

RESEARCH ARTICLE

Beyond the nation-state narrative: an empirical inquiry into the cross-country and cross-income-group carbon consumption patterns[‡]

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(Submitted 13 January 2020; revised 13 September 2020, 28 November 2020; accepted 22 December 2020; first published online 12 April 2021)

Abstract

The concern for inequality, growth and development is undoubtedly crucial in the context of climate change mitigation and adaptation. However, most studies either rely on the nation-state estimates of carbon emissions to propose a uniform nation-wide growth (or degrowth) strategy, or they tailor the method to assess the inequality of one country at a time, making a cross-country cross-income comparison difficult. To fill this analytical gap, we synthesize the existing methods of emission calculations and calculate the level of carbon emissions associated with given income deciles of household consumption in five countries, namely China, Germany, India, the UK and USA. We find that the within-country inequality varies among countries, with the ratio between the top and bottom income deciles ranging from three to nine at the household level. We also find that the carbon emissions of the top income group in urban China is almost comparable to that of their peer group in the US, UK and Germany. Based on these results, we discuss the use of the remaining global carbon budget in the context of development and inequality.

Keywords: degrowth; environmental justice; global warming; growth; inequality; mitigation

JEL classification: F64; Q54; Q56

1. Introduction

The capacity of the Earth's ecosystems to soak up greenhouse gases is part and parcel of the environmental commons. It is humanity's common heritage and property: every human activity relies on this common heritage and its preservation. With this in mind,

[‡]The online version of this article has been updated since original publication. A notice detailing the changes has also been published at: <https://doi.org/10.1017/S1355770X21000164>

we believe that the correct way to frame climate stabilization policy is through the lens of the remaining global carbon budget.

With the latest IPCC (2018) report cautioning that the remaining global carbon budget is only 420 billion tons or approximately 10 years of emissions at current rates,¹ it has become ever more pressing to propose a fair distribution mechanism of the global carbon budget taking into account the global and domestic inequality, as well as growth and development questions.

This framing alleviates the apparent conflict between income growth and poverty alleviation on the one hand, and scaling down of emissions to levels compatible with 1.5°C (or 2°C) global warming on the other. Growth and degrowth are both required, in selective ways for different income groups; so too groups of goods and services must be defined and differentiated.

This becomes all the more clear when the perspective is extended from substantial domestic inequalities to cross-country and cross-income-group inequalities in income, emissions and infrastructure. Within nation-states, inequality has been rising or staying high almost without exception both in the Global South (Xie and Zhou, 2014; Anand and Thampi, 2016; Sulemana *et al.*, 2019) and the Global North (Piketty and Saez, 2014). Such inequality is also reflected in the carbon emissions (Jorgenson *et al.*, 2016, 2017). Thus, policies targeting the poor, including the 940 million without access to electricity and the 3 billion without access to clean fuels, cannot be the same as policies designed for population groups with per capita emissions well beyond what is sustainable. This is a problem that cuts across nations and sovereign political entities (Ritchie and Roser, 2019).

To overcome the limits and biases of measurements based on the nation-state as a unit, it is imperative to have solid empirics on carbon emissions by class (or income groups as a proxy for class) within and comparable across countries. However, to the best of our knowledge, few studies have attempted to apply a consistent measure for a cross-country comparison of energy consumption and carbon emissions by income groups.

Skepticism about current measures of carbon emissions and the implied ignorance towards hierarchical power structures within and between countries has been sporadically hinted at in existing literature. Peters and Hertwich (2008), for example, developed a consumption-based carbon emissions dataset as a recognition of the disproportionately heavier production responsibilities assumed by the Global South. Such asymmetric production and consumption patterns across the world caused biased estimations of the total carbon emissions in countries with less political leverage to impose strong environmental regulation on domestic and foreign capital.

On the other hand, studies also show that the energy consumption and associated carbon emissions of people from different income groups varies significantly within and across countries (Symons *et al.*, 2002; Clarke-Sather *et al.*, 2011; Gore, 2015; Michael and Vakulabharanam, 2016; Wiedenhofer *et al.*, 2017; Wu *et al.*, 2017; Fremstad and Paul, 2019; Azad and Chakraborty, 2020). Correspondingly, Foster *et al.* (2011) pointed out that the widely-used term ‘American way of life,’ and the related measure of per capita emissions in the US, largely ignore the class differences with respect to carbon emissions within the country.

To fill this analytical gap, we synthesize the methods of calculation adopted by Mathur and Morris (2014), Fremstad and Paul (2019) and Azad and Chakraborty (2020), and

¹This is related to the goal of limiting global warming to 1.5°C with medium confidence (a probability of 66 per cent).

apply the resulting unified method to a total of five countries: the USA, India, Germany, UK and China. We calculate carbon emissions associated with household consumption by income deciles in these five countries, including a breakdown of urban and rural sectors in the case of India and China. We also supplement the incomplete picture painted by territorial production estimates alone, by estimating consumption-based footprints.

We found that within-country inequality regarding carbon emissions varies across countries, with the ratio between the top and bottom income deciles ranging from three to nine at the household level. On the other hand, a cross-country and cross-income-group comparison suggests that the carbon emissions of the top income group in urban China is almost comparable to that of their peer group in the US, UK and Germany.

Based on these empirical findings, we argue that real-world inequality in carbon emissions is more complicated than what a nation-state perspective can capture. This complication stems not only from considering the class composition of each country, but also the hierarchical position each country holds in the global division of labor. Moreover, a one-size-fits-all growth or degrowth proposal cannot be the answer. Growth is an indicator representing an aggregate, which is not very informative unless put in relation with its social foundations and ramifications. Rather, the correct questions should be 'growth and degrowth of what' and 'growth and degrowth for whom'.

