissions 1,490% (15.9x) and 7,134% (72.3x) larger than their population share and 39,300% (394x) and 179,300% (1,794x) higher than bottom decile households (Fig. 3.5). Indeed, in both frameworks the differences between deciles 1-8 are almost indistinguishable due to the extreme inequality at the very top.

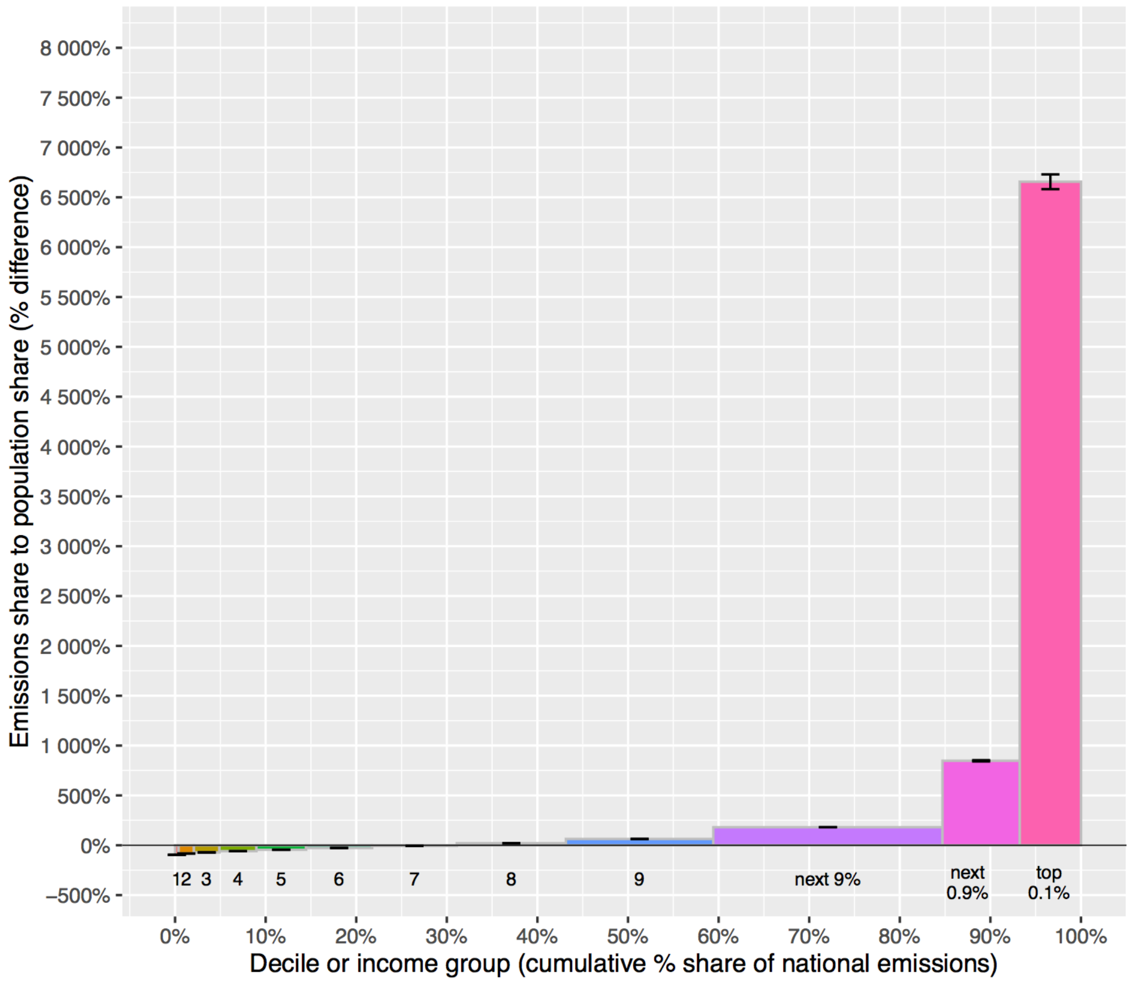

Fig. 3.4: Supplier income emissions share relative to population share (% difference) for deciles 1-9, *next 9%*, *next 0.9%* and *top 0.1%* (2015). A zero value on the y-axis indicates an equitable distribution: i.e. the group's share of national emissions equals its population share. The width of each income group, on the x-axis, corresponds with each group's share of total national CO_2e emissions. Note, the negative emissions of deciles 1-6 and extreme inequality of the *next 0.9* and *top 0.1%*.

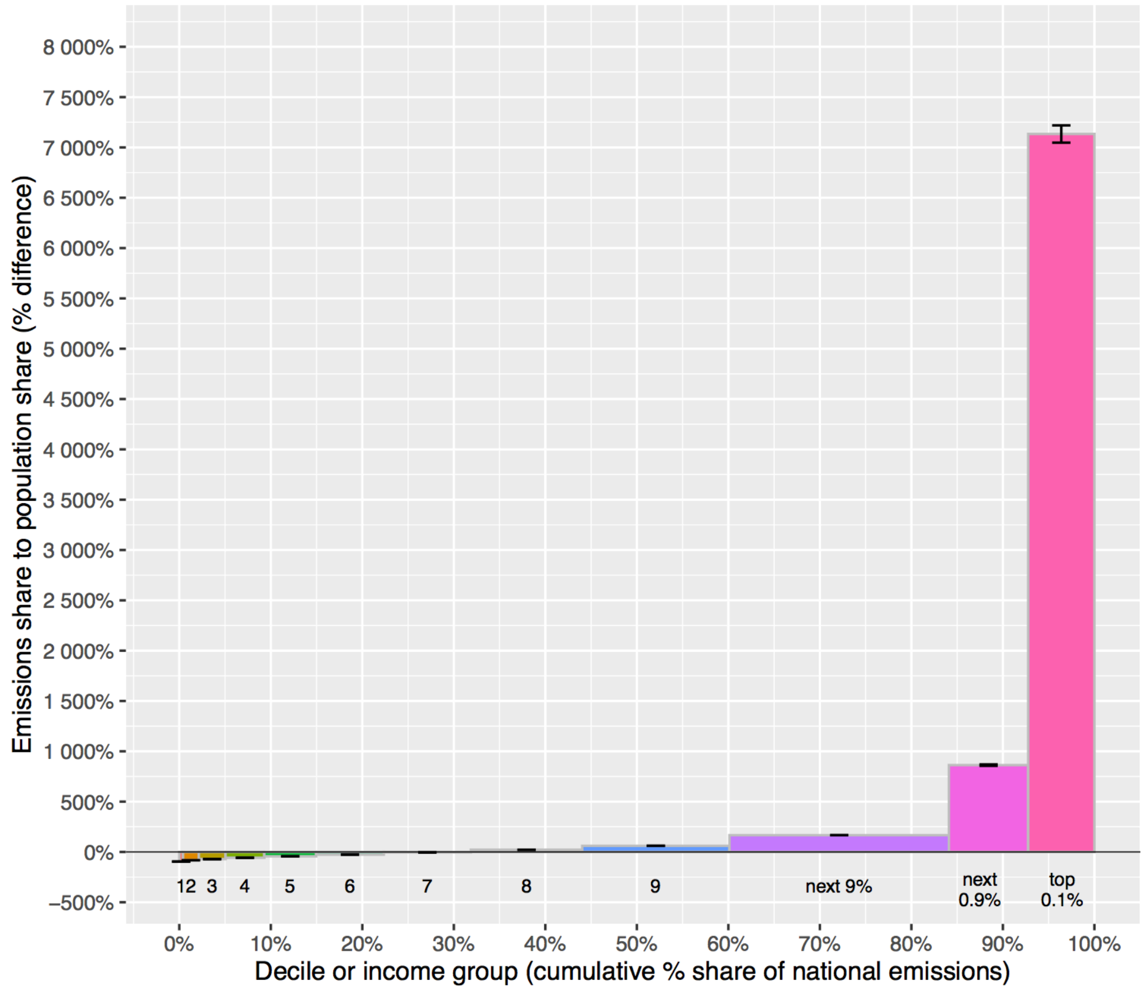

Fig. 3.5: Producer income emissions share relative to population share (% difference) for deciles 1-9, *next 9%*, *next 0.9%* and *top 0.1%* (2015). A zero value on the y-axis indicates an equitable distribution: i.e. the group's share of national emissions equals its population share. The width of each income group, on the x-axis, corresponds with each group's share of total national CO_2e emissions. Note, the negative emissions of deciles 1-6 and extreme inequality of the *next 0.9* and *top 0.1%*.

Post-tax the emissions distribution becomes more equitable as taxes reduce top income group footprints and social transfers increase lower decile footprints (Fig. 3.6). Indeed, social transfers make up a significant share of lower income groups post-tax footprint, while the top income group's emissions footprint is

dominated by capital gains and compensation (Fig. 3.7) (Fig. 3.8). But in both supplier and producer methods the *top 0.1%* emissions' share is still 49x-51x larger than its population share and 171x-185x larger than bottom decile household average emissions.

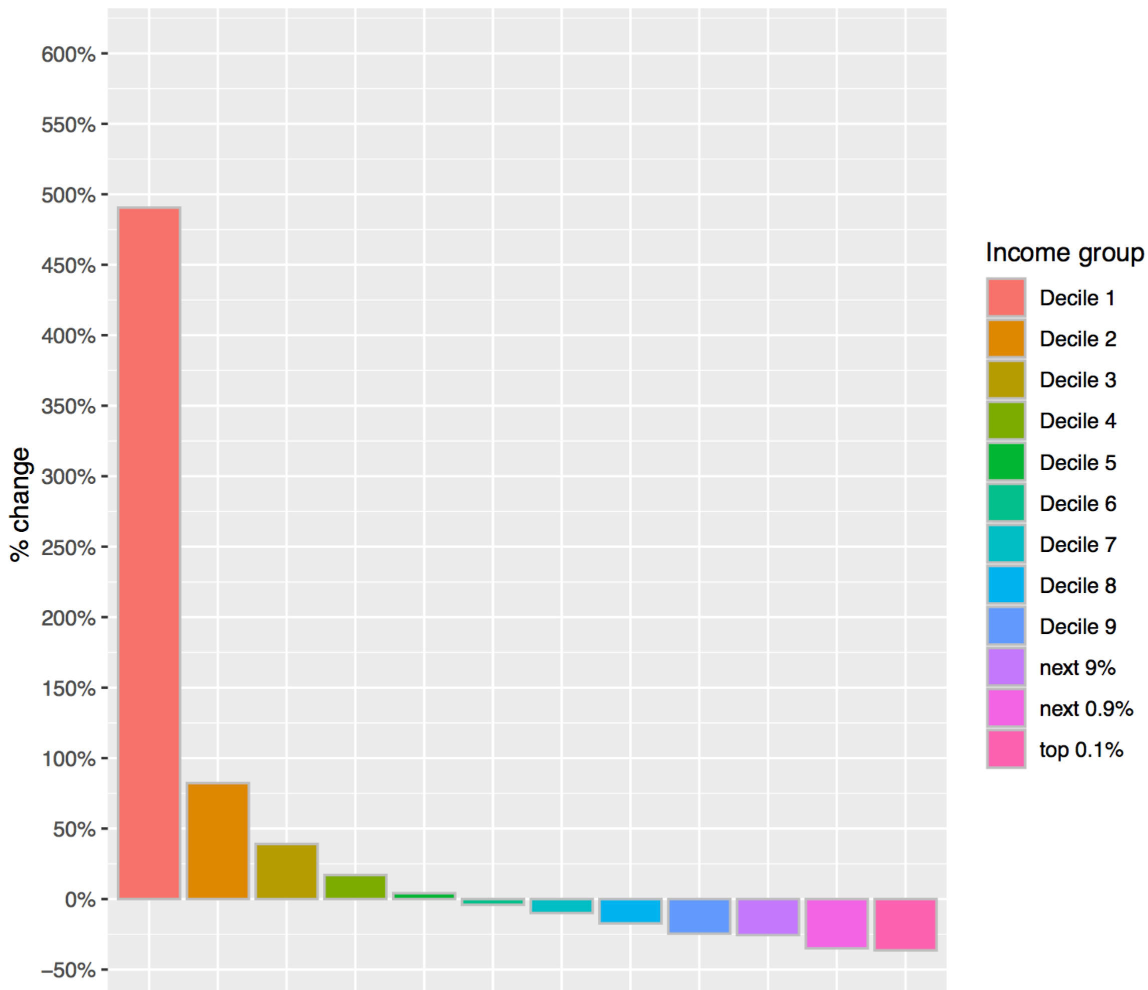

Fig. 3.6: Supplier income, percent change from pre-tax to post-tax footprints (2015). Note, that deciles' 1-6 increase their footprint, while those in decile 7 and above decrease. Producer income has a similar trend.

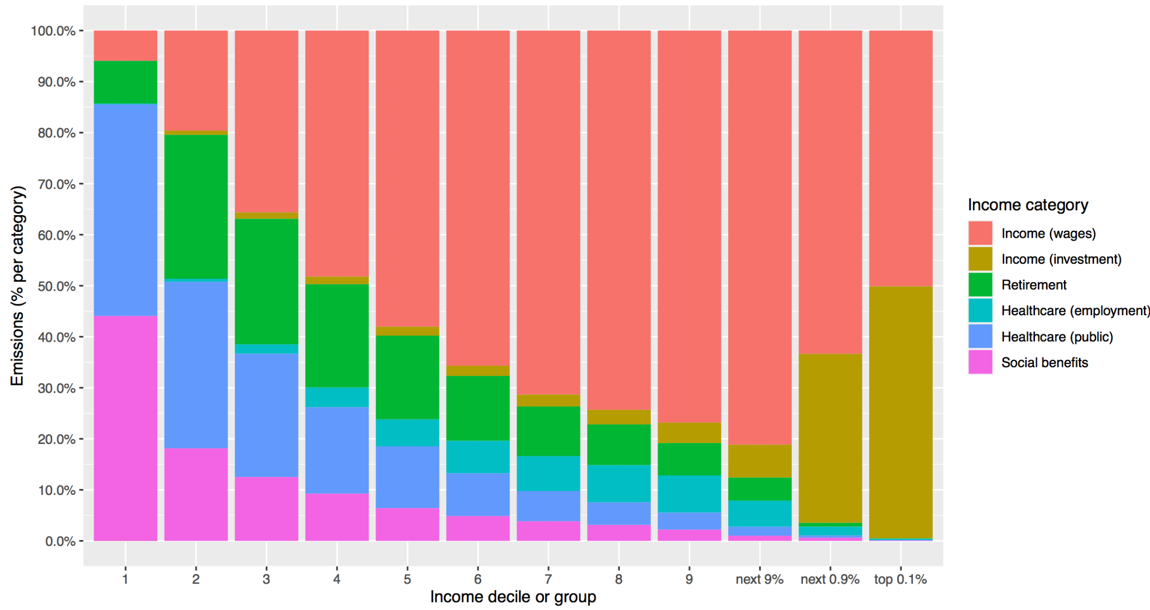

Fig. 3.7: Supplier responsibility-based share of emissions from each income category, by income group (2015).

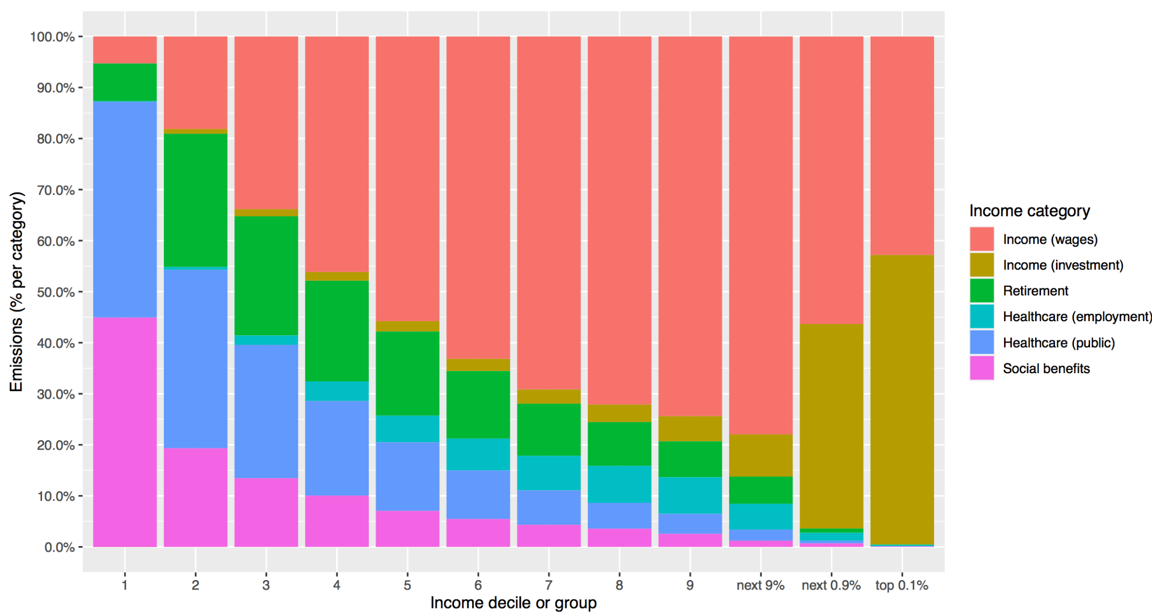

Fig. 3.8: Producer responsibility-based share of emissions from each income category, by income group (2015).

