JOINT RESEARCH REPORT SEPTEMBER 2020

THE CARBON INEQUALITY ERA

An assessment of the global distribution of consumption emissions among individuals from 1990 to 2015 and beyond

SIVAN KARTHA, ERIC KEMP-BENEDICT, EMILY GHOSH AND ANISHA NAZARETH, STOCKHOLM ENVIRONMENT INSTITUTE, AND TIM GORE, OXFAM

In the 25 years from 1990 to 2015, annual global carbon emissions grew by 60%, approximately doubling total global cumulative emissions. This has brought the world perilously close to exceeding 2°C of warming, and it is now on the verge of exceeding 1.5°C. This paper examines the starkly different contributions of different income groups to carbon emissions in this period. It draws on new data that provides much improved insight into global and national income inequality, combined with national consumption emissions over this 25-year period, to provide an analysis relating emissions to income levels for the populations of 117 countries. Future scenarios of carbon inequality are also presented based on different possible trajectories of economic growth and carbon emissions, highlighting the challenge of ensuring a more equitable distribution of the remaining and rapidly diminishing global carbon budget.

SEI Stockholm Environment Institute

OXFAM

CONTENTS

INTRODUCTION

With the close of the hottest decade in recorded history, and with climate impacts steadily worsening along with their human and ecological toll, the urgent need to keep warming well below 2°C – and to aim to keep warming below 1.5°C – has only become clearer.

Those mitigation objectives, agreed by all signatories to the Paris Agreement, imply that the available carbon budget is finite and rapidly diminishing. The recent IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels (SR1.5: IPCC 2018) concludes that the available budgets are as shown in Table 1 below.

Temperature (°C)	Risk of exceeding (%)	Budget (GtCO2)	Years remaining at current emission rate	Year of depletion
1.5°C	33%	340	9	2029
1.5°C	50%	500	14	2034
2°C	33%	1,090	30	2050
2°C	50%	1,420	39	2059

Source: IPCC 2018, Table 2.2, p.108.

Table 1: Remaining global carbon budget (as of January 2020) for specified temperature levels and levels of risk

Clearly, an urgent decarbonization transition is needed. And despite how stark these figures are, they may be overly optimistic. They define an ‘acceptable’ level of warming as a level that is still significantly higher than today’s warming, which is already bringing devastation to many communities, from the Arctic to the Amazon to Australia. They assume that it is acceptable to pursue a future course in which there is a one-in-three risk of exceeding the specified threshold, or even a one-in-two chance. They are derived from mixed ocean-atmosphere general circulation models of the climate that do not account for certain feedbacks that could lead to much more warming, especially in the long term (Rogelj et al. 2019).

Still, the effort even to stay within such an arguably inflated carbon budget requires society to make deliberate and morally justified choices about its use. This report presents information on the use of the carbon budget, in the past, at present and in the future. Its focus is on the stark inequalities in income and emissions across the global population, and what they may imply for practical, feasible, politically acceptable and morally equitable options for the future.

1 INCOME, EMISSIONS, INEQUALITY AND GROWTH 1990–2015

METHODOLOGICAL APPROACH

There are many ways to allocate responsibility for global carbon emissions. This report is concerned with understanding the global distribution of emissions associated with the consumption of individual households at different income levels, building on Oxfam's previous work in this area (Gore 2015). A full description of the methodology is available in Appendix 1.

Our starting point is the assumption that household income drives household consumption, which in turn drives the level of household consumption emissions. We present an analysis that draws on newly available income distribution data to derive results regarding the global distribution of consumption emissions among households over the period from 1990 to 2015. In Section 2, we also provide some observations about the possible consequences over the coming decades, considering different possible routes along which socio-economic development and carbon emissions could unfold.

To estimate the relationship between income level, consumption and emissions, many studies have relied on country-based household-level surveys of income and consumption, combined with technical estimates of the carbon emissions associated with the consumption and upstream production of different products and services using lifecycle analyses or aggregate input-output analyses (Hubacek et al. 2017; Dorband et al. 2019; Oswald et al. 2020; Ivanova and Wood 2020). Such studies have provided country-specific insights into the relationship between income, consumption and emissions, including insights into different sectors, countries at different levels of development, and the distributional incidence of climate policies such as a carbon tax for different consumers.

This study is a global scale analysis requiring highly granular data from as large a set of countries as possible, covering as much of the world's income and emissions as possible. To construct this dataset, we do not attempt to draw directly on the extensive and varied literature on country-specific consumption surveys and technical emission estimates. Instead, adopting the approach routinely used in economic analyses and similar to a number of previous studies (Baer et al. 2008; Chakravarty et al. 2009; Chancel and Piketty 2015; Gore 2015), we use a functional relationship between income and aggregate national consumption emissions. We draw on the broader literature on country-specific consumption surveys and technical emission estimates to define and parameterize this relationship.

As shown in Table 2, our dataset covers 117 countries and close to 90% of the global population and global carbon emissions across the 1990–2015 period. Income data is taken primarily from the World Inequality Database (WID.world: Alvaredo et al. 2016), which combines national accounts, survey, wealth and fiscal data in a systematic manner in order to address well-known problems with under-reporting of incomes at the top end of the distribution. We supplemented this with data from the World Income Inequality Database (WIID: UNU-WIDER 2018) for 11 significant missing countries. Historical carbon emissions data were taken from the Global Carbon Project, with gaps filled in by the Carbon Atlas, using consumption emissions data wherever possible and for the majority of countries.

	Population (billions)			GDP (trillion 2011 $PPP)			Emissions (GtCO2/yr)		
	Sample	**Total**	**%**	**Sample**	**Total**	**%**	**Sample**	**Total**	**%**
1990	4.6	5.3	87%	42.6	47.4	90%	20.4	22.2	92%
2010	6.1	6.9	88%	82.9	91.5	91%	29.6	33.1	89%
2015	6.5	7.3	89%	97.8	108.8	90%	31.3	35.5	88%

Table 1: Coverage of the dataset used in this study.

To allocate national consumption emissions across national populations, we proceed in three stages. Firstly, we apply a country-specific emissions floor below which we assume a household's emissions will not fall, relative to the national median, and an emissions ceiling above which we assume a household's emissions will not increase, anchored to discussions of very high-income carbon footprints in the literature (Ummel 2014; Chancel and Piketty 2015; Otto et al. 2019; Gössling 2019).

Between the floor and ceiling we assume that emissions rise monotonically with income, based on the findings of the range of studies that apply technical emissions estimates to specific consumption categories in household consumption surveys (including, for example Ummel 2014; Hubacek et al. 2017; Dorband et al. 2019; Oswald et al. 2020; Ivanova and Wood 2020). We carry out analysis and present results in Appendix 2 using elasticities of 0.9, 1.0 and 1.1, using an elasticity of 1.0 as the base case for presenting the full set of results, as did Chakravarty et al. (2009) and Gore (2015).

We note that Chancel and Piketty (2015) explored a wider sensitivity range (0.6 to 1.5), and used an elasticity of 0.9 as their base case. Importantly, however, in our case this elasticity of 1.0 is only applied to a constrained income range between the country-specific floor and ceiling. If one can define an 'effective elasticity' as the weighted average across the population of local elasticity, then our methodology yields an effective elasticity that varies by country, and is generally approximately 0.82. This is comparable to the average elasticity of 0.86 found by Oswald et al. (2020) for the elasticity of household energy consumption footprints across 86 countries, and lower than the elasticity found by Hubacek et al. (2017) for a large majority of the 109 (primarily low- and middle-income) countries assessed.

For the global distribution, we compiled, for each year between 1990 and 2015, populations, average incomes and emissions for every WID.world generalized percentile in every country. We then sorted that list of generalized-percentile-country combinations by average income and summed cumulative population, income and emissions from lowest to highest income. Because of large differences in national populations (e.g., when a percentile from China enters the distribution), this leads to a somewhat granular global distribution. Nevertheless, it is sufficiently smooth to draw conclusions about global trends towards greater or lesser inequality.

PRINCIPAL FINDINGS

The full datset is publicly available at https://www.sei.org/projects-and-tools/tools/emissions-inequality-dashboard. In this report we present inequality statistics in two ways. The first is to show how shares of global income relate to shares of global emissions, treating each individual as a 'citizen of the world'. The second, which also takes a global view, is to decompose inequality into two terms, one capturing average within-country inequality, and the other between-country inequality.

The global distribution of consumption emissions among households

From 1990 to 2015, carbon dioxide emissions rose by roughly 60%, or 13.5 GtCO2. Figure 1 shows the change in the shape of the emissions distribution during this period, often referred to as a 'champagne glass'. From bottom to top, the width of the 'glass' corresponds to the contribution to global emissions of the world's poorest people (at the bottom), and to the world's richest people (at the top), showing that people at increasing income levels contribute a growing amount to global emissions.

The figure indicates that emissions have grown in that the 2015 glass is wider than the 1990 glass, and that this growth has occurred overwhelmingly in the higher-income half of the world's population. This is true even though the relative shares of the richer and poorer income groups have not changed by very much at all.

Figure 1: The 'champagne glass' of global carbon inequality in 1990 and 2015, showing the shares of annual global carbon emissions in each year that are attributed to individuals in three global income groups. The global population is arranged by income vertically, and the corresponding share of annual global carbon emissions is represented horizontally.

Figure 2 shows how the growth in emissions in this period was distributed among the world's population. Each bar represents the share of the total global growth in emissions across the period associated with the consumption of one ventile (5%) of the world's population, ordered from poorest (on the left) to richest (on the right).

The overall shape of the bars is reminiscent of Lakner and Milanovic's 'elephant graph' (Lakner and Milanovic 2016, fig. 1a) – which plots the per capita income growth rate at different points in the global income distribution – although it is even more striking, with the impact of the richest ventile resembling a long 'dinosaur' neck. This is instructive, given that it is the absolute level of emissions which is decisive in terms of the extent of the climate crisis.

The disproportionate impact of the world's richest people is unmistakeable – nearly half of the total growth in absolute emissions was due to the richest 10% (the top two ventiles), with the richest 5% alone contributing over a third (37%). The remaining half was due almost entirely to the contribution of the middle 40% of the global income distribution (the next eight ventiles). The impact of the poorest half (the bottom ten ventiles) of the world's population was practically negligible.

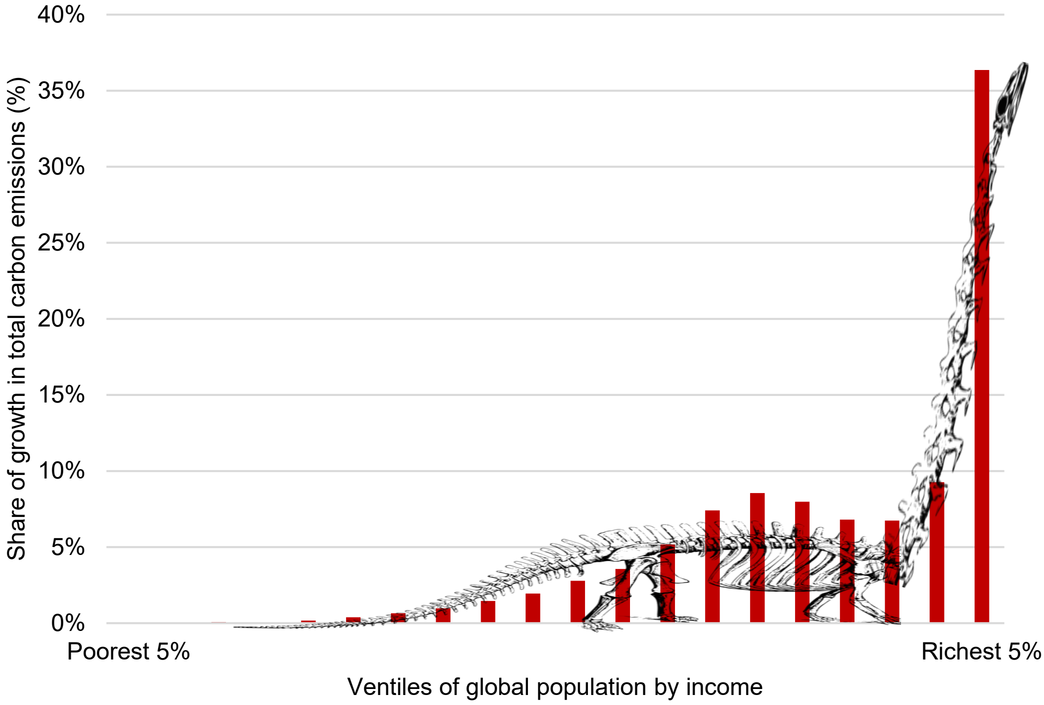


Figure 2: The carbon inequality 'dinosaur' of emissions growth from 1990 to 2015. The world's population is arranged in ventiles by income, from the poorest 5% on the left to the richest 5% on the right. The line shows each ventile's increase in per capita emissions (as a percentage of its 1990 per capita emissions), while the bars show each ventile's increase in total emissions (as a percentage of total global emissions increase).

Further details of the evolution in carbon inequality over the period are shown in the following two tables and three charts. Table 3 and Figures 3 and 4 show how annual consumption emissions for individuals in five global income groups have evolved over the 1990–2015 period. Table 4 shows the corresponding shares of cumulative emissions – the total emissions added to the atmosphere over the period, also depicted in Figure 5 – and their respective shares of a range of global carbon budget estimates from 1990.

It is notable that – as suggested by the similar shapes of the 'champagne glass' distributions for 1990 and 2015 – shares among the income groups have not changed markedly over this period, and the high-income groups continue to generate by far a disproportionate share of global emissions.

We find that in 2015 the top 10% were linked to nearly half of global emissions, similar to the middle 40%, whose share increased only very modestly over the previous 25 years. The emissions linked to the top 10% grew by nearly as much as the middle 40% over the period. The emissions linked to the top 1% alone grew more than three times as much as those linked to the bottom 50%. Since the bottom 50% has 50 times more people in it, the average per capita consumption emissions linked to the top 1% in 2015 were over 100 times greater than the average per capita consumption emissions of the poorest half of the world's population.

Global income groups	1990 emissions: Share of total carbon emissions (%)	Total carbon emissions (GtCO2)	Per capita average carbon emissions (tCO2)	Per capita minimum income ($1000s)	2010 emissions: Share of total carbon emissions (%)	Total carbon emissions (GtCO2)	Per capita average carbon emissions (tCO2)	Per capita minimum income /capita ($1000s)	2015 emissions: Share of total carbon emissions (%)	Total carbon emissions (GtCO2)	Per capita average carbon emissions (tCO2)	Per capita minimum income /capita ($1000s)	Growth between 1990–2015: Growth in total carbon emissions (GtCO2/yr)	Share of growth in total carbon emissions (%)
top 0.1%	4%	0.8	155	229	4%	1.4	209.1	361	4%	1.6	216.7	402	0.8	6%
top 1%	13%	2.9	56	71	15%	5.1	74	101	15%	5.4	74	109	2.5	19%
top 10%	50%	11.2	21	27	50%	16.4	23.8	34	49%	17.2	23.5	38	6.1	46%
middle 40%	41%	9.2	4.4	2	43%	14.3	5.2	5	44%	15.7	5.3	6	6.5	49%
bottom 50%	8%	1.8	0.68		7%	2.3	0.67		7%	2.5	0.69		0.7	6%
Total	100%	22.2	4		100%	33.1	4.8		100%	35.5	4.8		13.3	100%

Table 2: Share of total carbon emissions, total carbon emissions, per capita average carbon emissions and per capita minimum income associated with the consumption of individuals in different global income groups in 1990, 2010 and 2015, and corresponding growth in total emissions and shares of the growth in total carbon emissions from 1990 to 2015.

Global income groups	Total cumulative emissions (1990–2015)		Share of carbon budget from 1990: 1.5°C (33% risk)	1.5°C (50% risk)	2°C (33% risk)	2°C (50% risk)
	GtCO2	*%*	*1,205*	*1,365*	*1,955*	*2,285*
top 0.1%	32	4%	2%	2%	1%	1%
top 1%	111	15%	8%	7%	5%	5%
top 10%	372	52%	27%	25%	18%	15%
middle 40%	299	41%	22%	20%	14%	12%
bottom 50%	51	7%	4%	3%	2%	2%
Total	**722**	**100%**	**53%**	**48%**	**34%**	**30%**

Table 3: Total cumulative carbon emissions and shares of total cumulative carbon emissions from 1990 to 2015 associated with the consumption of individuals in different global income groups, and corresponding shares of the global carbon budget from 1990 under different temperature objectives.

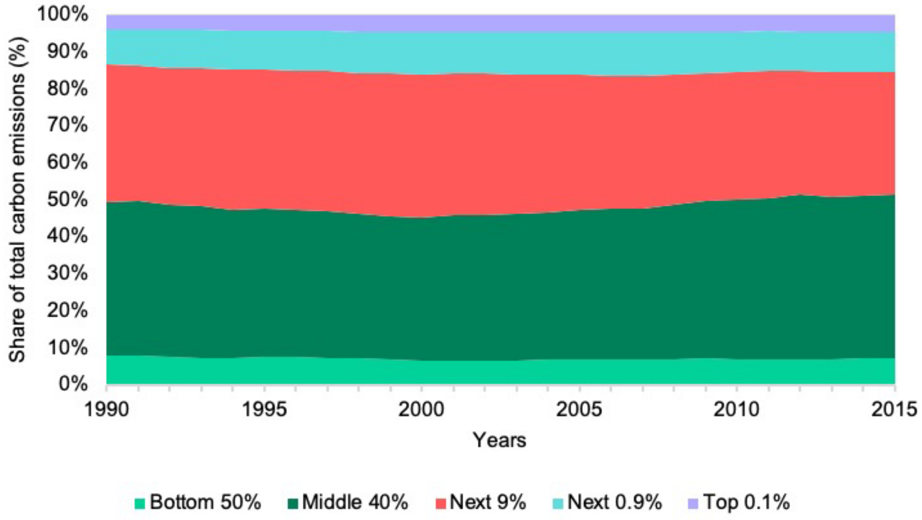


Figure 3: Shares of total carbon emissions associated with the consumption of individuals in different global income groups from 1990 to 2015.