In section 2, we present our method for calculating the carbon emissions of different income groups for the countries in our sample. We compare our method to those used in current studies and discuss the strengths and weaknesses of each approach. In section 3, we report the empirical results obtained from both household and per capita levels. Section 4 wraps up the discussion and concludes the paper.

2. Data and method

One of the most widely-cited statistics regarding the income-based inequality in carbon emissions is that the richest 10 per cent is responsible for 50 per cent of global carbon emissions while the poorest half of the world population is responsible for only 10 per cent of total emissions, as reported in the OXFAM report (Gore, 2015). The crucial assumption behind the method of calculation in this report is the unitary elasticity between income and emissions.² That is to say, although the report claims to estimate the actual carbon emissions attributed to individual consumption, it is not effectively doing so for each income percentile group based on the commodities they consume. In actuality, the estimation represents a *de facto* measure of the income distribution expressed by the unit of carbon emission. Moreover, variations in the energy mix (i.e., differences in countries' relative reliance on coal, oil and natural gas to produce energy) are neglected by this approach, and the different carbon intensities that emerge from these energy mixes are consequently also ignored.

Oswald *et al.* (2020) improved the method by considering the income elasticity of energy demand across income groups and showed that, in the 86 countries covered in their study, the energy footprint of the bottom half of the population is less 20 per cent of the total final energy footprint, and less than that for the top 5 per cent.

Others use a more enhanced approach on the production side by making use of multi-regional input-output (MRIO) analysis to take trade into account and compute

²Unitary elasticity implies that the ratio between the income level of the top 1 per cent and average income should be equal to the ratio between the carbon emissions level of the top 1 per cent and the average carbon emissions level for all countries.

consumption-based emissions associated with a selected region (for a brief survey of studies using MRIO, see Wiedmann (2009)). However, such approaches rarely rely on a detailed decomposition of actual household consumption expenditures when it comes to distributing aggregate emissions across income groups (Hubacek *et al.*, 2017).

Following Mathur and Morris (2014), Fremstad and Paul (2019) and Azad and Chakraborty (2020), we adopt a more sophisticated method that consists of two main steps. First, we calculate the carbon dioxide (CO₂) content of commodities found in input-output (IO) tables. Second, by mapping commodities found in IO tables into expenditure categories found in consumer expenditure surveys, we obtain a distribution of per capita and household-level CO₂ emissions resulting from household consumption according to income distribution.

Comprising the US, UK, Germany, China and India, our sample both accounts for a significant share (about 52 per cent in 2012) of global emissions resulting from fossil fuel combustion and allows for comparisons between countries with different fiscal and technological capacities. We used the most up-to-date data for all five countries: 2017 data for the US, 2013 data for Germany, and 2012 data for the UK, India and China. In this section, we describe the method we use for the case of the US in detail, which, thanks to data availability, is the most elaborate. In other empirical cases, some of the intermediate steps described below are not included because the associated data does not exist, as briefly described in section 2.1.2. All the data sources we have utilized in the calculations are listed in appendix B.

2.1 CO₂ content of input-output commodities

2.1.1 United States

We first construct an interindustry transactions table based on the Make and Use tables for 2017 available from the Bureau of Economic Analysis (BEA).³ Next, we obtain the coefficients matrix, also known as the **A** matrix, by normalizing the columns of the transactions matrix with the corresponding column sums. The final step in this stage is to calculate the so-called Leontief inverse, or, the total requirements matrix:

$$L = (I - A)^{-1} \quad (1)$$

Let each element of the total requirement matrix **L** be represented by tr_{ij} . The latter represents the total amount of commodity *i* required directly and indirectly in order to produce a dollar's worth of commodity *j* for final demand. We will use the total requirement coefficients to calculate the total amount of CO₂ embodied in each commodity.

Our basic assumption is as follows: a significant portion of CO₂ enters the economy through the combustion of fossil fuels. In fact, in 2016, 76 per cent of total anthropogenic greenhouse gas (GHG) emissions, and 94 per cent of total anthropogenic CO₂ emissions in the US, were produced by burning fossil fuels for energy (EIA, 2018).⁴ The Energy

³To do so, we normalize the Make matrix by dividing each column by its column sum, namely the total commodity output. The product of this adjusted Make matrix and the Use matrix generates the interindustry transactions matrix. In our case, the dimensions of the latter are 64 by 64 due to aggregation and disaggregation steps described in appendix A.

⁴Other anthropogenic activities accounted for about 6 per cent of total CO₂ emissions and 5 per cent of total GHG emissions. Other GHGs such as methane and nitrous oxide that resulted from human activity accounted for about 18 per cent of US anthropogenic GHG emissions in 2016 (EIA, 2018).

Information Administration (EIA) provides data on CO₂ emissions in 2017 associated with the combustion of fossil fuels, namely coal, oil and natural gas (EIA, 2019: 203).

In terms of the US IO accounts, we relate the CO₂ emissions (in 2017) from coal combustion (1,318 million metric tons (mmt) of CO₂) to the ‘Coal Mining’ industry, and the total CO₂ emissions generated by oil and natural gas use (3,812 mmt CO₂) to the ‘Oil and Gas Extraction’ industry because these are the proxies through which fossil fuels enter the economy. We divide the total amount of CO₂ attributed to each industry by the row sum (total intermediate output) of that industry to obtain the direct carbon intensities DCI_c and DCI_{og} for the coal industry and oil and gas industries, respectively.

