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Abstract

The relationship between income inequality and carbon emissions remains ambiguous in both theory and evidence. A decliningâ€“marginalâ€“propensity-to-emit (MPE) framework predicts a short-term trade-off between reducing inequality and limiting emissions, whereas political-economy perspectives suggest that higher structural inequality increases carbon output. Empirical studies often report negative associations, but these frequently conflate within-country dynamics with cross-country differences. We argue that distinguishing these levels can reconcile the evidence: the MPE mechanism primarily operates within countries over time, while political-economy channels shape structural, cross-country variation. Using data from the World Inequality Database, we conduct two complementary analyses. First, simulations on a global sample of 162 countries from 2019 test whether shifts in national income distributions alter carbon emissions at constant GDP, isolating the within-country MPE effect. Second, cross-sectional panel analyses examine whether households at equivalent income levels generate more emissions in more unequal societies. Our results show a modest within-country trade-off â€” most pronounced in low- and middle-income countries and when the income share of the middle class rises â€” alongside a cross-country pattern in which higher inequality is systematically associated with higher emissions across the income distribution. These findings highlight the coexistence of opposing dynamics and underscore that climate policy should balance short-term trade-offs against the structural benefits of *reducing inequality.*

Keyword: Inequality, Carbon emissions, Climate change, Marginal propensity to emit, Redistribution

JEL Cassification: D31, Q53, Q54, Q56

The Climate Cost of Inequality: Trade-offs and Structural Effects

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The relationship between income inequality and carbon emissions remains ambiguous in both theory and evidence. A declining–marginal–propensity-to-emit (MPE) framework predicts a short-term trade-off between reducing inequality and limiting emissions, whereas political-economy perspectives suggest that higher structural inequality increases carbon output. Empirical studies often report negative associations, but these frequently conflate within-country dynamics with cross-country differences. We argue that distinguishing these levels can reconcile the evidence: the MPE mechanism primarily operates within countries over time, while political-economy channels shape structural, cross-country variation. Using data from the World Inequality Database, we conduct two complementary analyses. First, simulations on a global sample of 162 countries from 2019 test whether shifts in national income distributions alter carbon emissions at constant GDP, isolating the within-country MPE effect. Second, cross-sectional panel analyses examine whether households at equivalent income levels generate more emissions in more unequal societies. Our results show a modest within-country trade-off — most pronounced in low- and middle-income countries and when the income share of the middle class rises — alongside a cross-country pattern in which higher inequality is systematically associated with higher emissions across the income distribution. These findings highlight the coexistence of opposing dynamics and underscore that climate policy should balance short-term trade-offs against the structural benefits of reducing inequality.

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1. Introduction

Climate change and economic inequality are defining challenges of our time, and policy makers increasingly seek solutions that address both. The empirical literature often implies a trade-off: numerous studies find that lower income inequality comes along with higher carbon emissions (e.g. Grunewald et al., 2017; Kopp & Nabernegg, 2022; Rojas-Vallejos & Lastuka, 2020; Sager, 2019; Scherer et al., 2018). This finding stands in contrast to numerous theoretical arguments predicting that inequality should drive emissions upward and downward through different channels. Understanding why the evidence diverges from theory is crucial for crafting policies that advance both sustainability goals.

To explain this apparent contradiction, we propose a distinction between mechanisms that operate within countries over time and those that act between countries. Our central claim is that the marginal-propensity-to-emit argument (Hailemariam et al., 2020; Holtz-Eakin & Selden, 1995; Ravallion, 2000) — the core rationale for a trade-off — predicts that reducing inequality will raise aggregate emissions inside a given country as income is redistributed, but has no obvious cross-country implications. In contrast, political-economy channels (Boyce, 1994; Vona & Patriarca, 2011) imply that more unequal societies differ systematically in their overall emissions from more equal ones, even absent short-term redistribution. Taken together, these perspectives suggest a dual pattern: a negative inequality–emissions relationship within countries over time, and a positive one across countries in cross-section.

We evaluate this argument with two complementary empirical exercises, drawing on data on income distribution and carbon emissions from the World Inequality Database (WID) for 2000–2019. First, to assess within-country dynamics, we examine the core mechanism behind the hypothesized trade-off: the declining marginal propensity to emit across the income distribution. Using 2019 data for a global sample, we run simulation-based counterfactuals to see whether reducing inequality — while holding GDP constant — could plausibly raise aggregate emissions, as the theory predicts. Second, to capture cross-country variation, we analyze the carbon intensity of income across nations, asking whether the emissions associated with a given personal income level differ systematically with national inequality.

Our within-country analysis shows that a short-term trade-off between inequality reduction and carbon mitigation is theoretically plausible but far from universal. The estimated marginal emissions curves generally exhibit a declining marginal propensity to emit at higher incomes, consistent with the trade-off mechanism. Yet notable deviations emerge, particularly in upper-middle- and high-income countries, where the curve flattens or even rises in a number of countries. The distributional details matter: changes in aggregate emissions depend on who gains income, not just on overall inequality measures. In most cases, increases in national emissions coincide with rising income shares for the middle classes, underscoring how single-score inequality indices can mask the underlying shifts that drive emissions outcomes.

Our second analysis, comparing the carbon intensity of income across nations, points to a different pattern. Holding individual income levels constant, people living in more unequal countries tend to account for higher per-capita emissions. In other words, a given income converts into more carbon emissions in unequal societies. This suggests that national inequality shapes the broader energy mix, policies, and production structure — consistent with political-economy channels — rather than merely reflecting the spending patterns of individuals. The result complements the within-country findings by revealing a positive inequality–emissions association in the cross-section.

This study contributes to three main strands of research. First, it engages the long-standing theoretical and empirical literature on the inequality–emissions nexus, which has largely relied on longitudinal panel data and typically finds that higher inequality coincides with lower carbon emissions (e.g. Demir et al., 2019; Huang & Duan, 2020; Kopp & Nabernegg, 2022; Ravallion, 2000; Wan et al., 2022), supporting the idea of an "inequality–pollution dilemma" (Sager, 2019). That body of work does not always distinguish between within-country and between-country dynamics. Negative coefficients are often interpreted as evidence for the marginal-propensity-to-emit mechanism and against political-economy explanations. Our results offer a different reading: multiple mechanisms can operate simultaneously but in opposing directions. The predominance of within-country variation in many econometric designs likely explains why earlier studies report negative associations, which were then sometimes generalized — incorrectly — to cross-country conclusions. It should be noted that a number of within-country studies have also identified a positive correlation between inequality and carbon emissions (e.g. Baek & Gweisah, 2013; Hou et al., 2024; Jorgenson et al., 2025; Wang & Qu, 2024), calling into question the universal validity of the "inequality-pollution dilemma" even in within-country perspective.

Second, our study connects to the recent literature examining the marginal-propensity-to-emit (MPE) channel. In a comparable analysis to our within-country exercise (section 3), Sager (2019) simulates the effects of income redistribution in the United States in 2009, finding that reducing inequality to Swedish levels would raise carbon emissions by 1.5%, while full equalization of incomes would increase emissions by 2.3%. Similar patterns emerge in the simulation studies of Rao and Min (2018) and Scherer et al. (2018). Rao and Min (2018), who simulate a reduction in within-country inequality from a Gini coefficient of 0.55 to 0.30 for a hypothetical country, estimate that this reduction in equality would result in an 8% increase in emissions. Scherer et al. (2018) simulate environmental effects of inequality reductions in a global sample of 166 countries for the year 2010. Specifically, they reduce the Gini coefficient to 0.3, regardless of initial levels of inequality, and predict an average increase in carbon footprints of 0.8%. Millward-Hopkins and Oswald (2021) study the effect of expenditure inequality on emissions and report no significant effect. Our work extends this line of research by applying the MPE framework to a global sample of countries, using country-specific reductions and increases in inequality and investigating specifically the role of income shares held by various groups along the distribution. This allows for a broader empirical assessment of the channel's relevance across different national contexts.

Third, our study contributes to research focusing on cross-country variation in the inequality–carbon emissions relationship. Prior studies offer mixed evidence: Baloch et al. (2020) analyze 40 Sub-Saharan countries (2000–2016) and find that higher inequality is associated with higher emissions, and Khan et al. (2022) report a similar pattern for 18 Asian countries. In contrast, earlier work by Heerink et al. (2001) shows that, across 64 countries in 1985, higher Gini coefficients correlate with lower emissions, and Hübler (2017) reaches a similar conclusion using quantile regressions on a pooled panel of 149 countries (1985–2012). Our paper advances this strand of literature in several ways: we use a Mundlak decomposition to clearly isolate between-country effects, analyze a global sample, employ multiple inequality measures beyond the Gini (including the Palma ratio and income shares), and introduce new, relevant controls — tropical nights, thermal stress, and the share of renewable energy in the electricity mix — that have been largely omitted in previous studies (with only a few exceptions; Bai et al. (2020) and Coşkun (2025) include renewable energy). These improvements allow for a more precise assessment of how structural differences across countries shape the inequality–emissions nexus.

Taken together, our study makes two overarching contributions. First, it connects the different strands of the literature by situating within-country and between-country dynamics in perspective. We show that while a short-term trade-off between inequality reduction and climate protection may exist — particularly in low- and lower-middle-income countries — it occurs against a structural backdrop in which higher inequality is generally associated with greater ecological damage. Evaluating short-term trade-offs therefore requires consideration of these longer-term, structural benefits of lower inequality. Second, our work demonstrates the importance of moving beyond the Gini coefficient. Many prior studies rely exclusively on the Gini, potentially obscuring relevant distributional dynamics (see also Hailemariam et al., 2020; Jorgenson et al., 2025). In our simulations, we find that changes in the income share of the middle classes are especially consequential for trade-off dynamics, rather that increases or decreases in the Gini coefficient *per se*.

The remainder of the paper is structured as follows. Section 2 summarizes theoretical perspectives and proposes a distinction between theoretical mechanisms that apply to within-country versus between-country levels. Section 3 simulates the carbon effects of inequality dynamics within countries, before section 4 investigates the relationship between inequality and average emissions across countries. Section 5 concludes.

2. Theory

The literature identifies a range of theoretical links between economic inequality and carbon emissions. Some arguments predict a positive relationship, whereas others suggest a negative one. Importantly, these theories differ in the type of variation they address: as we propose in this section, some focus on within-country changes over time, while others emphasize cross-country comparisons. In the following, we review these contributions with an eye toward this distinction, highlighting how different mechanisms operate at different levels and over different time horizons.

We begin with theoretical perspectives predicting a positive relationship between income inequality and carbon emissions. A long-standing literature has identified several such mechanisms, often summarized as political economy channels. For instance, public policy solutions to ecological problems, are more difficult to implement in highly unequal societies. Wealthier groups may resist these initiatives because they benefit from carbon-intensive production and consumption while being better able to shield themselves from the negative consequences of rising emissions and climate change (Boyce, 1994; Leach et al., 2018; Magnani, 2000). Moreover, in unequal societies, economic and social tensions may dominate the policy agenda, leaving climate protection a lower priority (Franzen & Vogl, 2013). Political fragmentation and reduced cooperation between actors (Borghesi, 2000), along with generally weaker governance (Kyriacou, 2019), further reduce the likelihood of ambitious climate policies and the effective enforcement of environmental regulations. This weaker environmental regulation can increase the carbon intensity of otherwise similar products and services — for example, lax enforcement of exhaust gas limits leads to higher emissions per vehicle. Moreover, the development and diffusion of new environmentally friendly technologies is more arduous in unequal societies. Firstly, the development is constrained by more concentrated firm ownership, and secondly, the diffusion is impeded by a lack of consumers with the financial means to procure these technologies (Vona & Patriarca, 2011). Another aspect is the provision and quality of public goods. More unequal countries tend to provide fewer or lower-quality public goods (Moene & Wallerstein, 2001; Osberg et al., 2004), such as public transport, which typically has lower carbon intensity than private alternatives (Borken-Kleefeld et al., 2010). When these goods are unavailable, individuals must rely on more carbon-intensive options. Together, these dynamics imply that consumers in more unequal countries often generate higher carbon emissions even at the same income level, reinforcing the link between structural inequality and aggregate environmental damage.