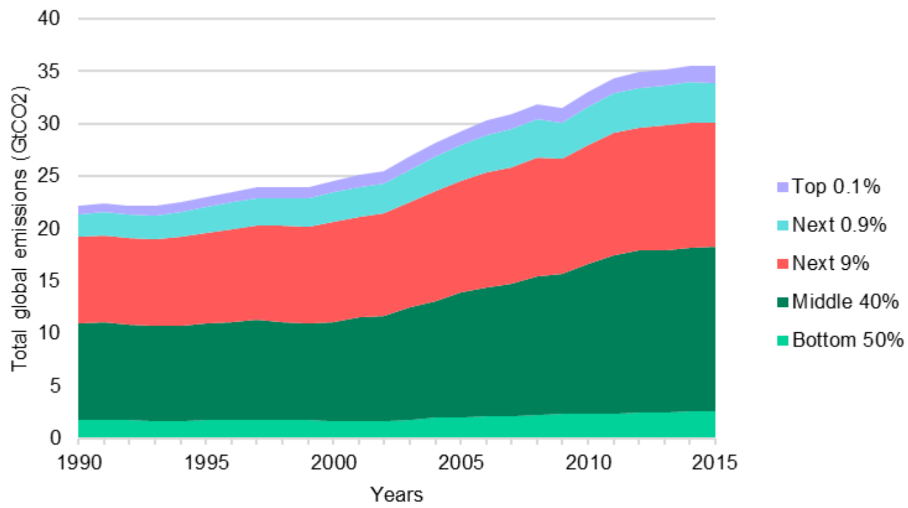


Figure 4: Total carbon emissions associated with consumption of individuals in different global income groups from 1990 to 2015.

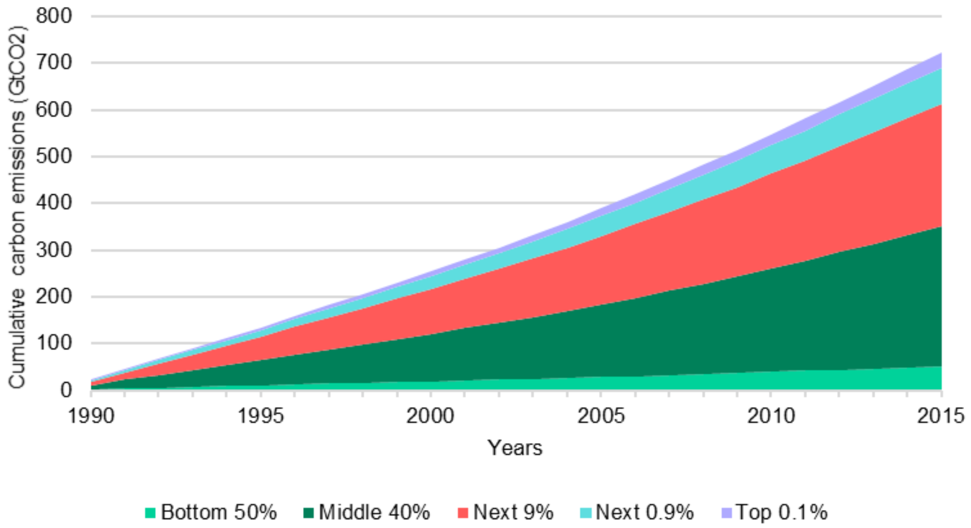


Figure 5: Cumulative carbon emissions associated with consumption of individuals in different global income groups from 1990 to 2015.

Table 5 shows the geographic composition of the emissions associated with the consumption of individuals in each global income group in 1990 and 2015. While an increasing share of emissions associated with the consumption of the richest 10% and 1% of people in the world is located in rapidly growing and industrializing countries such as China and India, it is notable that in 2015, a clear majority of the emissions of those top global income groups were still from people living in North America and Europe. Among the bottom 50% of the distribution, people in China and India remained, in 2015, the most significant contributors to the very low overall share of emissions.

2015							
Top 1%	**15%**	**Top 10%**	**49%**	**Middle 40%**	**44%**	**Bottom 50%**	**7%**
North America	5.7%	North America	16%	China	17.5%	India	2.5%
Middle East and North Africa	2.7%	Europe	8.5%	Europe	5.8%	China	2%
China	2.1%	China	7.3%	North America	4.6%	Other Asia	1.1%
Europe	1.6%	Other Asia	4.7%	Other Asia	4.6%	Sub-Saharan Africa	0.68%
Russia/Central Asia	1.2%	Middle East and North Africa	4.5%	Russia/Central Asia	3.2%	Middle East and North Africa	0.49%
India	0.8%	Russia/Central Asia	2.6%	Middle East and North Africa	3%	Latin America	0.2%
Latin America	0.6%	India	1.9%	India	2.4%	Europe	0.1%
Other Asia	0.4%	Latin America	1.3%	Latin America	2.2%	Russia/ Central Asia	0.1%
Sub-Saharan Africa	0.3%	Sub-Saharan Africa	0.9%	Sub-Saharan Africa	0.8%	North America	<0.1%
Other rich	0.2%	Other rich	0.9%	Other rich	0.3%	Other rich	0%
1990							
Top 1%	**13%**	**Top 10 %**	**50%**	**Middle 40%**	**41%**	**Bottom 50%**	**8%**
North America	6.9%	North America	21.2%	Europe	10.2%	China	6.1%
Europe	2.5%	Europe	14.2%	Russia/Central Asia	8.6%	India	1.4%
Middle East and North Africa	1.2%	Other Asia	5.1%	North America	6.4%	Other Asia	0.3%
Russia/Central Asia	0.9%	Russia/Central Asia	4.7%	China	5.1%	SS Africa	0.2%
Other Asia	0.9%	Middle East and North Africa	1.8%	Other Asia	4.5%	Middle East and North Africa	0.1%
Latin America	0.6%	Latin America	1.3%	Latin America	2.2%	Russia/ Central Asia	0.1%
Sub-Saharan Africa	0.1%	Other rich	0.8%	India	1.6%	Latin America	<0.1%

Other rich	0.1%	Sub-Saharan Africa	0.6%	Middle East and North Africa	1.6%	Europe	<0.1%
China	0.1%	China	0.2%	Sub-Saharan Africa	0.9%	North America	0%
India	<0.1%	India	0.1%	Other rich	0.4%	Other rich	0%

Table 5: Shares of total carbon emissions associated with individuals in different global income groups from different countries and regions.

The evolution of carbon inequality between countries and within countries

In order to evaluate the extent to which global carbon inequality has been driven by inequality between and within countries, we use an inequality measure called the Theil index (see Appendix 1 for technical details). This represents the inequality inherent in an income distribution in terms of a single number where larger values mean higher inequality. A perfectly equal society would have a Theil index of zero, while a society where 10% of the population held all of the income equally and the remainder had none would have a Theil index of about 2.3 (= $\log_e 10$). A convenient feature of the Theil index is that it is decomposable, meaning that the inequality of a global population can be disaggregated into the inequality between individuals within countries, plus the inequality between countries, by world regions or other classifications.

Making use of this feature of the Theil index, we show in Figure 6 the decomposition of global inequality into within-country and between-country inequality. Just as has been pointed out with regards to income (Milanovic 2015), most of global inequality in 1990 was due to inequality between countries. That component has been declining, in keeping with a general trend in which countries in poorer regions have grown faster than countries in richer regions in relative terms. This is the period when China and India, in particular, began to grow substantially. These differences are compounded in the case of carbon emissions, due to changes in carbon intensity in some growing lower- and middle-income economies compared to declines in some higher-income countries. Owing to its heavy industry-focused and coal-intensive development, China has had a higher carbon per GDP intensity than many in its income cohort, though this has declined.

At the same time, within-country emissions inequality has been on the rise. While this is not true for every country, Figure 6 shows that it is a general trend. This result is consistent with that found by Chancel and Piketty (2015), although we show higher levels of inequality and our estimates show within-country inequality exceeding between-country inequality as early as 2008, rather than in 2013 as reported by Chancel and Piketty. The differences can be traced back to the data on within-country inequality (using the 127 generalized percentiles of the most recent WID.world database rather than the 11 generalized deciles used by Chancel and Piketty), and a different source for national consumption-based emissions.

This shift towards somewhat less between-country inequality over time is shown in a different way in Figure 7. The figure shows countries ordered by per capita income, with the richest on the bottom and poorest on the top. The share of the total is seen to rise among the poorer countries, and fall among the richest. This reflects the shift towards lower international emissions inequality, consistent with Figure 6, even as intra-national inequality rises.

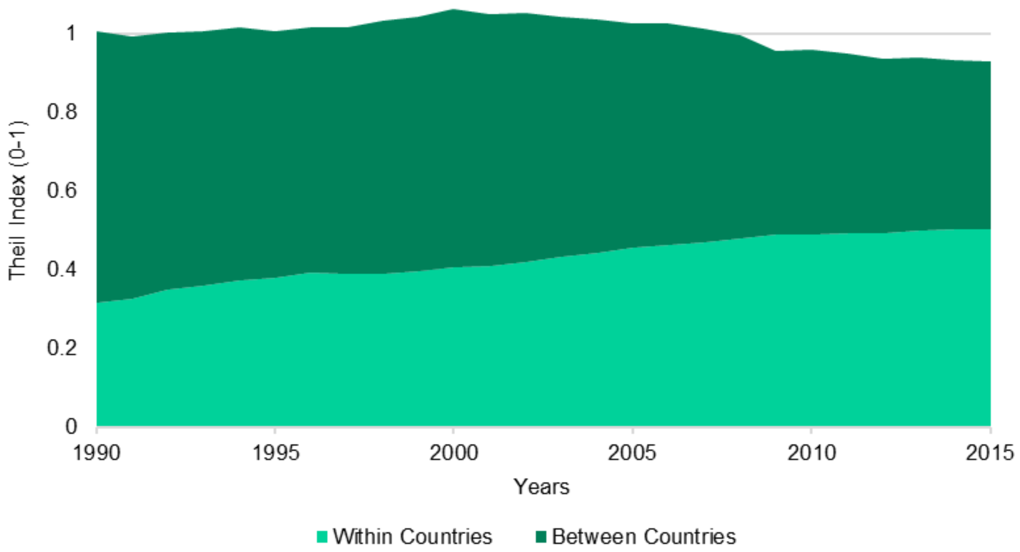


Figure 6: Emissions-weighted Theil index, showing within-country inequality rising and between-country inequality falling.

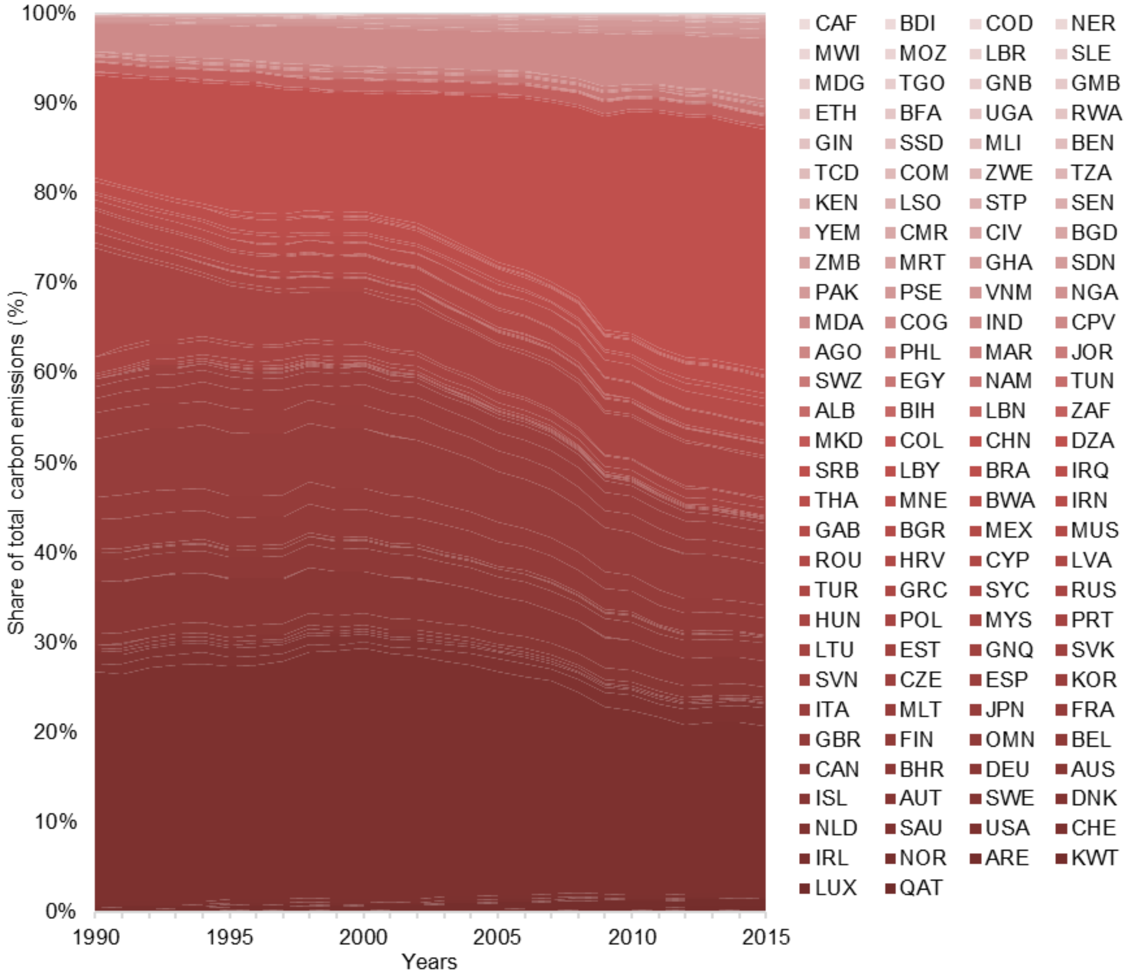


Figure 7: Share of total carbon emissions associated with the consumption of individuals by country, with countries ordered by highest per capita income (darkest colour, on bottom) to lowest per capita income (lightest colour, on top).

Box 1: Limitations and challenges related to gender and carbon inequality

While our new dataset reflects the world's stark verticle, income-based carbon inequalities, it is also important to consider the horizontal and intersectional nature of inequalities associated with the climate crisis – both in terms of responsibility for emissions, and in terms of exposure and vulnerability to the impacts of climate change.

Producing a gender-disaggregated global distribution of consumption emissions using the methods adopted in this study is, however, challenging for a number of reasons. In particular, the use of consumption and income surveys, which are generally collected at the household level – and which typically report data 'per household', 'per adult household member', 'per income unit', 'per family', etc. – obscures distinctions between household members based on gender. This is a significant limitation given that there is a substantial body of literature that suggests women and men do not share household resources equally (see for example Chant 2011.

There is a further conceptual difficulty in that many of the main consumption categories of household members are shared and overlapping, such as shelter, household amenities (heat, water, lighting, etc.), durable goods (vehicles, furniture, appliances, etc.), and a non-trivial portion of travel. Categories that can be assigned to one or another household member in terms of direct consumption are often for shared objectives (e.g., travel for an employed household member is often for the purpose of supporting the other family members). Therefore, examining gendered dimensions of carbon emissions inequality calls for alternative approaches.[1]

One approach could be to consider the evidence of an over-representation of women-headed households among the lowest income groups. However, classifying households in this way has been challenged on both conceptual and empirical grounds (Boudet et al. 2018, Chant 1997). Another could be to draw on country-specific surveys of consumption among sub-groups within households. Several such studies indicate a sizable gender gap in consumption, including, for example, evidence of poverty and nutritional deprivation among women in non-poor households (see, for example, Brown et al. 2017). However, the number of such studies remains inadequate for a representative number of countries.

Boudet et al. (2018) provide a new analysis of the World Bank harmonized consumption surveys in the Global Monitoring Database by relating survey answers that concern individual household members to their household's poverty status. They find that girls and women of reproductive age in the 79 lower- and middle-income countries in their sample are more likely to live in poor households than boys and men. This could imply, at least, that girls and women in lower- and middle-income countries at that stage in their lives are likely to have lower carbon footprints than boys and men.

In the context of higher-income countries, Cohen (2014) has attempted to disentangle the act of consumption from activities that constitute work to arrive at estimates of the gendered emissions related to paid and unpaid labour. In terms of paid labour, she notes that in Canada men are disproportionately represented in more carbon-intensive industries, a point supported by feminist proposals for an expansion and adequate recognition of the low-carbon care work in which women are disproportionately represented (Klein 2019).

The category of consumption which is most easily quantifiable by gender is transport, and several studies have found that men are more likely than women to drive long distances to work. For example, one study estimated that in Sweden men accounted for 75% of all driving in terms of person-kilometres, that women own just 25% of all cars in the country, and that they represented two-thirds of households in which no one has a driving licence (Johnsson-Latham 2007). Cohen's calculations for Canada suggest women account for just 11% of carbon emissions from transport, although domestic flights were found to be more equally distributed.

As this brief overview suggests, understanding the gendered distinctions in greenhouse gas emissions remains a challenge, to which a further range of intersectional inequalities of, for example, race or caste should be added. Since a more informed consideration of these issues is critical to building a public policy agenda that addresses social inequalities alongside action to address the climate crisis, this should be a key area for further research.

2 WHAT IF INEQUALITY WORSENS OR IMPROVES?

METHODOLOGICAL APPROACH

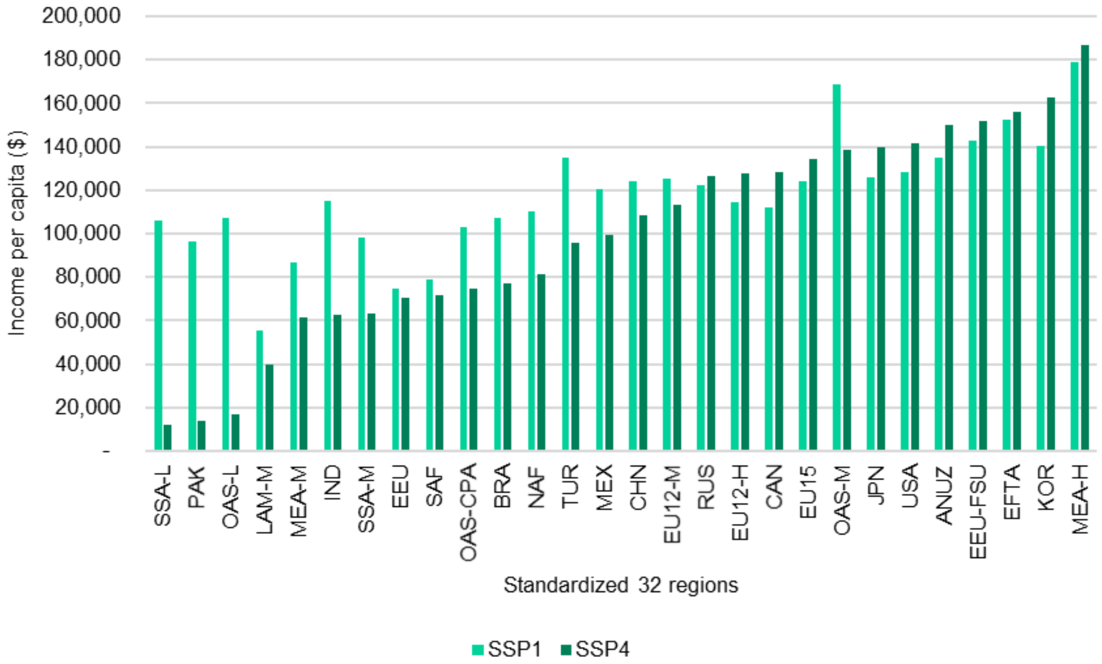
The future of inequality – whether it worsens or improves – will affect, among other things, the use of the limited carbon budget that remains. This section examines two possible scenarios of socio-economic development: one significantly less unequal than the current situation, and the other in which inequality remains at roughly its present level. In addition it examines two possible scenarios of future global carbon emissions: one which approximates our current emissions trajectory, and the other in which global carbon emissions are reduced broadly in line with limiting global heating to 1.5°C.