In the final step, we multiply the total requirement coefficient of each industry with respect to these two fossil fuel industries by the corresponding direct carbon intensities DCI_c and DCI_{og} to obtain the total CO₂ embodied in each commodity. In other words, the CO₂ content of commodity *j* is given by:

$$CC_j = tr_{cj} \times DCI_c + tr_{ogj} \times DCI_{og} \tag{2}$$

The total carbon content associated with a dollar’s worth of output for selected IO industries in the US is given in appendix [table A1](#), while [table A2](#) reports the carbon intensity of corresponding IO industries of the other countries in our sample.

2.1.2 Other countries

For all other countries included in our sample, we work with the OECD IO tables. Our data and results refer to 2012 in the cases of China, India and the UK, and 2013 in the German case. The choice of year is made considering the availability of most recent data on detailed household consumer expenditure surveys.

The two energy-related industries found in OECD IO tables, namely ‘Mining and Extraction of Energy Producing Products’ and ‘Coke and Refined Petroleum Products’ are merged into a single ‘Energy’ row and column vector. The detailed IO tables in the US case allow for singling out ‘Coal Mining’ and ‘Oil and Gas Extraction’ activities, while the level of disaggregation of the IO tables for the remaining countries does not. Thus, in non-US cases, the energy industry must be aggregated.

Total CO₂ emissions from fossil fuel combustion are obtained from the International Energy Agency (IEA) database at <https://www.iea.org/statistics>. We obtain the carbon intensity of one dollar’s worth of the Energy sector’s output by dividing the total amount of CO₂ resulting from fossil fuel combustion by the total intermediate output of the Energy sector. Carbon content of commodities is calculated by multiplying this direct carbon intensity by the total requirement coefficient each industry has with respect to the Energy sector.

2.2 CO₂ content of household consumption expenditure categories

2.2.1 United States

Once we have the carbon content for the 64 US industries represented in the IO tables, the next major step is to trace the CO₂ on its way to consumption by households. In terms of household consumption expenditures, we rely on the Consumer Expenditure Survey (CEX) annual tables. More precisely, consumer expenditure by decile of income before taxes, from the Bureau of Labor Statistics (BLS) for 2018, is utilized as the crucial variable. In contrast to Mathur and Morris (2014) and Fremstad and Paul (2019), we have decided to use the original consumption categories presented in the CEX instead of creating new

ones. Neither of the mentioned papers provides a clear presentation of how the new consumption categories were constructed from the BEA's existing empirical categories.

In order to map the IO industries into consumer expenditure categories, we make use of the Personal Consumption Expenditures (PCE) Bridge Table provided by the BEA. This table maps more than 100 PCE categories found in the National Income and Product Accounts (table 2.4.5) into the IO categories. The PCE and CEX categories are not identical, but the mapping and the relevant weights are already included in the Bridge Table.⁵

Another advantage of using the latter table is that it allows us to translate producers' to purchasers' prices by incorporating the role of the transportation, wholesale and retail industries. We thereby have information on the share of different IO industries as well as the three intermediate industries (transportation, wholesale and retail) for every dollar spent for each of the 26 CEX categories. In other words, the CO₂ content of each consumption category is a weighted average of the relevant producer IO categories and the three intermediate industries.

Since we already have the CO₂ content of producer industries as represented in appendix table A1, we obtain the CO₂ content of each consumer expenditure category by multiplying the industrial CO₂ content with the weight of each IO industry in that consumption category. We thereby obtain CO₂ emissions associated with each dollar spent on each consumption category. The results are reported in appendix tables A1 and A2.

Finally, the carbon footprint of the representative US household of the *j*-th decile of income distribution is then given by:

$$\text{Carbon Footprint}_j = \sum_{i=1}^{26} \text{CEX carbon content}_i \times \text{CEX expenditures}_{ij} \quad (3)$$

2.2.2 Other countries and consumption-based accounting

In the rest of our sample, we work with a smaller number of household consumption expenditure categories: eight for China, 11 for India, 10 for Germany and 12 for the UK. Part of the reason is that no equivalent to the PCE Bridge Table is available for these countries, making a detailed mapping impossible. Hence, following Azad and Chakraborty (2020), we suggest our own mapping. Since we are interested in inter-country comparisons, we aimed to attain the maximum possible consistency in the mapping between the US and other countries.

Another difficulty that arises from the lack of an equivalent to the Bridge Table is that we do not have the weight of different products mapped into a household consumption expenditure category readily available. Hence, we construct these weights by multiplying the carbon intensity of each product with the gross output of that industry, and then summing up the aggregate CO₂ emissions associated with that consumption expenditure category. Finally, this aggregate is divided by the gross output sum of the included IO industries so as to obtain a weighted CO₂ intensity of each consumption expenditure category. Appendix B provides more information on data sources for these countries.

Last but not least, we complement the analysis with a rough estimation of emissions obtained by consumption-based accounting. The method described above accounts only

⁵If the BEA provided information on the distribution of PCE over different deciles of income, we would not need the CEX data. However, as we are ultimately interested in the distribution of CO₂ associated with household consumption, we need to rely on the CEX data.

for emissions resulting from the domestic combustion of fossil fuels, which inevitably fails to capture the difference between what is produced and consumed in a given territory. Countries like the US and UK are net importers not only of goods and services, but also of the CO₂ embedded in those imports. Thus, as a complementary approach, we calculate the direct carbon intensity of energy industries by dividing countries' aggregate consumption-based emissions obtained from Friedlingstein *et al.* (2019) by the intermediate output of their energy industries.

This implies that imports (of goods and emissions) are assumed to result from the technology of the country where they are consumed. We should note that this only gives a rough estimate of consumption-based emissions. We do not trace imported commodities back to their production site, and hence cannot observe how they are allocated by households in different income groups. Still, consumption-based results help us visualize the cross-country gap in household and per capita emissions much more clearly, through adjustments of aggregate territorial emissions for the impact of exports and imports.