Regardless of framework, household footprints are sensitive to the income source, but the GHG intensity of income source also does vary between accounting

methods. In a supplier income framework, *mining and quarrying* has the largest carbon intensity per dollar (Fig. 3.9), since here they are responsible for emissions that occur when the fossil fuels they supply are combusted. Whereas in the producer framework, *manufacturing*, which is a heavy user of fossil fuels, has the highest GHG intensity, while *mining and quarrying* (which includes fossil fuel extraction) ranks relatively modestly, since their operational emissions are lower than others (Fig. 3.10).

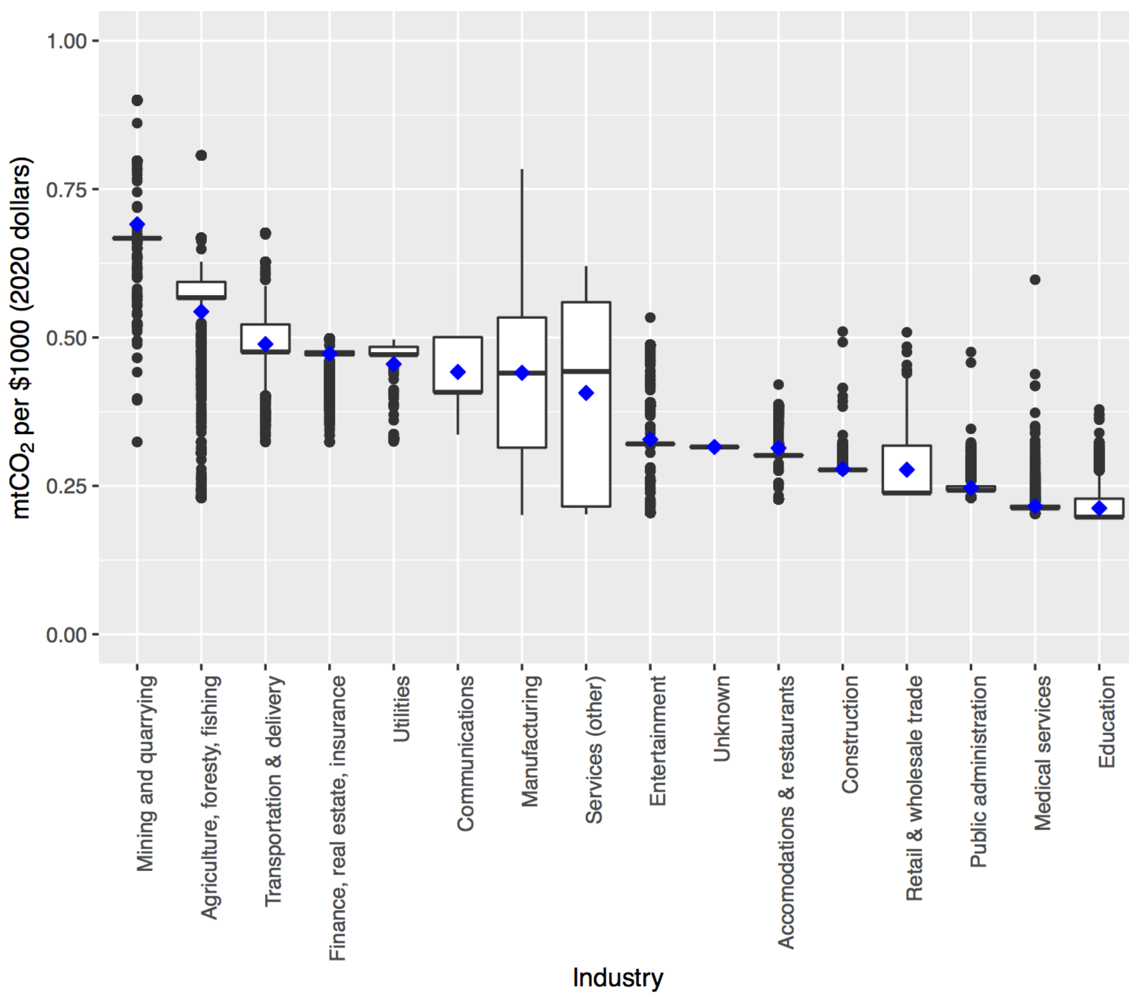

Fig. 3.9: Supplier income, CO_2e intensity per $1,000 income, by industry (2015). Blue diamond denotes mean.

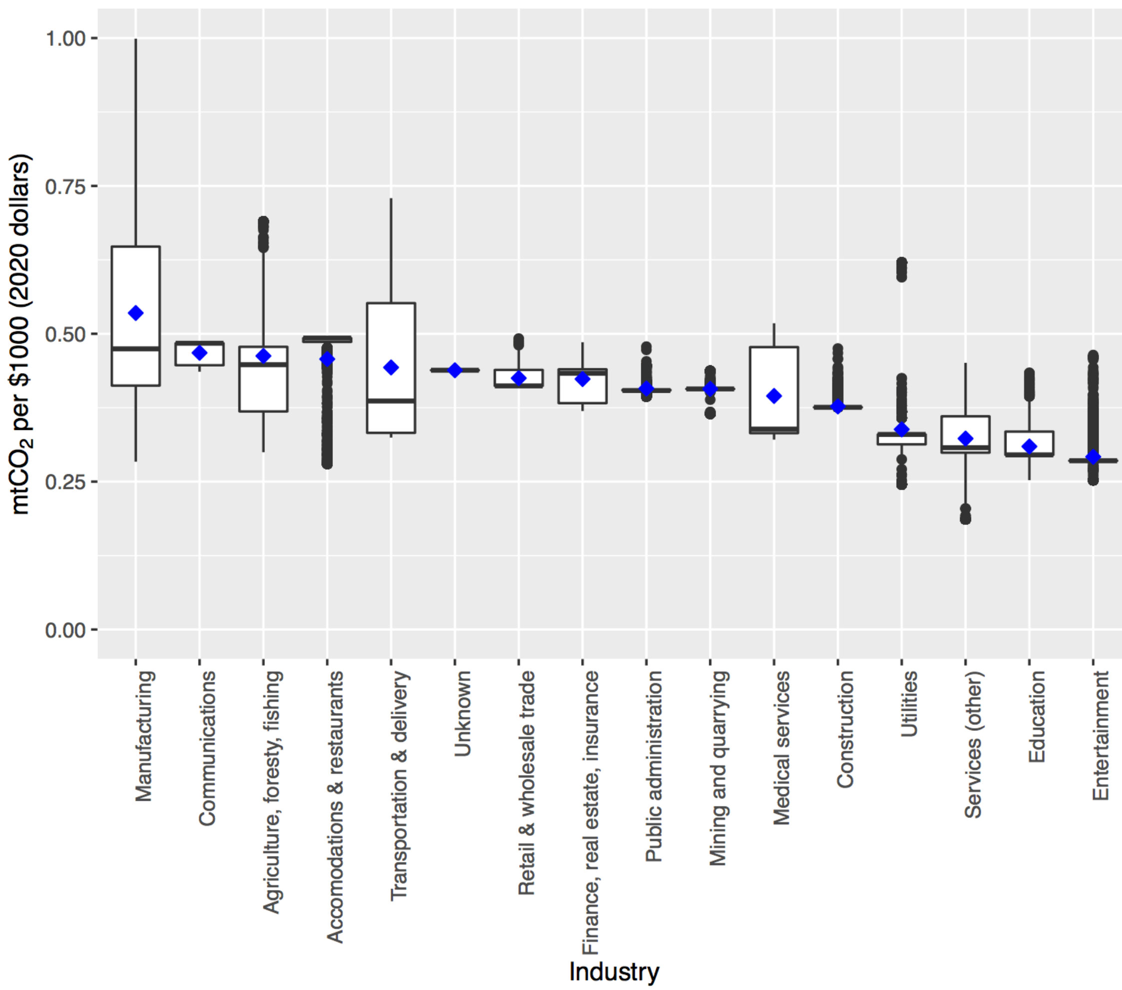

Fig. 3.10: Producer income, CO_2e intensity per $1,000 income, by industry (2015). Blue diamonds denote mean.

3.4.3.3 Relationship to Racial Inequality

Across all economic groups, black households had average pre-tax footprints of 21.0 mt CO_2e (supplier) and 30.2 mt CO_2e (producer), white Hispanic households 25.5 mt CO_2e (supplier) and 27.5 mt CO_2e (supplier), and white non-Hispanic households 38.0 mt CO_2e (supplier) and 44.3 mt CO_2e (producer). There is a striking degree of racial inequality in how the income benefits of GHG emissions are distributed, as white non-Hispanic households emissions were 49% (supplier) and

47% (producer) higher than white Hispanic households and 81% (supplier) and 63% (producer) higher than black households. Post-tax the racial emissions gap closes somewhat, but white households still have emissions 30-55% higher than other groups.

This emissions inequality reflects the extreme racial inequity of the underlying income distribution. The *top 1%* is 79% white non-Hispanic (the highest share of any income group), 8% Hispanic, and only 3% black (the lowest share of any income group). The bottom decile is 46% white non-Hispanic (the lowest share of any decile), 16% Hispanic, and 27% black (the highest share of any decile).

3.4.3.4 Super Emitters

I estimate about 25% of the *top 0.1%* households have pre-tax income responsibility emissions over 3,000 mt CO_2e with the supplier framework and about 37% with the producer framework. These super emitters average 3,942 mt CO_2e ($\tilde{x}$ = 3,780) with supplier income and 4,497 mt CO_2e ($\tilde{x}$ = 4,152) with producer income accounting. Post-tax, this drops to 3% for supplier-based accounting with a mean of 3,427 mt CO_2e ($\tilde{x}$ = 3,352) and 10% for producer-based accounting with a mean of 3,831 mt CO_2e ($\tilde{x}$ = 3,658).

3.5 Discussion

3.5.1 Relationship of Emissions Inequality to Income Inequality

Income-based emissions responsibility closely correlates with income inequality. In 2015, the bottom 50% of the population captured just 12.9% of pre-tax national income, while the top 10%, *top 1%*, and *top 0.1%* captured 46%, 19%,

and 8.5% of national income (78). In terms of income-based emissions (pre-tax), these same groups were respectively responsible for 41%, 15%, and 6.7% of U.S. supplier-based emissions and 40%, 16%, and 7.2% of U.S. national producer-based emissions. Post-tax and social transfers income-based emissions begin to slightly decouple from earned income, with the top decile and top 1% seeing a reduction in their share of national emissions and the lowest deciles seeing an increase. This reflects the power of tax policy to transfer economic benefits, and the emissions embodied in those benefits, between households.

3.5.2 Factors shaping household footprints

With consumption-based GHG emissions accounting, a household's income is not their GHG emissions destiny; meaning households have some agency over how they spend their income. For example, they can choose to purchase less GHG intensive goods and services. This agency increases with wealth. With income-based accounting approaches, a household's footprint is a direct result of their income and they have extremely limited agency in shaping it. Here a household's pre-tax footprint is a function of GHG intensity of the industry/ies they work for and the amount of income they earn. While individuals and households have some agency in choosing which industry to seek employment or invest in, which leads to variability in footprints at a given income level (Fig. 3.11), they generally have extremely limited individual agency in influencing that industry's GHG intensity, though they may have some agency to influence their individual firm.

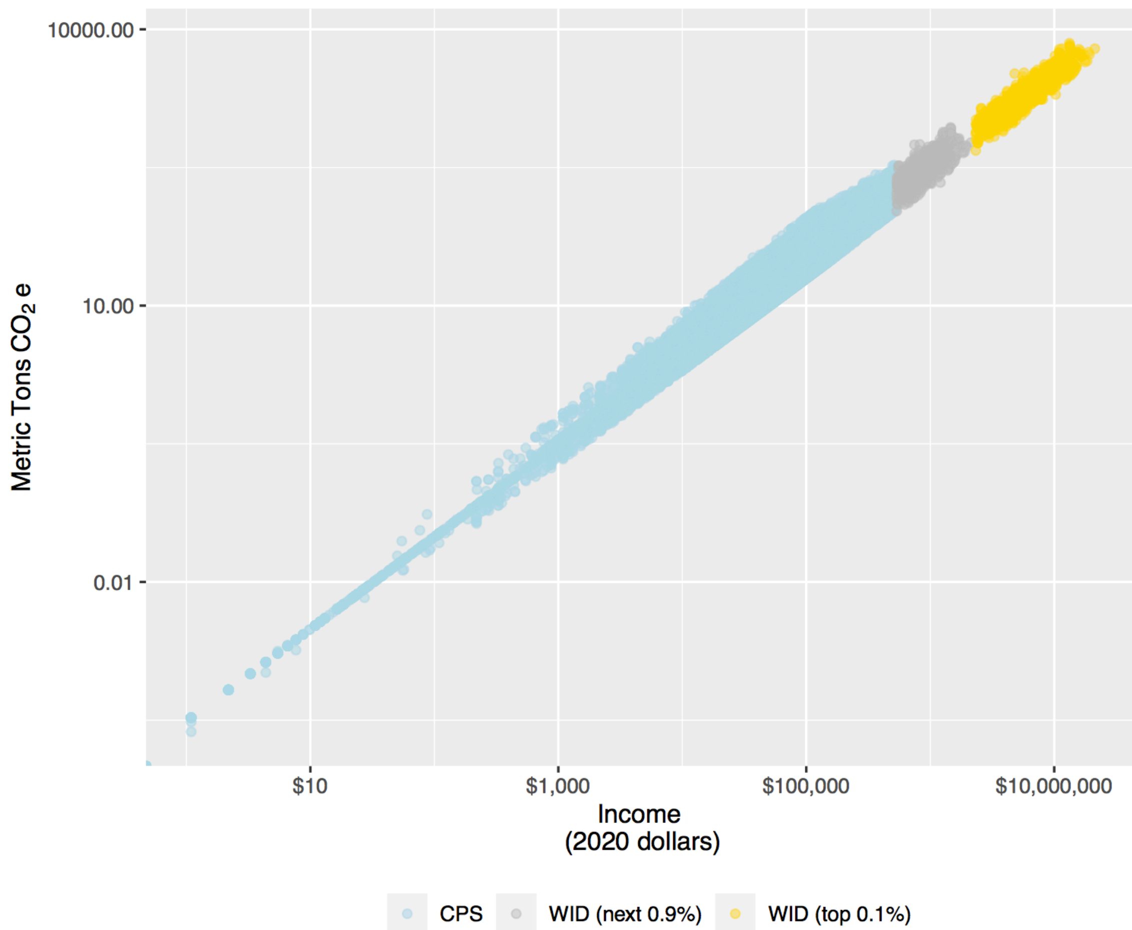

Fig. 3.11: Relationship between income and household GHG footprint (log-log) using the pre-tax supplier income method (2015). Supplier income has a similar trend.

For low-income households, including the value of employer provided healthcare, government assistance (such as healthcare, housing, tax credits, food, or heating assistance) and direct social transfers (such as monetary gifts, education, child support, or alimony) in income-based footprints increase their responsibility. At the top of the income distribution, taxes significantly reduce household footprints: about 35% for top 1%.

Individual households are also sensitive to the accounting method choice. For example, households working for an oil company will have a higher GHG footprint when using the supplier accounting method than they would with the producer accounting method. In 2015, the producer method also generates a higher absolute GHG estimate per income group, than the supplier method (Fig. 3.12). This averages 19% across income groups, and varies between 11%-21% within income groups.[13]

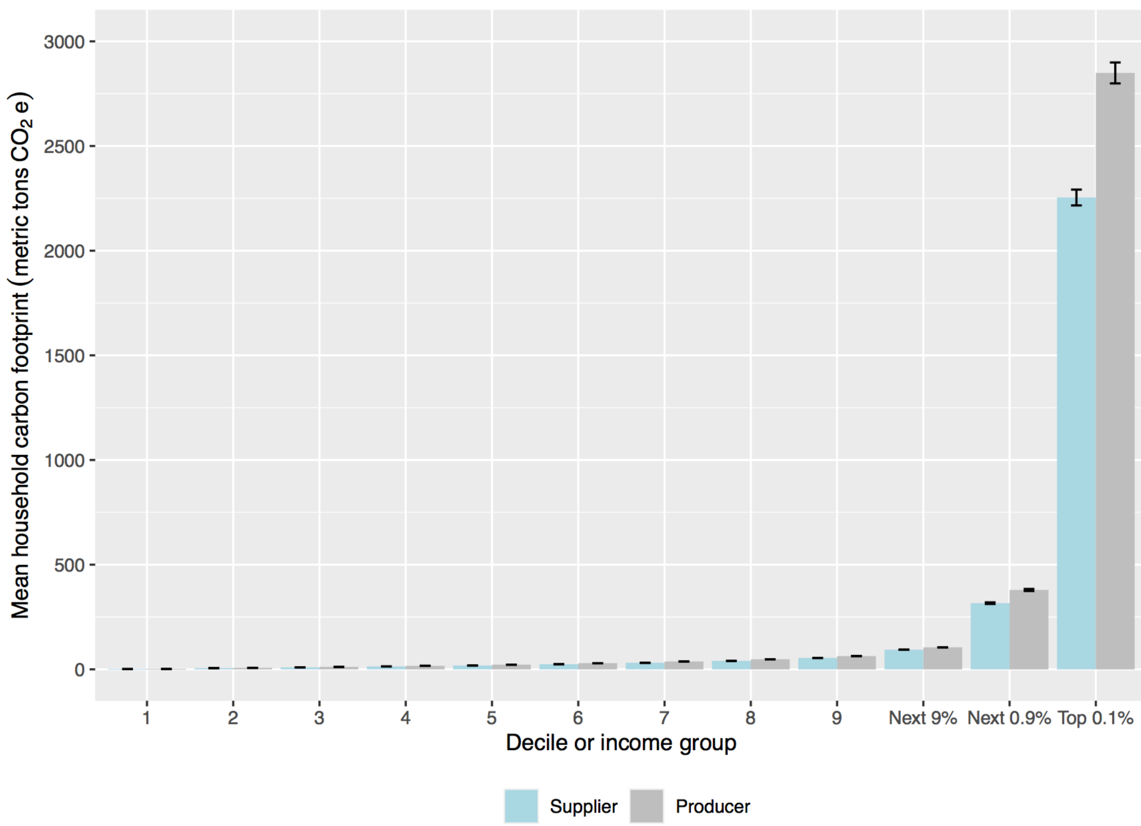

Fig. 3.12: Comparing pre-tax mean household GHG footprints from supplier and producer frameworks (2015).