We defined the two socio-economic development scenarios with reference to the Shared Socio-economic Pathways (SSPs), one of a set of elements prepared for the climate research community to provide a common framework for integrated assessment modelling (Moss et al. 2010; van Vuuren et al. 2012).[2] The SSPs are framed around a set of five narratives describing different plausible socio-economic development pathways, each capturing a vision of how the future might unfold in terms of broad societal trends (O'Neill et al. 2017). Below we provide a brief description of the two SSPs on which we based our analysis.

> **SSP1: Sustainability – Taking the Green Road.** The world shifts gradually, but decisively, towards a more sustainable path, emphasizing more inclusive development. Educational and health investments accelerate the demographic transition, and the emphasis on economic growth shifts towards a broader emphasis on human well-being. Driven by an increasing commitment to achieving development goals, inequality is reduced both across and within countries.
>
> **SSP4: Inequality – A Road Divided.** Highly unequal investments in human capital, combined with increasing disparities in economic opportunity and political power, lead to increasing inequalities and stratification both across and within countries. Over time, a gap widens between an internationally-connected society that contributes to knowledge- and capital-intensive sectors of the global economy, and a fragmented

collection of lower-income, poorly educated societies that work in a labour intensive, low-tech economy.

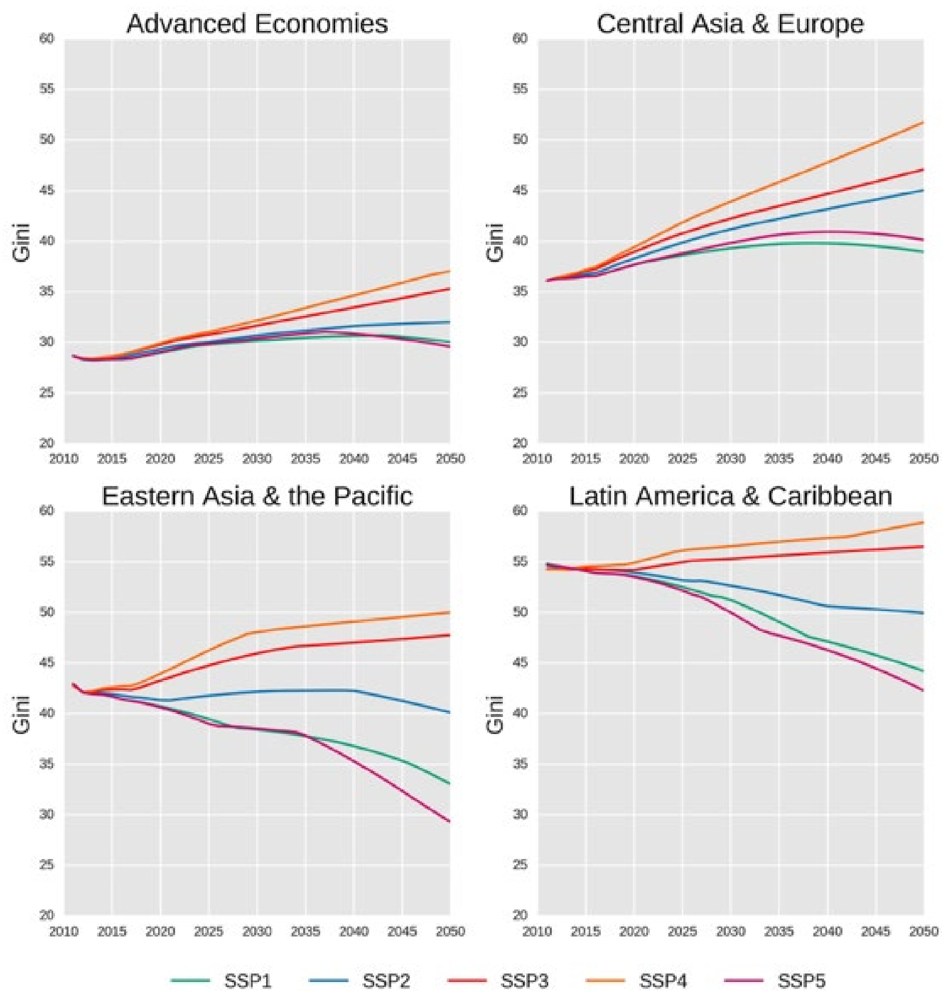
The different national GDP growth projections of SSP1 and SSP4 reflect their different visions of future inequality. Within the SSP database are different quantitative realizations of the storylines. We drew on the national GDP figures prepared by the OECD (Dellink et al. 2017) for SSP1 and SSP4. Figure 8 shows GDP per capita for 32 standardized regions for SSP1 (light green) and SSP4 (dark green) in 2100 (our regions are listed in Appendix 3). The extreme disparity in per capita incomes in the latter case, and relative comparability in the former, is evident: in SSP1, the ratio of the highest to lowest region is roughly three; in SSP4, it is greater than 15.



Source: SSP Database

Figure 8: Income per capita (in 2100) for the more equal SSP1 (light bars) and the more unequal SSP4 (dark bars), for the standardized 32 regions of the SSP Database. The variance in income in SSP4 is visibly broader than in SSP1.

Alongside these projections of national per capita incomes consistent with the SSPs, Rao et al. (2019) developed a set of national-level Gini coefficients meant to reflect an evolution over time towards levels of intra-national inequality consistent with the characteristics of each SSP. This analysis was based on empirical assessment of historical drivers over the last three decades. Figure 9 reproduces a figure from Rao et al. showing the evolution of Gini coefficients for each SSP over the 21st century for four aggregate regions. In SSP1, inequality is either about the same in 2050 as in 2015 or significantly lower as measured by Gini coefficients, whereas in SSP4 inequality consistently worsens. We used the results of Rao et al. to drive changes in national income distributions at the generalized percentile level, as discussed and presented in Appendix 1.



Source: Rao et al (2019)

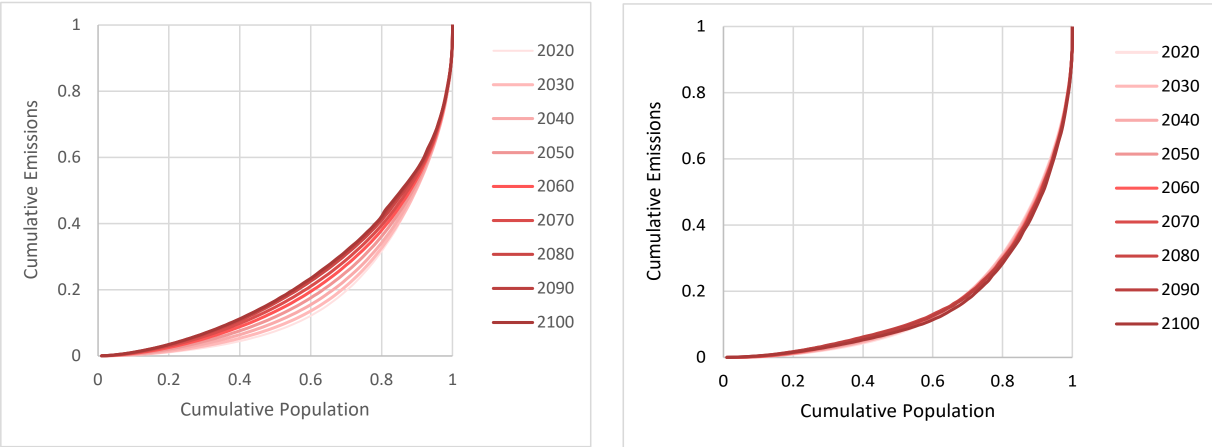
Figure 9: Evolution in Gini coefficients for major regions from Rao et al. (2019), showing that SSP1 generally demonstrates Gini coefficient improvement, whereas this worsens in SSP4.

Using these two scenarios as our representations of future development in which inequality improves (SSP1) or stays high (SSP4), we then show the impact of inequality on emissions by income group (using the same five groupings as for the historical analysis above), and calibrate them both to two Representative Concentration Pathways (RCPs), as derived from runs of the GCAM IAM model available in the SSP Database.

The warming associated with the RCP6.0 pathway – roughly 2.8°C by 2100 – is consistent with estimates of our current emission pathway, including full implementation of Paris Agreement pledges and targets, which is also estimated to yield 2.8°C of warming.[3] In short, this emission path represents our current societal trajectory well. The RCP1.9 pathway, by contrast, has been developed since the Paris Agreement to represent mitigation pathways broadly compatible with the 1.5°C temperature limit.

Figure 10 shows emission distribution curves, similar to Lorenz curves, in that the X-axis represents the world's residents arrayed from the poorest on the left to the richest on the right, and the Y-axis represents the cumulutative percentage of global emissions. It differs in that the curve reflects contributions to total global emissions, instead of contributions to total global income. For any given income percentile of the world's population, the curve shows the cumulative emissions emitted by the population at or below that percentile. It can be considered a 'quasi-Lorenz' curve.

Figure 10a shows the emissions Lorenz curves in five-year increments for the RCP6.0 and SSP1 future, starting in 2020 (lightest curve) to 2100 (darkest curve). Each successive curve is closer to the diagonal, meaning emissions are distributed among people in a manner that is progressively closer to equality. Figure 10b shows the analogous time series for the RCP6.0 and SSP4 future, starting from the same distribution in 2020 (identical curve as in Figure 10a). The curve gets no closer to the diagonal, meaning emissions are distributed among people in a manner that is getting no closer to equal.



Figures 10a and 10b: The evolution of the emissions quasi-Lorenz curves for the SSP1 (a) and SSP4 (b) futures. In the SSP1 future, emissions are distributed in a progressively more equal way, while the SSP4 future maintans roughly current levels of inequality of emissions.

PRINCIPAL FINDINGS

Figure 11(a, b, c, d) shows the impact of inequality on emissions based on the five income groups as defined in Table 3 above, under the SSP1 and SSP4 scenarios applied to both RCP6.0 and RCP1.9. For the SSP1/RCP6.0 projection, a decreasing concentration of emissions among the top 10% (the top three bands) can be seen over the time period, while the bottom half of the population more than doubles to 17%. The opposite is seen in the SSP4/RCP6.0 scenario: the emissions of the top 10% of the population grow while those of the bottom 90% decline. Similarly, in the SSP1/RCP1.9 scenario, the share of the poorest 50% increases significantly, while the share of the top 10% correspondingly shrinks. (The growth again towards the end of the century is of no consequence; it is little more than an artifact of the diminishing global carbon emissions total, more clearly seen in Figure 12.)

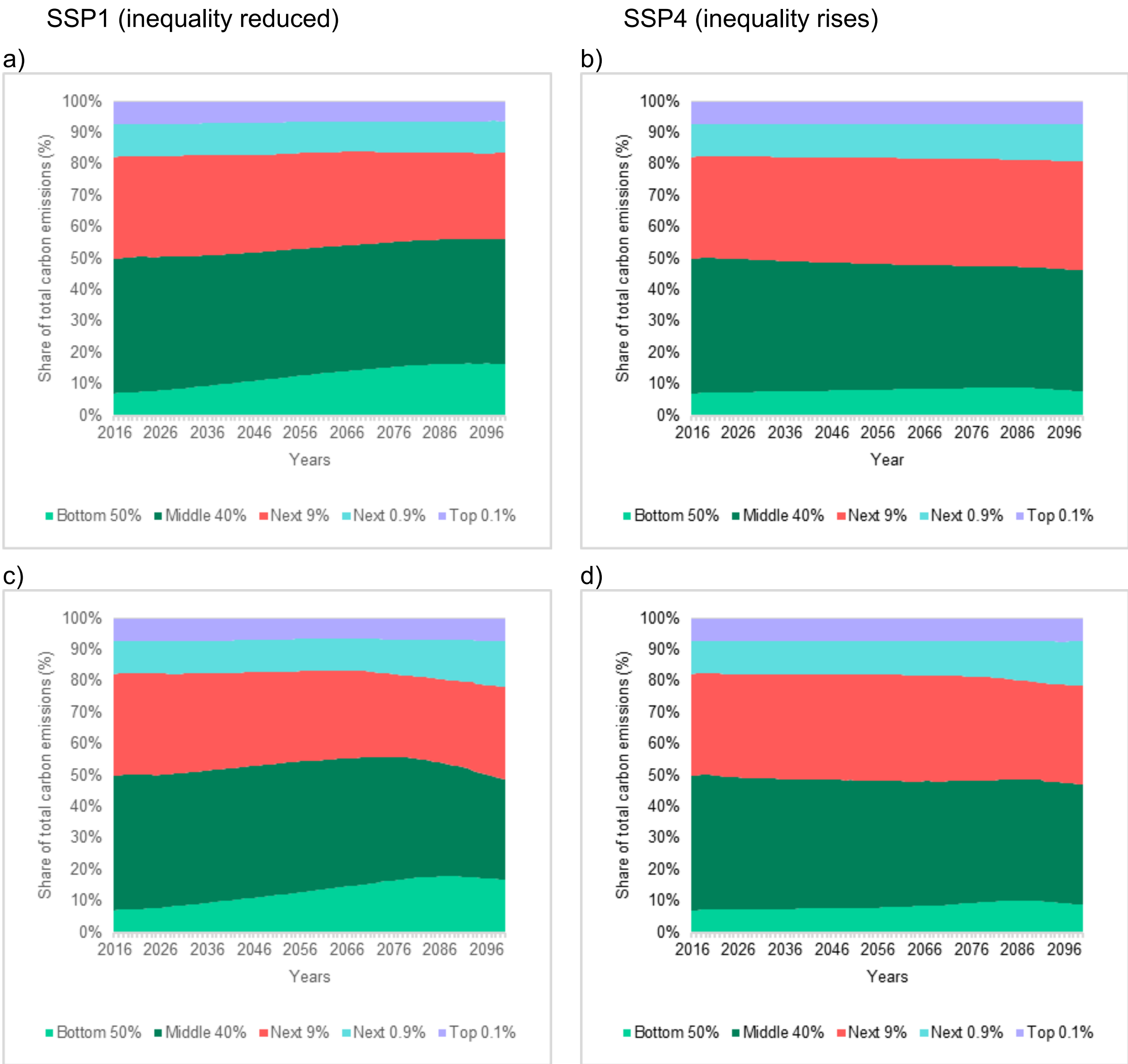


Figure 11(a, b, c, d): Share of total carbon emissions associated with consumption of individuals in different global income groups for the SSP1 (left) and SSP4 (right), and RCP6.0 (upper) and RCP1.9 (lower) scenarios.

Figure 12 shows the total emissions levels (GtCO2/yr) corresponding to the same income groups. It is important to note that the envelope of the curves in 12c and 12d reflects gross emissions, and that with negative emissions included, they are comparable to RCP1.9 (see Appendix 1.) Even in the RCP6.0 emissions scenario, emissions do decline after mid-century. Before peaking, the richest 1% of the global population account for 8% of the total rise in global emissions in the SSP1 projection, while the bottom 50% account for 41% of the rise. In the SSP4 projection, however, the richest 1% account for a remarkable 55% of global emissions rise, while the bottom 50% are responsible for a mere 3%.

It is difficult to justify such a skewed allocation of a resource as scarce and valuable as the remaining carbon budget. If a primary rationale of continued economic growth is to contribute to improving the welfare of poor people, it will need to be better targeted to avoid the collateral impacts of ever-rising consumption among the wealthier income groups, along with its inevitable environmental costs.