We argue that this type of mechanism primarily reflects structural inequalities. It is more relevant for explaining cross-country differences in income distribution and carbon emissions than for short-term within-country dynamics. Inequality within a single country typically evolves gradually, making it unlikely that small, incremental shifts in the distribution would generate large political economy effects. Instead, it is the long-term distributional structure that shapes industrial configurations, networks, and political dynamics, often with path-dependent effects. For example, in Latin America, the region's colonial history and the concentration of economic power have been cited as reasons why firm owners historically had little incentive to invest in new technologies (Hirschman, 1996; Karl, 2003; Sokoloff & Engerman, 2000).

From a consumption perspective, it has been proposed that higher inequality fosters greater consumerism and status competition through positional consumption (Bertrand & Morse, 2016; Duesenberry, 1949; Frank et al., 2014; Veblen, 1899), often accompanied by longer working hours that enable individuals to maintain higher consumption levels (Behringer et al., 2024; Bowles & Park, 2005). These dynamics increase the consumption of carbon-intensive goods and services (Jorgenson et al., 2017), thereby raising overall carbon emissions (Knight et al., 2013). Unlike political economy mechanisms, this argument is applicable to both within-country dynamics and cross-country comparisons (Behringer & Van Treeck, 2022; Pybus et al., 2022). Within countries, rising inequality can trigger more status-driven consumption, boosting aggregate emissions. Across countries, it implies that societies with higher inequality tend to have greater overall emissions even at comparable levels of economic activity

On the other hand, some arguments suggest that changes in inequality within a country can affect emissions in the opposite direction. The most prominent example is the marginal propensity to emit (MPE) — the additional emissions generated by an extra unit of income across the income distribution. While it is well documented that individuals at the top of the income distribution account for larger absolute shares of CO_2 emissions (Chancel, 2022), their relative contribution to ecological damage may decline at higher income levels due to decreasing marginal propensities to consume and emit (Berthe & Elie, 2015; Ravallion, 2000). Consequently, transferring income from richer to poorer individuals could, in some cases, increase emissions per unit of income. Relatedly, it has been proposed that wealthier individuals often exhibit higher climate awareness — partly due to greater education — and may engage in more environmentally friendly behaviors. As a result, their carbon intensity of consumption may be lower, meaning that shifting a larger share of income toward the rich could reduce aggregate emissions (Heerink et al., 2001; Scruggs, 1998). We conjecture that these mechanisms are strictly within-country: they do not speak to the overall level of carbon emissions but instead describe dynamic changes. In other words, they focus on the shape of a country's MPE curve and the carbon intensity of consumption across the distribution, while leaving the absolute emissions level undetermined.

Overall, we observe that arguments predicting a negative relationship between inequality and carbon emissions tend to focus on within-country dynamics, whereas those predicting a positive relationship are more relevant for cross-country comparisons (see Table 1). This distinction helps reconcile apparently conflicting empirical results: increases in inequality within a country can often be interpreted through the lens of MPE-type mechanisms, while cross-country comparisons are primarily shaped by the level effects of aggregate emissions.

Table 1: Distinction of within-country and between-country arguments

	Inequality → Higher Emissions	**Inequality → Lower Emissions**
Within	• Positional consumption	• Marginal propensity to emit • Climate consciousness of the rich
Between	• Positional consumption • Political power of elites • Quality of environmental governance • Diffusion of greener technologies • Priorities of public discourse	

Own elaboration. We propose that some mechanisms in the link between income distribution and carbon emissions play out in within-country-over-time comparison, whereas others play out in cross-country comparison.

Building on this theoretical framework, we focus on two empirical questions. First, we assess whether MPE-type mechanisms plausibly generate a negative link between inequality and carbon emissions within countries — a channel that has been suggested in prior studies but rarely tested in isolation and in a global setting. Second, we examine how the carbon intensity of income at a given personal income level varies with a country's overall inequality, which may reflect greater status competition and more carbon-intensive consumption in more unequal societies. If our proposed distinction of opposing within-country and between-country dynamics is correct, we should find evidence of the MPE mechanism in within-country comparison over time and a positive association between inequality and carbon emissions in cross-country comparison.

3. Quantifying the trade-off within countries: net aggregate emission effects of shifts in the income distribution

3.1. Data

All data used in this section are drawn from the World Inequality Database (WID). On the income side, the WID provides detailed information on the distribution of various income categories. For this analysis, we use pre-tax income, which allows for broader coverage across both high- and lower-income countries. Using post-tax income would exclude many low- and lower-middle-income countries, potentially introducing sample bias. Pre-tax income is defined as the sum of all personal income flows from labor and capital accruing to owners of these production factors, before taxes and transfers, but including pensions. The unit of analysis is the equal-split individual aged 20 and above.

On the environmental side, the WID provides information on the personal carbon footprint by percentile of the emissions distribution (Chancel, 2022). These estimates are based on country-level greenhouse gas emissions across the household, investment, and government sectors. Household incomes are linked to emissions from consumption using country-specific, constant income-emissions elasticities. Where country-specific estimates are unavailable, investment-related emissions rely on global elasticities, while government emissions are allocated on a per-capita basis. In this framework, emissions increase with income by construction, so percentiles of the income distribution align with percentiles of the emissions distribution, enabling a clear analysis of the association between income and carbon emissions.

Our simulation exercise is data-driven and relies critically on the quality of the income-emissions data and the patterns they reflect. As widely discussed in the literature, time series of income distribution can be constructed in multiple ways, and they must address the so-called "missing rich" problem (Lustig, 2020). A distinctive feature of the WID is its use of Distributional National Accounts (DINA), which integrate household surveys, administrative tax records, and national accounts to construct harmonized, consistent, and internationally comparable income time series (Blanchet et al., 2024; Villanueva et al., 2025). Inequality measures differ depending on the underlying data, so results must be interpreted with caution (Lustig & Vigorito, 2025). The WID provides the only source of percentile-level income data for a global panel, which is essential for the within-country simulations in section 3 and the design of our cross-country regression in section 4.

Constructing time series of the carbon footprint is similarly challenging. Linking emissions to income or consumption is a relatively recent endeavor, and various approaches have been proposed, each with strengths and limitations. A key advantage of the data used here (Chancel, 2022) is that they incorporate emissions not only from household consumption but also from investments and government activity. A limitation is the reliance on constant income-emissions elasticities. Survey data typically miss the richest individuals, so detailed information about their consumption-based carbon intensity is lacking. As a result, the income-emissions elasticity may increase at the top of the distribution, as suggested by some studies (Barros & Wilk, 2021; Oswald et al., 2023; Otto et al., 2019). If this is the case, our analysis could overestimate the magnitude of trade-offs between redistribution and climate protection.

For the simulation exercises in this section, we use data from 2019 covering 162 countries, of which 25 are low-income, 42 lower-middle-income, 43 upper-middle-income, and 52 high-income countries.

3.2. Empirical strategy: counterfactual income simulations

According to the MPE argument, redistributing income from richer to poorer households should increase carbon emissions. Empirically, testing this mechanism in a cross-country setting is challenging because few countries have the same average economic output but different income distributions, with comparable carbon emissions at each income level. Figure 1 illustrates this using data from the WID for Norway, Saudi Arabia, and the United States — three countries with nearly identical per-capita incomes in 2019, but distinct income distributions. The distance between mean and median income (dashed and solid vertical lines, respectively) is much smaller in Norway than in the US, and even smaller compared to Saudi Arabia, reflecting higher inequality in the latter two countries. The y-axis shows the marginal propensity to emit (MPE), calculated as the derivative of personal greenhouse gas emissions per percentile of the income distribution with respect to the income level of the respective decile. The MPE curves for Saudi Arabia and the US are broadly similar in shape and roughly comparable in level, despite some variation. By contrast, Norway's curve differs not only in shape but also in overall level, which is lower. Comparing marginal propensities or aggregate net emissions across countries requires assuming that MPE curves are on the same scale. Since this is empirically not the case, it is difficult to separate level effects — which we analyze in section 4—from effects arising purely from differences in income distributions.

Even when comparing within the same country over time, isolating the impact of heterogeneous MPEs across the income distribution is challenging. Changes in the economic distribution are typically accompanied by economic growth or decline and other concurrent dynamics, making it difficult to observe pure shifts in the distribution of the same aggregate income. In this analysis, we focus specifically on the effects of distributional patterns while holding aggregate income constant, abstracting from overall income growth.

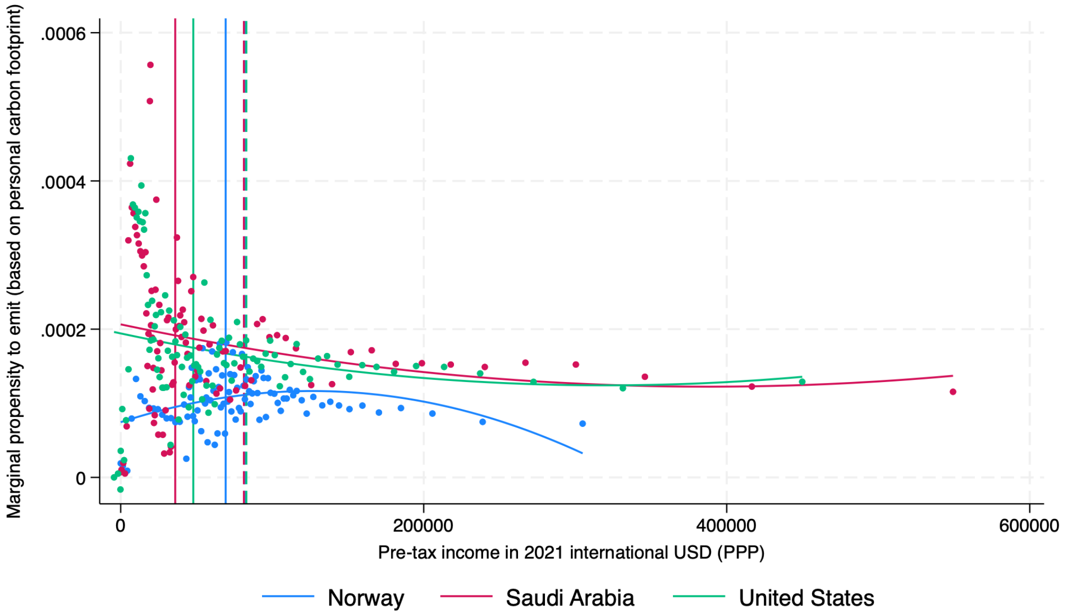
We therefore use simulations to investigate how each country's aggregate carbon footprint responds when average per-capita income is held constant, but the income distribution is varied in the following ways (see table 2).