[13] Note, the 19% difference observed in 2015 is higher than the average difference in other years (Fig. 3.1).

3.5.3 Policy Implications

There is general agreement among economists that carbon pricing, either through cap-and-trade or a carbon tax, are an essential and cost effective way to help decarbonize the US economy (82, 83). Prior work has shown a carbon tax could help phase out coal at a fairly low cost, but would need to be quite high, >$200 per ton CO_2e, to achieve even a 5% reduction in oil consumption. About 70-80% of this cost would be initially passed onto consumers (83). My work on consumption-based footprints highlights how a tax this high could be crushing to low-income families, who purchase more GHG intensive basic necessities, but have small absolute GHG footprints. In contrast, high-income households purchase less GHG intensive goods and services but have extremely high absolute emissions footprints. High savings rates, among this group, will allow them to simply absorb any tax increases and continue driving significant emissions.

The fact that income-based footprints are more inequitable than consumption-based footprints highlights a possible alternative approach to carbon pricing schemes that could be more equitable. Instead of taxing companies that pass on these costs to consumers, an income-based carbon tax, determined by the GHG intensity of the industry from which the income is earned, could be applied to wage earners and investors. While this too would impact low-income families, it would impact them less than a consumption-based tax, because income is more inequitable than consumption. Additionally, households below a given income threshold could be excluded, or graduated tax credits could be granted, to address equity concerns for low-income families.

Such a tax could be based on the producer income or supplier income principal, or some allocation that splits responsibility between the two. For example, calculating the GHG intensity tax by averaging both methods for an even 50/50 split. Revenue, from this tax, could be used to fund mitigation and adaptation efforts.

A significant complication with such an approach is in calculating the emissions responsibility of an individual business. For large fossil fuel suppliers and industrial facilities the GHG data requirement would be the same as in a traditional cap-and-trade or carbon tax scheme and the U.S. Environmental Protection Agency Greenhouse Gas Reporting Program (GHGRP) already collects relevant data, capturing about 85-90% of domestic emissions. Wage and investment income from those industries is already reported to the Internal Revenue Service by employers and financial institutions, so the data needed to link income source and industry is already being collected. A direct producer income tax would be based on direct emissions from industrial facilities. In a supplier responsibility framework, if all responsibility were to be assigned directly to the supplier of fossil fuels, this existing data could also be used to calculate the commensurate tax responsibility. Though for smaller firms, not captured by GHGRP, the producer and supplier emissions responsibilities would be missed.

Alternatively, instead of taxing wage income, this tax could just be applied to investment income or as a shareholder tax. Because investment income and stock and bond ownership is even more inequitable than wage income, this would help focus the tax on those at the very top of the income distribution who reap the most

economic benefit from GHG emissions. This could be applied as a tax at time of share sale, or an annual tax applied to ownership of shares. The latter would be a form of wealth tax, which has gained traction in recent years in progressive policy circles. Focusing on the embodied emissions in certain types of wealth (i.e. stock or bond ownership in fossil fuel intensive industries) may provide additional rationale for such a tax.

One advantage to a wealth-based tax is that unlike an income-based tax it does not come as a huge financial burden in one year. 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, as households may see huge profits one year from the sale of a business, but far less income in subsequent years. An income-based tax that affects households with a heavy tax in one year may be less desirable than having a wealth-based tax that is lower, but more stable year to year. Because wealth is even more inequitably distributed than income, it is also a more effective tool to address systemic inequality and capture the GHG emissions in unrealized capital gains. To make this income versus wealth distinction concrete, in 2019, *top 1%* and *0.1% income* earners respectively had entry thresholds of $510,000 and $2.4 million, averaged $1.4 and $6.4 million, and captured 19% and 8% of national income. Meanwhile*, top 1%* and *0.1%* wealth holders respectively had entry thresholds of $4.2 and $17.8 million, averaged $13.7 and $70 million, and captured 35% and 18% of national wealth.

Whether the tax is applied at time of sale or annually, based on ownership, both approaches would also have a beneficial secondary effect in spurring fiduciary fund managers to divest from GHG intensive industries. Such a tax could again be targeted to supplier or direct emitter companies, using the same GHGRP data. Large and particularly publicly traded companies would be the easiest to apply the tax to, but the challenge here is applying it to private and smaller companies.

Under any such plan a key challenge will be that the households that would see the most direct effect of such an income or shareholder tax are also the households who dominate policy making. Indeed they are the only group whose preferences determine policy outcomes (53). Convincing this group to support such a tax is a significant hurdle. Additionally workers in industries that would directly feel the effects of such a tax would also likely fight such a measure. Though focusing solely on investment income may help galvanize broad public support.

3.5.4 Equity, Climate and Environmental Justice

Climate change is an existential threat to humanity and the natural world. Its effects (deadly heat waves, sea level rise, exacerbated wildfires, flooding, drought, extinction) are already being felt today and will worsen throughout this century. These effects will be broadly felt by current and future generations, but will largely fall hardest on the poorest countries and poor, socially, and racially marginalized communities within countries. Meanwhile, the benefits made possible by GHG emissions (wealth and the goods and services that wealth can purchase) are

concentrated heavily in the present[14] and are disproportionately captured by wealthy countries and wealthy, socially, and racially favored groups within countries.

It is a basic principle of fairness that those responsible for harm bear a commensurate responsibility to repair that harm. As GHG emissions create income, those reaping this income have a responsibility to address the harm caused by the emissions used to produce it. In the U.S., income is extremely inequitably distributed, with those at the very top capturing income and driving emissions >1,000x more than those at the bottom. Because of this inequitable distribution, these highest earning households also have a disproportionate responsibility in repairing emissions damage. Here, public policy, such as income or shareholder carbon tax, can ensure that those benefiting the most from GHG emissions are contributing equitably to the climate mitigation and adaptation efforts needed to ensure the human and natural world can flourish in the future.

3.6 Materials and Methods

For both the producer and supplier approach I link income to GHG emissions using an Environmentally-Extended Multi-Region Input-Output Model (EE-MRIO). The GHG intensity per dollar of income, for each industry, is calculated and multiplied by an individual's income from that industry. The GHG intensities of benefits and social transfers are also accounted for and the emissions responsibility

[14] Intergenerational fortunes and assets that passed onto future generations do provide some benefit to the future. Though these are heavily concentrated in wealthy households.

of taxes are subtracted. Individuals are aggregated into households and households are ranked into percentiles and deciles for income group comparisons.

To calculate the embodied CO_2e intensity of income, I use the Eora MRIO database (57, 58) covering 14,839 sectors, 190 countries, and 1,140 final demand and value added categories. For each of the 20 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 (95). Current year dollars are adjusted to *constant* 2020 US$. Emissions data, from the PRIMAPHIST database (available in Eora), capturing the six Kyoto GHG (90), are used for both income accounting methods. In a producer income approach the direct emissions of each industry are divided by that industry's value added inputs (which includes compensation of employees). This yields direct emissions in mt CO_2e per dollar value added. In the supplier income emissions framework I calculate the enabled emissions, in mt CO_2e e per dollar value, using the Ghosh inverse. This captures all *direct* and *indirect* CO_2e emissions, along the whole downstream global supply chain (~ 100 million inter-sectoral transfers each year) that were enabled in order 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. This is done by first 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. Individual-level wage data in CPS, includes both the amount (in dollars) and the industry from which income is earned.

Individual-level wage data are then multiplied by the corresponding CO_2e intensity for that industry. Other forms of income such as capital gains, interest, dividends, retirement pensions or social security, and the value of employer healthcare contributions are also accounted for. Here, when the source of income is not from an employer, CO_2e multipliers are based on the average emissions intensity of the U.S. economy. The income value of employer healthcare contributions is based on the employing industry CO_2e multiplier. After multiplying by the corresponding CO_2e intensity, individuals are merged into their respective households and mt CO_2e are summed. This yields the pre-tax emissions footprint of each household.

To calculate the post-tax footprint, the value of social transfers such as monetary gifts and publically provided benefits such as veterans benefits, unemployment, heating, rental, educational assistance and others are also included. CO_2e multipliers are based on the average emissions intensity of the U.S. economy. Finally, post-tax footprints are reduced by the percent paid in taxes.

To do this I use IPUMS CPS, a harmonized dataset drawn from the Census Bureau's Current Population Survey (63). It includes approximately 65,000 U.S. households and about 189,000 individuals per year. From CPS, I extract 31 income categories, 3 retirement and employer healthcare variables, and 11 social benefits and 44 other variables related to individual or household characteristics. Each year yields 17,000,000 data points, totaling about 350,000,000 data points across the 20-year period.

While CPS is the most authoritative source on U.S. household income, top coding and sampling challenges with top income households limit its accuracy for

those at the very top of the income distribution. To address this, I create an over-sampled synthetic dataset for the *next 0.9%* and *top 0.1%* households and estimate their income. This is done by creating a distribution of 1,000 households, for each of these groups. Mean pre-tax income and upper and lower thresholds come from the World Inequality Database (WID). These synthetic dataset distributions are right-skewed to reflect within-group income inequality (See *Appendix A* for detailed methodology).

For IPUMS CPS households that meet the WID threshold I extract their CO_2e intensity per dollar income values, bootstrap these into the same size as the synthetic datasets and allow the values to vary +/- 25%, to reflect the natural variation in GHG intensity that exists across households income sources. This is separately done for both wage income and investment income because they have different CO_2e multipliers. In addition to under-sampling *top 1%* household CPS, top coding and limited reporting on capital gains and investment income necessitated an additional treatment of the share of income coming from capital (as opposed to wages). Here I use annual Congressional Budget Office (CBO) estimates on the share of *top 1%* income from capital and estimate the *next 0.9%* and *top 0.1%* share based on CBO's estimation (96). The WID income estimates and the bootstrapped CPS households are both ordered and matched based on total income rank. Income related to retirement, healthcare, and public benefits from the CPS households are then directly subtracted from the WID income estimates, though these make up an exceedingly small share of income (and emissions) for *top 1%* households. The remainder is considered earned income. Using CBO estimates, this income is broken

into the share related to wages and share related to capital. These, along with healthcare and benefits are matched with the corresponding GHG intensities and multiplied. Summing all categories yields pre-tax income-based GHG footprints for *next 0.9%* and *top 0.1%* groups. Post-tax footprints are calculated by reducing this footprint in proportion to the household's tax rate, which comes from the bootstrapped CPS *top 1%* households.

CHAPTER 4

TOTAL-RESPONSIBILITY BASED U.S. HOUSEHOLD CARBON FOOTPRINTS

4.1 Abstract

Anthropogenic greenhouse gas emissions occur to produce wealth, goods and services for people. Yet, extreme inequality, both between and within countries often results in a powerful disconnect between those who ultimately benefit from these emissions and those who are harmed. Harms disproportionately accrue to economically, socially, or racially marginalized people (and to future generations) while benefits are disproportionately captured by wealthier, socially, and racially favored groups within and across societies (and by the current generation). Chapters 2 and 3 examined this flow of benefits to U.S. households using consumer-based and income-based (supplier and producer) responsibility principles. This Chapter examines 20-years of U.S. household total (or shared) GHG responsibility, based on the total benefits a household receives, as both a producer and consumer, from GHG emissions. I find significant inequality across groups, with the *top 1%* of U.S. households increasing their total-responsibility GHG emissions over the last 20 years (+11%), while the bottom 99% of households have decreased their emissions, with all deciles showing an 8-21% decline. The total responsibility framework best captures the full range of benefits a household receives from GHG emissions and policies that take into account total household responsibility may be best suited to address the unsustainably high GHG footprint of U.S. households.

4.2 Significance Statement

At least since the start of the industrial revolution, the creation of income, goods and services has involved the emission of GHGs. In modern economies the income and consumption benefits, enabled by these emissions, largely ultimately flow to households. Yet a holistic household-level accounting of GHG emissions, that includes both income and consumption responsibility, has never been done, either for the U.S. or indeed for any country. In this chapter, I investigate and report what I believe is the first total GHG responsibility accounting of households that captured their dual role as both producers and consumers. I find significant inequality across income groups, with the *top 1%* of U.S. households, increasing their emissions over time, driving a significant share of national emissions, and having emissions well above an equitable distribution. This work informs environmental justice and domestic and international climate policy discussions; particularly those centered on climate equity.

4.3 Introduction

Over the last century, humanity transformed nature at an unprecedented scale. Such transformation produced incredible *benefits* across a variety of human well-being metrics; including greater wealth, material abundance, nutritional access, longer lifespans, clean water access, safe shelter, and creating an infrastructure that fosters human connections across space (97, 98). However, at scales ranging from local to global, anthropogenic environmental transformation also creates *harm* (5,

15, 99). Harm is done to nature, most dramatically in biodiversity loss and extinction and harm is done to people from toxic pollution exposure, deadly heat waves, homes and communities made uninhabitable by climate change, novel virus exposure, and a range of other damages to economic life, social well-being, and health.

The distribution of these benefits and harms is not equitably shared. At both the national and sub-national level, the rich disproportionately capture benefits while the poor are disproportionately burdened with harm (66, 68–70). Chapters 2 and 3 explored household-level greenhouse gas (GHG) emissions responsibility based on how the consumption (21, 25, 28–30, 38) and income benefits (40–46), created by GHG emissions, are distributed across U.S. households. While separately analyzing consumption and income-based emissions highlight different scales of inequality, drivers, and policy responses for GHG inequality they do not fully capture the total responsibility of households based on their dual roles as *both* producers and consumers. Here I present results for a shared responsibility (44, 47–50) framework where emissions related to a household's income and consumption contribute equally to its overall GHG footprint.[15]

Results cover twenty years (1996-2015) and link consumption, production, and supplier emissions responsibility to U.S. households. Emissions multipliers are derived from Eora, a highly granular global multi-region input-output (MRIO) model covering 190 countries (57, 58). Consumption multipliers are derived from a 10,211

[15] Income-responsibility is calculated as the average of supplier and producer responsibility. This is then averaged with the consumption responsibility emissions to obtain a GHG footprint that is a 50-50 split between income and consumption footprints.

x 10,211 commodity-by-commodity table, while income responsibility is based on a 9,812 x 9,812 industry-by-industry model (see *Materials and Methods*). Consumption data come from Consumer Expenditure Surveys (CES) and Income from IPUMS harmonized Current Population Survey (CPS) (63). Households are binned into income groups that include a breakout of decile 10 into the *next 9%* (90-99th 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 I estimate consumption and income for *top 1%* households, which are under sampled in both CES and CPS).

4.4 Results

4.4.1 Time Series: 1996-2015

4.4.1.1 Supplier and Producer - shared income responsibility

Income is generated when fossil fuels are extracted by industries and when they are used by industries. The downstream supplier accounting method links emissions to income generated by the first and the direct producer accounting method links income with emissions related to the second. As my work on income-responsibility shows, depending on the framework used, households will have different emissions responsibilities. One way to handle the discrepancy between methods is to allocate some responsibility from each method to the household. Here I create a *shared-income responsibility* by having each method count for half of the household's income responsibility.

I find the post-tax national average declined 15%, from 37.5 to 32.0 metric tons (mt) CO_2e. Deciles 1 and 2 remained essentially flat, respectively decreasing 4% and increasing 2%. Deciles 3-10 all fell between 8% - 25%. Meanwhile the top 1% increased 6%, with the top 0.1% increasing 21% to 1,623 mt CO_2e (Fig. 4.1). With a post-tax income responsibility, the *next 0.9%* emissions declined 2%. Whereas in a pre-tax calculation all deciles fell 6% - 25% and the *next 9%* fell 15%. In contrast, the *next 0.9%*, *top 1%* and *top 0.1%* respectively increased 6%, 17%, and 35% in the pre-tax calculation.