In the RCP1.9 scenarios in which total emissions are reduced much more aggresively, the minor share of the global carbon budget that is left for the poorest half of the global population – even in the SSP1 scenario – is a striking and powerful illustration of the inter-generational impact of the unequal historical use of the carbon budget. The excessive rate at which the very richest groups in the world have depleted the global carbon budget over the last 30 years, in particular, lock in a permanent inequality in access that suggests the need for substantially equalizing socio-economic policies.

a) b)

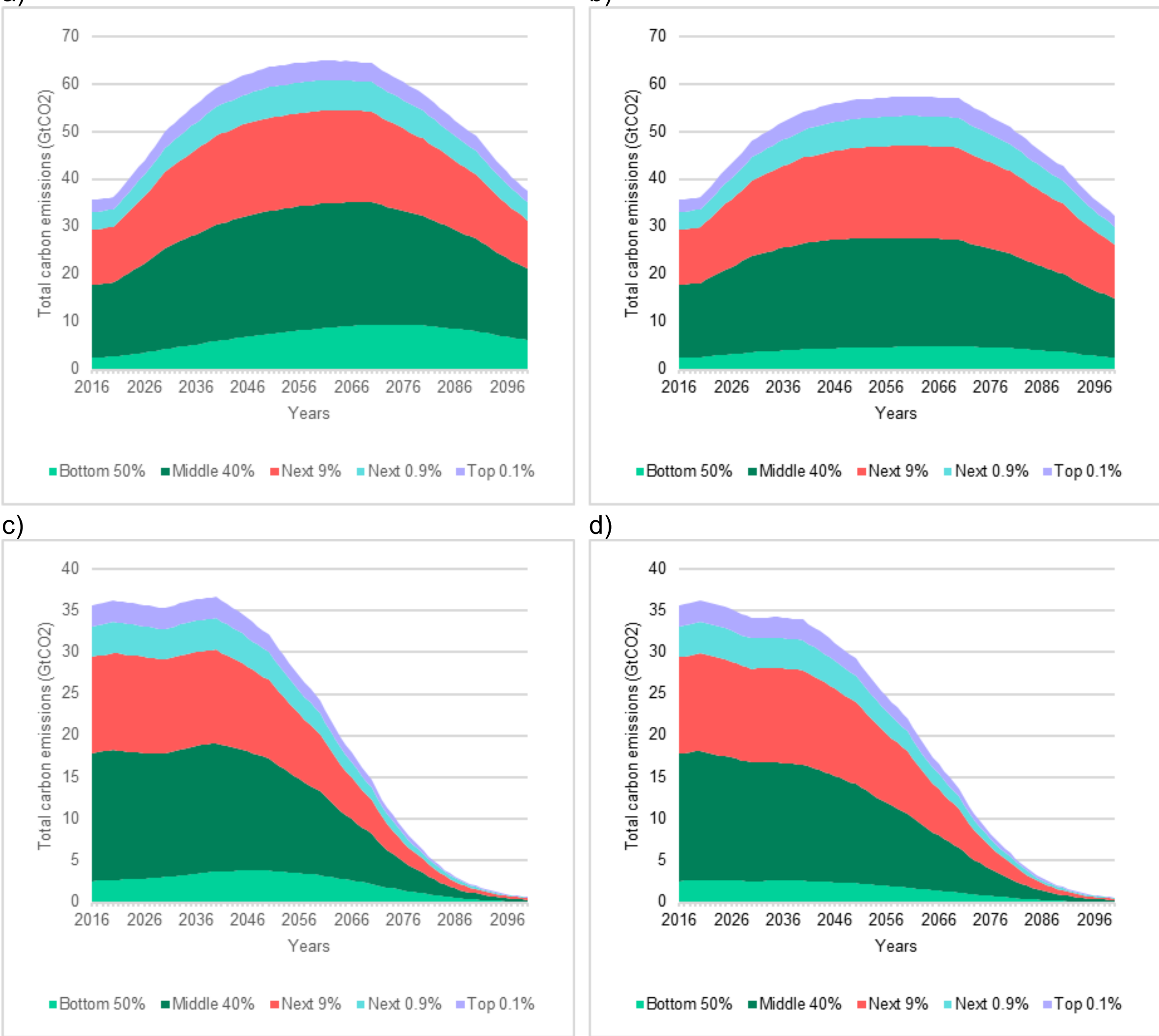
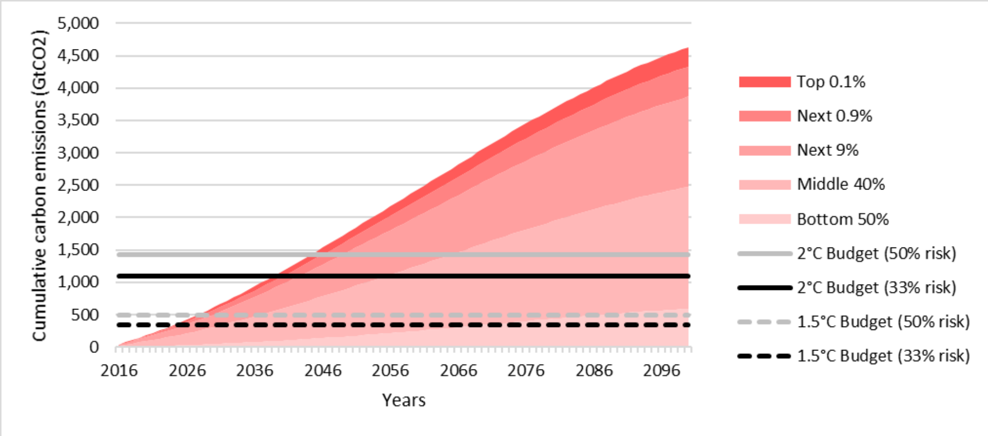


Figure 12(a, b, c, d): Total carbon emissions associated with the consumption of individuals in different global income groups from 2020 for the SSP1 (left) and SSP4 (right), and RCP6.0 (upper) and RCP1.9 (lower) scenarios.

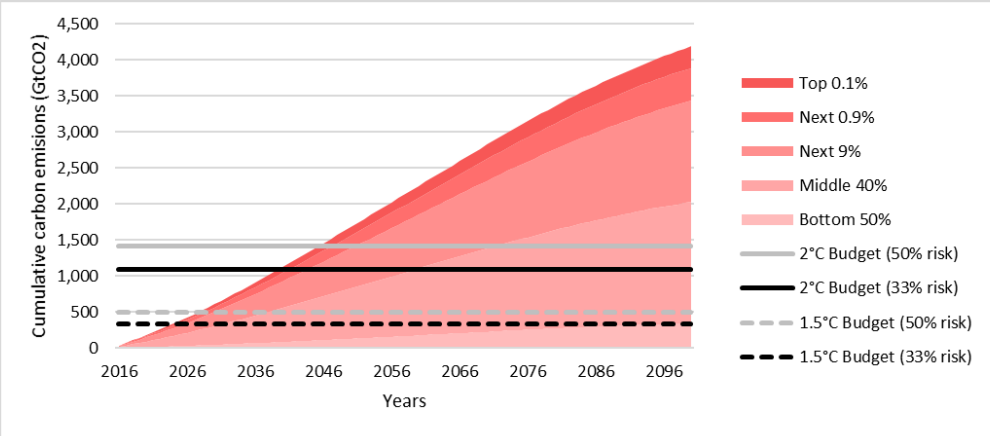
Table 6 numerically summarizes several of the key outputs of the two emissions projections. Even though the SSP1 scenario leads to a less unequal emissions distribution than the SSP4 scenario, a disproportionate share of the atmospheric commons is still appropriated by the relatively wealthy. Over the course of the remainder of the century, 44% of the cumulative emissions arises from the richest 10% of the world's population. While this is significantly less than the 60% share in the SSP4 scenario, it still reflects a world of pervasive inequality.

Figure 13 and Figure 14 show the projected cumulative emissions of CO2 from 2020. In Figure 13, the income groups are stacked, and so the figure shows the point in time at which *global* emissions hit one of the four definitions of the available carbon budget. In Figure 14 the income groups are individual lines, not stacked, and thus the figure shows the point in time when any given income group would by itself exceed each budget. In all these cases, it is the income group in the middle 40% of the global population that would first hit the budget limit. However, in aggregate, as shown in Table 6, the top 10% (i.e., the top income groups together) exceed the 1.5°C budget limit before the middle 40% in both the SSP1 and SSP4 scenarios, and even exceed it before the bottom 90% in SSP4. The top 1% exceed the limit before the bottom 50% in both SSP1 and SSP4.

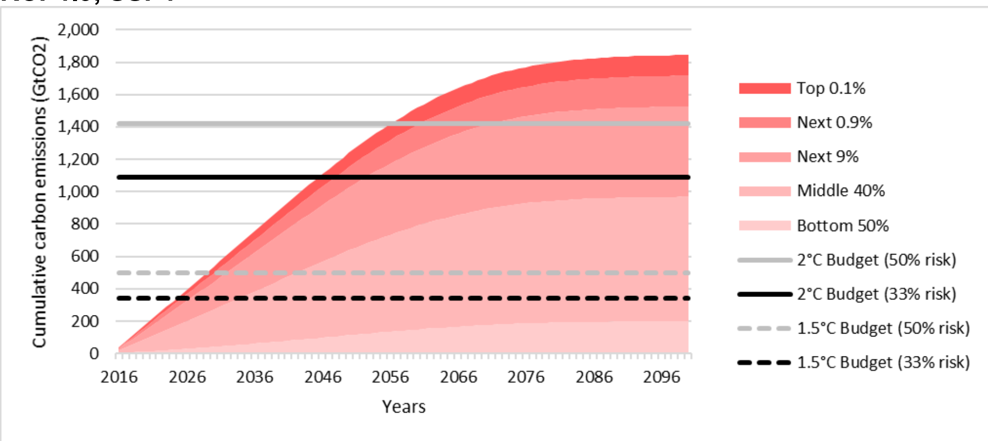
RCP6.0, SSP1



RCP6.0, SSP4



RCP1.9, SSP1



RCP1.9, SSP4

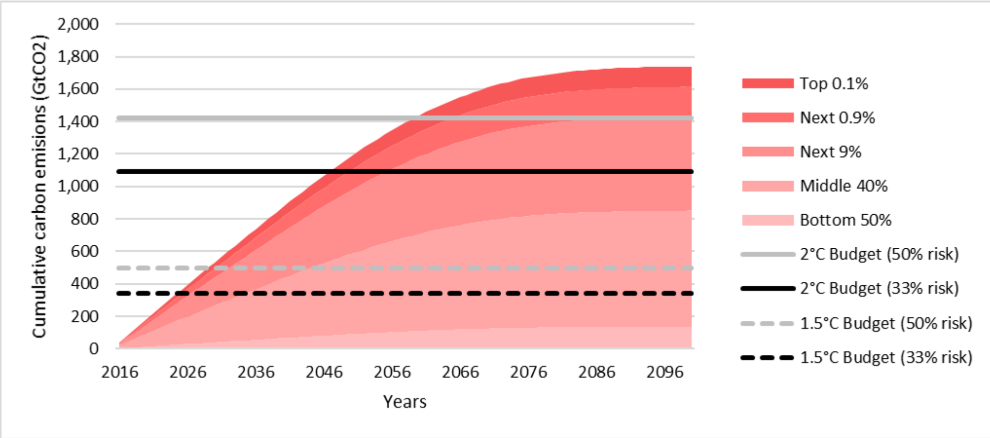
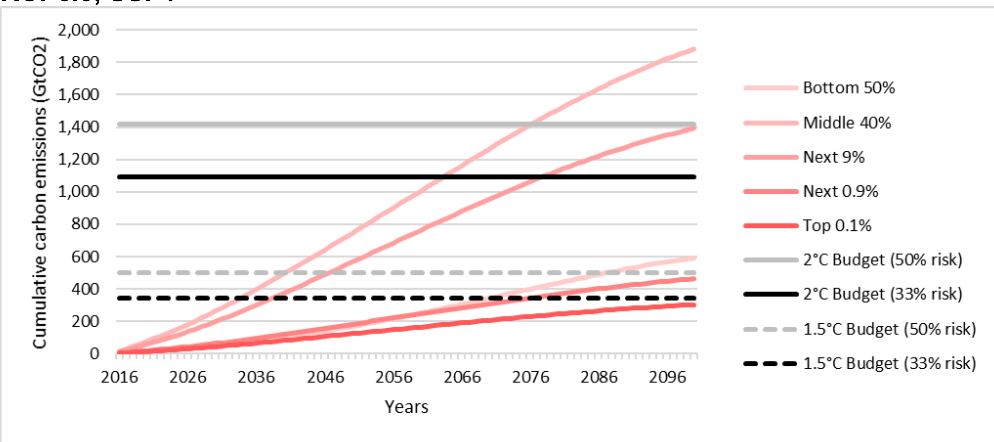
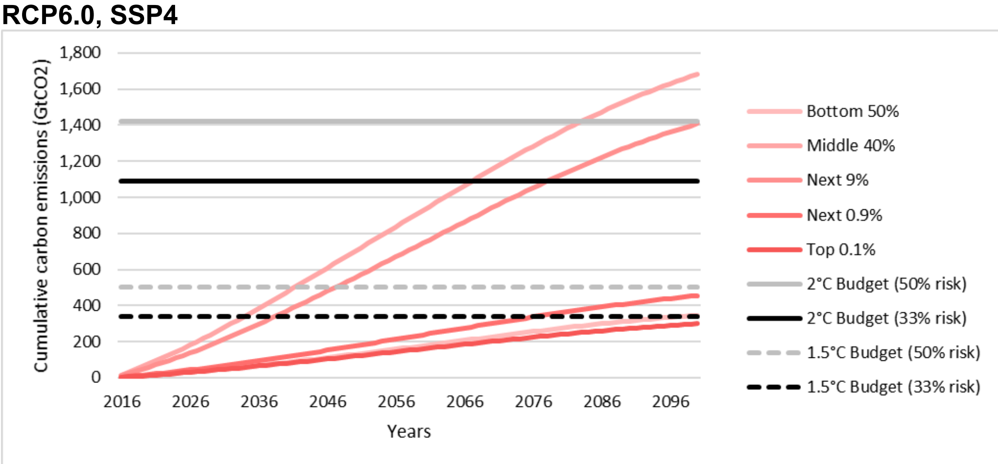


Figure 13(a,b, c, d): Global cumulative emissions associated with the consumption of individuals in different global income groups from 2020 for the SSP1 and SSP4, and RCP6.0 and RCP1.9 scenarios. The horizontal lines reflect the remaining budget for 1.5°C (dashed) and 2°C (solid) warming levels, each with a 50% (grey) and 33% (black) risk of failure.

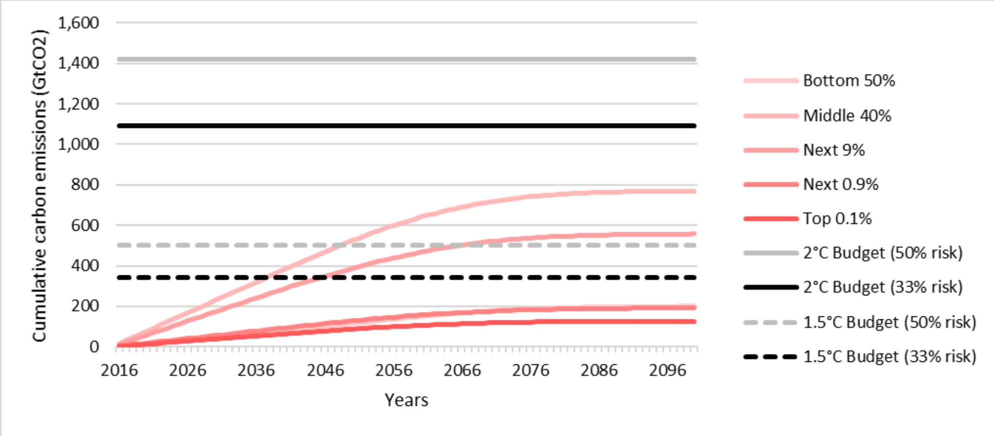
RCP6.0, SSP1



RCP6.0, SSP4



RCP1.9, SSP1



RCP1.9, SSP4

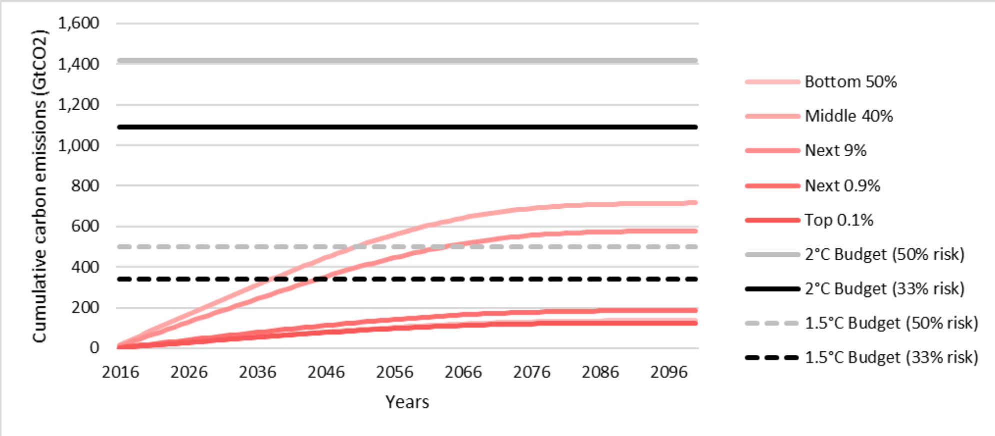


Figure 14(a, b, c, d): Global cumulative emissions associated with the consumption of individuals in different global income groups from 2020 (not stacked for the SSP1 and SSP4, and RCP6.0 and RCP1.9 scenarios). The horizontal lines reflect the remaining budget for 1.5°C (dashed) and 2°C (solid) warming levels, each with a 50% (grey) and 33% (black) risk of failure.