Table 2: Simulation scenarios: Gini changes and income-group shifts

#	Change in Gini coefficient	Income groups benefiting
1	**More equal** (Gini −5 points)	Middle gains; bottom and top lose
2		Bottom and top gain; middle loses
3	**More unequal** (Gini +5 points)	Middle gains; bottom and top lose
4		Bottom and top gain; middle loses
5	**Same Gini**	Middle gains; bottom and top lose
6		Bottom and top gain; middle loses

We simulate income distributions that are approximately five Gini points more equal or more unequal than the observed distribution. To account for the fact that a given change in the

Figure 1: Marginal propensities to emit: Norway, Saudi Arabia and the United States of America (percentiles 1 to 99) (2019)



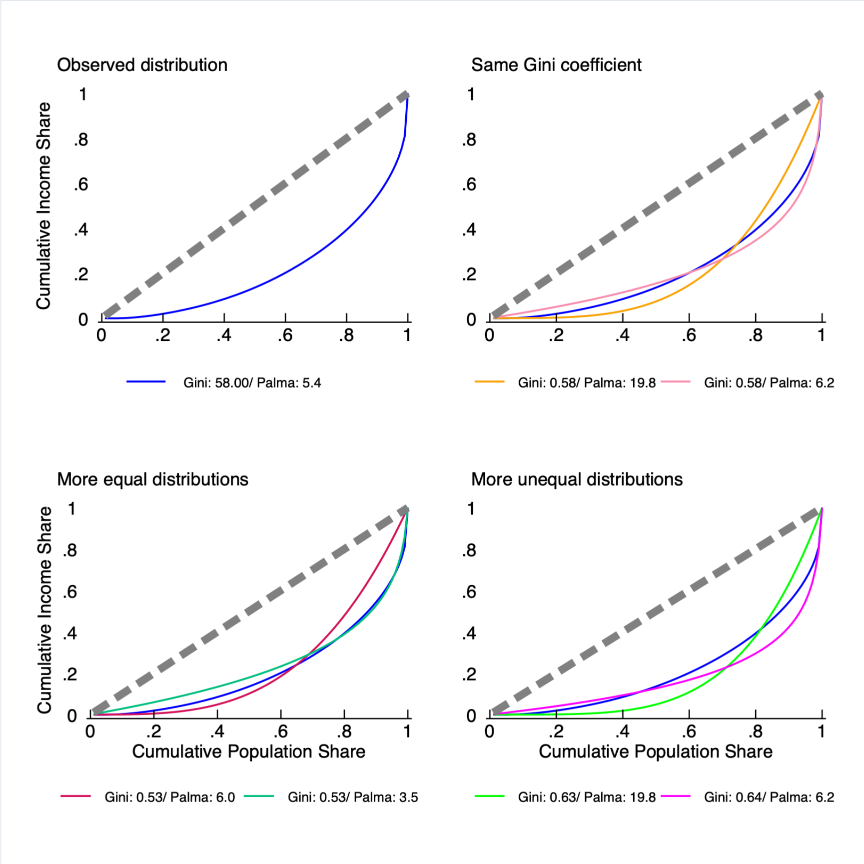
Notes: Own Figure. Data: World Inequality Database (WID). Vertical solid lines show median income, dashed lines show mean income. Figure comprises deciles 1 to 99 (top 1% excluded to improve visibility along the rest of the distribution).

Gini can occur in multiple ways, we create two variants for each: one in which the middle part of the distribution gains, and another in which the bottom and top gain. In addition, we generate two scenarios that maintain the observed Gini, but reshuffle income shares so that either the middle part or the bottom and top earn larger portions. The exact parts of the distribution that gain or lose, as well as the magnitude of gains and losses, vary across countries; for instance, the "middle" does not necessarily correspond to the commonly used middle 40% (percentiles 50–90). Figure 2 illustrates all simulated scenarios via Lorenz curves compared with the observed distribution.

It should be noted that not all shifts strictly follow the descriptive pattern of middle-class gains (or losses) versus bottom and top losses (or gains). To construct income distributions that achieve a given Gini coefficient while holding per-capita GDP constant, it is often necessary — depending on the country's original distribution — to adjust the incomes of specific percentiles in ways that run counter to the general pattern. For example, in the more equal scenario where the bottom and top gain (panel b, green scenario in Figure 3), the richest percentile must actually lose, while percentiles 90–99 still gain. Similarly, in the more equal scenario where the middle class gains, some of the very lowest percentiles must also gain to ensure that both the Gini coefficient and GDP per capita remain at their target values. These adjustments usually concern only a few percentiles and therefore should not confound the overall patterns observed in the simulations.

These six scenarios collectively allow us to isolate the effects of distributional changes on carbon emissions while holding aggregate income constant. The first four scenarios manipulate overall inequality, whereas the final two examine redistribution patterns at a fixed level of

Figure 2: Lorenz curves of the simulated income distributions, United States 2019



inequality. Together, they enable a detailed assessment of the marginal-propensity-to-emit mechanism and the short-term trade-offs between redistribution and climate outcomes.

3.3. Predictions of carbon emissions for the simulated income distributions

Next, we investigate the implications of reshuffling the income distribution for aggregate carbon emissions. For the simulated income distributions, we cannot directly use the corresponding carbon footprints from our data. To analyze how changes in the income distribution affect carbon emissions, we assign a personal carbon footprint to each percentile's simulated income level. This is done using the following high-order polynomial, which estimates personal carbon footprints based on the observed distribution:

$$\text{footprint}_p = \beta_0 + \beta_1 \log(\text{pre-tax income}_p) + ... + \beta_6 \log(\text{pre-tax income}_p)^6 + \epsilon \qquad (1)$$

Here, p denotes the percentile of the income distribution. We use the coefficients from these estimations to predict carbon emission levels for the simulated pre-tax income levels. In doing so, we abstract from potential behavioral changes that could result from reshuffled income distributions; for instance, large increases in inequality could potentially boost status-driven consumption across the distribution, raising carbon emissions at given income levels. Following standard economic terminology, we refer to this setup — where only the income distribution varies while all else is held constant — as the short-term scenario. Figure A2 demonstrates that the estimated personal carbon footprints closely align with the income-emissions relationship observed in the World Inequality Database.

3.4. Aggregate net carbon effects under the simulated distributions

Figure 3 shows the absolute differences between observed and simulated personal carbon footprints across the income distribution, using the United States as an example.[1] Positive values indicate that a given percentile has higher carbon emissions in the simulated scenario compared to the observed scenario. The various panels shows the shifts under the three Gini scenarios. We note that these shifts in emissions are a purely mechanical consequence of the corresponding changes in the income distribution.

Ultimately, we are interested in the aggregate net effects of the various heterogeneous shifts illustrated in Figure 3 for all countries. Figure 4 presents these net effects in four panels, grouping countries by GDP per capita. In low-income countries (panel a), we generally observe that scenarios in which the middle of the income distribution gains produce higher aggregate net emissions, regardless of whether the Gini coefficient increases, decreases, or remains unchanged. Conversely, when the distribution becomes more unequal or the Gini remains unchanged while the middle share decreases, aggregate net emissions decline slightly. The scenario in which the Gini is reduced at the expense of the middle class produces a small increase in net emissions, showing that reduced inequality is associated with higher emissions not only when it is driven by the income share of the middle. Importantly, the changes resulting from a decreased middle share are very small. Overall, in low-income countries, the results support the existence of a trade-off between inequality reduction and climate protection, with this trade-off primarily linked to the income share of the middle class.

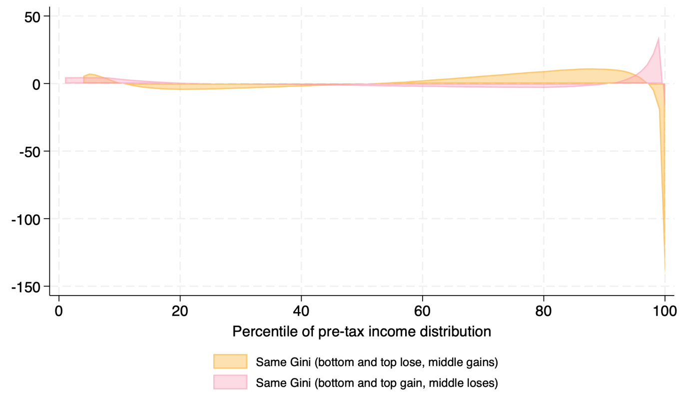
Patterns of aggregate net emissions in lower-middle-income countries closely resemble those observed in low-income countries (Figure 4, panel b). A few outliers appear in scenarios where the bottom and top gain, but otherwise the findings mirror those described above. In upper-middle-income countries, the number of outliers increases. Specifically, several countries show reduced net aggregate emissions in scenarios where the middle class gains. An interesting case is China: here, aggregate net emissions decrease when inequality is reduced at the expense of the bottom and top (top-left panel), but increase when inequality rises at the expense of the middle (bottom-middle panel). Recall that aggregate net changes are mechanical consequences of the income shifts along the distribution, which themselves translate into carbon effects according to the MPE curves. Figure 5(b) shows the estimated MPE curve for China. Contrary to the theoretically hypothesized declining MPE curve, we observe a U-shaped curve: emissions decline toward the middle of the distribution, but then increase again. Under such a pattern, it is plausible that aggregate emissions rise when top earners increase their income share, particularly at the expense of the middle class. This shape of the Chinese MPE curve is also found in a country case study by (Golley & Meng, 2012).

In high-income countries, we consistently observe that increasing the income share of the middle class—regardless of whether the Gini coefficient rises or falls — is associated with higher

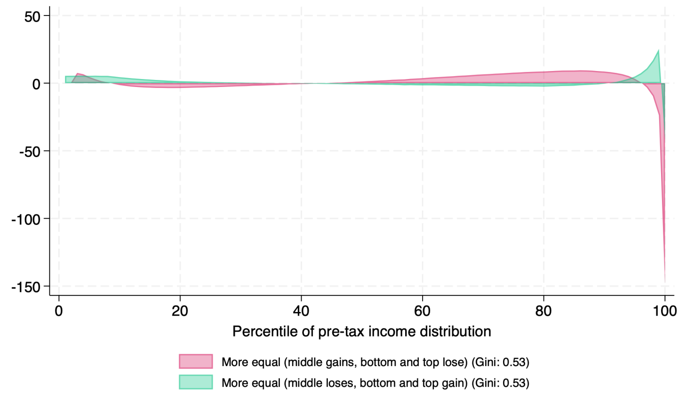
[1] Curves for all countries in the study are available through the replication package.