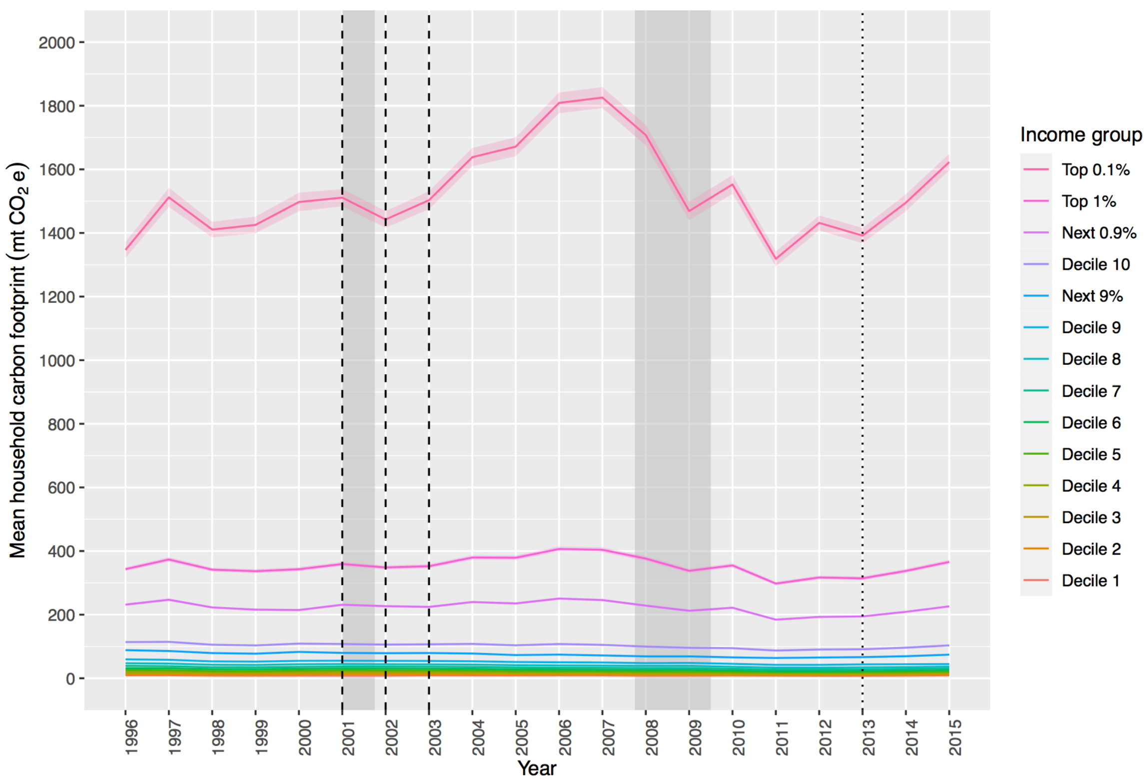

Fig. 4.1: Shared producer and supplier income responsibility (post-tax) average metric tons CO_2e emissions (1996-2015), per income group. Shading is standard error. Colored shading is standard error, gray box shading indicates recession, vertical dashed lines (2001-2003) and dotted line (2013) respectively indicate tax cuts and tax increase for the highest tax bracket.

4.4.1.2 Supplier, Producer, Consumer – total shared responsibility

Here I calculate a comprehensive total household responsibility based on post-tax income (supplier and producer 50-50 split) and consumption. This captures emissions related to the full range of economic and consumption benefits of households and accounts for emissions transfers via taxes and social benefits. I find a 14% decline, in national average emissions, from 43.4 to 37.1 mt CO_2e (Fig. 4.2). All deciles declined between 8% and 21%. Even the relatively affluent *next 9%* group fell 15%. But unlike the lower 99% of the income distribution, the *top 1%*, *next 0.9%,* and *top 0.1%* increased their total emissions 11%, 2%, and 28%. The *top 1%* and *top 0.1%* had average emissions of 311 and 1,280 mt CO_2e, in 2015.

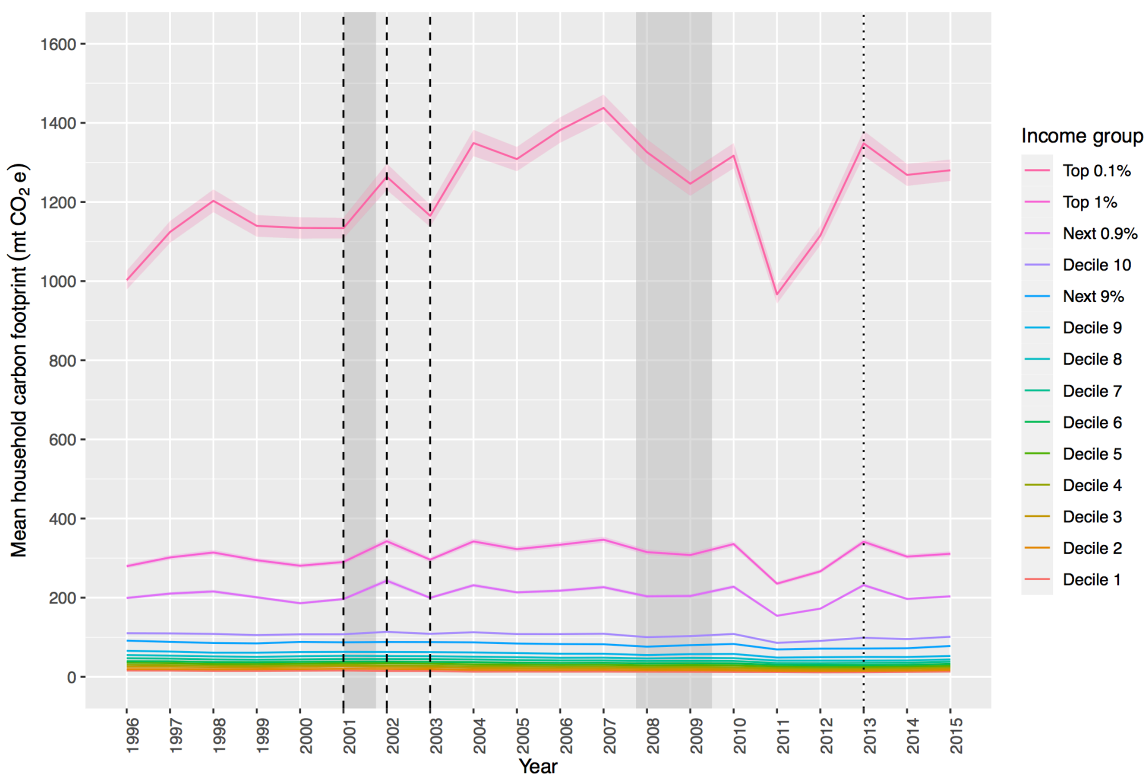

Fig. 4.2: Total responsibility (supplier, producer, consumer) mean household metric tons CO_2e emissions (1996-2015) per income group. Colored shading is standard error, gray box shading indicates recession, vertical dashed lines

(2001-2003) and dotted line (2013) respectively indicate tax cuts and tax increase for the highest tax bracket.

4.4.2 Income, Population and Emissions Trends

Per household and per dollar CO_2e intensity fell under the supplier, producer, and consumer frameworks, as did total U.S. supplier and producer emissions (Fig 4.3). Total U.S. consumer emissions increased slightly, but far less than the growth in total population and dollars per household. Yet, this national average income growth belies the truly remarkable income growth within the *top 1%* groups. Higher income directly affects these households income-emissions responsibility and results in increased consumption that drives consumption-based GHG emissions.

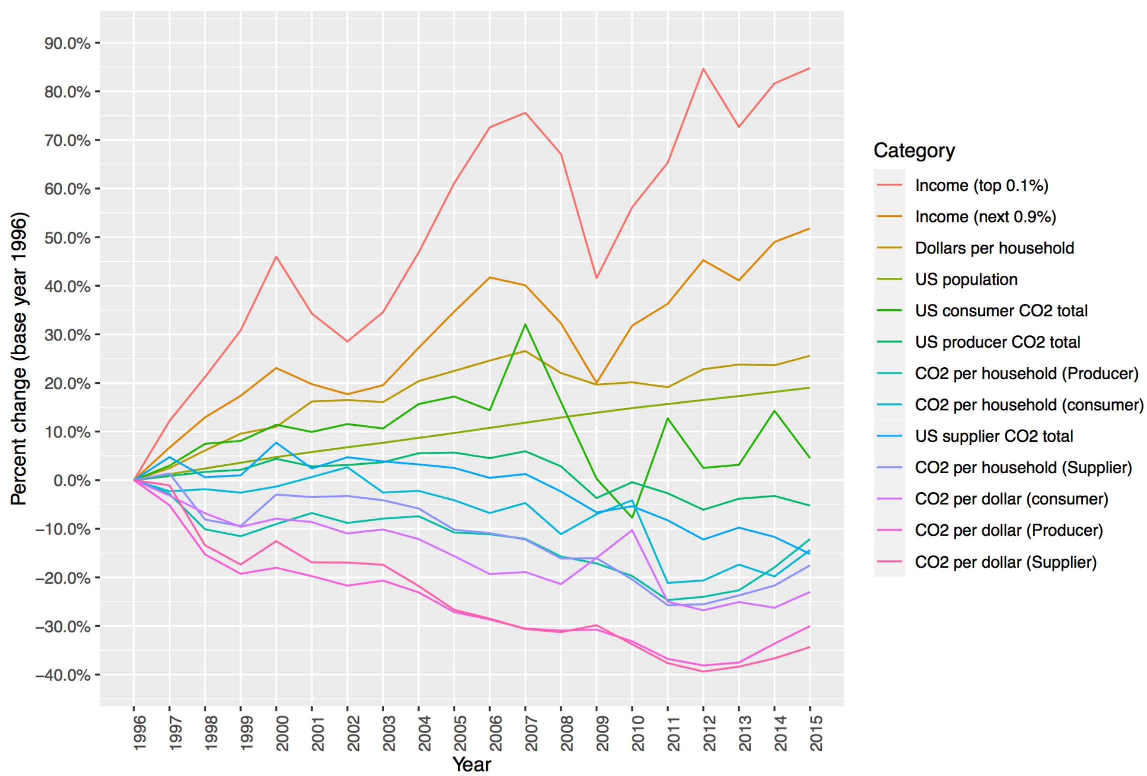

Fig. 4.3: Percent changes (1996-2015) in income, population, spending, total and average U.S. CO_2e emissions, and CO_2e intensity for both producer, supplier, and consumer frameworks, relative to 1996 base year.

4.4.3 Most Recent Year (2015)

With the total household responsibility framework the top decile, in 2015, had mean ($\bar{x}$) emission of 101.2 mt CO_2e (median ($\tilde{x}$) = 72.6) (Fig 4.4) and accounted for 27% of U.S. emissions. The emissions share of these top 10% households is just about equal to the collective emissions from the bottom 50% of households (deciles 1-5), who account for 28% of national emissions. Within the top decile, the *top 1%* alone account for 8% of total national emissions ($\bar{x}$ = 311, $\tilde{x}$ = 193 mt CO_2e). The *next 0.9%* accounted for 5% of national emissions ($\bar{x}$ = 203, $\tilde{x}$ = 182 mt CO_2e), and the *top 0.1%* was responsible for 3.5% of national emissions ($\bar{x}$ = 1,280, $\tilde{x}$ = 1,014 mt CO_2e).

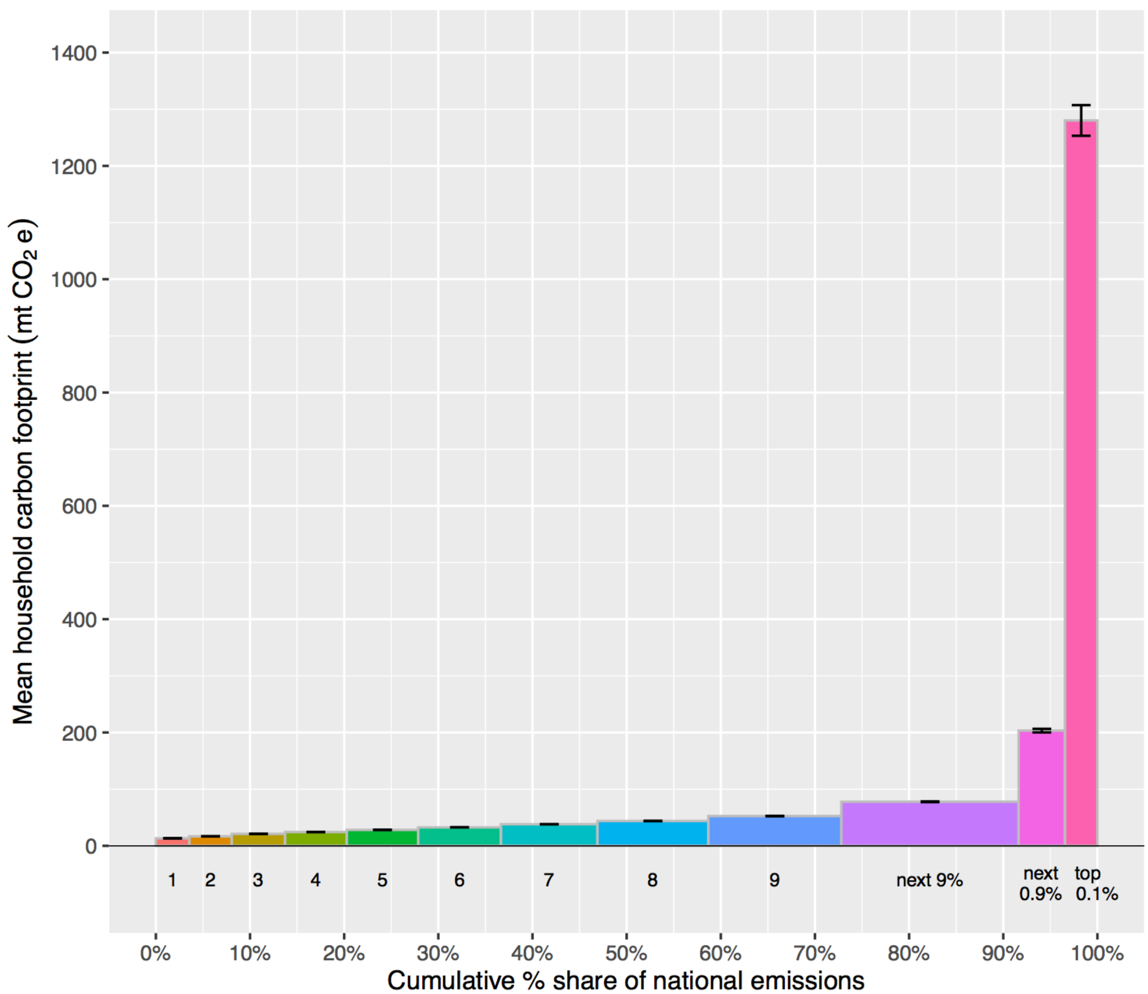

Fig. 4.4: Mean total household responsibility mt CO_2e emissions (2015) per income decile, with Decile 10 broken into *top 1%* and *next 9%*. The width of each income group, on the x-axis, corresponds with each group's share of total national CO_2e emissions. Bars are standard error.

The absolute scale of inequality between groups is stark, with *next 0.9%* and *top 0.1%* households having emissions 15x and 97x (1,438% and 9,582%) larger than decile 1 households (Table 4.1). This inequality comes into even sharper focus when comparing the share of national emissions used by each group in relation to their population share. In an equitable distribution, there would be no difference between these two. Here though, I find deciles 1-6 have negative emissions share

(Fig 4.5). Decile 1's emissions share is 65% lower than what it would be in an equitable distribution, decile 7 is essentially equal to it's share, and the *top 1%* is 8.4x (736%) larger than its population share. The *top 0.1%* is responsible for a share of national emissions 34x (3,343%) higher than its population share.

Table 4.1: Comparison (times larger) of mean household emissions, per U.S. income group.