3. Results and discussion

3.1 Household-level emission results

Table 1 reports the household CO₂ emissions for the five countries under consideration, based on the calculation procedure described in the previous section.⁶ In the average, stark inequality is observed between the camps of three advanced countries and two emerging economies. The average household emissions in the US, UK and Germany are 17.08, 14.29, and 14.37 tons, respectively. The figure drops to 9.45 tons in urban China and 5.03 tons in rural China, while the Indian emissions remain at 0.84 and 0.45 tons in the urban and rural cases, respectively.

The gap in average emissions between the US on the one hand, and the UK and Germany on the other is smaller than expected. In the year of analysis, per capita CO₂ emissions were about 14.6 tons in the US, 7.2 tons in the UK and 9.5 tons in Germany.⁷ The gap between the US and UK seems to have narrowed most dramatically. A possible reason for this is that our method accounts only for emissions associated with household consumption, leaving out emissions associated with military expenditures, for instance. This leads to only partial coverage, probably excluding asymmetric portions of total national emissions in each case.

The enormous gap between emissions of both rural and urban Indian households and those in other countries deserves some further discussion. Based on our calculations, the emissions of the richest 10 per cent of urban Indian households (2.50 tons) make up only a fraction of the poorest US (7.88), UK (8.03) and German (5.63) households' emissions. Although it is likely that consumption expenditures, and therefore emissions, of highest income groups are tendentially understated, it is reasonable to believe that such underestimation on the higher-end is consistent among the countries. Hence, there is no reason to assume the inequality pattern would be invalidated by these biases.

It might be shocking to see that the richest urban Indian households emit less carbon than the poorest rural Chinese households (2.5 versus 2.9 tons), but it is worth noting that the data on the rural Chinese households are divided into quintiles. This means that 2.9 tons is the average annual emission for the poorest 20 per cent of rural Chinese

⁶Since original Chinese data for urban and rural household consumption expenditures is given in a mixture of deciles and quintiles, the results are also reported in a corresponding manner.

⁷The years were 2012 for the UK, 2013 for Germany and 2017 for the US.

Table 1. Distribution of household CO₂ emissions (in tons) across income groups

Decile groups	US	UK	Germany	Rural India	Urban India	Quintile/ Decile groups	Urban China	Quintile groups	Rural China
1 st	7.88	8.03	5.63	0.19	0.27	1 st decile	4.01	1 st	2.90
2 nd	8.81	8.74	7.33	0.25	0.37	2 nd decile	5.13		
3 rd	11.72	10.63	9.05	0.28	0.44	2 nd quintile	6.59	2 nd	3.51
4 th	13.78	12.63	10.58	0.32	0.52				
5 th	15.06	13.68	12.45	0.35	0.60	3 rd quintile	8.44	3 rd	4.38
6 th	16.74	14.57	14.13	0.39	0.69				
7 th	19.17	15.24	16.29	0.44	0.80	4 th quintile	10.6	4 th	5.74
8 th	21.31	17.03	18.76	0.51	0.98				
9 th	24.96	17.80	21.37	0.62	1.26	9 th decile	13.79	5 th	8.60
10 th	31.33	24.44	28.10	1.10	2.50	10 th decile	20.28		
Average	17.08	14.29	14.37	0.45	0.84		9.45		5.03
Top-to-bottom ratio	4	3	5	5.8	9.2		5		3
Population in each group (millions)	32.5	6.4	8.1	83	43.3		140		140

Source: Authors' own calculations based on data from the Bureau of Economic Analysis (BEA) for the US (2017); OECD and Office for National Statistics (ONS) for the UK (2012); OECD and Federal Statistical Office (DeStatis) for Germany (2013); OECD and Ministry of Statistics and Program Implementation (MOSPI) for India (2012); and OECD and National Bureau of Statistics (NBS) of China for China (2012). Population size data is extracted from the World Bank Dataset.

households rather than representative of what the bottom 10 per cent is truly emitting. We may note the large emission gap between the top decile groups in both India and China. This is largely because our calculation is based on the consumption data we were able to retrieve for both countries. From the consumption data, urban Indian top decile income household's annual consumption expenditure is \$2,333.5, and the annual consumption expenditure for the Chinese household counterpart is \$17,531.1. This ratio is close to the emission ratios between the two groups reported in [table 1](#). Moreover, the fact that the CO₂ intensity of energy mix in China was 33 per cent higher than its Indian counterpart in 2012 (based on the IEA database) partly explains why emissions associated with rural and urban Chinese household consumption are in general higher than in India.

We also report the population size of each decile for each country in order to demonstrate the fact that, in the two emerging economies, the number of people subject to this extreme inequality is massive. For example, the number of people from the poorest rural Indian decile – responsible for emitting 0.2 tons of CO₂ – is equivalent to the size of the entire German population, and larger than the UK population by 30 per cent. The poorest 20 per cent of rural Chinese households responsible for 2.9 tons of CO₂ emission comprise 130 million people, 40 per cent of the US population.⁸

Though more modest in size, a substantial gap is observed between household emissions in rural China on the one hand (5.03 tons) and advanced countries (17.1, 14.3 and 14.4 for US, UK and Germany respectively) on the other. It is notable that each of these rural Chinese quintiles, comprising 130 million people, is equivalent to the combined population of the UK and Germany. Thus, the total emissions of a Chinese rural population of around 650 million are barely comparable to their counterparts in advanced countries.

Emissions inequality in Germany seems to be particularly high. A possible explanation for this is the fact that poorer households benefit more from public goods and services, which lowers the emissions associated with private consumption captured by our method. The same cannot be said for the US where consumption unmediated by the market is almost non-existent.