RCP6.0, SSP1

		Share of total carbon emissions by year				*Growth in total carbon emissions between 2020–2095*		*Total cumulative carbon emissions between 2020–2095*		*Year each global income group would deplete global carbon budget*			
		2020	*2030*	*2050*	*2095*					*1.5°C*		*2.0°C*	
		%	%	%	%	GtCO2/yr	%	GtCO2	%	33% risk	50% risk	33% risk	50% risk
SSP1 projection (more equal)	**top 0.1%**	7%	7%	7%	6%	4.2	6%	291	7%	Post-2095	Post-2095	Post-2095	Post-2095
	top 1%	17%	17%	17%	16%	10.7	16%	735	17%	2054	2069	Post-2095	Post-2095
	top 10%	50%	49%	48%	44%	30.3	46%	2072	47%	2032	2038	2058	2069
	middle 40%	43%	42%	41%	40%	26.1	40%	1805	41%	2034	2041	2064	2077
	bottom 50%	7%	9%	12%	17%	9.5	14%	561	13%	2070	2088	Post-2095	Post-2095
	Total	100%	100%	100%	100%	65.9	100%	4437.9	100%	2025	2028	2039	2045

RCP6.0, SSP4

		Share of total carbon emissions by year				***Growth in total carbon emissions between 2020–2095***		***Total cumulative carbon emissions between 2020–2095***		***Year each global income group would deplete global carbon budget***			
		2020	*2030*	*2050*	*2095*					*1.5°C*		*2.0°C*	
		%	%	%	%	GtCO2/yr	%	GtCO2	%	33% risk	50% risk	33% risk	50% risk
SSP4 projection (more unequal)	**top 0.1%**	7%	7%	7%	7%	4.1	7%	287	7%	Post-2095	Post-2095	Post-2095	Post-2095
	top 1%	17%	17%	18%	19%	10.2	18%	721	18%	2055	2070	Post-2095	Post-2095
	top 10%	50%	50%	51%	53%	29.4	52%	2070	52%	2032	2038	2059	2070
	middle 40%	43%	42%	40%	39%	22.8	40%	1616	40%	2034	2042	2068	2084
	bottom 50%	7%	8%	8%	8%	4.9	9%	331	8%	Post-2095	Post-2095	Post-2095	Post-2095
	Total	100%	100%	100%	100%	57.1	100%	4017.0	100%	2029	2032	2044	2050

RCP1.9, SSP1

		Share of total carbon emissions by year				***Growth in total carbon emissions between 2020–2095***		***Total cumulative carbon emissions between 2020–2095***		***Year each global income group would deplete global carbon budget***			
		2020	*2030*	*2050*	*2095*					*1.5°C*		*2.0°C*	
		%	%	%	%	GtCO2/yr	%	GtCO2	%	33% risk	50% risk	33% risk	50% risk
SSP1 projection (more equal)	**top 0.1%**	7%	7%	7%	7%	2.6	7%	126	7%	Post-2095	Post-2095	Post-2095	Post-2095
	top 1%	17%	18%	17%	21%	6.4	17%	317	17%	Post-2095	Post-2095	Post-2095	Post-2095
	top 10%	50%	49%	46%	49%	18.1	48%	873	47%	2035	2044	Post-2095	Post-2095
	middle 40%	43%	42%	42%	33%	15.6	42%	768	42%	2038	2049	Post-2095	Post-2095
	bottom 50%	7%	9%	12%	17%	3.8	10%	199	11%	Post-2095	Post-2095	Post-2095	Post-2095
	Total	100%	100%	100%	100%	37.4	100%	1840.4	100%	2025	2029	2046	2057

RCP1.9, SSP4

		Share of total carbon emissions by year				*Growth in total carbon emissions between 2020–2095*		*Total cumulative carbon emissions between 2020–2095*		*Year each global income group would deplete global carbon budget*			
		2020	*2030*	*2050*	*2095*					*1.5°C*		*2.0°C*	
		%	%	%	%	GtCO2/yr	%	GtCO2	%	33% risk	50% risk	33% risk	50% risk
SSP4 projection (more unequal)	**top 0.1%**	7%	7%	7%	7%	2.6	7%	125	7%	Post-2095	Post-2095	Post-2095	Post-2095
	top 1%	17%	18%	18%	21%	6.2	17%	310	18%	Post-2095	Post-2095	Post-2095	Post-2095
	top 10%	50%	51%	51%	52%	18.0	50%	887	51%	2035	2044	Post-2095	Post-2095
	middle 40%	43%	42%	41%	38%	15.6	43%	714	41%	2039	2051	Post-2095	Post-2095
	bottom 50%	7%	8%	8%	10%	2.3	7%	136	8%	Post-2095	Post-2095	Post-2095	Post-2095
	Total	100%	100%	100%	100%	35.8	100%	1737.0	100%	2029	2034	2051	2064

Table 4(a, b, c, d): Comparison of emissions projections based on SSP1 (more equal) and SSP4 (more unequal) scenarios, for RCP6.0 and RCP1.9 (as labelled).

CONCLUSIONS

Our analysis of the distribution of global consumption emissions among households in different income classes between 1990 and 2015 adds weight to previous studies of the extent of global carbon inequality, including Gore (2015), by demonstrating the strikingly unequal way in which the finite global carbon budget was depleted in this period, and its lasting consequences for future generations.

Despite the significant increase in per capita incomes and associated consumption emissions in what can be called the 'global middle class' in the last 20–30 years – as millions of people have escaped poverty in countries such as China and India – the consumption emissions associated with the world's richest households have continued to grow, leaving the distribution of emissions essentially unchanged. In other words, the rapidly accelerating growth in total emissions – and the attendant rise in climate crisis risks and damage – has categorically not occurred to the benefit of the poorer half of the world’s population. In fact, nearly half the growth has merely allowed the already wealthy top 10% to augment their consumption and enlarge their carbon footprints.

Our analysis of future scenarios of global carbon inequality further reveals the extent to which this historic and ongoing inequality is passed on to future generations. Even under moderately progressive scenarios of socio-economic development, we show that very little atmospheric space is left for the world's poorest households.

While there has been substantial debate on the carbon impact of economic growth in so-called 'emerging economies' over the past 20–30 years, our results suggest a need for increased attention to be paid to the continuing outsized impact of the minority of the world's richest citizens, wherever they reside, and the continuing outsized economic development needs of the world’s poorest citizens. Even as renewable technologies become a viable part of our energy future, the global carbon budget remains a precious natural resource. Our socio-economic and climate policies should be designed to ensure its most equitable use.

BIBLIOGRAPHY

Alvaredo, F., Atkinson, A. B., Chancel, L., Piketty, T., Saez, E. and Zucman, G. (2016). *Distributional National Accounts Guidelines: Methods and Concepts Used in WID.world*. WID.world Working Paper Series, 2016/2. Working Paper. https://wid.world/document/dinaguidelines-v1/

Alvaredo, F., Chancel, L., Piketty, T., Saez, E. and Zucman, G. (2017). *World Inequality Report 2018*. World Inequality Lab, Paris, France. https://wir2018.wid.world/

Anderson, K. and Peters, G. (2016). *The trouble with negative emissions*. *Science*, 354(6309). 182–83. DOI:10.1126/science.aah4567. https://science.sciencemag.org/content/354/6309/182

Atkinson, A. B. and Piketty, T., eds. (2007). *Top Incomes over the Twentieth Century: A Contrast between Continental European and English-Speaking Countries*. Oxford University Press, Oxford; New York.

Baer, P., Fieldman, G., Athanasiou, T. and Kartha, S. (2008). *Greenhouse Development Rights: towards an equitable framework for global climate policy*. *Cambridge Review of International Affairs*, 21(4). 649–69. https://doi.org/10.1080/09557570802453050.

Brenner, M., Riddle, M. and Boyce, J. K. (2007). *A Chinese sky trust?: Distributional impacts of carbon charges and revenue recycling in China*. *Energy Policy*, 35(3). 1771–84. https://doi.org/10.1016/j.enpol.2006.04.016.

Brown, C., Ravallion, M., and Van De Walle, D. (2017). *Are poor individuals mainly found in poor households?* Evidence using nutrition data for Africa. The World Bank. https://doi.org/10.1596/1813-9450-8001.

Boudet, A. M. M., Buitrago, P., de la Briere, B. L., Newhouse, D., Matulevich, E. R., Scott, K., and Suarez-Becerra, P. (2018). *Gender Differences In Poverty And Household Composition Through The Life-Cycle.* UN Women and the World Bank. https://www.unwomen.org/en/digital-library/publications/2018/4/gender-differences-in-poverty-and-household-composition-through-the-life-cycle

Calvin, K., Bond-Lamberty, B., Clarke, L., Edmonds, J., Eom, J., et al. (2017). *The SSP4: A world of deepening inequality*. *Global Environmental Change*, 42. 284–96. https://doi.org/10.1016/j.gloenvcha.2016.06.010.

Chakravarty, S., Chikkatur, A., de Coninck, H., Pacala, S., Socolow, R. and Tavoni, M. (2009). *Sharing global CO2 emission reductions among one billion high emitters*. *Proceedings of the National Academy of Sciences*, 106. 11884–88. https://doi.org/10.1073/pnas.0905232106.

Chancel, L. and Piketty, T. (2015). *Carbon and Inequality: From Kyoto to Paris*. Unpublished. http://rgdoi.net/10.13140/RG.2.1.3536.0082.

Chant, S. (1997). *Women‐Headed Households: Poorest of the Poor?: Perspectives from Mexico, Costa Rica and the Philippines[1]*. IDS bulletin, 28(3), 26-48. https://opendocs.ids.ac.uk/opendocs/bitstream/handle/20.500.12413/9205/IDSB_28_3_10.1111-j.1759-5436.1997.mp28003003.x.pdf;jsessionid=41A04070C4F29E73D4AF0897E0DE3FEA?sequence=1

Chant, S. H. (Ed.). (2011). *The international handbook of gender and poverty: concepts, research, policy*. Edward Elgar Publishing.

Cohen, M. G. (2014). *Gendered emissions: counting greenhouse gas emissions by gender and why it matters*. *Alternate Routes: A Journal of Critical Social Research*, 25. http://www.alternateroutes.ca/index.php/ar/article/view/20595

Dellink, R., Chateau, J., Lanzi, E. and Magné, B. (2017). *Long-term economic growth projections in the Shared Socioeconomic Pathways*. *Global Environmental Change*, 42. 200–214. https://doi.org/10.1016/j.gloenvcha.2015.06.004.

Dooley, K. and Kartha, S. (2018). *Land-based negative emissions: risks for climate mitigation and impacts on sustainable development*. *International Environmental Agreements: Politics, Law and Economics*, 18(1). 79–98. https://doi.org/10.1007/s10784-017-9382-9.

Dorband, I. I., Jakob, M., Kalkuhl, M. and Steckel, J. C. (2019). *Poverty and distributional effects of carbon pricing in low- and middle-income countries – A global comparative analysis*. *World Development*, 115. 246–57. https://doi.org/10.1016/j.worlddev.2018.11.015.

Gore, T. (2015) *Extreme Carbon Inequality: Why the Paris climate deal must put the poorest, lowest emitting and most vulnerable people first*. Oxfam. https://policy-practice.oxfam.org.uk/publications/extreme-carbon-inequality-why-the-paris-climate-deal-must-put-the-poorest-lowes-582545

Gössling, S. (2019). *Celebrities, air travel, and social norms*. *Annals of Tourism Research*, 79. 102775. https://doi.org/10.1016/j.annals.2019.102775.

Heck, V., Gerten, D., Lucht, W. and Popp, A. (2018). *Biomass-based negative emissions difficult to reconcile with planetary boundaries*. *Nature Climate Change*, 8(2). 151–55. https://doi.org/10.1038/s41558-017-0064-y.

Holz, C., Kartha, S. and Athanasiou, T. (2018). *Fairly sharing 1.5: national fair shares of a 1.5°C-compliant global mitigation effort*. *International Environmental Agreements: Politics, Law and Economics*, 18(1). 117–34. https://doi.org/10.1007/s10784-017-9371-z.

Holz, C., Kemp-Benedict, E., Athanasiou, T. and Kartha, S. (2019). *The Climate Equity Reference Calculator*. *Journal of Open Source Software*, 4(35). 1273. https://doi.org/10.21105/joss.01273.

Hubacek, K., Baiocchi, G., Feng, K., Muñoz Castillo, R., Sun, L. and Xue, J. (2017). *Global carbon inequality*. *Energy, Ecology and Environment*, 2(6). 361–69. https://doi.org/10.1007/s40974-017-0072-9.

IPCC (2018). *Global Warming of 1.5°C: An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty*. V. Masson-Delmotte, P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, et al. (eds.). Intergovernmental Panel on Climate Change, Geneva, Switzerland. http://www.ipcc.ch/report/sr15/.

Ivanova, D. and Wood, R. (2020). *The unequal distribution of household carbon footprints in Europe and its link to sustainability*. *Global Sustainability*, 3. e18. https://doi.org/10.1017/sus.2020.12.

Jantzen, R. T. and Volpert, K. (2012). *On the mathematics of income inequality: splitting the Gini index in two*. *The American Mathematical Monthly*, 119(10). 824. https://doi.org/10.4169/amer.math.monthly.119.10.824.

Johnsson-Latham, G. (2007). *A study on gender equality as a prerequisite for sustainable development.* Report to the Environment Advisory Council, (2007), 2. Stockholm: Ministry of the Environment.

Klein, N. (2019). *On fire: The (Burning) Case for a Green New Deal.* Simon & Schuster.

Lakner, C. and Milanovic, B. (2016). *Global Income Distribution: From the Fall of the Berlin Wall to the Great Recession*. *The World Bank Economic Review*, 30(2). 203–32. https://doi.org/10.1093/wber/lhv039.

Li, Q., Wu, S., Lei, Y., and Li, S. (2020). *Dynamic features and driving forces of indirect CO2 emissions from Chinese household: A comparative and mitigation strategies analysis. Science of The Total Environment*, 704, 135367. https://doi.org/10.1016/j.scitotenv.2019.135367.

Liang, Q.-M. and Wei, Y.-M. (2012). *Distributional impacts of taxing carbon in China: Results from the CEEPA model*. *Applied Energy*, 92. 545–51. https://doi.org/10.1016/j.apenergy.2011.10.036.

Milanovic, B. (2015). *Global Inequality of Opportunity: How Much of Our Income Is Determined by Where We Live? Review of Economics and Statistics*, 97(2). 452–60. https://doi.org/10.1162/REST_a_00432.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., et al. (2010). *The next generation of scenarios for climate change research and assessment*. *Nature*, 463(7282). 747–56. https://doi.org/10.1038/nature08823.

O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., et al. (2017). *The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century*. *Global Environmental Change*, 42. 169–80. https://doi.org/10.1016/j.gloenvcha.2015.01.004.

Oswald, Y., Owen, A. and Steinberger, J. K. (2020). *Large inequality in international and intranational energy footprints between income groups and across consumption categories*. *Nature Energy*, 5(3). 231–39. https://doi.org/10.1038/s41560-020-0579-8.

Otto, I. M., Kim, K. M., Dubrovsky, N., and Lucht, W. (2019). *Shift the focus from the super-poor to the super-rich. Nature Climate Change*, 9(2), 82–84. https://doi.org/10.1038/s41558-019-0402-3

Pareto, V. (1896). *Cours d'économie politique: professé à l'Université de Lausanne*. F. Rouge, Paris, France.

Rao, N. D., Sauer, P., Gidden, M. and Riahi, K. (2019). *Income inequality projections for the Shared Socioeconomic Pathways (SSPs)*. *Futures*, 105. 27–39. https://doi.org/10.1016/j.futures.2018.07.001.

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., et al. (2017). *The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview*. *Global Environmental Change*, 42. 153–68. https://doi.org/10.1016/j.gloenvcha.2016.05.009.

Rogelj, J., Forster, P. M., Kriegler, E., Smith, C. J. and Séférian, R. (2019). *Estimating and tracking the remaining carbon budget for stringent climate targets*. *Nature*, 571(7765). 335–42. https://doi.org/10.1038/s41586-019-1368-z.

Smith, P., Davis, S. J., Creutzig, F., Fuss, S., Minx, J., et al. (2015). *Biophysical and economic limits to negative CO2 emissions*. *Nature Climate Change*, advance online publication. https://doi.org/10.1038/nclimate2870.

Song, K., Qu, S., Taiebat, M., Liang, S., and Xu, M. (2019). *Scale, distribution and variations of global greenhouse gas emissions driven by US households*. *Environment International*, 133, 105137. https://doi.org/10.1016/j.envint.2019.105137

Ummel, K. (2014). *Who Pollutes? A Household-Level Database of America's Greenhouse Gas Footprint*. 381. Center for Global Development, Washington, DC, US. http://www.ssrn.com/abstract=2622751. Working Paper.

UNU-WIDER (2018). *World Income Inequality Database (WIID4)*. United Nations University World Institute for Development Economics Research, Helsinki, Finland. https://www.wider.unu.edu/project/wiid-world-income-inequality-database.

van Vuuren, D. P., Riahi, K., Moss, R., Edmonds, J., Thomson, A., et al. (2012). *A proposal for a new scenario framework to support research and assessment in different climate research communities*. *Global Environmental Change*, 22(1). 21–35. https://doi.org/10.1016/j.gloenvcha.2011.08.002.

Wang, Q., Hubacek, K., Feng, K., Wei, Y.-M. and Liang, Q.-M. (2016). *Distributional effects of carbon taxation*. *Applied Energy*, 184. 1123–31. https://doi.org/10.1016/j.apenergy.2016.06.083.

Wiedenhofer, D., Lenzen, M., and Steinberger, J. K. (2013). *Energy requirements of consumption: Urban form, climatic and socio-economic factors, rebounds and their policy implications. Energy Policy*, 63, 696–707. https://doi.org/10.1016/j.enpol.2013.07.035.

Wiedenhofer, D., Guan, D., Liu, Z., Meng, J., Zhang, N., and Wei, Y. M. (2017). *Unequal household carbon footprints in China. Nature Climate Change*, 7(1), 75–80. https://doi.org/10.1038/nclimate3165.

APPENDIX 1: METHODOLOGY

DATA

We drew upon income distributions data primarily from the World Inequality Database (WID.world: Alvaredo et al. 2016). The WID.world dataset combines national accounts and survey, wealth and fiscal data in a systematic manner in order to estimate the full distribution of national income, including tax-exempt income, undistributed profits, etc., to address well-known problems with under-reporting of incomes at the top end. For a large number of countries, this database provides information in much greater detail, and to much higher income levels, than previously available. For each country, the database includes ‘generalized-percentile’ data: percentiles from 1% to 99%, tenths of percentiles from 99.0% to 99.9%, hundredths of percentiles from 99.90% to 99.99%, and thousandths of percentiles from 99.990% to 99.999% (127 in total).

These figures are reported for a variety of measures. The most frequently available were disposable and pre-tax income (codes **diinc** and **ptinc**), both from surveys, and ‘fiscal income’ (**fiinc**), which takes tax receipts, national accounts and other data into account, beyond what is available in surveys. Unlike household surveys, fiscal income, particularly tax data, are only available for adults. Accordingly, most generalized percentiles data in the WID.world database are reported for adults over 20 years of age (code **992**). Per capita income is then reported as total household income divided by the number of adults (code **j**). We thus selected data for adults over 20 years of age, with household income split evenly between adults, for the years between 1988 and 2017. Due to data limitations, we subsequently chose a subset of those data that extended from 1990 to 2015. From the codes given above, data on income shares (code **s**) for our selections correspond to WID.world database codes **sptinc992j**, **sdiinc992j** and **sfiinc992j**. For a given country we then selected the series for which the most data was available between 1998 and 2017, breaking ties by this ordering: disposable income > pre-tax > fiscal. This provided data for 123 countries.

The countries available from WID.world excluded 13 that are important in terms of global emissions, population or GDP: Argentina, Australia, Bangladesh, Canada, Colombia, Indonesia, Japan, South Korea, Mexico, Pakistan, the Philippines, Venezuela and Vietnam. Of these, we found decile-level data for 11 countries (no data were available for Argentina or Indonesia) in the World Income Inequality Database (WIID: UNU-WIDER 2018). WIID offers an extensive compilation of primary data, with metadata that allows for careful selection. For these 11 countries we fit a distribution.[4] With the fitted distributions we then generated values for the WID.world’s generalized percentiles as described above, and added them to the database.

Whether from WID.world or WIID, inequality data was not available for all years in all countries. For a given country, we linearly interpolated values between years with data. If the data ended before 2017, or began after 1988, we assumed the endpoint values for all following or prior years out to 2017 or 1988.