Figure 3: Comparison of net carbon footprints in the various simulated income distributions: United States, 2019

(a) Scenarios 1 and 2: Same GDP per capita and Gini coefficient, but reshuffled underlying distributions



(b) Scenarios 3 and 4: more equal distributions (- 5 Gini points)



(c) Scenarios 3 and 4: more unequal distributions (+ 5 Gini points)

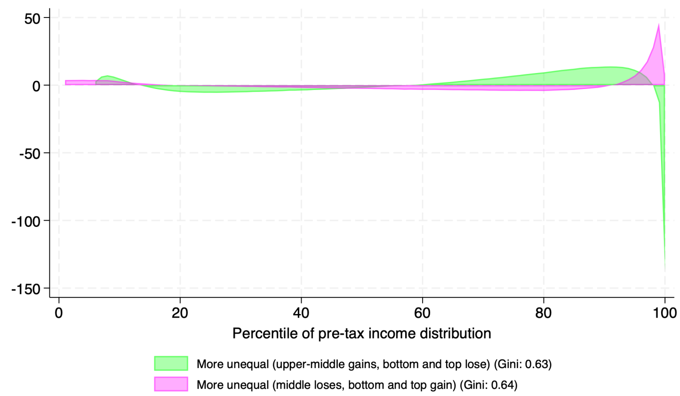
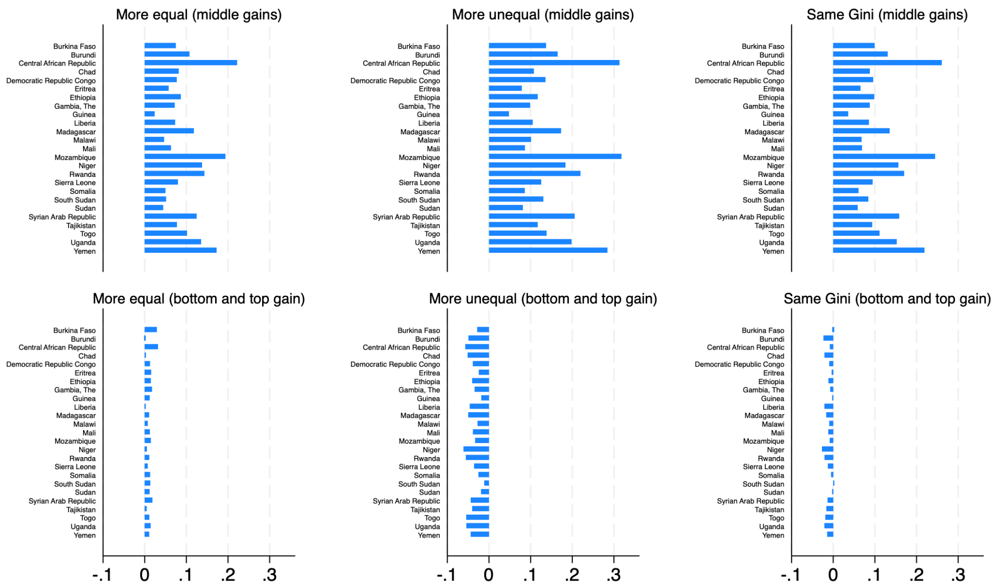


Figure 4: Net aggregate carbon effects in the simulated income distributions

(a) Low-income countries



(b) Lower-middle-income countries

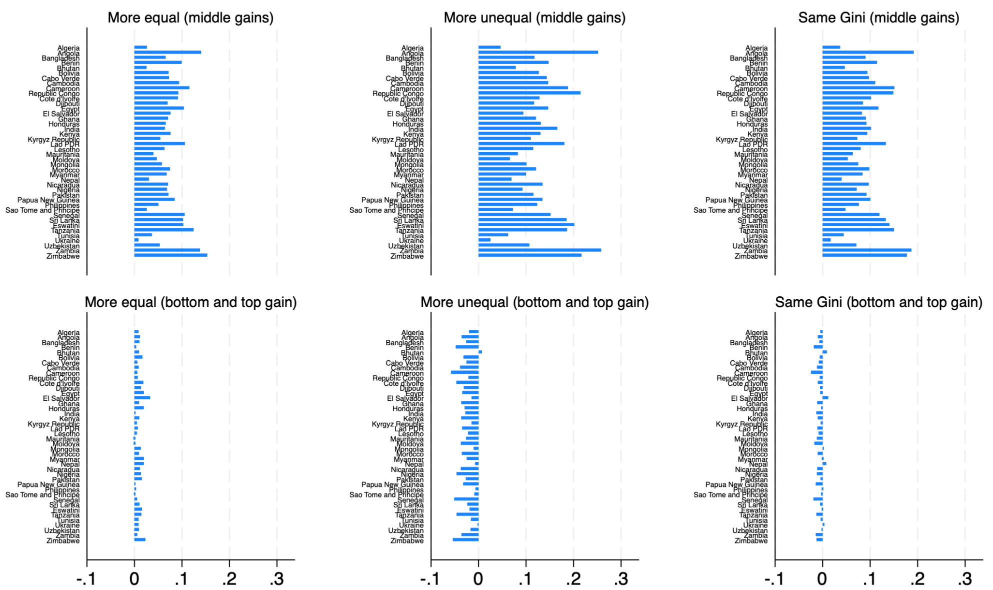
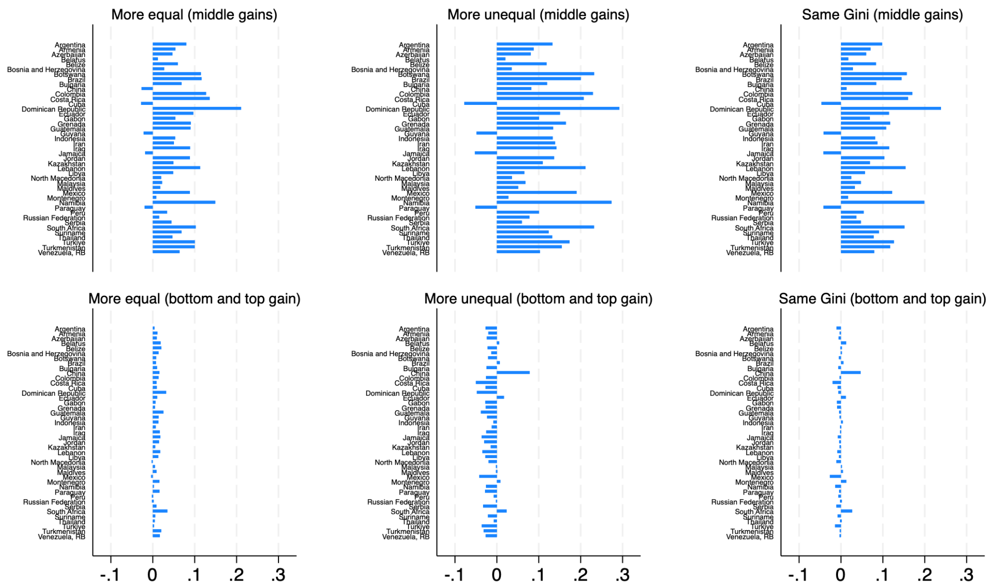


Figure 4: Net aggregate carbon effects in the simulated income distributions (continued)

(c) Upper-middle-income countries



(d) High-income countries

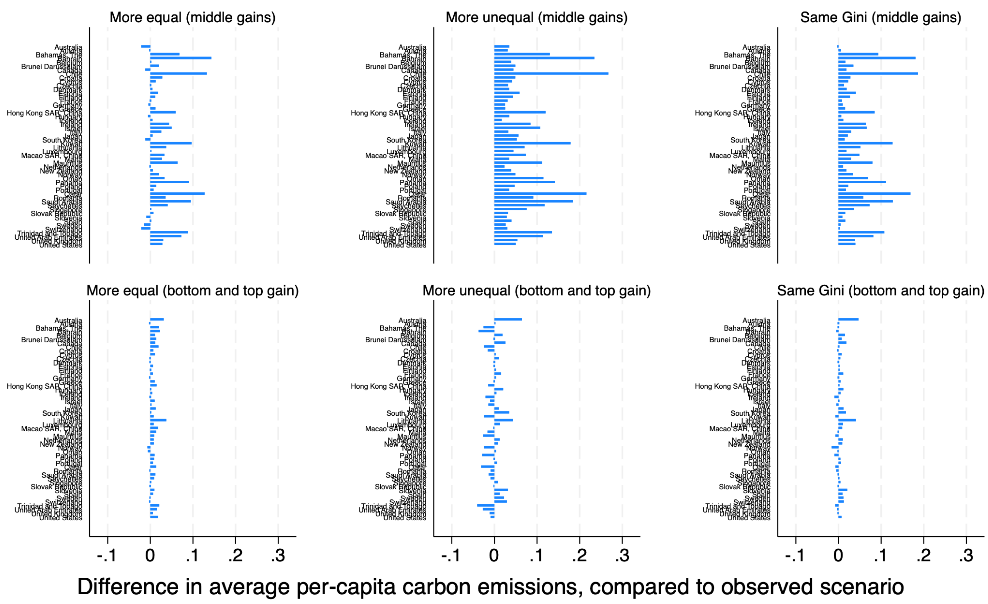
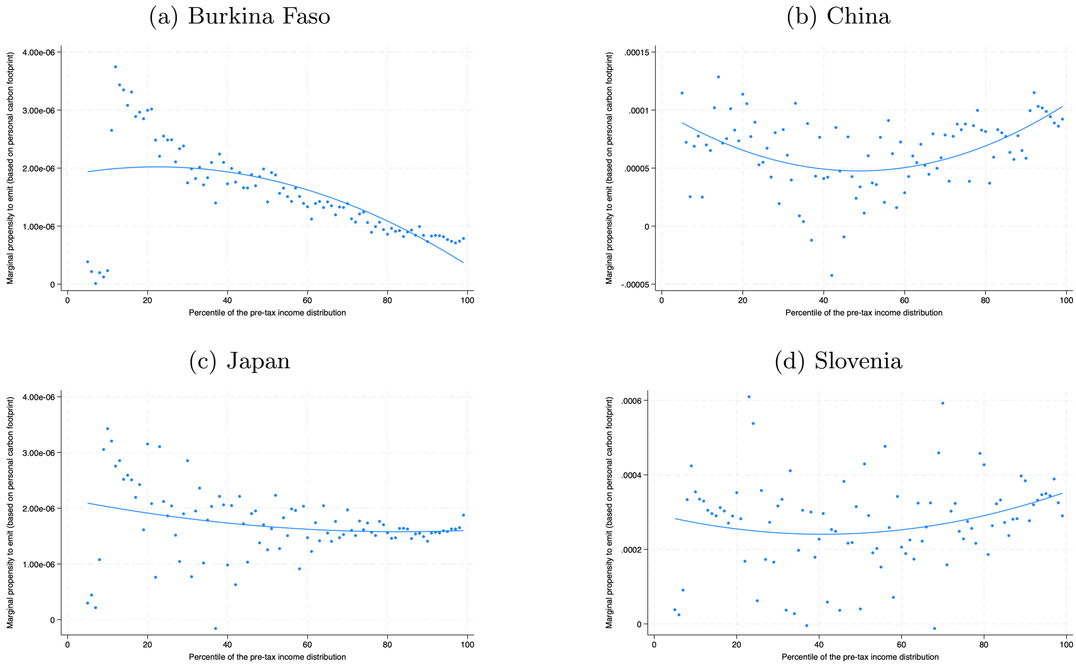


Figure 5: MPE curves of selected countries, 2019



net aggregate emissions. Magnitudes are generally larger in the more unequal scenarios (top-middle panel) compared to the more equal scenarios (top-left panel), suggesting that increases in the middle class's income share at the expense of the bottom (and thus raising the Gini) have stronger effects. In scenarios where the bottom and top gain, aggregate effects are more mixed. While the theoretically predicted declining MPE curve is generally observed in non-rich economies (e.g., Burkina Faso, panel a of Figure 5), MPE curves in high-income countries are highly heterogeneous. Many instances show marginal emissions increasing toward the top of the distribution; as in China, this is inter alia observed in Japan and Slovenia as well (panels c and d of Figure 5). The upward-facing slope at the top aligns with research on the carbon intensity of luxury consumption and consumption patterns of top earners (Barros & Wilk, 2021; Oswald et al., 2023; Otto et al., 2019). When marginal emissions rise at the top, this partially counteracts the trade-off between redistribution and climate protection. At the same time, the shape of the MPE curve for the rest of the distribution also matters: differences in the marginal emissions of the middle versus the top mean that redistribution from top to middle can have positive or negative aggregate effects on carbon emissions, depending on the specific country context.

Regarding the magnitude of the aggregate net effects, two points are noteworthy. First, cross-country comparisons should be made with caution. The percentile-level income shifts needed to achieve a five-point change in the Gini while holding per-capita income constant differ by country. Because we impose an absolute, rather than relative, Gini change, the implied relative degree of redistribution also depends on each country's initial inequality. Country-specific effect sizes are therefore not directly comparable. Second, the overall changes are small relative to observed per-capita carbon footprints. Figure 4 reports the simulated increase or decrease in the average personal footprint, and Figure A3 places these changes alongside baseline levels.