An important caveat to the results in [table 1](#) is that it accounts only for territorial emissions resulting from fossil fuel combustion. [Table 2](#) reports the distribution of the household-level emissions taking aggregate consumption-based emissions rather than territorial emissions as the point of departure.

The use of consumption-based data leads to an overall increase of 7.8, 31.6 and 11.1 per cent in the US, UK and German emissions, respectively. Indian and Chinese aggregate emissions, on the other hand, decrease by 7.4 and 15 per cent, respectively. The cross-country inequality of emissions becomes much more pronounced through consumption-based accounting. This is true both in terms of country averages and various income groups of different countries.

The average emissions of a rural Chinese household from even the richest quintile are now significantly below what the poorest households in the UK and US emit. The same holds for (rural and urban) Indian emissions where the gap is huge. Moreover, the average emissions in the second-richest urban Chinese decile now only match emissions of the second- and third-poorest US and UK deciles.

⁸Comparison made with 2012 World Bank population data.

Table 2. Distribution of consumption-based household CO₂ emissions (in tons) across income groups

Decile groups	US	UK	Germany	Rural India	Urban India	Quintile/ Decile groups	Urban China	Quintile groups	Rural China
1 st	8.58	10.57	6.10	0.19	0.26	1 st decile	3.41	1 st	2.46
2 nd	9.57	11.50	7.94	0.24	0.35	2 nd decile	4.36		
3 rd	12.74	13.99	9.80	0.27	0.41	2 nd quintile	5.60	2 nd	2.98
4 th	14.95	16.62	11.47	0.30	0.48				
5 th	16.26	18.00	13.49	0.34	0.55	3 rd quintile	7.18	3 rd	3.73
6 th	18.20	19.17	15.31	0.38	0.63				
7 th	20.73	20.06	17.66	0.42	0.73	4 th quintile	9.01	4 th	4.88
8 th	23.13	22.41	20.33	0.49	0.87				
9 th	27.29	23.42	23.16	0.58	1.11	9 th decile	11.73	5 th	7.31
10 th	35.06	32.16	30.45	0.98	2.11	10 th decile	17.25		
Average	18.65	18.80	15.57	0.42	0.75		8.03		4.27
Population in each group (millions)	32.5	6.4	8.1	83	43.3		140		140

Source: Authors' own calculations based on data from Friedlingstein *et al.* (2019). Population size data is extracted from the World Bank Dataset.

Extreme carbon inequality within countries is another salient feature of the results presented in both tables. The lowest top-to-bottom ratios are found in [table 1](#) in rural China and the UK, where the emissions of households in the richest quintile and decile are three times the emissions of those in the poorest quintile and decile, respectively. This is followed by the US with a ratio of four, and Germany, urban China and rural India where the ratio is around five. With 9.3, urban India has the highest domestic inequality between the emissions of the poorest and richest segments of the population.

A cross-country cross-income group comparison suggests that class is a more useful unit than nation-state for us to understand the severity of world-wide emissions inequality. Our results suggest that at each level of income group, urban Chinese and urban Indian households emit systematically less than their counterparts in the advanced countries. The overall pattern as well as the cross-country gap becomes clearly more pronounced when a consumption-based approach is taken.

3.2 Per capita level emissions

Another caveat to the results in [table 1](#) is that population, and therefore household size, varies significantly across countries. Although China is the largest emitter with 8.9 gigatons at the national scale, followed by the US (4.8 gigatons), the picture is very different in terms of per capita emissions: the US emissions (14.6 tons per capita) are more than two times the Chinese emissions (6.5 tons per capita). Similarly, India, which attracts a lot of attention for its national emissions (1.8 gigatons), posts per capita emissions (1.4 tons) that are nowhere near the other two (based on IEA data).⁹

Studies find that per capita CO₂ emissions decline with dense urbanization and increasing household size (Fremstad *et al.*, 2018). This is usually attributed to the economies of scale that emerge from sharing carbon-intensive commodities. For our sample, it is of particular interest to see the impact of adjusting the results for the average household size in each income group.

[Table 3](#) reports emissions adjusted for the average household size in each quantile. The overall pattern of per capita CO₂ emissions resembles the pattern at the household level presented in [table 1](#), albeit with significantly less domestic inequality within the US and UK. The top-to-bottom ratio dropped from four to two for the US case and from three to 1.3 in the UK case, measured per capita.

The UK constitutes a particularly interesting case in which emissions are almost evenly distributed, apart from in the top decile. The most important source for the eminently flat distribution is the rate of increase in the weighted average number of persons per household reported by the Office for National Statistics (ONS). The increase in household size when moving from lower to higher deciles of income distribution more than offsets the increase in household emissions, bringing about the unintuitive distributional pattern at the per capita level. The distribution of per capita consumption expenditures reported by the ONS closely resembles the pattern found in [table 3](#). Further details can be found in [appendix C](#).

The most pronounced aspect of the per capita results concerns both rural and urban India. The overall level (0.09 for rural and 0.20 for urban) is now lower than the results reported in Azad and Chakraborty (2020). Although the latter do not distinguish between urban and rural population, they also find that all deciles except for the top two have a per capita CO₂ footprint lower than a ton. As intriguing as our results may

⁹A table with summary statistics is provided in [appendix C, table C1](#).