	U.S. income groups **(times larger)**								
U.S. income groups	Decile 1	Decile 5	National household average	Decile 10	Decile 10		*top 1%*		
					next 9%	*top 1%*	*next 0.9%*	*top 0.1%*	*super emitters*
($mtCO_2e$)	*(13.2 mt)*	*(28.2 mt)*	*(37.1 mt)*	*(102 mt)*	*(77.8 mt)*	*(311 mt)*	*(203 mt)*	*(1280 mt)*	*(3738 mt)*
Decile 1 *(13.2 mt)*	**1**	**2.1**	**2.8**	**7.6**	**5.9**	**23.5**	**15.4**	**96.8**	**283.2**
Decile 5 *(28.2 mt)*	**0.5**	**1**	**1.3**	**3.6**	**2.8**	**11.0**	**7.2**	**45.4**	**132.6**
National househol d average *(37.1 mt)*	**0.4**	**0.8**	**1**	**2.7**	**2.1**	**8.4**	**5.5**	**34.5**	**100.8**
Decile 10 *(101.1 mt)*	**0.1**	**0.3**	**0.4**	**1**	**0.8**	**3.1**	**2.0**	**12.7**	**37.0**

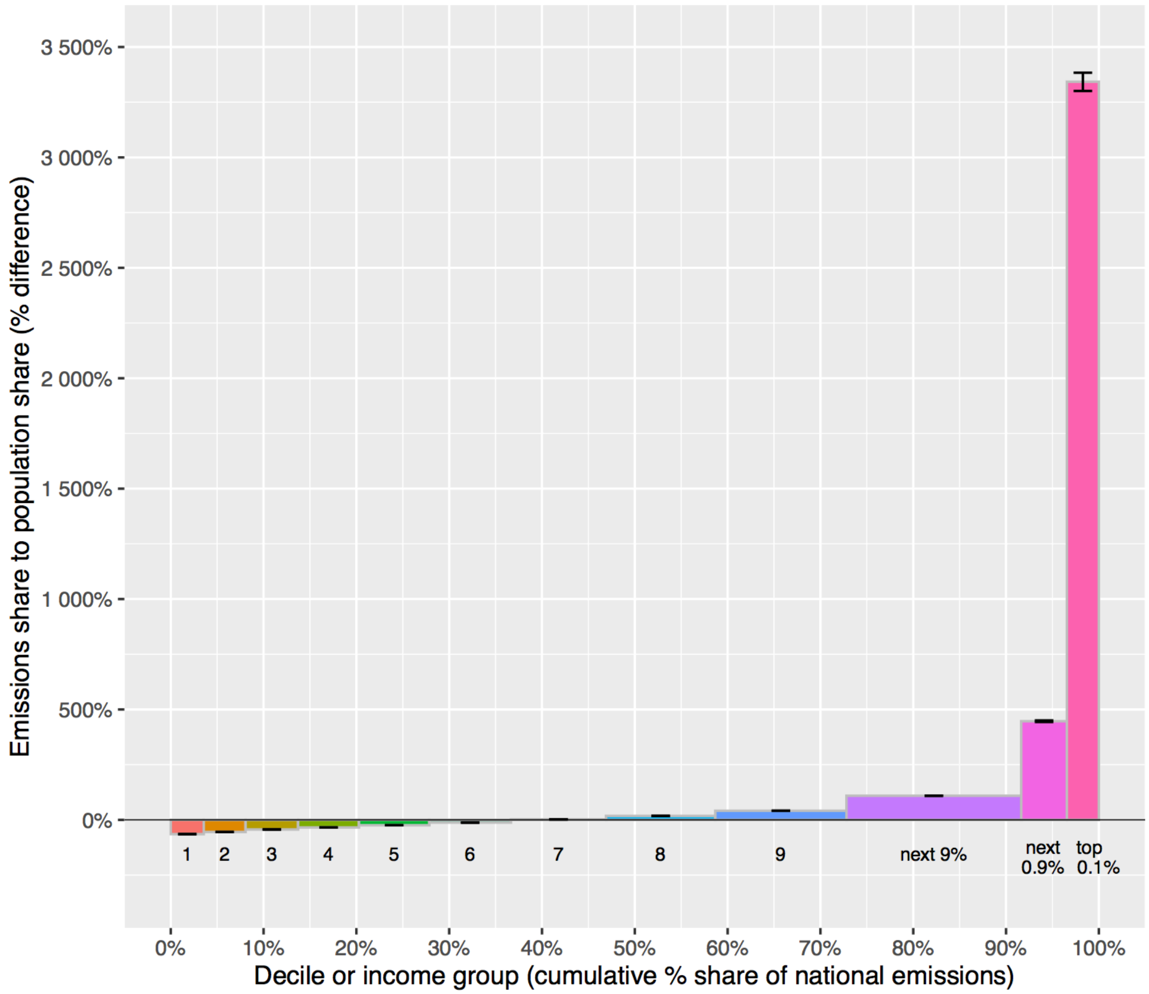

Fig. 4.5: Total household emissions share relative to population share (% difference), for income groups (2015). A zero value on the y-axis indicates an equitable distribution. Width on the x-axis represents the group's share of national emissions.

In all responsibility frameworks (supplier, producer, consumer, and shared total responsibility) top income households are responsible for significantly absolute emissions and a meaningful and disproportionate share of national emissions. Yet, the accounting choice does change group emissions estimates. For the lower 99% of households, moving from an income responsibility (post-tax supplier producer split) to the total household footprint increases their emissions

footprint (Fig. 4.6). This is because social welfare programs, at the bottom of the distribution, and very high savings rates, at the top of the income distribution, make consumption more evenly distributed than income. Thus consumption footprints are higher than income footprints for most income groups. But for *next 0.9%* and *top 0.1%* households this trend is reversed (Fig. 4.7). A key factor here is that high savings rates for top income households reduce their consumption emissions, but don't reduce their income-based footprints, even if that income is saved for future use.

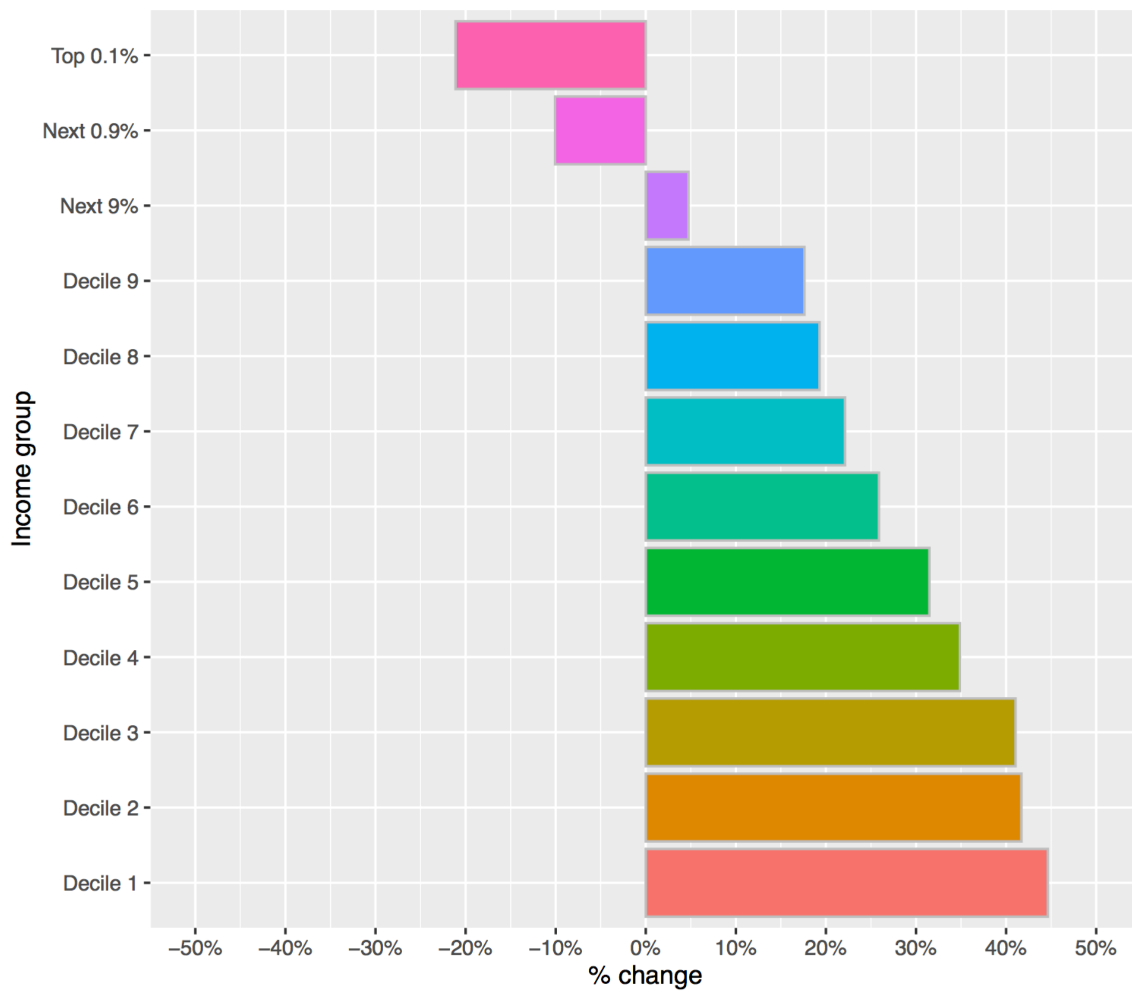

Fig. 4.6: Percent difference, for each income group, between their post-tax shared supplier and producer average and the total responsibility footprint (including consumptions) (2015).

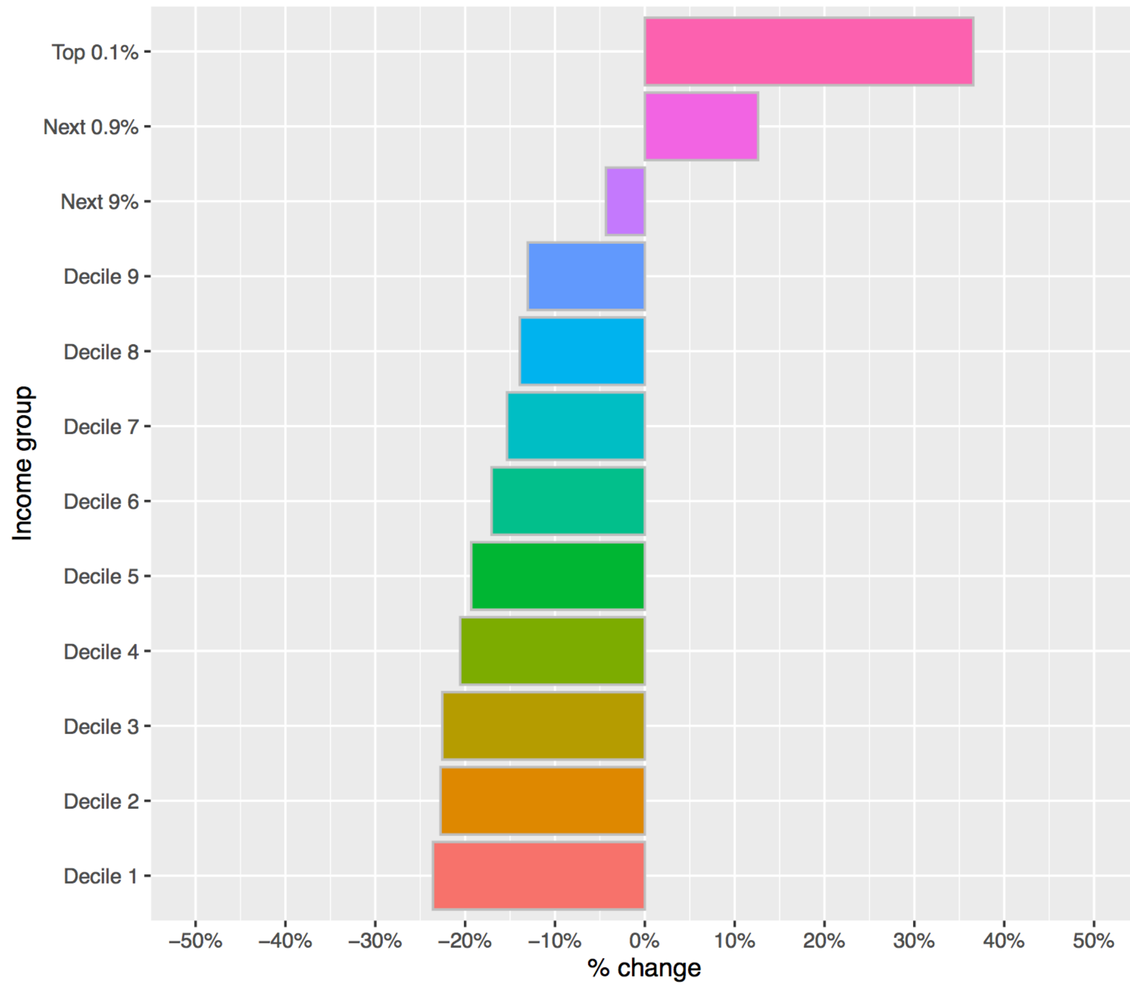

Fig. 4.7: Percent difference, for each income group, between their consumption-based footprint and the total responsibility footprint (including post-tax shared supplier and producer average) (2015).

4.4.4 Relationship to Racial Inequality

In the post-tax total responsibility framework, white non-Hispanic households have emissions (40.0 mt CO_2e) that are 44% higher than black households (27.7 mt CO_2e) and 30% higher than white Hispanic households (30.8 mt CO_2e). Across all post-tax emissions frameworks (supplier, producer, and consumer) white non-Hispanic households have emissions that are between 42-

55% higher than black households and 28-33% higher than white Hispanic households.

This emissions inequality reflects the larger issue of racial economic inequality in U.S. society. Median income of white households is 69% higher than black households and 35% higher than Hispanic households. This income inequality results in different levels of consumption and results in significant income-based and consumption-based differences in GHG emissions responsibility across racial lines.

4.4.5 Super Emitters

I estimate 4% of *top 0.1%* households have consumption-based emissions above 3,000 mt CO_2e and 3-10% of *top 1%* households have income-based emissions above this “super emitter” threshold. In the total responsibility framework super emitters average 3,623 mt CO_2e when consumption based-emissions above 5,000 mt CO_2e are dropped, or 3,738 mt CO_2e when they are included. About 5-6% of *top 0.1%* households likely count as total-responsibility super emitters.

4.5 Discussion

4.5.1 Relationship of Emissions Inequality to Income Inequality

In 2015, the top 10%, *top 1%*, and *top 0.1%* captured 46%, 19%, and 8.5% of all pre-tax national income (78). With the GHG total responsibility framework those groups were responsible for 27%, 8%, and 3.5% of national household emissions. Emissions responsibility at the very top is lower than their share of income because

taxes, very high savings, and the purchase of less intensive GHG services reduce emissions responsibility at the top. Meanwhile, social benefits, very low (or nonexistent) savings rates, and the purchase of relatively higher GHG intensive goods increase emissions footprint for lower decile households.

4.5.2 Factors shaping household footprints – comparing approaches

In pre-tax supplier or producer accounting, income is GHG footprint destiny. Household footprints are directly determined by the amount of money received and GHG intensity of the industry from which it is received. Because supplier and producer footprints calculate GHG intensity differently, household's footprints are sensitive to the method chosen. In so much as they have agency in shaping their GHG footprint, individuals may choose which companies to work for (constrained by what options are available to them) or invest in. Tax policy and the value of social benefits play an important role in shaping household's post-tax income footprints. Progressive taxation and regressive social welfare helps even out some of the most extreme inequality, seen in the pre-tax pre-benefit accounting.

Consumption based footprints are determined by a household's total amount of spending and the types of goods and services purchased. Household agency related to both of these drivers varies across income groups. Low-income households have low or nonexistent savings rates and purchase more basic necessities that tend to be more GHG intensive. Wealthier households tend to purchase less GHG services and enjoy very high savings rates (46% for *top 1%* and

57% for *top 0.1%* groups, in 2015). The latter significantly reduces their consumption-based emissions.

By including both income and consumption in the total-responsibility framework I better capture the true GHG responsibility of households related to the benefits those emissions enable. One downside to the income-only approach is that household choices on how that money is spent have no impact on their GHG footprint. For example, a household actively choosing to limit their consumption and purchase less GHG intensive goods and services will not see these personal life-style choices reflected in their income footprint. At the same time, a consumption-only approach misses the GHG emissions that were required to create income benefits for a household. For example, imagine a household with a seven figure annual income, from a fossil fuel or coal utility company, but it has extremely high savings rates and consumes very little. High savings rates will significantly reduce consumption emissions, yet this saved income still provides the household with real immediate benefit, in the form of financial security, social status, and political influence. The income-based footprint helps to capture that benefit. By combining both approaches, the total responsibility framework better accounts for the true range of benefits received, while including a household agency.

4.5.3 Policy Implications

Carbon pricing schemes, like cap-and-trade and carbon taxes internalize some of the environmental and social damage, caused by GHG emissions, into the price of final demand goods and services (82, 83). These price signals aim to shift

consumer behavior to less GHG intensive alternatives. As I discuss in the consumption-footprint chapter, such taxes would hit low-income families the hardest, while extremely high savings rates of high-income families allow them to simply absorb the tax without making any meaningful lifestyle modification.

With income-based GHG responsibility, taxing income above a certain threshold, based on the GHG emissions it enabled or on the GHG emissions that were used to generate it is an approach to internalize costs on the producer side. Another approach is taxing shareholders of fossil fuel suppliers or high emitting companies. Because stock ownership is highly concentrated among the wealthiest households this could help focus efforts on those top income households that are driving a disproportionate share of GHG emissions. It also has the benefit of stimulating fiduciary fund managers to shift investment away from the taxed industries. It would encourage divestment on fiduciary grounds alone. More work is needed to analyze the regulatory and other costs that might be associated with such a plan.

Considering the total-responsibility approach, where households are simultaneously responsible as both producers that gain an income from GHG emissions and consumers that drive GHG emissions through their purchasing suggests that policy efforts that simultaneously target both consumption and income may be more effective than either is alone. Carbon taxes related to income help address the fact that high savings rates, among wealthy households, limits the impact consumption-based taxes will have on this group. While consumption-based

taxes would provide price signals that can help shift behavior, or at the very least generate revenue to fund de-carbonization efforts.