Table 3: Summary: net aggregate carbon increases and decreases under the various simulation scenarios, in % of observed per-capita carbon footprint

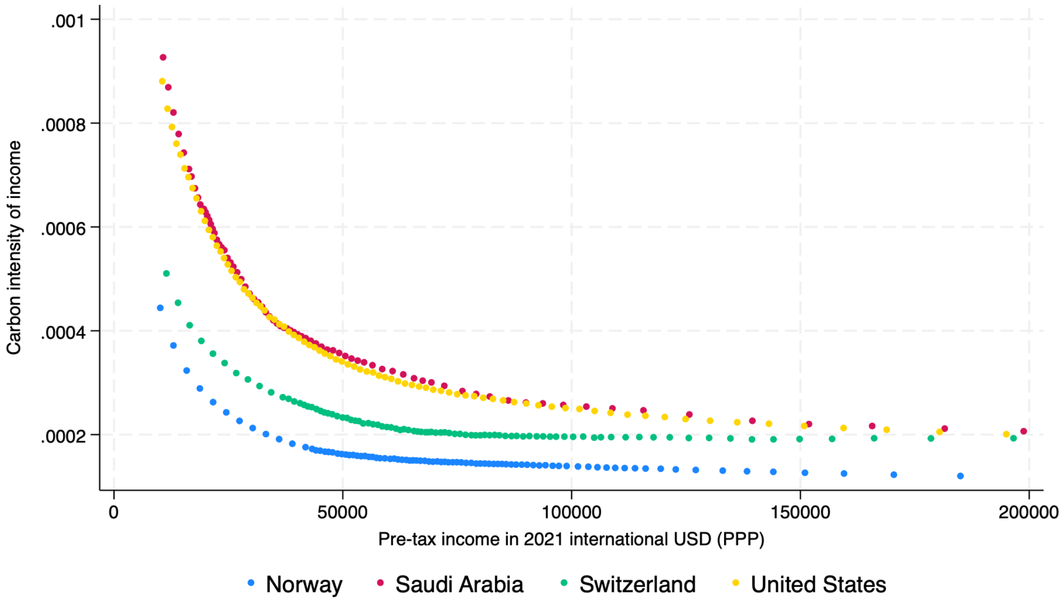
Scenario	Country group	Mean	Std. dev.	Min	Max	# obs.
More equal (middle gains)	Low	9.65	4.83	2.38	22.17	25
	Lower-middle	7.52	3.24	0.84	15.33	42
	Upper-middle	6.15	5.07	-2.8	21.07	43
	High	2.89	3.96	-2.14	14.32	52
	All	6.00	4.89	-2.8	22.17	162
More equal (middle loses)	Low	1.21	0.71	0.10	3.20	25
	Lower-middle	1.05	0.68	-0.01	3.31	42
	Upper-middle	1.14	0.81	-0.40	3.49	43
	High	0.84	0.89	-0.68	3.74	52
	All	1.03	0.80	-0.68	3.74	162
More unequal (middle gains)	Low	15.01	7.12	4.79	31.79	25
	Lower-middle	13.11	5.15	2.50	25.80	42
	Upper-middle	11.40	8.44	-7.77	29.24	43
	High	7.37	5.78	1.72	26.73	52
	All	11.11	7.22	-7.77	31.79	162
More unequal (middle loses)	Low	-3.92	1.32	-6.10	-1.13	25
	Lower-middle	-2.83	1.44	-5.79	0.70	42
	Upper-middle	-1.76	2.19	-5.02	7.82	43
	High	-0.07	2.10	-4.03	6.44	52
	All	-1.83	2.33	-6.10	7.82	162
Same Gini (middle gains)	Low	11.69	5.73	3.58	26.04	25
	Lower-middle	9.69	3.96	1.70	19.16	42
	Upper-middle	8.04	6.34	-4.66	23.88	43
	High	4.68	4.62	-0.28	18.64	52
	All	7.95	5.74	-4.66	26.04	162
Same Gini (middle loses)	Low	-1.22	0.77	-2.71	0.24	25
	Lower-middle	-0.72	0.74	-2.42	1.18	42
	Upper-middle	-0.23	1.17	-2.66	4.69	43
	High	0.44	1.11	-1.61	4.71	52
	All	-0.30	1.16	-2.71	4.71	162

The effects across income groups are generally modest, though they vary by scenario. It appears that increasing the share held by the middle group has a relatively stronger impact on emissions than making the distribution more or less equal. When the middle class gains (scenarios 1, 3, and 5 in Table 3), low-income countries show the largest average increases—around 10 to 15 percent—while high-income countries exhibit average increases between 2 and 8 percent. When the middle class loses (scenarios 2, 4, and 6 in Table 3), the global average change remains below 2 percent, with similarly low figures within individual income groups. These magnitudes are not directly comparable to earlier studies such as Rao and Min (2018) and Scherer et al. (2018), which simulated larger inequality reductions (for example, Gini drops from 0.55 to 0.30) and reported carbon-footprint increases of roughly 8 percent and 0.8 percent, respectively. Our simulations involve much smaller changes in inequality, yet the more equal scenario in which the middle of the distribution increases yields a similar effect to the former, with a 6 percent increase in carbon emissions. In contrast, the redistribution that bypasses the middle produces a 1 percent increase in carbon emissions that resembles the latter more closely.

4. Structural effects across countries: emission curves at varying levels of inequality

In the previous section, we examined how within-country shifts in income distribution could plausibly influence net aggregate carbon emissions. In this section, we turn to cross-country

Figure 6: Carbon intensity of income along the income distribution of countries with similar levels of GDP per capita



comparisons, asking whether living in a more unequal society is associated with higher personal carbon footprints. Specifically, we investigate whether two individuals with identical income (in PPP terms) have systematically different carbon footprints depending on whether they live in a high-inequality or low-inequality country.

Figure 6 motivates this analysis: it shows that countries differ in the overall level of emissions. The four countries have similar levels of GDP per capita and are thus comparable in terms of their level of economic development. The carbon intensity of income across the entire income distribution is lower in the more equal countries of Norway and Switzerland than in the more unequal countries of Saudi Arabia and the US. Such differences in the level of personal carbon footprints across countries are common. Of course, countries differ in many respects that may explain these variations: highly urbanized societies may have higher emissions, as may countries with larger industrial sectors. Geographical and climate differences can create varying energy needs for heating and cooling, while countries with higher shares of renewable energy may meet these needs at lower emissions. Beyond these factors, our analysis investigates whether economic inequality itself plays a systematic role in explaining cross-country differences in carbon emissions of income levels. In other words, we ask whether inequality has a structural effect on emissions.

4.1. Data

This section also relies primarily on data from the World Inequality Database (WID), introduced in Section 3.1. We use pre-tax income distribution percentiles to construct various inequality measures, which serve as the key explanatory variables, while the personal carbon footprint is the dependent variable. To ensure comparability of income levels across countries and over time, we convert local currencies into purchasing power parity (PPP) at 2021 prices. The dataset covers 174 countries, representing approximately 97% of global population and GDP (Chancel, 2022). Our analysis focuses on the period 2000–2019.

The regressions include a set of control variables (see the next subsection for the rationale behind their inclusion). GDP per capita (constant 2015 USD), the urbanization rate (percentage of the population living in urban areas), and the shares of agriculture, industry, and services value added (% of GDP) are drawn from the World Bank's World Development Indicators. Data on the share of renewable electricity production are taken from Ritchie et al. (2025), which combines information from Ember (2025) and the Energy Institute, covering solar, wind, hydropower, bioenergy, geothermal, wave, and tidal sources as a share of total electricity production. Human thermal stress and discomfort are measured using ERA5 reanalysis data from the European Centre for Medium-Range Forecasts (ECMWF) (Di Napoli et al., 2021). We use two variables: the number of tropical nights, defined as a night with minimum surface air temperature above 20°C, and the number of days where the Universal Thermal Climate Index (UTCI) falls between 9 and 26°C, based on daily minima.[2] Both indicators are provided on a regular latitude-longitude grid with near-global coverage. To align these data with countries, we compute simple averages across all grids within each country. This approach is not fully precise, as temperature and population density can vary across grids, which may affect the representation of average energy needs for heating and cooling. Nevertheless, we find that this method provides a reasonable approximation.

4.2. Empirical approach

Although our dataset spans multiple years (2000–2019), our aim is not to study whether temporal changes in a country's inequality correlate with carbon footprints. Instead, we focus on cross-country variation, examining how country-level inequality may be associated with personal carbon footprint levels. Our unit of analysis is percentile p (1,. . . ,100) in country j at time t, pooling information from multiple countries and years. A key issue is to leverage the panel structure of the data while accounting for the lack of independence among observations from the same country over time. Because observations from the same country are correlated, we use Driscoll–Kraay standard errors to account for cross-sectional dependence (Driscoll & Kraay, 1998; Hoechle, 2007), and include time fixed effects to control for common temporal shocks.

To focus strictly on cross-country differences, we employ a Mundlak decomposition (Mundlak, 1978). In this approach, the country mean of the variable of interest over the observation period captures cross-country variation, while deviations from the country mean reflect within-country over-time changes. In our application, the variable of interest for the cross-country comparison is the mean of each country's inequality measure:

$$\overline{\text{Inequality}}_j = \frac{1}{T_j} \sum_{t=1}^{T_j} \text{Inequality}_{jt} \tag{2}$$

[2]We also tested the same variable based on daily maxima; results remained essentially unchanged.

The within-country component is calculated by subtracting this country mean from the annual observation of the inequality variable in each country:

$$\text{Inequality}_{jt}^{\text{within}} = \text{Inequality}_{jt} - \overline{\text{Inequality}}_j \tag{3}$$

We introduce both variables in the following panel regression with time fixed effects:

$$\begin{aligned}\log FP_{ijt} = \alpha + \beta \log income_{ijt} + \delta \overline{Inequality}_j + \gamma Inequality_{jt}^{\text{within}} \\ + \lambda countryGDP_{jt} + \theta countryGDP_{jt}^2 + \kappa X_{jt} + \psi year_t + \varepsilon_{ijt}.\end{aligned} \tag{4}$$

FP_{ijt} is the carbon footprint of percentile i of the emission distribution in country j in year t. $income_{ijt}$ is the income of the respective percentile of the income distribution.[3] Our main interest is to assess if the carbon footprints of people at internationally comparable income levels vary with inequality levels in country of residence. Thus our variable of interest is $\overline{Inequality}_j$, the mean of the level of inequality in country j, measured by the pre-tax Gini coefficient in our main analysis (and other inequality measures, including the Palma ratio and various income shares, in robustness tests, see Appendix B). $countryGDP_{jt}$, the country's GDP per capita and $countryGDP_{jt}^2$ control for the possibility that not inequality but simply differences in the level of economic development of the country affect personal carbon emissions. Using squared GDP accounts for the inverted U-shape relationship of economic growth and carbon emissions suggested by the environmental Kuznets curve (Dinda, 2004). Vector X_{jt} includes country- and time-variant control variables and year dummies $year_t$ control for common time shocks. Given the structure of our data, we use log values for the carbon footprint, income, and GDP variables. As some percentiles of the income distribution have an income of zero and would thus convert into missing values when logarithmised, we replace these zeros by a marginal positive value of 0.01 to avoid biases from omitting the bottom of the income distribution.

In a variation of this approach, we investigate potential heterogeneities according to a country's level of economic development, as prior literature suggests that the relationship between income inequality and carbon emissions may depend on income levels (Coşkun, 2025; Flechtner & Middelanis, 2025; Grunewald et al., 2017; Jorgenson et al., 2016; Nicolli et al., 2025; Rojas-Vallejos & Lastuka, 2020). To capture such heterogeneities in our analysis, we include interaction terms between a country's World Bank income group classification and the inequality variables, using historical classifications to match each year in our dataset.