Table 3. Distribution of per capita CO₂ emissions (in tons) across quantiles of income

Decile groups	US	UK	Rural India	Urban India	Quintile/Decile groups	Urban China	Quintile groups	Rural China
1 st	4.93	6.18	0.04	0.05	1 st decile	1.38	1 st	0.74
2 nd	5.18	5.46	0.04	0.07	2 nd decile	1.77		
3 rd	5.58	5.60	0.05	0.09	2 nd quintile	2.27	2 nd	0.90
4 th	5.99	5.74	0.06	0.11				
5 th	6.27	5.70	0.07	0.13	3 rd quintile	2.91	3 rd	1.12
6 th	6.44	5.83	0.08	0.16				
7 th	6.85	5.65	0.09	0.20	4 th quintile	3.65	4 th	1.47
8 th	7.10	5.87	0.11	0.26				
9 th	8.05	6.14	0.14	0.37	9 th decile	4.75	5 th	2.20
10 th	10.11	7.88	0.29	0.90	10 th decile	6.99		
Average	6.83	6.21	0.09	0.20		3.25		1.29

Note: We leave out the estimates for Germany because the German national statistics do not provide data on the average household size over deciles of household consumption expenditures.

Source: Authors' own calculations based on data from the Bureau of Economic Analysis (BEA) for the US (2017); OECD and Office for National Statistics (ONS) for the UK (2012); OECD and Ministry of Statistics and Program Implementation (MOSPI) for India (2012); and OECD and National Bureau of Statistics (NBS) of China for China (2012). Population size data is extracted from the World Bank Dataset.

look, especially in the context of cross-country comparisons, they fit well with the fact that around 25 per cent of the Indian population (more than 300 million people) lacked access to electricity in the year of analysis (Pargal and Banerjee, 2014: 8). This gives an idea about the strikingly low carbon intensity of the average lifestyle.

Extreme inequality in cross-country per capita emissions associated with household consumption is depicted in figure 1 where territorial and consumption-based results are pictured in the left and right panels, respectively, and emission levels are normalized, taking the median (fifth decile) in the United States as baseline.¹⁰ Similar to the Indian case, the vast majority of the Chinese (in fact, the entire population apart from the two richest urban deciles), have per capita emissions that are considerably lower than what the poorest in advanced countries emit. Around a billion Chinese (the entire rural population plus the first two quintiles of the urban population) emit (0.74 to 2.27 tons), significantly less than half of what the poorest in the US emit in per capita terms (4.9 tons), according to territorial emissions.

The picture is even more striking when consumption-based accounting is used: per capita emissions of the poorest 10 per cent in the US are 5.36 tons a year, while that of the rural Chinese (700 million people) is in the range of 0.63–1.87 tons, and that of the urban Chinese except for the richest decile (560 million people) ranges from 1.18 to 4.04 tons. Figure 2 depicts the gap in terms of consumption-based per capita emissions between the US, urban China and urban India.

¹⁰Chinese household consumption data is organized into a mixture of deciles and quintiles. Quintiles are presented as two deciles with an equal level of emissions for purposes of visual convenience.

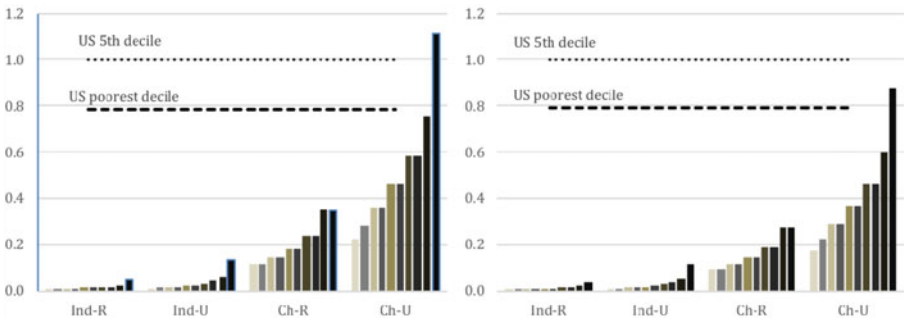


Figure 1. Per capita CO₂ emissions of Indian and Chinese income deciles relative to the poorest and fifth US deciles: territorial (left panel) and consumption-based (right panel).

Source: Authors' own calculations based on data from the Bureau of Economic Analysis (BEA) for the US (2017); OECD and Office for National Statistics (ONS) for the UK (2012); OECD and Ministry of Statistics and Program Implementation (MOSPI) for India (2012); and OECD and National Bureau of Statistics (NBS) of China for China (2012); and Friedlingstein *et al.* (2019) for consumption-based emissions.

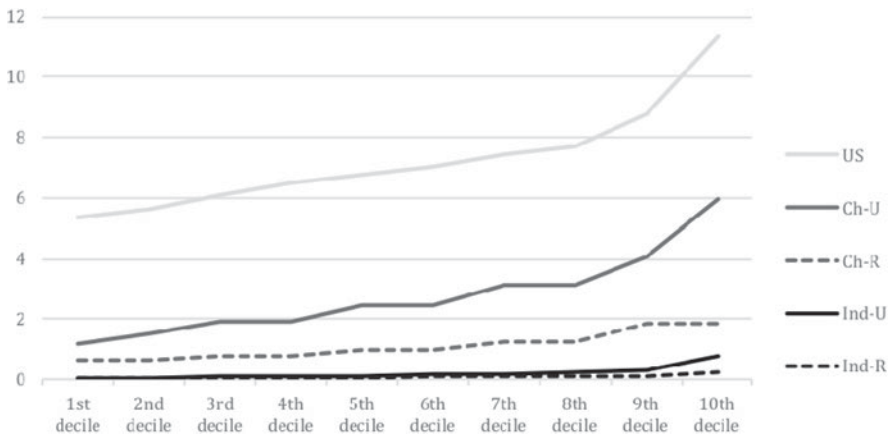


Figure 2. Consumption-based per capita emissions in the US, and in rural and urban China and India.