Yet total-responsibility also highlights some of the limitations of households to independently act as agents of de-carbonization. Certainly among the lowest deciles, even in the face of a carbon tax, shifting consumption is limited by the fact that basic necessities still need to be purchased and overly taxing income, based on GHG emissions, is unfeasible since there is no slack in low-income household budgets to absorb such a tax. At the high end, households have more agency to shift spending, but they also have enough savings to simply absorb any consumption-based taxes and maintain their consumption patterns. They also have extremely limited individual agency in determining the GHG intensity of the industry from which they draw a wage. Perhaps the most agency households have is in their role as investors. This points to a strength of the shareholder-based GHG taxing approach, since households do have high agency in nimbly redirecting investments. While few households have significant investments, thus limiting agency for most households, interest, dividends, and capital gains account for a significant share of wealthy household's income-based carbon footprint and thus a shareholder tax could be an effective tool to encourage these households (and their fiduciary financial advisors) to redirect investments away from fossil fuel intensive industries.

Yet, the limits of households as independent change agents suggest other policies are also needed to decarbonize areas of the economy over which households have limited agency. For example, transportation infrastructure

including high speed rail, electric vehicle charging stations, electric buses, and adequate bike lanes impact household travel choices, but households have limited independent influence on this infrastructure. Likewise, households generally have little choice over the GHG intensity of their electric utility supply. But together transport and utilities make up 50-59% of consumption-based emissions for deciles 1-9. Legislative or regulatory actions that eliminate coal power, restrict fossil fuel development on public lands, and make investments in renewables can change the GHG intensity of the U.S. economy in ways that household decisions simply cannot.

Simultaneously implementing a range of policies, such as carbon tax, GHG-based income and shareholder taxes, and regulatory action that reduce fossil fuel intensive activities while stimulating less intensive alternatives would be the quickest approach to reducing the GHG intensity of the U.S. economy. Yet, each policy proposal brings with it a legislative fight and those most impacted by these proposals, the wealthiest households, are the same households whose preferences determine policy (53).

4.5.4 Equity, Climate and Environmental Justice

Over the last decade plus the scale of economic inequality and racial injustice, within U.S. society, have become increasingly clear and urgently necessary to address. At the same time, the existential threat posed by climate change has worsened with another decade of insufficient action. My work reveals some of the connections between economic and racial inequality and the GHG emissions that drive climate change: namely, how the income and consumption benefits of these

emissions are distributed within U.S. society and the scale of inequity in this distribution. The total emissions responsibility of *top 0.1%* households is 100x larger than bottom decile households and super emitters emissions are about 280x larger. U.S. society cannot successfully address the climate crisis without understanding which groups within society are driving this crisis, assigning an appropriate level of responsibility to those households, and using this to develop just and effective public policy. My work shows how emissions footprints vary across economic and racial lines, how the income and consumption responsibilities of groups differ, and the scale of GHG emissions in the total benefits received by different groups. By illuminating these differences and proposing policies that recognize these inequalities my work provides a new perspective on the connections between economic class, race, and climate change and informs more effective policy formation.

4.6 Materials and Methods

The consumer and income based GHG emissions responsibilities, that determine total household responsibility, are calculated using an Environmentally-Extended Multi-Region Input-Output Model (EE-MRIO), consumer expenditures, and income data.

Mt CO_2e per dollar of consumption or income is derived from the Eora MRIO (57, 58) covering 14,839 sectors, 190 countries, and 1,140 final demand and value added categories. For each of the 20 years, EORA is converted from a 14,839 x 14,839 heterogeneous classification system to a square input-output table. A 10,211

x 10,211 commodity-by-commodity IO table, using the Industry Technology Assumption, is generated for consumption GHG intensity. A 9,812 x 9,812 industry by industry IO table, using the Fixed Product Sales Structure assumption, is generated for income GHG intensity (95). Direct emissions data, for six Kyoto GHGs, come from the PRIMAPHIST database (available in Eora) (90). Consumption-based emissions are linked to household purchasing using Consumer Expenditure Surveys from the Bureau of Labor Statistics (see the Chapter 2 for detailed methodology). Income-based emissions are linked to household income using IPUMS CPS, a harmonized Current Population Survey database (63) (See Chapter 3 for detailed methodology). For both, *top 1%* households are under-sampled in the underlying survey data. I estimate the consumption and income of these households by bootstrapping *top 1%* households that are in the surveys and matching them with simulated high income household income distributions, using data from the World Inequality Database (78). Household GHG footprints are estimated and households are binned into income groups. To calculate the shared total responsibility, the supplier and producer income responsibility, of each group, are averaged. This yields an income-based footprint where half the responsibility comes from the supply-based emissions responsibility and half from production-based income responsibility. This income footprint, for each group, is then averaged with the group's consumption-based responsibility. Yielding a total household responsibility where both income and consumption contribute 50% to the total footprint (see *Appendix A* for additional methods).

CHAPTER 5

CONCLUSION

5.1 Introduction

Despite having about 4% of the global population, the U.S. accounted for about 14% of global production-based CO_2 emissions, in 2019 (100), and remains the largest historical GHG emitter. Within the U.S., households are a key group, as their direct emissions and consumption drive about 80% of U.S. emissions (35). Indeed, decades of high emissions (incompatible with climate stability) have yielded significant income and consumption benefits for U.S. households.

Thus, if the world is to successfully address the climate crisis, the U.S. is a critical player and U.S. households are a key group. Yet, significant economic and racial inequality within U.S. society results in very different levels of emissions responsibility across households. My work quantifies the scale of this inequality and its relation to GHG emissions responsibility. I have done this by tracking the flow of GHG emissions embodied in the consumption and income benefits received by U.S. households using four accounting frameworks: consumer, producer, supplier, and total (shared) responsibility. By revealing the scale of inequality within these different responsibility frameworks, my work reveals the true scale of emissions inequality within U.S. society, informs social justice narratives, and highlights possible policy opportunities.

5.2 Comparison with prior study and novelty of work

U.S. household consumption-based emissions have previously been investigated. For 2004, Weber and Matthews (38) estimated average U.S. household emissions between 43.5 - 60.8 mtCO_2e. My 2004 estimate is right in this range, at 48.2 mt CO_2e. Jones and Kammen find household emissions of about 43.5 mt CO_2e, for 2005, close to my findings of 47.3 mt CO_2e. For 2007, Ivanova et al. (52), estimated U.S. *per capita* emissions were 18.6 mt CO_2e, while my 2007 results align quite well at 18.66 mt CO_2e. Feng *et al*. (28) estimate 2015 *per capita* emissions at 16.4 mt CO_2e, while I estimate 17.3 mt CO_2e. Finally, the only time series analysis I am familiar with for U.S. households is Song et al. (29), they find *per capita* emissions between 1995-2014 averaged between 16.1 and 18.7 mt CO_2e. I find 1995-2015 emissions averaged between 15.6 and 20.0 mt CO_2e. At the household and per capita level my estimates seem to fit in line with previous work.

While general agreement on these average estimates ground my work in prior research, the novelty of my approach is in the *granularity* of the analysis and the focus on top income households. Prior work at the individual household-level has only gone up to about $160,000 (in 2020 dollars) and 100 mt CO_2e (Fig. 5.1). I expand the income bounds roughly 100x and emissions bounds 50x. While prior work has found the scale of inequality between their top groups and bottom group was about 3x (28) to 5x (29) different, I find, in 2015, the difference between my top income group (*top 0.1%*) and the bottom decile is 54x, and the difference between super emitters and the bottom decile is 209x. The scale of inequality I reveal is at least 10x larger than what has previously been reported.

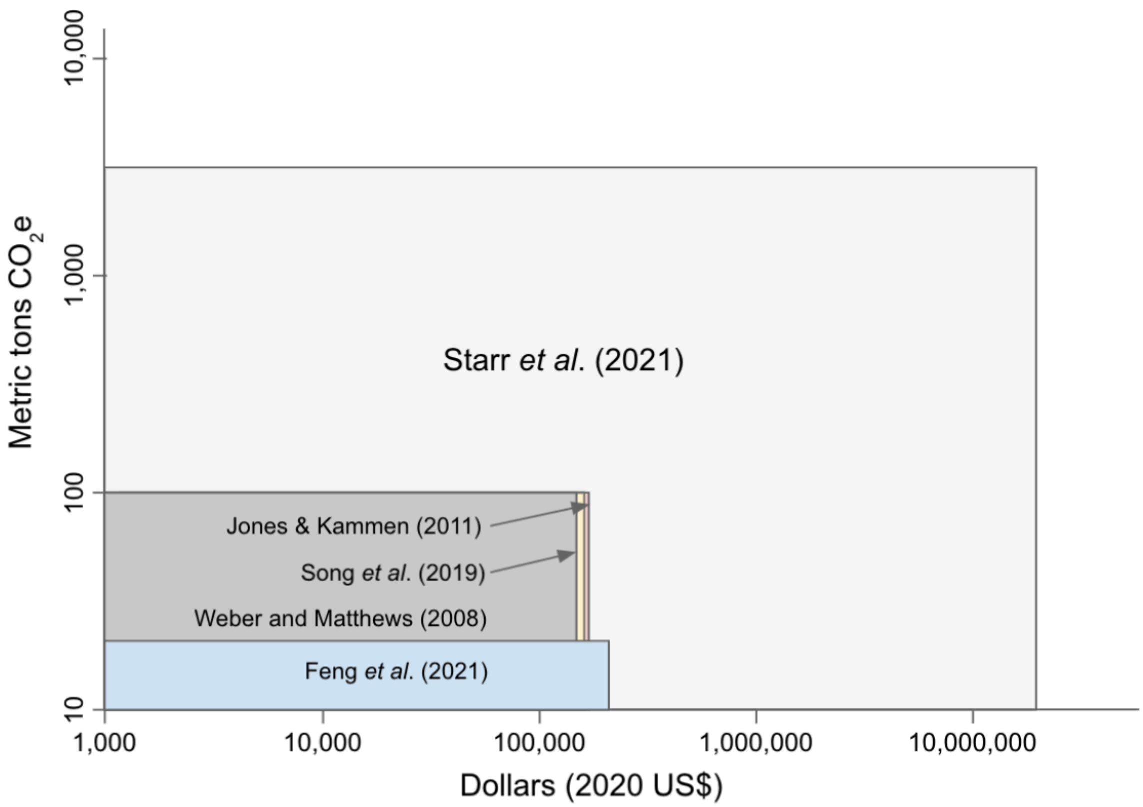

Fig. 5.1: Comparison (log-log), of my study with prior work, in terms of dollars and mt CO2e in scope. Prior study upper income boundary is based on threshold for highest income group reported. My household-level approach allows us to estimate emissions for individual households above $10,000,000. Feng *et al.* is per capita. Note: these are visual approximations.

In terms of supplier or producer income responsibility, a visual like Fig. 5.1 is not possible because no prior work at all has been done to calculate household-level GHG emissions using income-based accounting for the U.S. or any other country. To my knowledge, *all prior work has been done at national, regional, or sectoral levels* (40–46). This misses a key connection between GHG emissions and the economic benefits these emissions enable for households. I find the scale of inequality in this distribution is even more striking than consumption-based inequality. If just pre-tax income is counted here (before social benefit transfers accrue to the bottom and

taxes reduce income at the top) the difference between the *top 0.1%* and the bottom decile is about 1,700x – 2,000x higher, depending on the choice of producer or supplier framework.

Another novel contribution of my work is determining how footprint inequality differs by race. While racial inequality related to the environment has been previously studied (67, 69, 70, 74), to my knowledge it has never been analyzed in the context of household GHG emissions. I reveal significant disparity between households, with white non-Hispanic household emissions far higher than black (42-81% higher depending on accounting method) and Hispanic households (28-37% higher).

5.3 Narratives

Over the last decade plus there has been growing social and political engagement (Occupy Wall Street, the Sunrise Movement, and Black Lives Matter) focused on issues of inequality, racial fairness, and climate justice. Recently there has been a growing understanding that these issues are connected. Yet the scale of emissions inequality between groups has not been well understood. Even in the Green New Deal, perhaps the most ambitious policy proposal to date, to address both economic inequality and climate change, the connection between these two are only made in terms of environmental *harm* (how environmental harm exacerbates systematic injustice of poor or socially marginalized groups) (101). It does not articulate that this harm is ultimately driven by an inequitable distribution of *benefits*; namely an uneven consumption distribution where top income households

disproportionately drive CO_2e emissions. This is perhaps unsurprising as both political considerations and the data needed to inform such an analysis were barriers to its inclusion. But my work here provides a powerful new narrative on how these issues are connected; how income inequality drives emissions inequality and why the scale of this inequality matters for public policy.

5.4 Household agency

One application of my findings is in determining the scale of GHG reduction that is possible due to individual household agency. One way to access the range of agency available to households is by comparing households within an income group to see the emissions spread. In 2015, the *top 1%* of households had consumption-based emissions ranging from a minimum of 21 to a maximum of 4,910 mt CO_2e. Yet, this includes households with just over $500,000 in income to those earning over $10 million. Looking at the more narrow *next 0.9%* group (where the maximum income spread is about $1.7 million), the range is 21 - 813 mt CO_2e with consumption-based footprints, 92 - 1,078 mt CO_2e (supplier income), 131 - 1,895 mt CO_2e (producer income), and 44 – 890 mt CO_2e with total-responsibility accounting. This spread is determined by a range of factors including differences in income, regional differences that impact consumption (like GHG intensity of the electric grid), regional differences in GHG of employment, and household choice.

Because I model individual household emissions, I can control the within-group income spread by focusing on households at a given income level. In 2015, households around $1 million in after-tax income had consumption emissions

between about 100 – 900 mt CO_2e, producer income around 300 - 1000 and supplier income around 200 to 900 mt CO_2e. This large spread suggests households do have some agency in shaping their footprints, though as described above, household choice is only one of several factors shaping this spread.

5.5 Policy implications and future directions

The potential policy applications of my findings are discussed in the individual chapters. Here I discuss how all of these findings together may inform policy and what future work could be done to further develop these applications. Considering all the footprints together, one thing is abundantly clear: regardless of the accounting method chosen there is a startling difference between those at the very top and everyone else. The degree of emission inequality is quite striking. This presents both a challenge and an opportunity for policy making. If some kind of consumer-facing carbon pricing is to be implemented, via cap and trade or a carbon tax, setting such a tax high enough to change behavior of this extremely wealthy group is likely quite challenging. Because savings rates are so high among this group, they can largely choose to maintain their consumption habits, absorb the tax, and still have very high savings rates. Setting the tax high enough where it would actually change behavior would likely be so high that it would be impossible for less wealthy households to pay it and thus politically untenable. Perhaps the best effect such a tax might have vis-à-vis this top income group is generating revenue to fund government de-carbonization efforts. Alternatively, an income or shareholder tax may be a tool to better focus on top income households. Because the tax could be

targeted to those over a certain income, or on investment income (which is disproportionately the realm of wealthy households) a tax here may better shift behavior among top income households. For example, by putting a tax on shares of fossil fuel companies, it may encourage them to divest from fossil fuel companies, whereas a consumption-based carbon tax hitting private jet fuel cost, perhaps wouldn't be high enough to encourage less flying. This approach fits with and could help justify existing policy proposals, such as a wealth tax. Basing a wealth tax on the carbon intensity of the sources of that wealth provides a straightforward justification for the tax, provides an opportunity to reduce or avoid the tax by shifting investments to less GHG industries, and by using tax-generated revenue to fund government de-carbonization efforts, like cleaner transportation or energy infrastructure the tax would not only shift behavior but would fund carbon reduction efforts. Yet, while policy can help shift some household actions and fund de-carbonization, households are also only one actor in the economy and their agency is limited. They can't directly determine the GHG intensity of basic necessities, for example, the public transportation options available to them, the availability of electric vehicle charging stations or the GHG intensity of their employers. Coordinated efforts by government via legislation and regulation, such as a clean power plan that sets carbon efficiency standards or investments in renewable energy and public transportation infrastructure are also desperately needed.

Finally, while the policy window to turn any of these ideas into reality is limited, there doesn't have to be a choice between one policy or the other. The most

effective solution would likely be all of the above: a consumer facing carbon tax that encourages less GHG intensive consumption, an income tax for high income households that reflects the scale of GHG emissions used to generate that income, a shareholder tax on fossil fuel supplier or large emitters that internalizes the social and environmental damage caused by those corporations, and direct government action (at least partly funded through some of these taxes) that invests in green infrastructure, sets electric vehicle fleet standard, and restricts fossil fuel extraction and combustion activities. By simultaneously implementing a range of policy solutions it could move the U.S. economy to a level of emissions that will preserve life on this planet. Though I am not naïve about the extreme difficulty in actually turning these ideas into law and the additional work that needs to be done to analyze the effectiveness and cost of these proposed policies. Indeed, now that I have articulated the scale of inequality and identified some of its implications, I hope this is an area of future research that others will pursue, namely analyzing an income or shareholder carbon tax.