Researchers commonly include several control variables when examining the link between inequality and carbon emissions in panel data analyses. Typically, control variables encompass the degree of urbanization and the shares of value added by industry, services, and agriculture in GDP (see e.g. Grunewald et al., 2017; Jorgenson et al., 2016; Wan et al., 2022). These variables help account for structural factors that may influence carbon emissions and otherwise confound their relationship with inequality. Urbanization is included because city residents generally

[3] As discussed in section 3.1, because Chancel (2022) uses a constant income-emissions elasticity to allocate carbon emissions along the income distribution, these percentiles coincide. This is plausible given that previous research has also found that emissions increase monotonously with income (Büchs & Schnepf, 2013; Christis et al., 2019; Duarte et al., 2012; Golley & Meng, 2012; Hardadi et al., 2021; Irfany & Klasen, 2016; Sager, 2019; Seriño & Klasen, 2015; Theine et al., 2022).

consume more than rural populations, potentially increasing emissions, while urban workers tend to be more productive and urban economies are more service-oriented, factors that can lower emissions. As a result, the direction of the urbanization–emissions relationship is ex ante not clear (Li & Lin, 2015; Xu & Lin, 2015). The sectoral shares of agriculture, manufacturing, and services capture the economy's structure, with manufacturing typically being more carbon-intensive than services (Dinda, 2004).[4] Going beyond these standard controls, we also include the share of renewable energy in a country's electricity mix. A higher renewable share lowers the carbon intensity of production and, to a lesser extent, consumption (Saidi & Omri, 2020). In addition, we account for temperature and climate, since energy use and carbon emissions can vary with heating and cooling demands. To prevent such climatic differences from obscuring the relationship with inequality — particularly given that economic disparities and thermal discomfort can be interlinked (Dang et al., 2023; Pereira et al., 2021; Robinson, 2025; Zapata, 2023) — we alternately incorporate the number of tropical nights and the number of days when the universal thermal climate index (UTCI) ranged between 9 °C and 26 °C, representing periods that are neither notably cool nor hot.

We treat these control variables with caution, recognizing that many may function not only as confounders in the inequality–carbon emissions relationship but also as potential mediators. Urbanization, sectoral composition, and the share of renewable energy can all serve as channels through which inequality affects emissions. Political-economy perspectives (see section 2) suggest precisely that: for example, higher inequality might foster a larger service sector due to abundant cheap labor, encourage rural-to-urban migration, or hinder investment in technologies such as renewable energy (Uzar, 2020). Including these factors as controls could therefore block genuine transmission pathways and equally introduce bias. To address this concern, we present analyses both with and without these control variables.

4.3. Results

The variable *Pre-tax Gini: mean* in Table 4, indicates that countries with higher income inequality tend to exhibit higher personal carbon footprints at a given income level. This positive association appears in six of the seven model specifications. The only exception is column (1), which omits controls for the overall size of a country's economy. Omitting this control is likely problematic, since per-capita carbon footprints often rise with GDP per capita—not only through individual consumption, but also because larger public infrastructures and broader public service provision add to emissions. This tendency is also corroborated by our results, which indicate a positive and statistically significant relationship between GDP per capita and carbon emissions across all specifications in which GDP per capita is included. Across the remaining specifications, which include various combinations of controls, per-capita carbon footprints at any given income are consistently greater in countries with higher Gini coefficients. The estimated association indicates that a one-point increase in the Gini coefficient is associated with a 0.46 to 1.84 percent increase in personal carbon footprints, with a 1.48 percent increase in our preferred estimation (column 7).

In accordance with the within-country simulation results outlined in Section 3, the coefficients associated with the within-country deviation variable are negative. This indicates that

[4]The industry share would however be more important for production-based emissions than it is for consumption-based emissions.

Table 4: Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Personal carbon footprint (log)						
Pre-tax income (log)	0.171***	0.117***	0.117***	0.116***	0.117***	0.116***	0.115***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pre-tax Gini: mean	-3.274***	0.554***	0.460***	0.645***	1.112***	1.842***	1.484***
	(0.064)	(0.039)	(0.045)	(0.055)	(0.035)	(0.054)	(0.187)
Pre-tax Gini: dev.	-0.854	-1.054***	-1.030***	-0.910***	-1.077**	-1.013**	-0.762
	(0.949)	(0.245)	(0.257)	(0.206)	(0.469)	(0.453)	(0.503)
GDP per capita (log)		0.599***	0.830***	0.592***	0.786***	0.664***	0.430***
		(0.009)	(0.030)	(0.034)	(0.035)	(0.038)	(0.042)
GDP per capita $(\log)^2$			-0.014***	-0.000	-0.011***	-0.006***	0.003
			(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Renewable energy				-0.003***			-0.003***
				(0.000)			(0.000)
Tropical nights					-0.001***		
					(0.000)		
Temperate days						-0.002***	-0.002***
						(0.000)	(0.000)
Urban population							0.002***
							(0.000)
Industry share							0.007***
							(0.001)
Services share							0.000
							(0.002)
Agricultural share							-0.002
							(0.001)
Constant	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes
Obs.	327,948	321,248	321,248	318,348	309,348	309,348	297,648
R^2	0.322	0.711	0.711	0.717	0.715	0.725	0.740

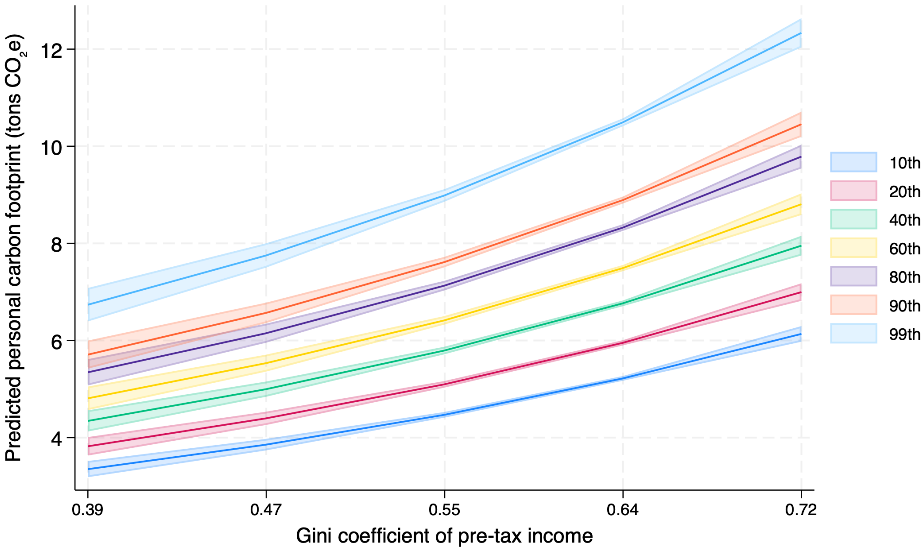
Standard errors (Driskoll-Kraay) in parentheses. Constants and year dummies not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Preferred specification with all controls and interaction terms with country income groups

	Personal carbon footprint (log)
Pre-tax income (log)	0.114***
	(0.000)
Low-income * mean of Gini coefficient	3.806***
	(0.429)
Lower-middle-income * mean of Gini coefficient	1.313***
	(0.327)
Upper-middle-income * mean of Gini coefficient	0.160
	(0.130)
High-income * mean of Gini coefficient	2.372***
	(0.090)
Low-income * yearly deviation of Gini coefficient	-1.845*
	(1.023)
Lower-middle-income * yearly deviation of Gini coefficient	-0.768
	(0.624)
Upper-middle-income * yearly deviation of Gini coefficient	1.702
	(1.531)
High-income * yearly deviation of Gini coefficient	-0.485
	(0.668)
Obs.	296,948
R2	0.749

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The specification corresponds to specification (7) in table 3 plus interaction terms of the inequality variable (between-component and within-component) with dummies for the four World Bank country income groups. Non-interacted dummies of the income groups and all control variables are included but not reported. # of observations by income group: 67,689 (low-income), 79,500 (lower-middle-income), 68,899 (upper-middle-income), 80,848 (high-income). Unit of analysis is percentile p (1,...,100) in country j in year t.

Figure 7: Predicted carbon emissions along the global distribution



Note: The figure shows predicted personal carbon footprints for selected points of the global income distribution (10th–99th percentiles). Predictions are based on the specification reported in Table 5.

increases in inequality within a given country are associated with lower per-capita carbon footprints. In the estimation that incorporates all control variables, the coefficient of the deviation is not statistically significant. Furthermore, the magnitude is approximately half of the between-country component at a decline of carbon emissions by 0.76 percent.

Previous studies note that analyses using worldwide country samples may obscure heterogeneous relationships across country groups (Coşkun, 2025; Flechtner & Middelanis, 2025; Nicolli et al., 2025). To address this concern, we extend specification (7) in Table 4 by adding interaction terms between a country's World Bank income-group classification (in each year) and both components of the inequality variable. Table 5 indicates that no income group departs from the overall pattern: the Gini coefficient demonstrates a positive correlation with personal carbon footprints across all income groups, although this correlation is not statistically significant in upper-middle income countries. The within-country component of the Gini coefficient is only marginally significant in low-income countries.

Figure 7 illustrates the economic relevance of the estimated association. Based on the specification reported in Table 5, the figure shows predicted personal carbon footprints for selected points of the global income distribution (10th–99th percentiles). Predictions are calculated across the observed range of national pre-tax Gini coefficients of our country sample (horizontal axis), holding all other covariates at their sample means. The regression was estimated with the dependent variable in natural logs; predictions were exponentiated to display footprints in original units for easier interpretation. At every global income percentile, higher national income inequality is associated with substantially higher predicted emissions. For example, an individual at the 10th percentile of the global income distribution who resides in a high-inequality country (pre-tax Gini of 0.72) is predicted to emit nearly twice as much as a person with the same income living in a low-inequality country (pre-tax Gini of 0.39). In the lower half of the distribution, the gap between the lowest and highest Gini values corresponds to roughly three metric tons of CO_2-equivalent or more. Absolute differences widen further up the income scale, reaching about four tons at the 80th and 90th percentiles and roughly five tons at the 99th percentile.

4.3.1. Robustness tests

To test the robustness of our findings, we first employ an alternative measure of inequality by using the Palma ratio instead of the Gini coefficient. The Palma ratio is defined as the income share of the top 10% divided by that of the bottom 40% ($P = \frac{\text{top } 10\%}{\text{bottom } 40\%}$). Compared to the Gini coefficient, the Palma ratio is particularly sensitive to changes at the extremes of the distribution, thereby providing a more precise picture of top- and bottom-end dynamics. The results, presented in Table A1 in the Appendix, confirm the robustness of our baseline findings. Specifically, we find a positive association between higher inequality and higher emissions across all specifications in which the Gini coefficient also indicated such a relationship. Moreover, the similarity of results with the baseline holds consistently across all income group classifications.

To obtain a more detailed picture of which parts of the income distribution are associated with higher carbon emissions, we use the income shares of the bottom 10%, bottom 50%, middle 40%, top 10%, and top 1% as explanatory variables (Tables A2–A6 in the appendix). In the cross-country comparison, larger income shares of the bottom 10%, bottom 50%, and middle 40% are generally linked to lower carbon emissions in most specifications and income classifications. Overall, the results indicate that higher income shares of the bottom 90% are associated with lower emissions, whereas higher income shares of the top 10% and the top 1% are linked to higher emissions. The main exception is observed in upper middle-income countries, where a higher share of the middle 40% is associated with higher emissions and the top 1% share marginally significantly with lower emissions, while all other shares are insignificant. This deviation of upper-middle income countries is consistent with previous findings in the literature (Flechtner & Middelanis, 2025).