Historical carbon emissions data were taken from the Global Carbon Project, with gaps filled in by the Carbon Atlas. We used national consumption-based emissions data, as opposed to production-based emissions, whenever possible. That is to say, we used national emissions net of emissions embodied in trade, as opposed to territorial emissions, as this better reflects the emissions impacts of the consumption of those within the country. Such data is available for the large majority of countries in our data sources. Historical population and GDP at 2011 US$ in purchasing power parity (PPP) terms were drawn from the World Bank World Development Indicators. After taking all data sources into account, the number of countries with full data gradually increased from 100 in 1990 to reach 118 in 2001, rising slowly from there to a peak of

120 in 2011, and then declining slowly to reach 117 in 2015. Table A1 shows the coverage of the dataset in terms of population, GDP and emissions (as a percentage of the global total) in 1990, 2010 and 2015.

	Population (billions)			GDP (trillion 2011 $PPP)			Emissions ($GtCO_2$/yr)		
	Sample	**Total**	**%**	**Sample**	**Total**	**%**	**Sample**	**Total**	**%**
1990	4.6	5.3	87	42.6	47.4	90	20.4	22.2	92
2010	6.1	6.9	88	82.9	91.5	91	29.6	33.1	89
2015	6.5	7.3	89	97.8	108.8	90	31.3	35.5	88

Table A1: Population, GDP and emissions coverage of the dataset.

We must state an important caveat about the assumption that household incomes in different countries' currencies can be compared on a PPP basis. This, it must be said, is a bold assumption, and it has implications. Compared to an MER (market exchange rate) comparison, it arguably overestimates the representation in the upper global income classes of residents of poor countries, which makes poorer and wealthier countries seem more similar than they may be in actuality. As is unequivocally explained in the World Inequality Report (2018), 'the level of global income inequality is therefore substantially higher when measured using market exchange rates than it is with purchasing power parity'. It points out that using market exchange rates, the richest global 1% have four times as much income as the bottom 50%, whereas using PPP exchange rates, they have twice as much. In general, PPP is a more appropriate comparison between households that are overwhelmingly spending their incomes on domestic, non-traded goods, whereas MER is more appropriate for households that 'can easily spend their incomes where they want, which is the case for top global earners and tourists'.

A more accurate analysis should perhaps use a conversion between incomes in different countries that varies between PPP rates at lower incomes to MER rates at higher incomes. We have not done this, although something along these lines has been done by Baer and colleagues (Baer et al. 2008; Holz et al. 2018; Holz et al. 2019).

We allocate the full national consumption emissions to build a global dataset of individual emissions. This is the same approach taken elsewhere (Baer et al. 2008; Chakravarty et al. 2009; Chancel and Piketty 2015). We thus allocate total national consumption emissions to individuals, i.e., not only emissions from household consumption but also from government activities and investment in capital, reasoning that these activities ultimately lay the foundation for consumption by individuals. The Oxfam (2015) analysis allocated only the share of national emissions arising from household consumption, noting that although this excludes ~36% of national emissions, the results in terms of emissions inequality did not differ significantly from those of Chancel and Piketty.

THE RELATIONSHIP BETWEEN INCOME AND EMISSIONS

To allocate emissions across national populations, we used the following procedure.

First, we assume that emissions per capita would not fall below a minimal level, regardless of income. We assumed that even if income were zero, there would still be consumption and thus emissions. For the minimal emissions level, which varied by country, we chose emissions at an income equal to 30% of median income. This level corresponds to one-half the level defined for the European Union's risk-of-poverty threshold, which is 60% of median income after taxes and transfers.[5] This can be contrasted with the approach taken by Oxfam (2015), who assumed a threshold income of one-half the mean. While acknowledging that the median has better properties than the mean for highly skewed distributions,[6] and that the factor of one-half is arbitrary, they note that their estimates are consistent with the emissions figures for the US estimated by Ummel (2014). Ummel's study is indeed careful and interesting. However, his estimated emissions inequality is much farther below income inequality than is typically found.[7] Our approach also includes an arbitrary factor of one-half. We reason this way: our threshold is related to the median, rather than the mean; if 0.6 of the median indicates a risk of poverty in a high-income region, then it is a plausible relative benchmark; actual minimal emissions should be well below that of a household at risk of poverty. Until better (or at least less ambiguous) data become available, we assume a factor of one-half of that threshold, or 0.3 of the median.

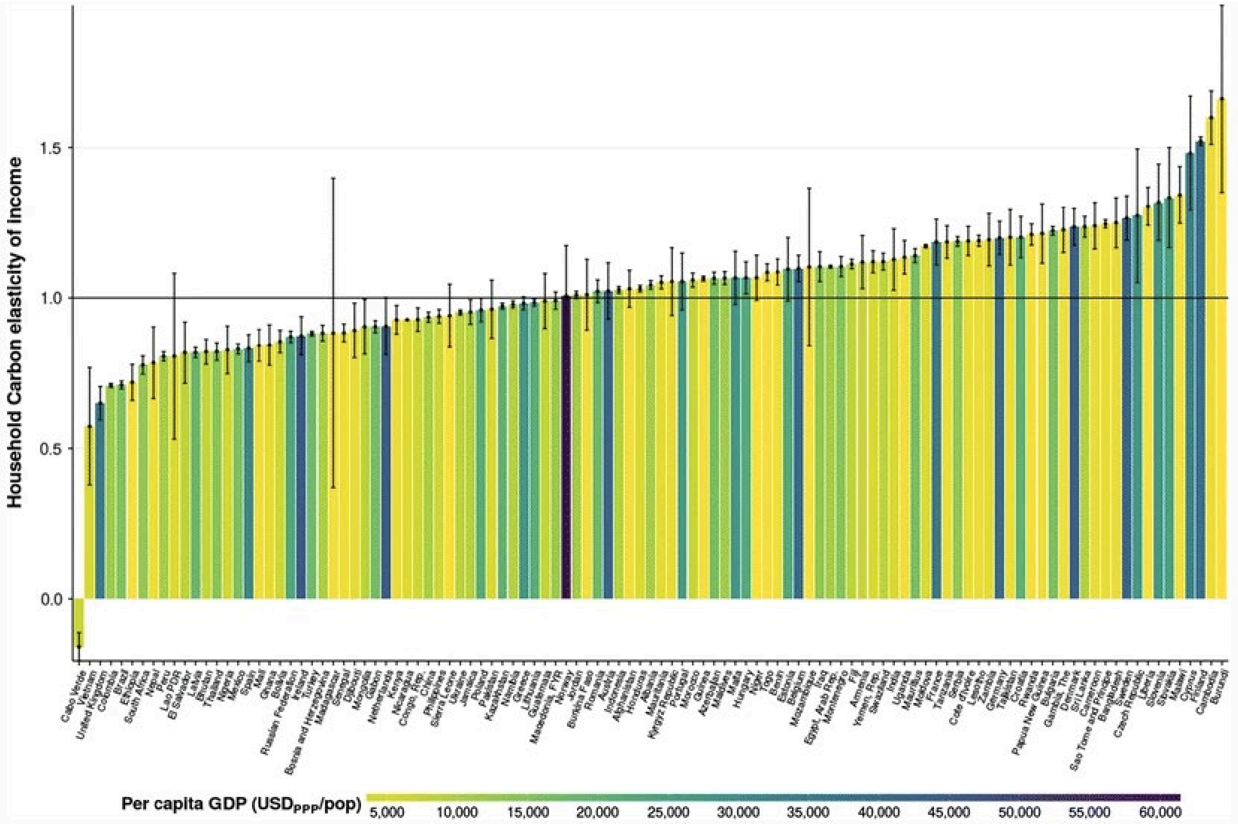
Second, we assume that above a certain level, emissions do not continue to rise with income. Rather we make the extremely conservative assumption that emissions are limited at a hard upper bound, regardless of income, as opposed to continuing to rise with income at a perhaps diminished rate. We set that ceiling at a conservative value of 300 tCO2/cap, notwithstanding clear empirical evidence that this is below the emissions associated with high-income, high-consumption lifestyles. For example, Gössling (2019) estimated the emissions associated with air travel in 2017 for a set of ten public personalities who regularly broadcast their travels on social media. Of the ten, six had emissions exceeding 300 tCO2, including three with emissions exceeding 1,000 tCO2. The analysis by Chancel and Piketty (2015) estimated average emissions of the richest 1% of particularly wealthy countries, such as the US, Luxembourg, Singapore and Saudi Arabia, to be in the 200–300 tCO2e/capita range. They demonstrated the plausibility of an emissions rate of 300 tCO2e/capita by outlining a plausible lifestyle with elements that would generate this level of emissions: travel by commercial airline and private vehicle, heating and cooling of a large home, upstream production of food and other consumables, etc. Ummel (2014) also provides evidence that 100 tCO2/capita is not unreasonable, by deriving an emissions level of 55 tCO2e/capita for the top 2% United States income group based on expenditure data. This seems consistent with our threshold of 300 tCO2/capita, which in our analysis lies at the threshold to the much wealthier top 0.1% United States income group.[8] Consistency with national inventories is maintained with a proportional upward scaling of emissions at lower incomes.

Third, we assume that between the upper and lower bounds discussed above, emissions rise monotonically with income, and that the relationship can be expessed as an elasticity of emissions with respect to income. Depending on income-dependent consumption behaviour in a given country, emissions may grow faster than income (elasticity >1), in proportion to income (e=1), or more slowly than income (elasticity <1). The same approach was taken by by Baer et al. (2008), Chakravarty et al. (2009), Chancel and Piketty (2015) and Gore (2015).

This assumption is grounded in the findings of numerous studies relating income, consumption, energy use and/or emissions, which draw upon a variety of methodologies (see for example Wiedenhofer et al. 2013; Ummel 2014; Hubacek et al. 2017; Wiedenhofer et al. 2017; Dorband et al. 2019; Song et al. 2019; Li et al. 2020; Oswald et al. 2020; Ivanova and Wood 2020). Some studies are based on consumption surveys of a set of households that span a range of incomes, coupled with national input-output matrices and emissions coefficients, or sometimes coupled with estimates from lifecycle analysis. Others are done through either partial or whole-economy general equilibrium modelling, and some assessing carbon tax incidence also purport to calculate indirect market-mediated effects, which is extraneous to an analysis of current consumption-based carbon emissions. Some additionally account for any of various mechanisms for revenue recycling (e.g., per capita dividend), which can also be neglected for our purposes.

Estimates of elasticity are sensitive to methodology, and in some countries, such as China, (Brenner et al. 2007; Liang and Wei 2012; Wang et al. 2016) some studies point to regressive and some to progressive elasticities – that is, to elasticities possibly being essentially proportional (elasticity = 1), mildly progressive (elasticity >1) or mildly regressive (elasticity <1). In some cases, it is found that a carbon tax is mildly regressive in wealthier countries and mildly progressive in poorer countries, although this is by no means a universal rule that provides a precise functional form between elasticity and income per capita (Dorband et al. 2019).

In their recent study of the distribution of energy consumption among individuals in 86 lower- and middle-income and highly-industrialized countries, based on an energy- and expenditure-extended input-output model, Oswald et al. (2020) find an average income elasticity of energy demand of 0.86. In a similar approach, Hubacek et al. (2017) calculate carbon elasticities for 109, primarily lower- and middle-income, countries, as shown in the Figure below, which cluster around an elasticity of 1.



Source: Figure 4, Household carbon elasticity, from Hubacek et al. (2017).

Figure A1: Household carbon elasticity results for a range of countries as described by Hubacek et al. (2017).

This variation in elasticities between countries can be the result of various factors that cause carbon intensities to differ substantially even between countries with similar income levels. These differences are caused by factors such as energy endowment, which may affect the carbon intensitiy of the electricity supply and industry, and settlement density, which affects transportation demand, as well as behavioural factors. Chancel and Piketty (2015) provide a thorough overview of the factors affecting emissions, between and within countries, concluding that ‘income or consumption level remains the main driver explaining variations in total CO2e emissions among households and individuals and it is the best available proxy if we want to construct a global distribution of CO2e with individual level emissions’. They note that they arrive at an average elasticity of 0.9 across the studies they review.

We carry out our analysis and present results using elasticities of 0.9, 1.0 and 1.1. We use an elasticity of 1.0 as the base case for presenting the full set of results, as did Chakravarty et al. (2009) and Gore (2015). Chancel and Piketty (2015) explored a wider sensitivity range (0.6 to 1.5), and used an elasticity of 0.9 as their base case. We note, however, that in our case this elasticity = 1.0 is only applied to a constrained income range: i.e., we apply an emissions floor to the lower end of the income range, and an emissions ceiling to the upper end of the range, as discussed above, which is equivalent to assuming an elasticity of 0 in those income ranges, and assuming an elasticity = 1.0 only in the range in between. In other words, we use a piecewise constant elasticity:

elasticity = 0.0 (low income: i.e., income < 1/3 national median income);

elasticity = 1.0 (medium income: i.e., above lower, and below higher);

elasticity = 0.0, (high income: i.e., income such that emissions > 300 tCO2/capita).

Thus, our analysis is not equivalent to assuming that the dependence of emissions on income is characterized by an elasticity of 1.0. If one can define an 'effective elasticity' as the weighted average across the population of local elasticity, then our methodology yields an effective elasticity that varies by country, and is generally approximately 0.82. If it is the case that we are using a form that is generally less progressive than Dorband et al., it would suggest that our estimate of emissions inequality is an underestimate.

For the global distribution, we compiled populations, average incomes and emissions for every WID.world generalized percentile in every country, for each year between 1990 and 2015. We then sorted that list of generalized-percentile-country combinations by average income and summed cumulative population, income and emissions from lowest to highest income. Because of large differences in national populations (e.g., when a percentile from China enters the distribution), this leads to a somewhat granular global distribution. Nevertheless, it is sufficiently smooth to draw conclusions about global trends towards greater or lesser inequality.

SCENARIOS

For scenarios, we drew on the Shared Socioeconomic Pathways (SSPs) database. The SSPs are a set of narratives that have been prepared by the global climate community (Moss et al. 2010; O'Neill et al. 2017). They are supported by quantitative indicators that are available through a database hosted by the International Institute for Applied Systems Analysis[9] (IIASA: Riahi et al. 2017) and are complemented by different climate forcings (the Representative Concentration Pathways, or RCPs). From that database, we drew population and GDP growth rate projections for all countries of the world to 2100 from the OECD simulations (Dellink et al. 2017). We drew (changes in) Gini coefficients for all countries of the world to 2100 from Rao et al. (2019). We explain how we made use of the Gini coefficient data below.

We use the GDP, population and Gini coefficient trajectories to distinguish SSP1 (a low-inequality 'sustainability' pathway) from SSP4 (a high-inequality pathway). We combined each of these with two emissions trajectories, one in which emissions reflect a high business-as-usual pathway. In the other, emissions are sufficiently low to reflect an ambitious level of mitigation consistent with the Paris temperature goals. These are, respectively, emissions pathways with with 6.0 Wm^{-2} and 1.9 Wm^{-2} radiatice forcing, known as RCP6.0 and RCP1.9.

We had to jump several hurdles to construct national-level trajectories consistent with these assumptions at the required level of detail, based on the results available in the SSP database. In the SSP database, emissions trajectories are available at the level of global regions, only some of which are countries. Different integrated assessment model (IAM) teams participating in round 6 of the Coupled Model Intercomparison Project (CMIP 6) reported results at a variety of geographical scales. The most detailed are from the GCAM4 model, which can report results for up to 32 regions (Calvin et al. 2017). The number of countries per region varies from one (for Argentina, Brazil, Canada, China, Colombia, India, Indonesia, Japan, Mexico, Pakistan, the Russian Federation, South Africa, South Korea, Taiwan and the US) to 29 (for South-East Asia, including the Pacific islands).

The need for fine spatial resolution suggested that we should use outputs from the GCAM4 model, but results are reported only for RCP3.4 and RCP6.0 (and for SSP4). Moreover, as we focus on responsibility for consumption-based emissions, we wanted to exclude carbon sequestration, which is not driven by consumption but by deliberate policy-induced mitigation action. To construct the needed country-level trajectories, we applied an approximate scaling procedure to GCAM's RCP3.4 scenario to calculate RCP1.9 trajectories. While it would have been preferable to carry out full runs of a single IAM for the specific SSP-RCP combinations of interest to this study, we argue that this procedure is consistent with our limited goal of constructing representative low-ambition and high-ambition mitigation trajectories. What is more, regional and national emissions trends can vary considerably between IAMs. Finally, we had to harmonize the model outputs to match our historical database. Thus, we were able to adapt available GCAM model outputs to construct national-level emissions profiles consistent with the needs of our study.

GCAM's SSP4-RCP6.0 scenario has no negative emissions in the energy or industrial sectors. In contrast, the SSP4-RCP3.4 scenario does have negative emissions in those sectors, so that sequestration is bundled together with emissions. The transport, residential and commercial sector emissions are strictly positive in both RCP6.0 and RCP3.4. We assumed the reduction in total emissions from the transport, residential and commercial sectors to reflect the level of mitigation effort between RCP3.4 and RCP6.0 scenarios, separately from sequestration. That gave us regional multipliers (which we call 'mitigation effort factors') for each year, which we applied to total RCP6.0 emissions to estimate direct emissions in the RCP3.4 scenario. We then subtracted reported RCP3.4 emissions to estimate sequestration at regional level. At the global level, GCAM also reports total sequestration from carbon capture and storage (CCS) and total land-use emissions. Combining net-negative land-use emissions with CCS sequestration gave us a control total to check our procedure. The results are comparable in magnitude, as shown in Figure 15, giving us some confidence in our procedure.

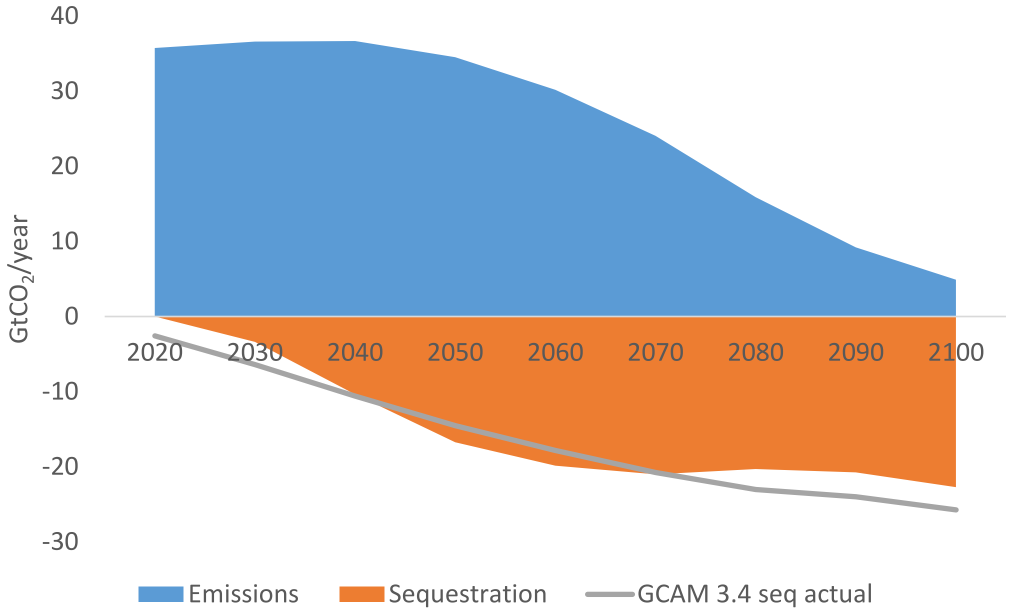


Figure 15: Consumption emissions and estimated sequestration compared with reported global sequestration in GCAM4 RCP3.4 scenario.