5.6 Other research directions

Beyond quantifying the scale of inequality across income groups, the databases I have created provide other opportunities to quantify GHG emissions footprints relationship to other variables. Here I quantified racial inequality in GHG footprints, in 2015. This can be done across the whole 20-year dataset to see trends in this inequity. Single year and time series state level or regional GHG analysis is also possible. How GHG footprints vary across age can also be calculated with this

dataset, giving insight into an important factor that influences inter-generational equity discussions. As additional years of Eora MRIO, emissions, income, and expenditure data become available, the code I have written to extract relevant data can quickly process it and update the analysis.

This database could be turned into an online tool where individuals or organizations could calculate their supplier-income, producer-income, or consumption based footprints. Giving the user insights into the scale of their emissions, the areas of their income or spending that are most GHG intensive, reveal how they compare to other groups in the country, and help give them agency to reduce their emissions. It could also be used to show what the effect of different policy solutions (like carbon tax, income carbon tax, or shareholder tax) might have on their budget.

Beyond GHG emissions, the relationship between economic, inequality, race, region and other variables can be examined. Eora contains additional environmental satellite accounts, such as water, nitrogen, and raw materials that can be calculated with minor code alteration and linked with U.S. households' income and consumption.

Furthermore, I analyzed one country. The novel method of bootstrapping *top 1%* household expenditures and income sources to account for under-sampling in national surveys could be applied to countries around the world. The World Inequality Database (WID) contains fine-grained income data for a growing collection of countries. Using WID data and relevant national surveys, the techniques I pioneer here could be used to better understand top income household

footprints within countries around the world. If other researchers pursue this, a further step is to then be able to compare the GHG, or other environmental footprint, of top income households across countries.

5.7 Conclusion

In my lifetime, global GHG emissions and the share of income going to the *top 1%* of U.S. households have both roughly doubled. Neither trend is sustainable. While fossil fuels have created wealth and previously unimaginable levels of material comfort, GHG emissions have begun undermining the wellbeing of both humanity and nature. The U.S. and most countries on earth are far from where we need to be if we are to maintain a livable climate. Likewise, extreme economic inequality cannot flourish while having a fair, stable, and just society. Cracks in democratic norms and the very fabric of our society have been exacerbated by many forces, but economic inequality and erosion of economic opportunity certainly plays a key role in the sense of cultural dispossession and grievance that has motivated a lurch towards despotism. By quantifying the scale of GHG emissions inequality, both within the U.S. and as compared to global income groups, and discussing some policies that recognize this inequality, my hope is that this work will contribute to the much needed social and policy debates that need to occur if U.S. society and indeed humanity is to successfully navigate the climate crisis and create a more just society as it does so.

Appendix A

Footprints Supplemental Material

6.1 Methods

6.1.1 Challenges with the Top Income Groups

The CES database that I use for extracting household consumer expenditure data and calculating consumption-based GHG footprints, under-samples high-income households and those that are present tend to be on the lower-income side of the *top 1%*. For example, in 2015, a *top 1%* income household, as reported by CES, earned at least $326,000 and had an average income of $451,000. Converting World Inequality Database (WID) *top 1%* adults to tax units, I estimate a U.S. household needed to earn at least $535,000 and had an average income of $1,480,000: this is over a million dollar difference in the group's mean income (78). Meanwhile, according to WID a *top 0.1%* household needed to earn at least $2.275 million, in 2015. There were no *top 0.1%* households in the CES database.

Like CES, the IPUMS CPS that I used to extract household income data and calculate their producer and supplier income-based GHG responsibility, also under samples *top 1%* households. For example, in 2015, a *top 1%* income household, as reported by IPUMS CPS, earned at least $536,000, which is *almost exactly* the same as the top 1% threshold reported by WID, but the average IPUMS CPS top 1% household income was $879,000. The WID average of $1.48 million is about $600,000 (68%) higher than the IPUMS CPS *top 1%* mean. In IPUMS, CPS to count as a *top 0.1%*, households needed to earn at least $1.2 million and they had an average

pre-tax income of $1.39 million. Meanwhile WID estimates a *top 0.1%* threshold of $2.28 million and a mean of $6.67 million, or about $5.3 million (383%) higher than the CPS *top 0.1%* average.

To account for this under-sampling, I estimate *top 0.1%* and *next 0.9%* expenditures and income by creating synthetic datasets of households with income, whose mean income matches WID estimates and whose distribution is right skewed (to capture the significant inequality even within these groups) (Fig. 6.1). The first challenge is that WID average and threshold income data is for adults, while CES data is in consumer units (i.e. households). To better match the WID and CES units I 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 (102). In practice, I estimate pre- and post-tax income of tax units are respectively about 6-8% and 7-9% higher than adult (equal-split) unit incomes.

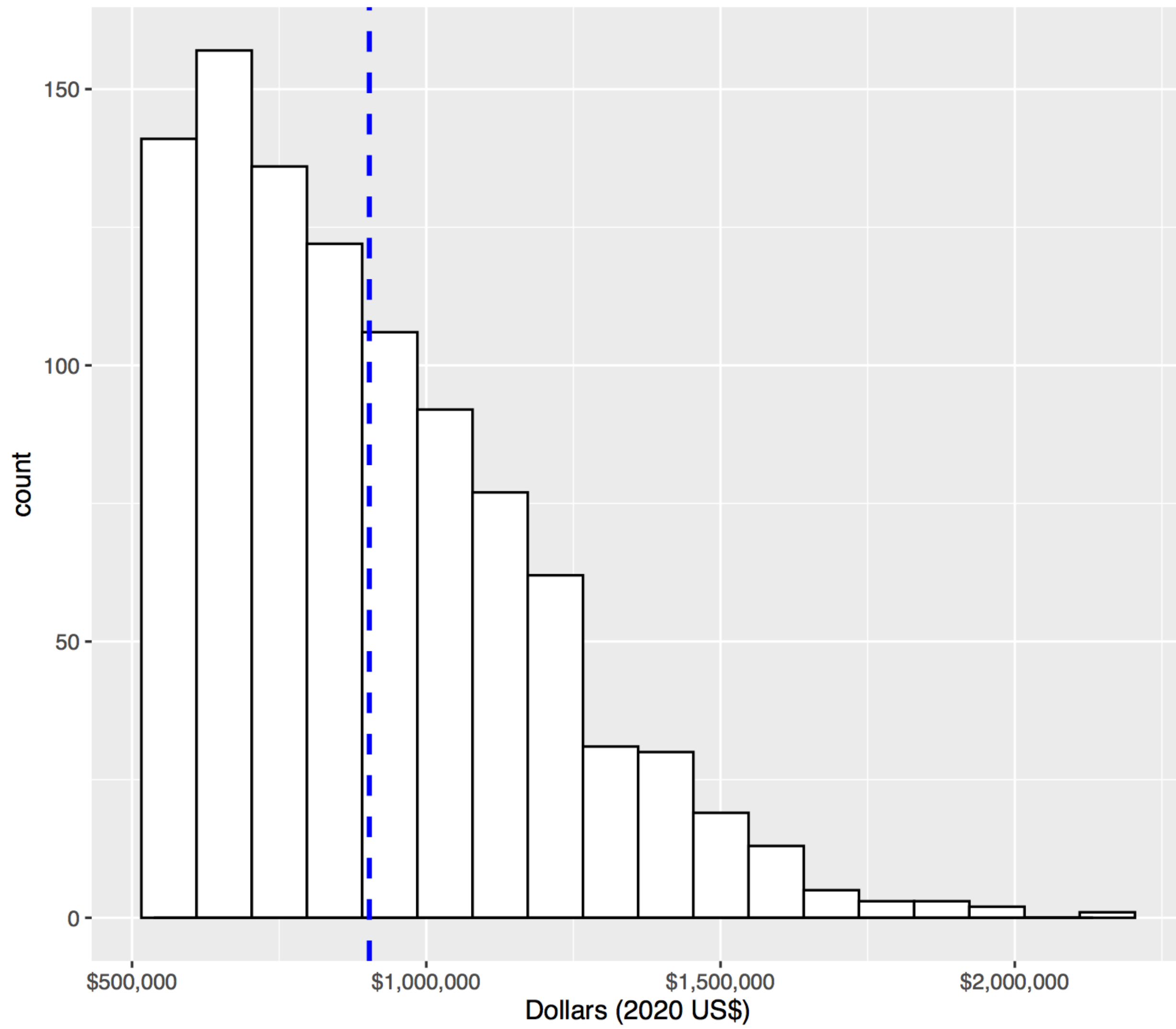

Fig. 6.1: The right-skewed synthetic household income distribution for the *next 0.9%* income group (2015) bounded within WID lower and upper income thresholds. The blue line represents the group mean: $903,187. (n=1000). The *top 0.1%* distribution has a similar form.

6.1.1.1 Estimating Income-based footprints

Income based footprints are estimated by first bootstrapping IPUMS CPS households that surpass the top 1% WID threshold into a matrix that matches the WID synthetic income estimate distribution length. Next, the CPS households are ranked into ascending order by total household income, the WID income estimates

are also ranked into ascending order and the WID estimates are applied to the correspondingly ranked household. From this I subtract the dollar value of retirement, healthcare, and public benefits received, with the remaining amount considered earned income that can be broken into wage income and capital income.

As mentioned in Chapter 3, the CPS estimates for capital income sources are lacking, particularly post-2009. For 2009 and earlier capital gains are estimated for households, but this is dropped post-2009. Capital gains and investment income is an import source of overall income for top 1% households. Failing to break the dataset up into wage income and capital income will lead to inaccurate CO_2e estimation since the CO_2e multipliers differ for these income sources. This is accounted for by extracting CBO estimates for capital and income share, for top income households (96). Using this average, I generate a normally distributed dataset whose mean is equal to CBO values and whose length equals the bootstrapped CPS households. These income share values are subtracted from 1, with the remaining percent representing wage income share. These shares are then multiplied by the WID total income estimates, yielding dollar value estimates related to each household's capital and wage income.

Along with retirement, healthcare, and benefits these are matched with the corresponding CO_2e multipliers and the pre-tax mt CO_2e per income category is calculated. Here, to account for natural variation between household *wage income* sources, I apply a +/- 25% random variation to the original bootstrapped household *wage*-based GHG intensity. This +/- 25% random variation is also done for household's *capital income* CO_2e multipliers. Summing all income categories yields

each household's total pre-tax mt GHG footprint. To calculate post-tax footprints, estimated tax rate (percent paid in taxes) is derived from the bootstrapped CPS *top 1%* households and household mt CO_2e footprints are reduced by this percent, yielding the household's post-tax footprint.

Households are then organized into different economic groups to compare emissions. The *top 1%* CO_2 emissions are estimated using a weighted mean, median, and weighted standard error of the *top 0.1%* and *next 0.9%* groups. The CO_2e per capita, per household and per dollar (Fig 3.2) and the racial breakdown of emissions per decile are calculated using a representative sample from the *top 0.1%* and *next 0.9%* groups.

6.1.1.2 Estimating expenditures and consumption footprints

To calculate consumption-based footprints I first take the synthetic WID estimated distribution of top income households and estimate and apply tax rates to each household. *Top 1%* tax rates are derived from the IPUMS Current Population Survey (CPS), which has better sampling of high-income households than CES. From the CPS, I 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 my synthetic income distribution. Savings rates are estimated by subtracting total expenditure dollars from total post-tax income, for CES *top 1%* households (Fig. 6.2), generating $\bar{x}$ and s, and creating a distribution of savings rates. Mean savings rates for the *top 0.1%* are estimated to be 25% higher than the *top 1%* group, to reflect the higher

savings that are possible for these extremely wealthy households. For each household in the synthetic income distribution, a tax and savings rate is applied, with the remaining post-tax post-savings income considered expenditure dollars.

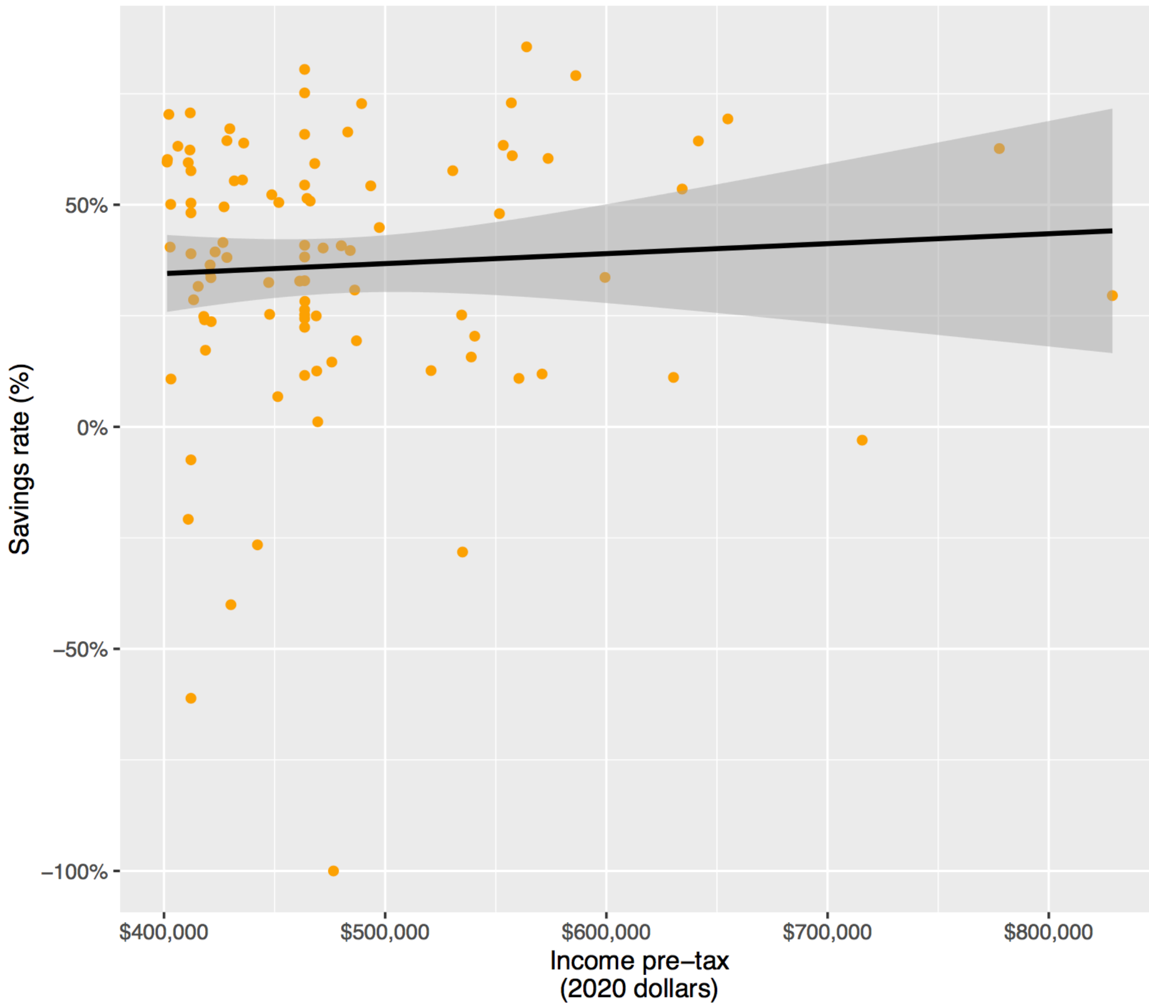

Fig. 6.2: Savings rates (%) for CES households above $400,000 (2015) with trendline and 95% confidence intervals (shaded).

To apply these total expenditure dollars across the 83 expenditure categories I extract the percent expenditure per category, from CES households that meet the WID *top 1%* income threshold. These are bootstrapped, with replacement, into 1,000 households, with percent spending per category allowed to vary +/- 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. I tested various randomization limits (+/- 5%, 25%, and 50%) and results were fairly insensitive to threshold choice. For example, in 2015, I find only a 1% difference in the mean and median mt CO_2e, for the *0.1%* income group, when comparing +/- 5% randomization limit to +/- 50%. These expenditure percentages per category are converted to dollar terms by multiplying them by the total expenditure dollars per household, from my synthetic distribution. This is multiplied by the CO_2e intensity per dollar for each category, direct 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 (Fig. 6.3).