The results for different income shares corroborate our baseline finding that greater inequality is associated with higher carbon emissions. More specifically, they highlight that it is primarily income concentration at the top that drives emissions, while the middle of the distribution is, in emissions terms, closer to the bottom. This contrasts with the results of our within-country simulations in Section 3, where the middle appeared as the main driver of emissions. However, the cross-country results align with political economy arguments, which identify high income concentration at the top as a key driver of carbon emissions, without directly linking emissions to consumption patterns. In addition, the arguments based on positional consumption illustrate that it is the income share held by the top that increases positional consumption in the middle and is therefore most detrimental for the environment (Frank, 2005; Frank et al., 2014). It is therefore unsurprising that, in the cross-country setting—where political economy mechanisms are especially relevant—top income shares, rather than middle shares, are most strongly associated with higher emissions.

4.4. Discussion

While arguments based on the MPE predict divergent levels of carbon emissions for differing income levels, they are unable to account for the phenomenon in which the same income level is associated with different levels of carbon emissions in different countries. The findings of this study indicate that individuals with equivalent income levels are responsible for higher carbon emissions in more unequal countries. This observation suggests a structural influence of inequality on carbon emissions. It appears that unequal countries demonstrate a number of distinct characteristics that are associated with a higher carbon intensity of the population's income. This trend is not dependent on the GDP or development status of a country. As outlined in section 2, the potential mechanisms under discussion are the following. Firstly, there is the possibility that inequality will increase consumerism and the carbon-intensive status competition experienced by the population as they attempt to emulate the living standards of the wealthiest members of society. Secondly, the lack in quality and quantity of public goods engenders a reliance on private solutions that are more carbon-intensive. Thirdly, due to a lesser degree of environmental regulation, the same products and services can exhibit a higher carbon intensity than in more equal countries.

5. Conclusion

This study advances the argument that theoretical arguments explaining the relationship between inequality and carbon emissions can be divided into two groups. One group focuses on dynamic changes in the distribution of income, referring to dynamic processes in the distribution of income within countries. The second group provides arguments related to the level of inequality. These are more static or structural differences in the income distribution, which are best identified through cross-country comparisons. Arguments grounded in changes in the income distribution tend to suggest that higher inequality is associated with lower emissions, while arguments based on the level of inequality suggest an inverse relationship.

We evaluate both perspectives separately. First, by simulating counterfactual income distributions within countries, we show that shifts toward greater equality are generally associated with higher emissions, ceteris paribus. Second, by comparing carbon emissions at given income levels across countries with different degrees of inequality, we find that individuals at similar income levels emit more in more unequal countries. Taken together, these results lend support to both theoretical positions. The mechanism of positional consumption plays an interesting role in our framework, as it relates to both within-country and cross-country changes and differences. In our cross-country analysis, the finding that top shares drive emissions is consistent with the positional consumption mechanism. In within-country simulations, the design of the simulations implies that we cannot identify the impact of positional consumption, as everything apart from the income distribution is held constant. Therefore, changes in consumption behavior due to higher inequality would not arise. Consequently, our within-country simulations may overestimate the trade-off between inequality and emissions reduction as they exclude this mechanism.

The existing literature has predominantly examined within-country variation in inequality over time and, in line with our results, frequently reports a negative correlation between inequality and emissions. However, this focus on distributional dynamics neglects structural elements of the inequality–emissions relationship. Our findings suggest that short-term increases in inequality may indeed reduce emissions, but when such dynamics accumulate into persistent structural inequality, higher inequality is associated with higher emissions. The converse holds for reductions in inequality: while initially associated with higher emissions, reductions that alter structural inequality ultimately reduce emissions. Beyond these environmental considerations, the adverse effects of inequality on societal well-being and development provide further grounds for avoiding increases in inequality (OECD, 2015; Stiglitz, 2012).

As all research in this field, our analysis is very sensitive to the data being used. The construction of comparable, consistent, and complete time series for both income and emissions are the subject of intense debates (see Lustig & Vigorito, 2025, for an overview of the income debate). Many assumptions need to be made to bridge gaps in our information basis. The most critical assumption for the work in this paper probably concerns the income-emissions elasticity. Our findings crucially rely on the income-emissions relationship that is built into the data that we use. As explained in the data section, Chancel (2022) uses constant elasticities to link income with emissions over the entire distribution. It could be that emissions do not increase constantly. Specifically, many studies have argued that the emissions of the richest individuals increase over-proportionally (Adua, 2022; Barros & Wilk, 2021; Gössling & Humpe, 2020; Otto et al., 2019). If it was true that the data we used underestimate the emissions-intensity of income at the upper tail of the distribution, we would have overestimated the magnitude of trade-offs that may arise with inequality reductions.

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Appendix

This appendix contains the following additional results and robustness tests:

A) Additional results for within-country simulations (section 3 of main paper)

1. Fit: estimated links between simulated income distributions and carbon footprints
2. Net aggregate carbon effects in simulated income distributions in comparison with levels of per-capita footprints

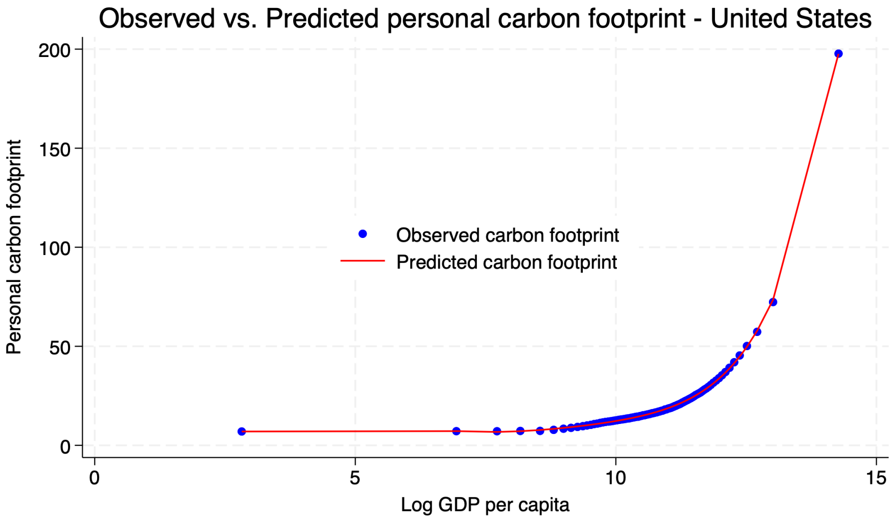
B) Additional results for between-country simulations (section 4 of main paper)

1. Robustness tests: different measures of inequality

A. Additional results for within-country simulations (section 3 of main paper)

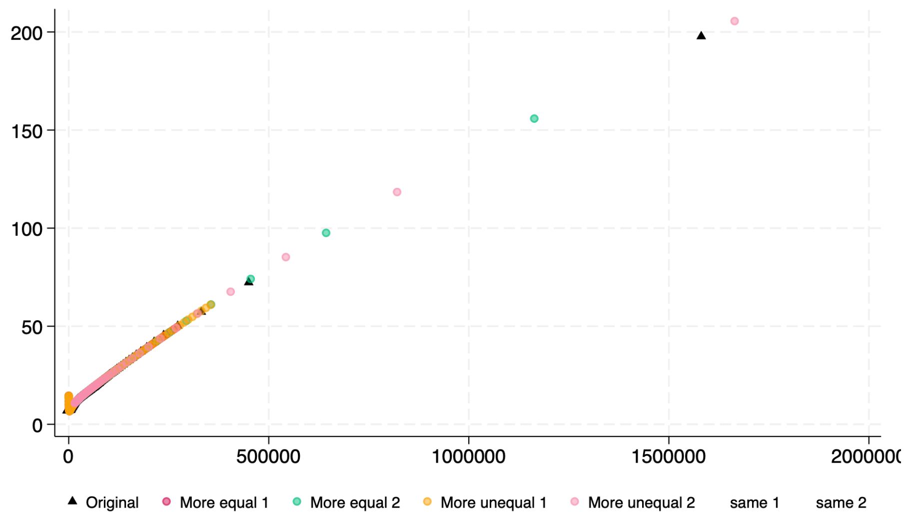
A.1. Fit: estimated links between simulated income distributions and carbon footprints

Figure A1: Estimated links between simulated income and carbon footprints, United States 2019



Note: Using data from the WID, the graph compares observed values for pre-tax income and percentile carbon footprints with predictions coming from equation (1).

Figure A2: Estimated links between simulated income and carbon footprints, United States 2019

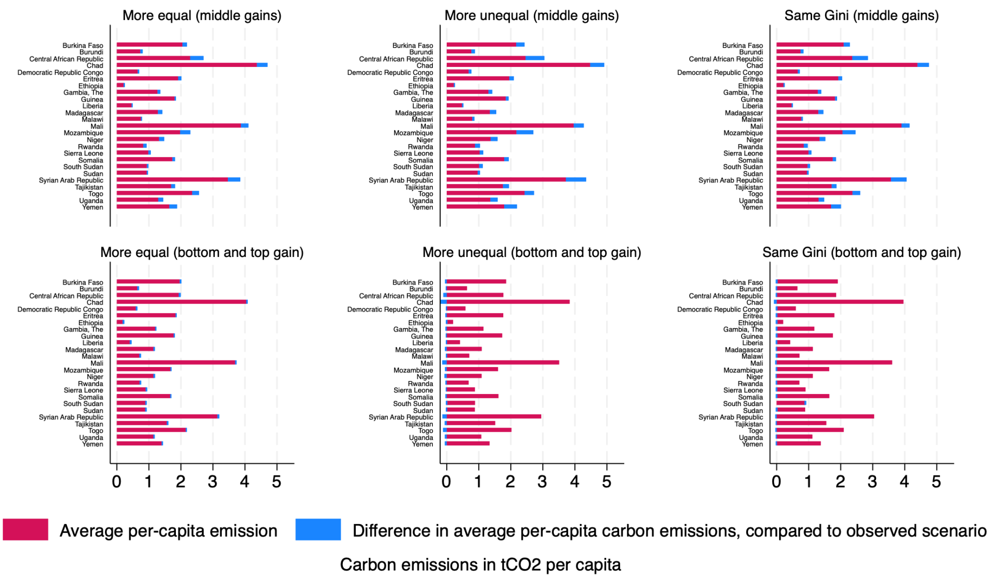


Note: The graph shows the predictions of percentile carbon footprints for the various income simulation scenarios, based on equation (1). It omits the 95th to 100th percentile of the more unequal distribution for the sake of visibility.