To construct an RCP1.9 scenario, we raised all of the mitigation effort factors for RCP3.4 relative to RCP6.0 to the same power. Holding total sequestration equal to the RCP3.4 level, we then adjusted the power until cumulative global emissions from 2015 to 2100 equalled cumulative global emissions from the IMAGE SSP1-RCP1.9 scenario. This was found to hold when the mitigation effort factors were raised to the 1.95 power. The results are shown in Figure 16. As shown in the figure, our RCP1.9 trajectory (light blue) declines more slowly at first and then more rapidly than the IMAGE trajectory (orange).

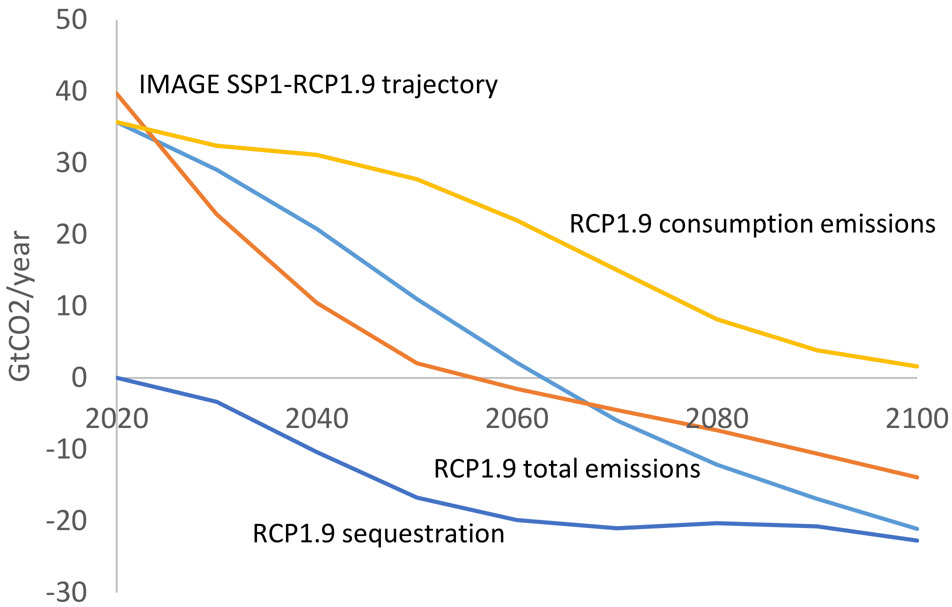


Figure 16: The global RCP1.9 trajectory used in this study, with breakdown into consumption emissions and sequestration, compared to the IMAGE RCP1.9 trajectory.

It is important to note that the IMAGE RCP 1.9 pathway – like many other modelled pathways – includes a large amount of negative emissions, seemingly persisting at a high level beyond 2100. This is not to say that this reliance on negative emissions is unproblematic, and several analyses suggest it presents considerable problems (Smith et al. 2015; Anderson and Peters 2016; Heck et al. 2018; Dooley and Kartha 2018).

These cautions about negative emissions make the inequity of vastly unequal emissions levels all the more stark. Not only do higher-income groups appropriate a disproportionately large share of the scarce remaining carbon budget, but they are also disproportionately responsible for imposing on other people, including future generations, the onerous burden associated with a large emissions debt. This debt would need to be paid either with a large amount of negative emissions – which could be costly – or it may come with considerable socio-ecological costs, or even prove unachievable, leading to even greater warming and climate impacts.

There are modelled 1.5°C pathways that do not rely on large volumes of negative emissions. Prominent among them is the ‘P1’ pathway highlighted in the IPCC 1.5°C Special Report (IPCC 2018). (Using this pathway, with its much more rapid ramp down in emissions, would have obscured even more the distinction between the share of emissions of different income groups in SSP1 and SPP4.)

THEIL INDEX

The Theil *T* index is a measure of inequality of incomes. It is defined, for a continuous income distribution *f*(*y*), as

$$T = \int_0^\infty dy\ f(y)\frac{y}{\bar{y}}\ln\left(\frac{y}{\bar{y}}\right), \quad \text{where} \quad \bar{y} = \int_0^\infty dy\ yf(y). \qquad (1)$$

The Theil index reflects the important principle that multiples of incomes, rather than simple additions to incomes, are most relevant. For example, for someone earning a dollar a day, an additional dollar each day is a very large change. For someone earning $1,000 a day it makes hardly a difference. In the first case, income has doubled – a factor of 2. In the second, it has increased by a factor of 1.001. Suppose that we have incomes in four units: y_1 = $1/day, y_2 =

\$10/day, y_3 = \$100/day, and y_4 = \$1,000/day. In this case, incomes increase by a factor of 10 with each incremental step – a meaningful increment.

For making use of the empirical data, we assume a piecewise constant distribution of income, so that the cumulative probability has a stair-step shape. For a given generalized percentile π_i, we assume that everyone has the same income y_i. For N generalized percentiles, we can then write the probability distribution in terms of Dirac delta functions as

$$f(y) = \sum_{i=1}^{N} \pi_i \delta(y - y_i). \tag{2}$$

It is then possible to show that the Theil indicator can then be written as

$$T = \sum_{i=1}^{N} \pi_i \frac{y_i}{\bar{y}} \ln\left(\frac{y_i}{\bar{y}}\right) = \sum_{i=1}^{N} \sigma_i \ln\left(\frac{\sigma_i}{\pi_i}\right), \tag{3}$$

where the σ_i are income shares. For the top group, we assume a Pareto distribution. We first estimate the Pareto exponent α by applying a procedure proposed by Atkinson (Atkinson and Piketty 2007) to the top two groups,

$$\alpha = \frac{1}{1 - \dfrac{\ln\left(\sigma_N / (\sigma_N + \sigma_{N-1})\right)}{\ln\left(\pi_N / (\pi_N + \pi_{N-1})\right)}} = \frac{1}{1 - \dfrac{\ln\left(1 + \sigma_{N-1}/\sigma_N\right)}{\ln\left(1 + \pi_{N-1}/\pi_N\right)}}. \tag{4}$$

Then, using the expression for the Theil index of a Pareto distribution (a standard formula, expressed in terms of the exponent α), we construct Pareto-corrected national-level Theil indices as

$$T = \sum_{i=1}^{N-1} \sigma_i \ln\left(\frac{\sigma_i}{\pi_i}\right) + \sigma_N \left[\frac{1}{\alpha - 1} + \ln\left(1 - \frac{1}{\alpha}\right)\right]. \tag{5}$$

The global distribution is made up as a sum of national distributions,

$$f_{\text{glob}}(y) = \sum_{c=1}^{C} \pi_c^{\text{glob}} f_c(y), \tag{6}$$

where c is one of a total of C countries and π_c^{glob} is that country's share of global population. The global Theil index is then given by equation (1) as

$$T_{\text{glob}} = \sum_{c=1}^{C} \pi_c^{\text{glob}} \int_0^{\infty} dy\, f_c(y) \frac{y}{\bar{y}_{\text{glob}}} \ln\left(\frac{y}{\bar{y}_{\text{glob}}}\right). \tag{7}$$

We can write

$$\frac{y}{\bar{y}_{\text{glob}}} = \frac{\bar{y}_c}{\bar{y}_{\text{glob}}} \frac{y}{\bar{y}_c} \tag{8}$$

and

$$\ln\left(\frac{y}{\bar{y}_{\text{glob}}}\right) = \ln\left(\frac{\bar{y}_c}{\bar{y}_{\text{glob}}}\right) + \ln\left(\frac{y}{\bar{y}_c}\right). \tag{9}$$

Substituting these into equation (7) gives

$$T_{\text{glob}} = \sum_{c=1}^{C} \pi_c^{\text{glob}} \frac{\bar{y}_c}{\bar{y}_{\text{glob}}} \left[\ln\left(\frac{\bar{y}_c}{\bar{y}_{\text{glob}}} \right) \frac{1}{\bar{y}_c} \int_0^\infty dy\, y f_c(y) + \int_0^\infty dy\, f_c(y) \frac{y}{\bar{y}_c} \ln\left(\frac{y}{\bar{y}_c} \right) \right]. \tag{10}$$

From equation (1), the expressions in the square brackets can be simplified. The second term is the national-level Theil index, and the first term includes the average income (as an integral) divided by average income (the value), which cancels out. We therefore have

$$T_{\text{glob}} = \sum_{c=1}^{C} \pi_c^{\text{glob}} \frac{\bar{y}_c}{\bar{y}_{\text{glob}}} \ln\left(\frac{\bar{y}_c}{\bar{y}_{\text{glob}}} \right) + \sum_{c=1}^{C} \pi_c^{\text{glob}} \frac{\bar{y}_c}{\bar{y}_{\text{glob}}} T_c. \tag{11}$$

In terms of income shares, we can write this to look similar to equation (3) as

$$T_{\text{glob}} = \underbrace{\sum_{c=1}^{C} \sigma_c^{\text{glob}} \ln\left(\frac{\sigma_c^{\text{glob}}}{\pi_c^{\text{glob}}} \right)}_{\text{between-country}} + \underbrace{\sum_{c=1}^{C} \sigma_c^{\text{glob}} T_c}_{\text{within-country}}. \tag{12}$$

The global Theil index is seen to separate into two terms – a ‘between-country’ term that looks like the national Theil index, but expressed in terms of national averages – and a ‘within-country’ term which is the income-weighted average national Theil index. This decomposability is an often-cited and desirable feature of the Theil index. Indeed, it can be decomposed to any level, such as world regions or other country classifications, or regions within countries. As in Chancel and Piketty (2015), we use the Theil indicator to show the different trends in between-country inequality (which has been falling) and within-country inequality (which has been rising).

USING THE SSP GINI COEFFICIENTS

Most of the scenario analysis is a straightforward translation of quantitative indicators from the SSP database into the format used for the historical analysis. The exception is the inequality indicators, which are provided from the SSP database as single values (Gini coefficients), whereas our analysis operates at the detailed generalized-percentile level.

To translate Gini coefficients into generalized percentiles, we begin with Lorenz curves, which are plots of cumulative income against cumulative population, ordered from lowest to highest income. By construction, Lorenz curves are nondecreasing functions that increase from a value of 0 at 0% of the population to 1 at 100% of the population. Denoting the Lorenz curve for a country by $L(x)$, the empirical Gini coefficient can be calculated as

$$G = 1 - 2\sum_{i=1}^{n} L(x_i)\Delta x_i, \tag{13}$$

where n is the number of generalized percentiles and Δx_i is the proportion of the population in generalized percentile i. The generalized percentiles sum to one, so this can be written

$$G = 2\sum_{i=1}^{n} \left(1 - L(x_i)\right)\Delta x_i - 1. \tag{14}$$

We derive a different Lorenz curve by applying an exponent a (we justify this assumption below). That is, in equation (14) we make the replacement

$$1 - L(x_i) \to \left(1 - L(x_i)\right)^a . \tag{15}$$

The equation for the Gini coefficient with exponent *a* is then given by

$$G(a) = 2\sum_{i=1}^{n}\left(1 - L(x_i)\right)^a \Delta x_i - 1. \tag{16}$$

Where the original (empirical) Gini coefficient *G* is given by the value of *G*(*a*) when *a* = 1. We approximate *G*(*a*) by the first two terms in the Taylor series expansion,

$$G(a) \cong G(1) + \left(a - 1\right)\left.\frac{\partial G}{\partial a}\right|_{a=1}, \tag{17}$$

so that our estimate for *a* is

$$a = 1 + \frac{G(a) - G(1)}{\left(\partial G/\partial a\right)_{a=1}}. \tag{18}$$

Taking the derivative of equation (16) with respect to *a* and setting *a* = 1 gives

$$\left.\frac{\partial G}{\partial a}\right|_{a=1} = 2\sum_{i=1}^{n}\left(1 - L(x_i)\right)\ln\left(1 - L(x_i)\right)\Delta x_i. \tag{19}$$

Combined with equation (18), this gives an algorithm for calculating *a* in terms of the change in the Gini coefficient *G*(*a*) − *G*(1), and therefore of calculating the Lorenz curve at all generalized percentiles using equation (15).

This procedure will give exact results for a Pareto distribution. In that case, the Lorenz curve is

$$L_{\mathrm{Par}}(x;\alpha) = 1 - \left(1 - x\right)^{1-\frac{1}{\alpha}}. \tag{20}$$

Solving for 1 − *x*, we find

$$\left(1 - L_{\mathrm{Par}}(x;\alpha)\right)^{\frac{\alpha}{\alpha-1}} = 1 - x. \tag{21}$$

Note that this is independent of *α*. If we consider two distributions with parameters α_1 and α_2, this independence means that we can set the corresponding equations equal to one another,

$$1 - L_{\mathrm{Par}}(x;\alpha_2) = \left(1 - L_{\mathrm{Par}}(x;\alpha_1)\right)^{\frac{\alpha_1}{\alpha_2}\frac{\alpha_2 - 1}{\alpha_1 - 1}}. \tag{22}$$

with $a = (\alpha_1/\alpha_2)(\alpha_2 - 1)/(\alpha_1 - 1)$, this is of precisely the same form as in equation (15).

In fact, while income distributions are Pareto in the upper tail, that is not the case in the lower tail. We therefore test the procedure using a form for the Lorenz curve that generalizes the Pareto and works well across the full distribution, which was proposed by Jantzen and Volpert (2012),

$$L_{\mathrm{JV}}(x;p,q) = x^p\left[1 - \left(1 - x\right)^q\right]. \tag{23}$$

When x is close to one (the high end of the Lorenz curve), or when p is close to zero, x^p is approximately equal to one, so this function looks like the Pareto distribution at the upper tail, as it should.

To test the approach, we define a function

$$F(x;p,q) \equiv \left(1 - L_{\mathrm{JV}}(x;p,q)\right)^{\frac{1}{q}}. \tag{24}$$

When $p = 0$, this gives $(1 - x)$ exactly, so we are back to equation (21), with $q = 1 - 1/\alpha$. More generally, we want this expression to be independent of q, parallel to the independence of the right-hand side of equation (21) on α. That is our test of the method.[10]

Dependence on q of the expression in equation (24) across generalized percentiles is shown in Figure 17. The figure shows that when p is close to zero (the solid lines), the deviations are small, at most 2–3%. This fits the expectation, because, as noted above, in that case the Pareto distribution is a good approximation. Likewise, when $p = 0.5$ (the dashed lines), the difference between the $q = 0.4$, 0.5, and 0.6 curves (ranging from blue-green to purple) is comparatively small.

Jantzen and Volpert (2012), using survey data that probably underestimated the Pareto tail, found values of $p = 0.8$ and $q = 0.6$ for the US in 2009. The value for q corresponds to a Pareto exponent $\alpha = 2.5$. That gives an estimated Gini coefficient of 0.45. In this case, the deviation from the $q = 0.5$ curve is close to, but slightly above, 5% (the dotted purple line). While the deviations in the most extreme case exceed 10% (the dotted red line, corresponding to $p = 0.8$ and $q = 0.7$), we conclude that this procedure performs reasonably well across a wide range of parameter values and we use it to translate Gini coefficients into generalized percentiles.

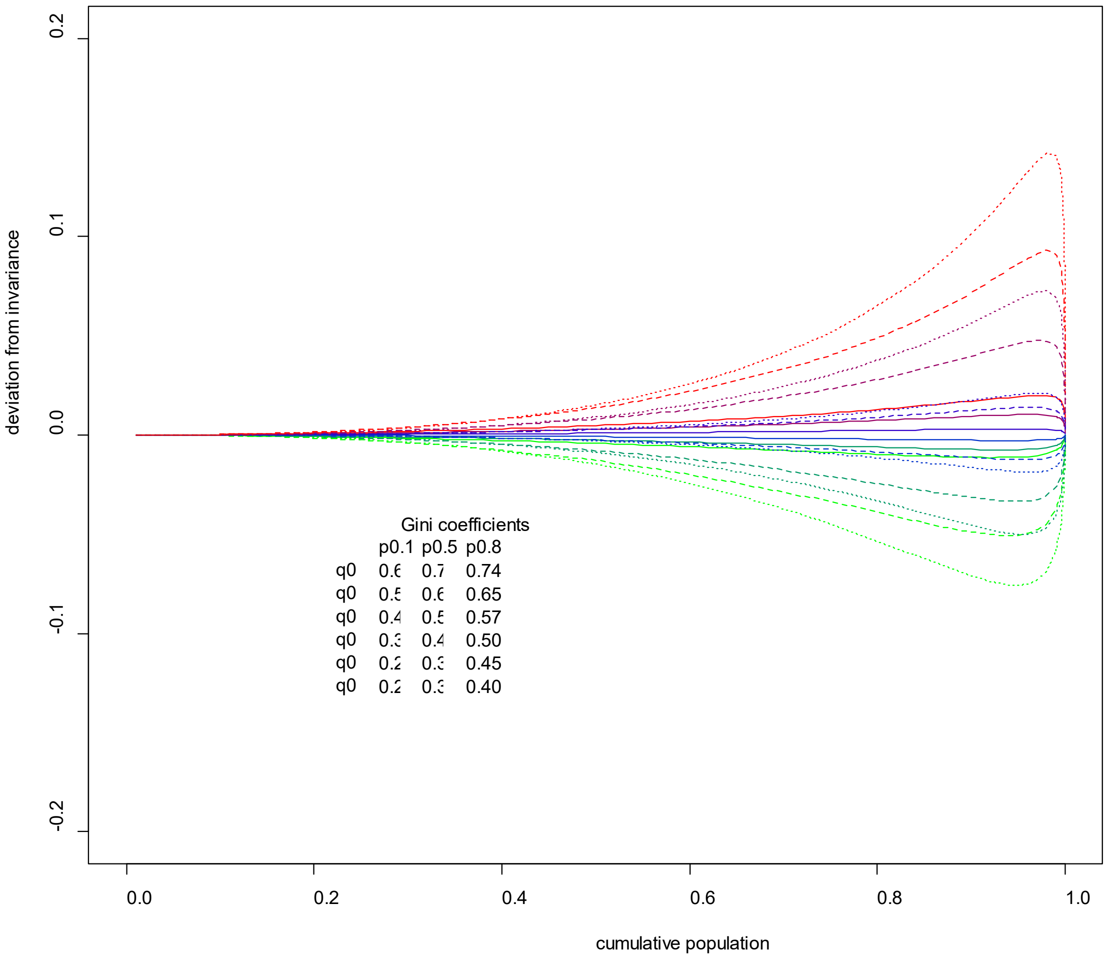


Figure 17: Fractional deviations from curve with q = 0.5; p runs from solid to dashed to dotted lines; q from green to red.