Source: Authors' own calculations based on data from the Bureau of Economic Analysis (BEA) for the US (2017); OECD and Office for National Statistics (ONS) for the UK (2012); OECD and Ministry of Statistics and Program Implementation (MOSPI) for India (2012); and OECD and National Bureau of Statistics (NBS) of China for China (2012); and Friedlingstein *et al.* (2019) for consumption-based emissions.

3.3 Comparison with existing estimates

The general pattern seems to match the findings of the small number of empirical studies using the same two-step procedure based on IO tables and household consumption expenditures. For India, Azad and Chakraborty (2020) report higher household and per capita emissions compared to our results, the difference being larger at the household level. Still, their findings on Indian emission levels are notably lower than those of other countries in our study, which confirms the large cross-country inequality.

For the US, our results are higher than those in Boyce and Riddle (2007), yet exhibit similar domestic distributional patterns. On the other hand, both household-level and

per capita emissions in our findings are about 1.5 times lower compared to Fremstad and Paul (2019). The pattern of distribution in the latter is also similar to the one presented in table 1, though with greater gaps between deciles in their results.

The differences in emission levels between our results and those in Fremstad and Paul (2019), and Azad and Chakraborty (2020) might stem from several sources. First, we work with average household expenditure data organized into deciles, while both mentioned papers rely on micro-level household survey data. Second, in contrast to both studies that focus on individual countries, we apply our method to five different countries, which raises the challenge of consistency. Household consumption expenditures are provided in nonuniform categories. We took the US mapping as a reference, because details are available in the Bridge Table provided by the BEA, and applied a mapping in the remaining four countries that is as consistent as possible with the US case. This is possibly part of the reason why our results differ from those of Azad and Chakraborty, who use a similar mapping, as well as from those of Fremstad and Paul, who follow Mathur and Morris (2014) rather than sticking with the empirical categories found in the BLS household consumption expenditure data.

For the US, part of the explanation is the fact that their model attributes 58 per cent of all territorial US emissions in 2012 to household consumption, while our model remains at 43 per cent. Multiplying the CO₂ intensity associated with the 'Government' industry in the IO table with the government's total expenditures on final use indicates that 21 per cent of aggregate CO₂ emissions are attributable to the government. Thus, according to our model, 64 per cent of CO₂ emissions resulting from fossil fuel combustion is associated with final use.

This inconsistency can be regarded as a shortcoming of the method which is not designed to capture emissions associated with activities that are not represented in consumer expenditure surveys. However, it can also be conceived of as a strength insofar as we deal with emissions directly associated with household consumption. For instance, by excluding emissions related to military activities, we omit emissions which, if distributed evenly to the population, would introduce a damping effect without making much of a difference in living standards.

Moreover, we should keep in mind that differences in institutional arrangements and consumption patterns associated with community types can affect our results. In places where part of household consumption takes place without market mediation, associated emissions will not be reflected in the results unless such consumption is imputed into household consumption expenditures.

Wiedenhofer *et al.* (2017) find that the consumption-based Chinese footprint is 1.7 tCO₂ per capita, which is close to our consumption-based estimate of 1.9 tCO₂ per capita. The richest urban dwellers have a footprint of 6.4 tCO₂ per capita, almost four times the Chinese average according to Wiedenhofer *et al.* (2017), while we find that the richest Chinese emit around 6 tCO₂ per capita, more than three times the average. They report per capita emissions for rural Chinese quintiles between 0.5 and 1.6 tCO₂, while our results are in the range of 0.6–1.9 tCO₂ (figure 2).

All in all, despite differences in emission levels between our results and relevant single-country studies in the literature that take the same approach, distributional patterns point to similar domestic inequality in emissions. Moreover, the most important contribution of this paper being the application of the same method to a number of countries, we obtain crucial results that highlight the multidimensionality of emission gaps. Although the accuracy of our estimates is constrained by the availability of relevant data,

we can still infer important conclusions by focusing on general patterns rather than the precision in levels.

4. Conclusion

The point of departure in this paper was our belief in the inadequacy of approaches that focus on inequality of emissions solely within or between countries' aggregate figures. Most studies in the literature pick either of the two approaches and find significant results which nonetheless fall short of offering an integrated framework to present the multidimensionality of inequality in emissions.

With the need in mind for such a comparison that captures inequality both between and within countries, we made use of a method applied in several papers to individual countries, the results of which were not suitable for direct comparison due to lack of consistency in the application of this method. For our study, we modified and applied the method to all five countries as consistently as allowed by variations in data availability. Nevertheless, our findings show that the inequality patterns (rather than levels) of emissions are quite robust and pronounced.

Our analysis reveals that, in the context of a limited remaining global carbon budget compatible with 1.5°C (or 2°C) global warming, the question of inequality and development becomes even more complicated. It is no longer just a question of poor countries catching up with the rich, but one of scaling down the consumption and emissions of rich classes in all countries.

The empirical results presented in this paper complement the picture related to the massively unequal use of the global carbon budget in the past two centuries (Ge *et al.*, 2014; Pollin, 2019: 317). Studies focusing on actual and historical emissions which take a hypothetical equal per capita distribution as a benchmark find that countries such as the US are climate debtors, while those such as China and India are climate creditors (Matthews, 2016). This historical and current inequality in carbon emissions, which implies that the fruits of industrialization have been reaped very unequally and resulted in huge contemporary disparities in standard of living, speaks against any one-size-fits-all response.

Conceptual and policy-related discussions have to take into consideration that target-oriented growth and degrowth are desperately required on a global scale so as to undertake a massive, rapid and all-embracing transformation to decarbonize the global economy. Throughout this process, the poor should not be condemned to underdevelopment by an ecological austerity in response to a crisis they are barely responsible for, and the planetary boundaries must not be overstepped more than they already are. The question is if the current economic and institutional structures, which have failed for decades to bring about any remarkable change, will be capable of nurturing such a massive transformation.