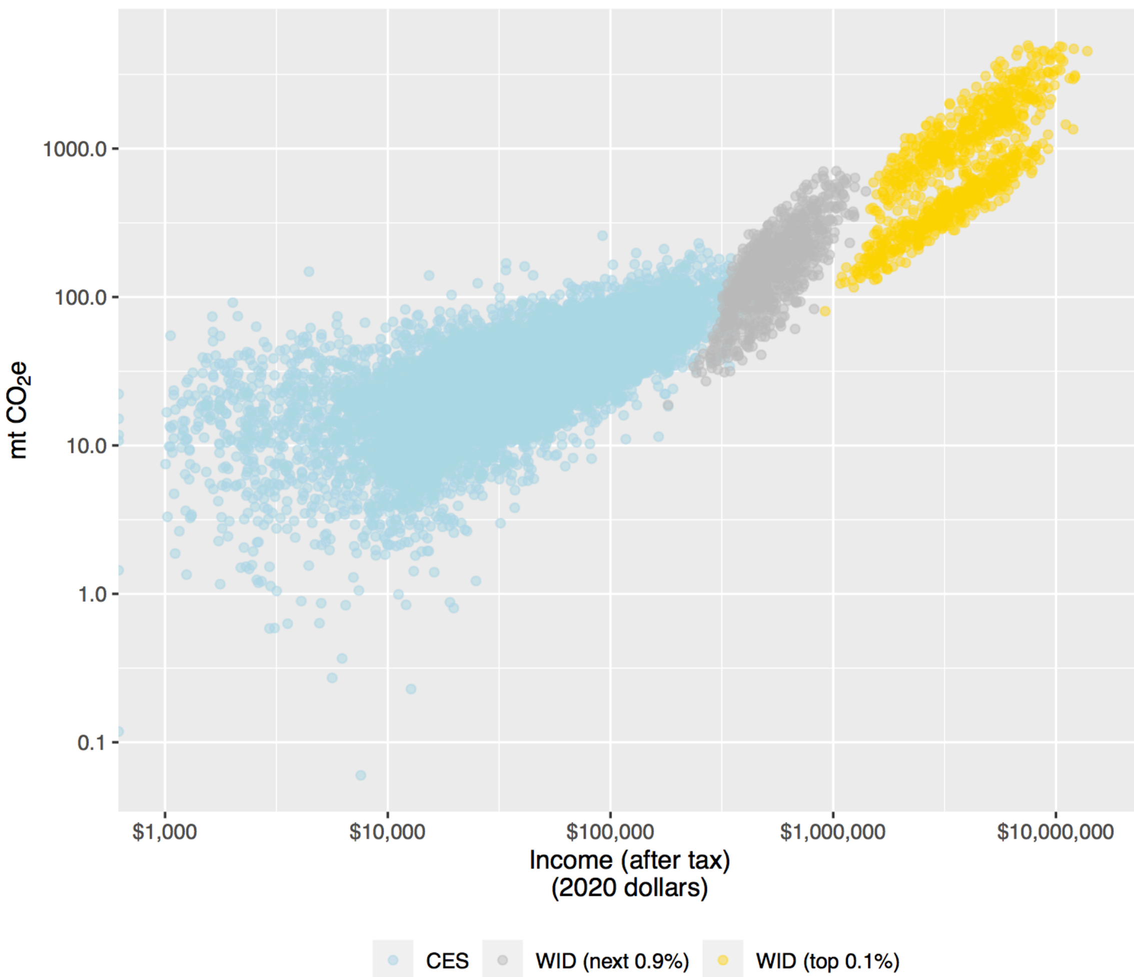

Fig. 6.3: Household post-tax income (2014) versus mt CO_2e footprint with color breakout for CES data (blue) and synthetic data: WID *next 0.9%* (grey) and WID *top 0.1%* (gold) (log-log) . (n=16,632).

Households can then be organized into different economic groups to compare emissions. The *top 1%* CO_2 emissions are estimated using a weighted mean, median, and weighted standard error of the *top 0.1%* and *next 0.9%* groups. The CO_2e per capita, per household and per dollar (Fig. 2.2 in main text) and the racial breakdown of emissions per decile are calculated using a representative sample from the *top 0.1%* and *next 0.9%* groups.

In the main text, I 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 lowest 9 deciles are difficult to distinguish. Here I present just deciles from 1996-2015, to better visualize the decile-level differences (Fig. 6.4). Note all deciles saw emissions declines across the 20 year period.

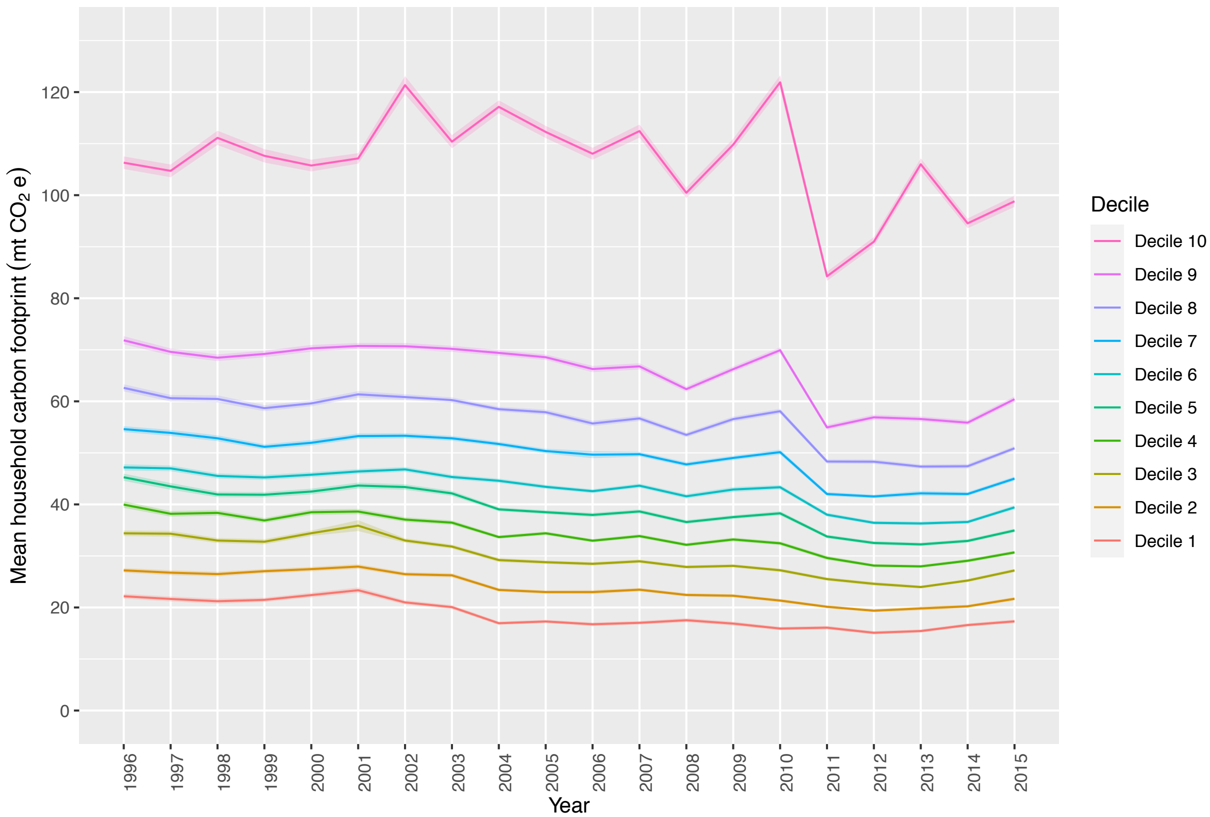

Fig. 6.4: Mean household metric tons CO_2e emissions (1996-2015) for each income decile. Shading is standard error.

Each estimation I make introduces some inherent error. Most notably I model *top 1%* and *top 0.1%* spending patterns, with some introduced variability, on the *top 1%* households in the CES sample. If these estimates are not representative of other *1%* and *0.1%* households, the corresponding CO_2e emissions footprints I calculate could be correspondingly over- or under-estimated. This challenge can be seen in high year-to-year variation in *top 0.1%* which is very sensitive to variations among the CES *1%* households' savings rates and expenditure patterns, particularly in high CO_2 intensity sectors like *Transport* and *Utilities and Home Energy*. Note, my crosscheck of super-emitter households suggests it is rare for households to have emissions in excess of 4,000 or 5,000 mt CO_2e. To control the effect of such outliers,

I drop emissions estimates higher than 5,000 mt CO_2e. In 2015, just 5 out of 1,000 *top 0.1%* households surpassed this threshold and were dropped.

In addition, the Leontief method I employ has an inherent assumption that CO_2 per US$ intensity is an appropriate measure of embodied CO_2. But, quality of goods is an important factor determining price, so a luxury good may have the same CO_2 emissions as a cheaper good in volume terms, but using a price term will yield a higher CO_2 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_2 intensity per dollar multiplier applied to spending of top income groups, or perhaps more simply reducing the estimated dollars expenditures, by some luxury estimation percent, to account for this decoupling from dollars and CO_2 intensity. I do not have any data estimates however, on which to base such a luxury good reduction. For this reason and for consistency with prior studies I maintain a constant CO_2 intensity per dollar expenditure. Despite these limitations, given my crosscheck of super-emitter footprints, I feel confident the results are a reasonable estimation and useful methodological advance.

6.1.1.3 Super emitters – consumption-based

For a crosscheck of my super-emitter results I acquired single family home square footage estimates from the U.S. Census Bureau. In 2015, 1% of new single family homes completed were a minimum of 8,235 square feet. (103). My mt CO_2e per square foot estimates are based on the average of Jones and Kammen (35) and Monahan and Powell (104). Mt CO_2e of first class commercial aviation, number of

private jets and miles travelled, number of private yachts, fuel use, and mt CO_2e per unit of fuel were acquired from a mix of non-profit, research reports, and government sources including Atmosfair, Knight Frank, Vista Jet and Wealth-X, Argus, Superyacht Intelligence, and U.S. Environmental Protection Agency. For context, there are over 13,500 private jets in North America, approximately 1,453 North American-owned motorized superyachts (30+ meter) and 124,587 *top 0.1%* households. Private jet ownership, fractional ownership, and 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 my estimates of 293 flight hours per year per jet (~12 full days of flight per year) and 1,009 hours of super-yacht operation per year (~42 full days of use).

6.1.2 Consumption-based methods

6.1.2.1 Direct emissions

Direct emissions by the consumer, during the use phase, are important for energy commodities that are combusted by the consumer; most notably automotive fuels and home heating and cooking fuels. 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 (91). CO_2e intensities per physical unit were converted to CO_2e intensity per US$. Annual price data were 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 plus direct use for a fuels (here gasoline is presented as an example) becomes

$$H_{Gas\ TOTAL} = Q_{Gas} \times E_{Gas} + D_{Gas} \times E_{Gas} \tag{15}$$

where $H_{Gas\ Total}$ is total household mt CO_2e related to gasoline *production* and *use*. Q_{Gas} is the CO_2e intensity of all direct and indirect emissions in *producing* one dollar of gasoline. D_{Gas} is CO_2e intensity of gasoline emissions from direct consumer *use* (i.e. emissions released when gasoline is combusted in a vehicle engine). E_{Gas} is consumer gasoline expenditure in dollars.

6.1.2.2 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, I convert currency from *current* year US$ to *constant* 2020 US$, using the Bureau of Labor Statistics (BLS) Consumer Price Index (CPI). Note that Eora currencies are already compatible across countries because Eora converts all currencies into current year US$[16], 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 (57).

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

6.1.2.3 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. I 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 mt CO_2e emissions would be. Indeed households, with large airline expenditures, were erroneously generating negative total household emissions footprints. To address this, I followed the EORA recommendation to set these seven negative Transport Sheet values to zero before adding to the other four sheets.

I discovered a very small number of other commodities occasionally had negative values at Purchaser Price. This was quite infrequent (between 6-34, per year, out of 10,211 sectors). When present I 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, I 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.

6.1.2.4 Limitations

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 CES survey data. This excludes foriegn purchases and government and nonprofit expenditures that directly benefit households, such as government benefits or government subsidized healthcare.

6.1.2.5 Handling Special Expenditure Categories

6.1.2.5.1 Food

The CES 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 (9) I 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, I 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).

6.1.2.5.2 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 (38) or assigned all emissions to a single year (28, 29). 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_2 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_2 emissions associated with its production. Producing a

\$200,000 sports car, for example, likely does not generate 10 times more CO_2 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.

6.1.2.5.3 Vehicles

I address the vehicle issue in a novel way. Instead of multiplying the vehicle purchase price by the Leontief derived $mtCO_2e$/\$ final demand, I take the total consumer-based $mtCO_2e$ emitted by the auto industry, and divide this by the *number* of vehicles produced.[17] 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 1990-2016. Domestic and Foreign auto production data is from the Bureau of Transportation Statistics. For each country, this yields mt 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.[18] I do this for each year in the study, 1996-2015, creating a 1 x 19 vector.

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[17] Number of vehicles owned or leased are acquired from the CES database.

[18] For example, in 2015 a vehicle produced in the U.S.A had a 39.18 metric ton CO_2e footprint, while a vehicle produced in Germany had a 15.98 metric ton CO_2e. Domestic vehicles captured 45% of sales in the U.S.A, while German vehicles captured 9% of the market. Thus the CO2 per U.S. vehicle 39.18 is multiplied by U.S. producers market share (0.45), the German CO2 footprint (15.98 mtCO2 per vehicle) is multiplied by German market share (0.09). Japan and South Korea are calculated in the

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, I 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.[19] 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. I use this to estimate the total $mtCO_2e$ of a vehicle in the U.S. fleet, in a given year.

The final step is to depreciate the total $mtCO_2e$ of a vehicle over its lifetime. Here, 15 years was chosen because about 95% of miles have been put on an average car by this time, even though a diminishing proportion of cars will remain on the road for another 10 years.[20] 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 (105). 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.

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same way, and the remaining 2-3% captured by other countries are treated as though they have German CO2 footprints. These scaled values are then summed to equal the average CO_2e footprint of a vehicle.

[19] In 2015 for example, I estimate about 9% of the cars are from 2015, 9% from 2014, about 5% from 2005, about 1.5% from 2000, etc...

[20] 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 $mtCO_2e$ in its production. This is divided by 15 years to yield 1.79 $mtCO_2e$ per vehicle in 2015. Each vehicle a household has in 2015 is multiplied by this amount.

6.1.2.5.4 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_2 emissions used in an older house, and prices may not correlate well with CO2 emissions. Prior studies have addressed this by using CO_2e per square foot (35). But existing estimates on this are somewhat out of date now. Additionally, while CES 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 I am 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, I 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. (28) and Song et al. (29) use this same approach. Weber and Matthews (38) explored both methods and found their results were insensitive to model choice.

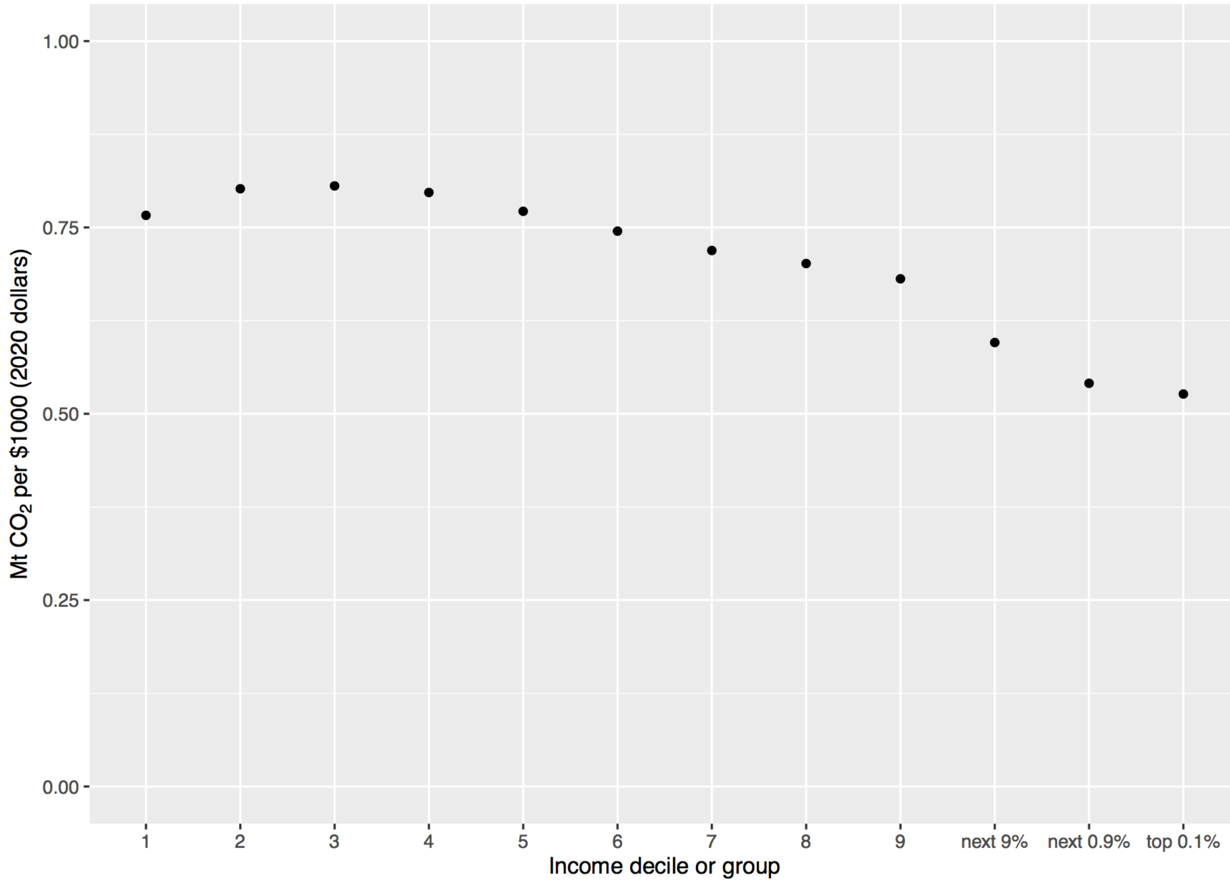

Fig. 6.5: CO_2e intensity (mt CO_2e per $1,000 (2020 USD) for each income group, in 2015.

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