APPENDIX 2: SENSITIVITY ANALYSIS

ELASTICITY

Elasticity, e = 0.9

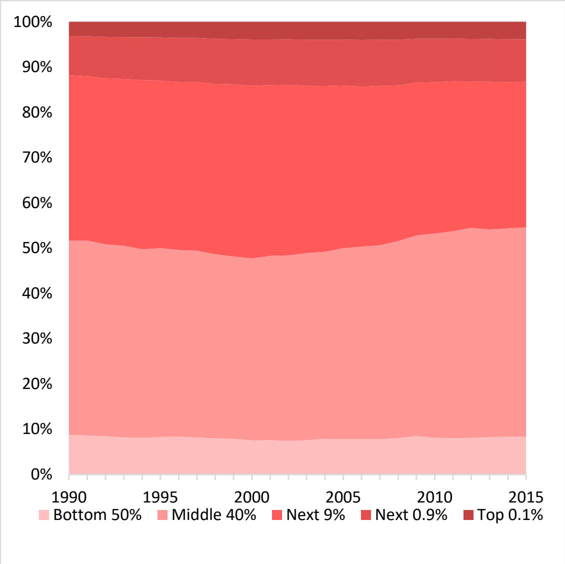
	Emissions Share			Growth (amount)	Growth (share)	Cumulative (amount)	Cumulative (share)
	1990	2010	2015	1990-2015			
Income Groups	%	%	%	GtCO2	%	GtCO2	%
top 0.1%	3%	4%	4%	0.7	5%	27	4%
next 0.9%	9%	10%	9%	1.4	11%	70	10%
next 9%	37%	33%	32%	3.3	25%	256	35%
middle 40%	43%	45%	46%	6.9	52%	311	43%
bottom 50%	9%	8%	8%	1.0	8%	58	8%
Total	100%	100%	100%	13.3	100%	722	100%

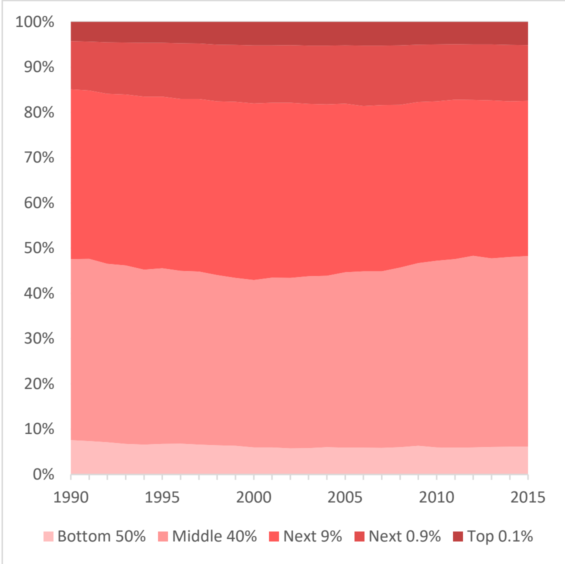
Table 2a: Share of global emissions in 1990, 2010 and 2015 by global income groups, along with growth in emissions and cumulative emissions, assuming an elasticity of emissions with respect to income e = 0.9.

Elasticity, e = 1.1

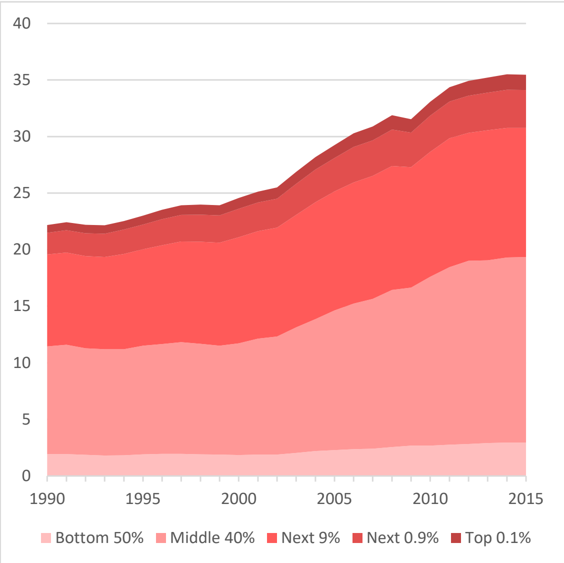
	Emissions Share			Growth	Growth	Cumulative	Cumulative
	1990	2010	2015	1990-2015			
Income Groups	%	%	%	GtCO2	%	GtCO2	%
top 0.1%	4%	5%	5%	0.9	7%	36	5%
next 0.9%	11%	13%	12%	2.0	15%	90	12%
next 9%	38%	35%	34%	3.8	29%	266	37%
middle 40%	40%	41%	42%	6.1	46%	286	40%
bottom 50%	8%	6%	6%	0.5	4%	45	6%
Total	100%	100%	100%	13.3	100%	722	100%

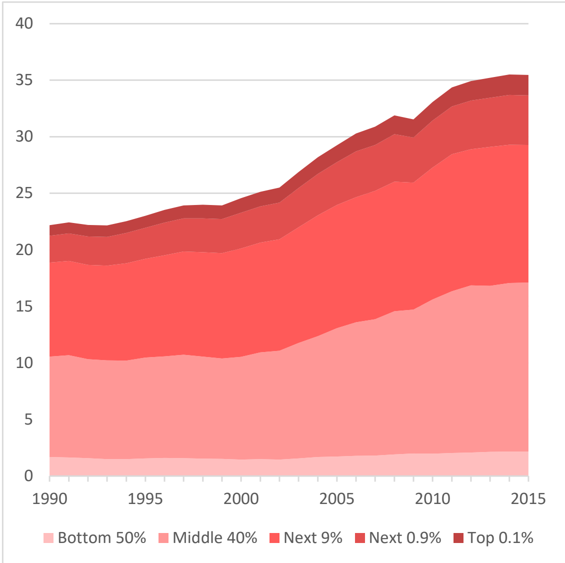
Table 2b: Share of global emissions in 1990, 2010 and 2015 by six global income groups, along with growth in emissions and cumulative emissions, assuming an elasticity of emissions with respect to income of e = 1.1.



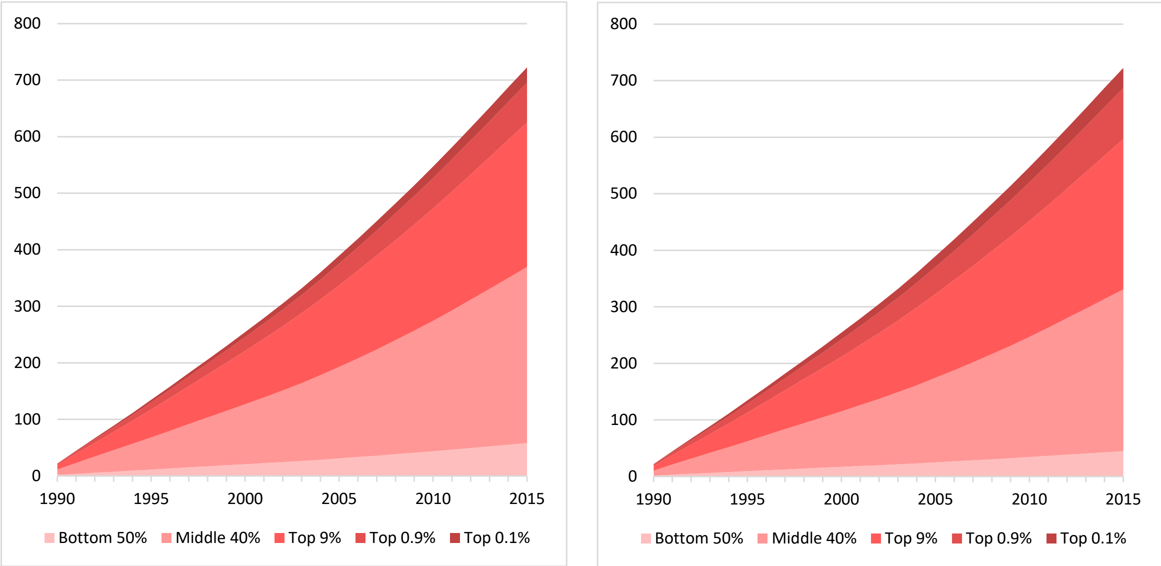


Figures 2a and 2b show the share of emissions divided by income group over time. In 2015, the top 10% are responsible for 46% (or 54%), assuming an elasticity of e = 0.9, left panel (or e=1.1, right panel).





Figures 3a and 3b show total emissions by income goup growing over time. Over the 1990–2015 period, the top 10% are responsible for 42% (or 56%) of the growth in emissions, assuming an elasticity of *e* = 0.9, left panel (or e=1.1, right panel).



Figures 4a and 4b show the cumulative emissions by each income group. The top 10% are responsible for 49% (56%) of the rise in cumulative emissions, assuming an elasticity of e = 0.9, left panel (or e=1.1, right panel).

APPENDIX 3: REGIONAL DEFINITIONS

These are the regional definitions as defined by the GCAM model, which provided the SSP1 and SSP4 results for the Shared Socioeconomic Pathway database used here, and shown in Figure 8.

See the SSP database for further details:
https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about

ANUZ	This region includes Australia and New Zealand.
BRA	Brazil.
CAN	Canada.
CAS	This region includes the countries of Central Asia: Armenia, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Uzbekistan.
CHN	China: Mainland, Hong Kong SAR, Macao SAR; excl. Taiwan.
EEU	Eastern Europe (excl. former Soviet Union and EU member states): Albania, Bosnia and Herzegovina, Croatia, Montenegro, Serbia,Republic of North Macedonia.
EEU-FSU	Eastern Europe, former Soviet Union (excl. Russia and EU members): Belarus, Republic of Moldova, Ukraine.
EFTA	This region includes Iceland, Norway and Switzerland.
EU12-H	New EU member states that had joined as of 2004 – high-income: Cyprus, Czech Republic, Estonia, Hungary, Malta, Poland, Slovakia, Slovenia.
EU12-M	New EU member states that had joined as of 2004 – middle-income: Bulgaria, Latvia, Lithuania, Romania.
EU15	This region includes EU member states that joined prior to 2004: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom.
IDN	Indonesia.
IND	India.

JPN	Japan.
KOR	Republic of Korea.
LAM-L	This region includes low-income countries in Latin America (excl. Brazil and Mexico): Belize, Guatemala, Haiti, Honduras, Nicaragua.
LAM-M	This region includes middle- and high-income countries in Latin America and the Caribbean (excl. Brazil and Mexico): Antigua and Barbuda, Argentina, Bahamas, Barbados, Bermuda, Bolivia (Plurinational State of), Chile, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, French Guiana, Grenada, Guadeloupe, Guyana, Jamaica, Martinique, Netherlands Antilles, Panama, Paraguay, Peru, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Suriname, Trinidad and Tobago, Uruguay, Venezuela (Bolivarian Republic of).
MEA-H	This region includes high-income countries in the Middle East: Bahrain, Israel, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates.
MEA-M	This region includes low- and middle-income countries in the Middle East: Iran (Islamic Republic of), Iraq, Jordan, Lebanon, Occupied Palestinian Territory, Syrian Arab Republic, Yemen.
MEX	Mexico.
NAF	This region includes the countries of North Africa: Algeria, Egypt, Libya (State of), Morocco, Tunisia, Western Sahara.
OAS-CPA	This region includes countries in the category ‘Other Asia’–- formerly referred to as ‘Centrally Planned Asia’: Cambodia, Lao People's Democratic Republic, Mongolia, Vietnam.
OAS-L	This region includes low-income countries in the category ‘Other Asia’: Bangladesh, Democratic People's Republic of Korea, Fiji, Micronesia (Fed. States of), Myanmar, Nepal, Papua New Guinea, Philippines, Samoa, Solomon Islands, Timor-Leste, Tonga, Vanuatu.
OAS-M	This region includes middle- and high-income countries in the category ‘Other Asia’: Bhutan, Brunei Darussalam, French Polynesia, Guam, Malaysia, Maldives, New Caledonia, Singapore, Sri Lanka, Thailand.
PAK	This region includes Pakistan and Afghanistan.
RUS	Russian Federation.
SAF	South Africa.

SSA-L	This region includes low-income countries in sub-Saharan Africa (excl. South Africa): Benin, Burkina Faso, Burundi, Cameroon, Cabo Verde, Central African Republic, Chad, Comoros, Congo, Côte d'Ivoire, Democratic Republic of Congo, Djibouti, Eritrea, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Nigeria, Rwanda, São Tomé and Príncipe, Senegal, Sierra Leone, Somalia, South Sudan, Sudan, Swaziland, Togo, Uganda, United Republic of Tanzania, Zambia, Zimbabwe.
SSA-M	This region includes middle-and high-income countries in sub-Saharan Africa (excl. South Africa): Angola, Botswana, Equatorial Guinea, Gabon, Mauritius, Mayotte, Namibia, Réunion, Seychelles.
TUR	Turkey.
TWN	Taiwan.
USA	United States of America. Includes: Puerto Rico, United States Virgin Islands, United States of America.

NOTES

1 There are now efforts in progress to improve data on gender and income disparities. The WID.world team noted specifically in the most recent World Inequality Report (Alvaredo et al. 2017) that they are integrating more data on gender inequality into the WID.world database.

2 In order to develop the scenarios, we made frequent use of the SSP Database, hosted by the International Institute for Applied Systems Analysis (IIASA): https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about.

3 An estimate of warming with RCP6.0 is provided in Table SPM 2, (IPCC AR5 SPM, p. 23). The estimate of warming including the effect of Paris pledges is from Climate Action Tracker, Warming Projections Global Update, December 10, 2019. https://climateactiontracker.org/press/global-update-governments-showing-little-sign-of-acting-on-climate-crisis/

4 We chose the Jantzen-Volpert distribution (2012), which approaches power-law behaviour at the low and upper tails of the distribution. The power law at the upper tail is a well-documented feature of observed income distributions, with foundational research carried out by Vilfredo Pareto (1896) in the late 19th century. A standard assumption is that income distributions are roughly lognormal throughout most of the distribution and Pareto-distributed at the top. The Jantzen-Volpert distribution has a similar shape, fits empirical data well and is straightforward to work with. We fitted decile data in R using the nls nonlinear solver's 'port' algorithm.

5 Eurostat. (n.d.). *Glossary: At-risk-of-poverty rate*. https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:At-risk-of-poverty_rate

6 The standard example is that a small business owner walks out of a bar while Bill Gates walks in. The median income of the people in the bar most likely does not shift at all, while the mean income rises enormously.

7 Ummel used survey data collected by the US Census Bureau. Those data typically experience under-reporting at high incomes, so distributions drawn from the data lack the long Pareto tail that can be seen when the survey is supplemented by tax data (Alvaredo et al. 2016). The Lorenz curves are approximately symmetric, suggesting that they will fit well to lognormal distributions. With that assumption, it is possible to estimate the elasticity of emissions with respect to income from the reported Gini coefficients, and it is about 0.65. This is much lower than the typical range of 0.9–1.1 for estimated emissions elasticities, as discussed in Appendix 1.

8 The Ummel (2014) analysis includes non-CO2 emissions, but excludes emissions other than household consumption. It is also based on expenditure survey data, which Chancel and Piketty point out is notoriously underreported.

9 International Institute for Applied Systems Analysis. (2018). SSP Database (Shared Socioeconomic Pathways) – Version 2.0. https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about

10 Note that we are *not* testing how well the Jantzen-Volpert distribution fits empirical data. We are accepting it as a good fit for empirical data in order to test our method for converting Gini coefficients into generalized percentiles.

ACKNOWLEDGEMENTS

This report was commissioned and edited by Tim Gore of Oxfam, and the quantitative work was conducted by Sivan Kartha, Eric Kemp-Benedict, Emily Ghosh and Anisha Nazareth of Stockholm Environment Institute. The authors gratefully acknowledge the peer review comments from Lucas Chancel, Richard King and Christoph Lakner, and the contributions of Mira Alestig and other Oxfam colleagues.

Research reports

This research report was written to share research results, to contribute to public debate and to invite feedback on development and humanitarian policy and practice. It does not necessarily reflect the policy positions of the publishing organizations. The views expressed are those of the authors and not necessarily those of the publishers.

For more information, or to comment on this report, email tim.gore@oxfam.org or sivan.kartha@sei.org.

The information in this publication is correct at the time of going to press.

Published by Oxfam GB for Oxfam International and SEI under ISBN 978-1-78748-649-2 in September 2020. DOI: 10.21201/2020.6492. Oxfam GB, Oxfam House, John Smith Drive, Cowley, Oxford, OX4 2JY, UK.

OXFAM

Oxfam is an international confederation of 20 organizations networked together in 67 countries, as part of a global movement for change, to build a future free from the injustice of poverty. Please write to any of the agencies for further information, or visit www.oxfam.org.

SEI

Stockholm Environment Institute is an international non-profit research and policy organization that tackles environment and development challenges.

We connect science and decision-making to develop solutions for a sustainable future for all.

Our approach is highly collaborative: stakeholder involvement is at the heart of our efforts to build capacity, strengthen institutions, and equip partners for the long term.

Our work spans climate, water, air, and land-use issues, and integrates evidence and perspectives on governance, the economy, gender and human health.

Across our eight centres in Europe, Asia, Africa and the Americas, we engage with policy processes, development action and business practice throughout the world.

SEI Stockholm Environment Institute

OXFAM