Supplementary material. The supplementary material for this article can be found at <https://doi.org/10.1017/S1355770X21000036>.

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Appendix A. Method

For the case of the US, we use the 2017 Make and Use summary tables provided by the Bureau of Economic Analysis in order to obtain the symmetric (industry by industry) transactions matrix. Before doing so, however, we introduce two intermediate steps to make the CO₂-related part of the calculation more accurate.

First, following Fremstad and Paul (2019), we decompose the empirical category of ‘Utilities’ that we find in the summary tables into three subcategories: ‘Electric’, ‘Natural

Table A1. Total (direct and indirect) carbon content associated with \$1’s worth of selected US industries’ output (in kgCO₂/\$)

Industry	Carbon intensity in kgCO ₂ /\$
Oil and gas extraction	11.60514
Coal mining	44.65687
Petroleum and coal products	6.589785
Food and beverage and tobacco products	0.290839
Apparel and leather and allied products	0.129878
Chemical products	0.493485
Utilities	1.224968
All transportation	0.434967
Warehousing and storage	0.188966
Educational services	0.108302
Ambulatory health care services	0.080598
Hospitals	0.115989
Nursing and residential care facilities	0.114903
Social assistance	0.107927

Source: Authors’ own calculation.

Table A2. Total (direct and indirect) carbon content associated with \$1's worth of selected industries in China, India, Germany and the UK (in kgCO₂/\$)

Industry	China	India	Germany	UK
Energy	13.049	13.271	9.733	6.819
Food products, beverages and tobacco	0.659	0.650	0.317	0.267
Textiles, wearing apparel, leather and related products	1.007	1.425	0.429	0.202
Chemicals and pharmaceutical products	2.509	3.122	0.940	0.462
Manufacture of basic metals	3.177	3.924	1.031	0.683
Electricity, gas, water supply, sewerage, waste and remediation services	4.788	4.101	1.311	1.514
Transportation and storage	2.409	3.612	0.795	0.319
Telecommunications	0.417	1.246	0.151	0.127
Education	0.329	0.464	0.094	0.068
Human health and social work	0.823	0.955	0.102	0.094

Source: Authors' own calculation.

Gas', and 'Water and Sewage' utilities. To do so, we calculate the weight of each subcategory based on the detailed Make and Use tables from 2012 (a requirement, as the detailed tables for 2017 are not available yet) and use these weights to split up both the column and row vector of 'Utilities' in the 2017 tables. Similarly, we split the subcategory of 'Coal Mining' from the aggregate category of 'Mining, except Oil and Gas' by using its weight obtained from the 2012 detail tables.

Second, we merge the five government industries into an industry called 'Government', and the seven separate transportation industries into a single industry called 'Transportation'.¹¹ These two intermediate steps are helpful when mapping the carbon content for IO categories into carbon content of consumer expenditure categories by using the BEA Bridge Matrix, a step described in the main body of the text.

Appendix B

We obtained the data for household consumption expenditures by income decile and average household size from the following sources:

- *National Bureau of Statistics of China* for data on Chinese household consumption expenditures by income quintiles (2012), and urban and rural average household size;
- *Statistisches Bundesamt* for German household consumption expenditures by income deciles (2013) and average household size;

¹¹The five government industries are 'Federal General Government (defense)', 'Federal General Government (nondefense)', 'Federal Government Enterprises', 'State and Local General Government', and 'State and Local Government Enterprises'. The seven transportation industries are 'Air Transportation', 'Rail Transportation', 'Water Transportation', 'Truck Transportation', 'Transit and Ground Passenger Transportation', 'Pipeline Transportation', 'Other Transportation and Support Activities'.

- *Level and Pattern of Consumption Expenditure 2011–12* published by the Indian Ministry of Statistics & Programme Implementation (MOSPI). Table 6B-R and 6B-U for rural and urban household consumption expenditures (July 2011 – June 2012), respectively. Table 1B for rural and urban household size;
- *The National Archives of the Office for National Statistics* for the UK, table A4 for household expenditure by gross income deciles (2012) and average number of persons per household.

Expenditures in national currencies are converted to US dollars at the rates provided by the OECD.

Appendix C

The flat distribution of per capita emissions in the UK primarily results from the relative flatness of household consumption expenditures, adjusted for weighted average number of persons per household as reported by the ONS. Figure A1, available in the online appendix, plots per capita expenditures in different consumption categories across groups of income. The pattern closely resembles the distribution of emissions reported in table 3 with the following characteristics:

- Per capita consumption expenditures of the poorest decile seem to be higher than that of the second decile.
- This distribution is relatively flat until the 8th decile, and there is a kink in the expenditures of the 7th decile.
- The expenditures of the top two deciles are clearly higher compared to the rest.

Table C1. Summary statistics for selected countries

	US	UK	Germany	India	China
Population (millions)	325	63.7	80.6	1,266	1,351
Per capita income ^a (thousands)	59	41.7	47.2	1.5	5.9
Territorial CO ₂ emissions (million tons)	4,761	461	764	1,804	8,865
Per capita CO ₂ emissions (tons)	14.6	7.2	9.5	1.4	6.5

^aGNI per capita in current US dollars, Atlas method (World Bank).

Source: World Bank Open Data and International Energy Agency database. All figures relate to the year that the calculations were made for each country.

Cite this article: Chen Y, Işıkara G (2022). Beyond the nation-state narrative: an empirical inquiry into the cross-country and cross-income-group carbon consumption patterns. *Environment and Development Economics* 27, 67–85. <https://doi.org/10.1017/S1355770X21000036>