A.2. Net aggregate carbon effects in simulated income distributions in comparison with levels of per-capita footprints

Figure A3: Net aggregate carbon effects in the simulated income distributions in comparison with levels of per-capita footprints

(a) Low-income countries



(b) Lower-middle-income countries

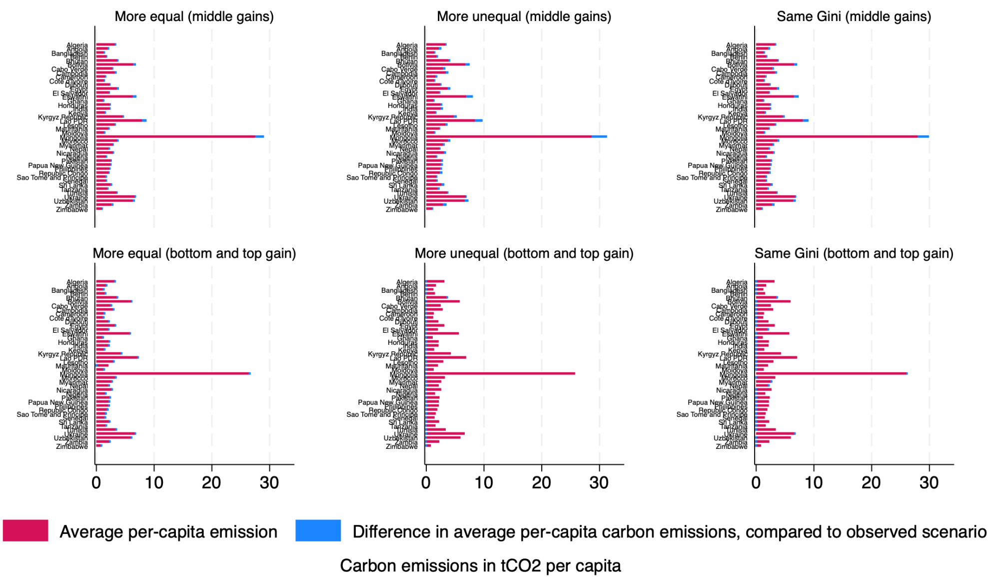
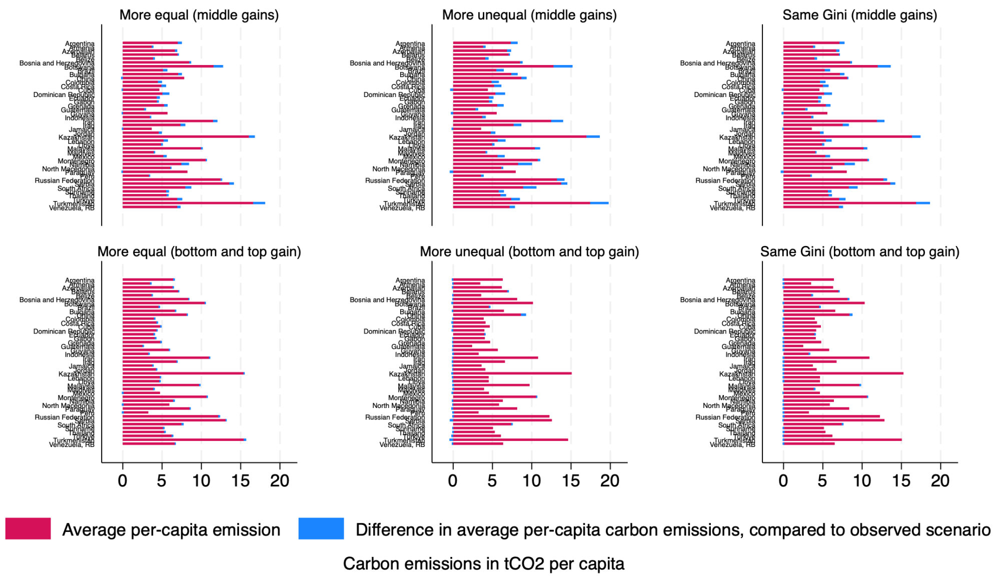
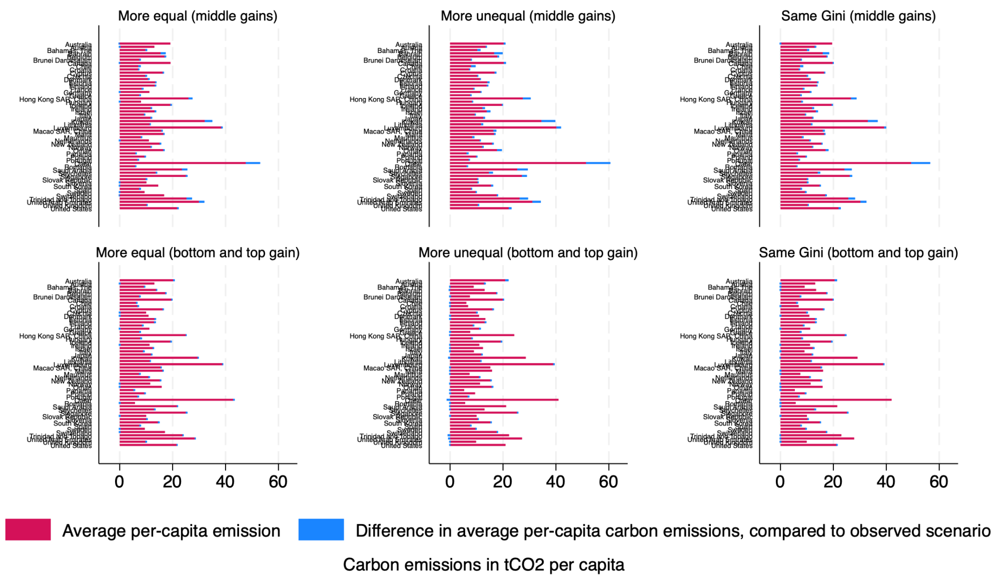


Figure A3: Net aggregate carbon effects in the simulated income distributions (continued)

(c) Upper-middle-income countries



(d) High-income countries



B. Additional results for between-country simulations (Section 4 of the paper)

B.1. Robustness tests: different inequality measures

Table A1: Robustness tests: **Palma ratio** (compare with table 3 in main paper)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Personal carbon footprint (log)						
Pre-tax income (log)	0.179***	0.117***	0.117***	0.116***	0.117***	0.117***	0.115***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pre-tax Palma ratio: mean	-0.037***	0.012***	0.010***	0.016***	0.018***	0.031***	0.026***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)
Pre-tax Palma ratio: dev.	-0.008	-0.012**	-0.011**	-0.010*	-0.011***	-0.010**	-0.010
	(0.010)	(0.004)	(0.005)	(0.005)	(0.003)	(0.005)	(0.007)
GDP per capita (log)		0.593***	0.827***	0.562***	0.813***	0.714***	0.431***
		(0.010)	(0.028)	(0.032)	(0.029)	(0.031)	(0.040)
GDP per capita $(\log)^2$			-0.014***	0.001	-0.014***	-0.010***	0.002
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Renewable energy				-0.003***			-0.003***
				(0.000)			(0.000)
Tropical nights					-0.001***		
					(0.000)		
Temperate days						-0.002***	-0.002***
						(0.000)	(0.000)
Urban population							0.002***
							(0.000)
Industry share							0.009***
							(0.001)
Services share							0.001
							(0.002)
Agricultural share							-0.001
							(0.001)
Constant	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes
Obs.	327,948	321,248	321,248	318,348	309,348	309,348	297,648
R^2	0.284	0.710	0.711	0.717	0.714	0.722	0.738

Standard errors (Driskoll-Kraay) in parentheses. Constants and year dummies not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness test: **Palma ratio** (compare with table 4 in main paper)

Pre-tax income (log)	0.115***
	(0.000)
Low-income * mean of Palma ratio	0.074***
	(0.008)
Lower-middle-income * mean of Palma ratio	0.040***
	(0.006)
Upper-middle-income * mean of Palma ratio	-0.000
	(0.003)
High-income * mean of Palma ratio	0.057***
	(0.003)
Low-income * yearly deviation of Palma ratio	-0.050***
	(0.010)
Lower-middle-income * yearly deviation of Palma ratio	-0.016**
	(0.007)
Upper-middle-income * yearly deviation of Palma ratio	0.018
	(0.018)
High-income * yearly deviation of Palma ratio	-0.030
	(0.024)
Obs.	296,948
R2	0.747

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Robustness tests: **Bottom 10% income share** (compare with table 3 in main paper)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Personal carbon footprint (log)						
Pre-tax income (log)	0.176***	0.116***	0.116***	0.115***	0.116***	0.116***	0.115***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bottom 10% share: mean	168.365***	-2.025	11.457***	-7.309*	-24.644***	-75.580***	-76.663***
	(5.008)	(3.145)	(3.730)	(3.729)	(5.605)	(8.850)	(17.207)
Bottom 10% share: dev.	36.880	41.314*	40.769**	24.178	39.218	37.681	24.055
	(50.570)	(20.958)	(18.964)	(24.741)	(29.484)	(30.600)	(35.361)
GDP per capita (log)		0.587***	0.920***	0.667***	0.862***	0.704***	0.349***
		(0.009)	(0.032)	(0.041)	(0.040)	(0.049)	(0.070)
GDP per capita $(\log)^2$			-0.020***	-0.005**	-0.017***	-0.010***	0.006
			(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Renewable energy				-0.003***			-0.003***
				(0.000)			(0.000)
Tropical nights					-0.001***		
					(0.000)		
Temperate days						-0.001***	-0.002***
						(0.000)	(0.000)
Urban population							0.003***
							(0.000)
Industry share							0.010***
							(0.001)
Services share							0.002
							(0.002)
Agricultural share							-0.002
							(0.001)
Constant	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes
Obs.	327,948	321,248	321,248	31,8348	309,348	309,348	297,648
R^2	0.296	0.709	0.710	0.715	0.712	0.719	0.737

Standard errors (Driskoll-Kraay) in parentheses. Constants and year dummies not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness test: **pre-tax bottom 10% income share** (compare with table 4 in main paper)

Pre-tax income (log)	0.114***
	(0.000)
Low-income * mean of bottom 10% share	-126.072**
	(53.200)
Lower-middle-income * mean of bottom 10% share	-76.768***
	(12.989)
Upper-middle-income * mean of bottom 10% share	-2.390
	(16.208)
High-income * mean of bottom 10% share	-127.359***
	(7.874)
Low-income * yearly deviation of bottom 10% share	150.880
	(133.008)
Lower-middle-income * yearly deviation of bottom 10% share	-3.150
	(117.764)
Upper-middle-income * yearly deviation of bottom 10% share	-115.222***
	(31.410)
High-income * yearly deviation of bottom 10% share	63.206***
	(21.832)
Obs.	296,948
R2	0.743

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Robustness tests: **Bottom 50% income share** (compare with table 3 in main paper)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Personal carbon footprint (log)						
Pre-tax income (log)	0.171***	0.117***	0.117***	0.116***	0.117***	0.116***	0.115***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bottom 50% share: mean	6.025***	-1.064***	-0.870***	-1.252***	-2.232***	-3.677***	-3.075***
	(0.134)	(0.071)	(0.083)	(0.083)	(0.097)	(0.146)	(0.393)
Bottom 50% share: dev.	1.815	2.269***	2.229***	1.829***	2.282**	2.165**	1.670**
	(1.530)	(0.579)	(0.583)	(0.528)	(0.920)	(0.821)	(0.669)
GDP per capita (log)		0.599***	0.823***	0.580***	0.760***	0.621***	0.380***
		(0.009)	(0.031)	(0.036)	(0.039)	(0.043)	(0.048)
GDP per capita (log)^2			-0.013***	0.000	-0.010***	-0.004*	0.006**
			(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Renewable energy				-0.003***			-0.003***
				(0.000)			(0.000)
Tropical nights					-0.001***		
					(0.000)		
Temperate days						-0.002***	-0.002***
						(0.000)	(0.000)
Urban population							0.002***
							(0.000)
Industry share							0.007***
							(0.001)
Services share							-0.000
							(0.002)
Agricultural share							-0.003*
							(0.001)
Constant	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes
Obs.	327,948	321,248	321,248	318,348	309,348	309,348	297,648 R^2
0.318	0.711	0.711	0.717	0.716	0.726	0.741	

Standard errors (Driskoll-Kraay) in parentheses. Constants and year dummies not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness test: **pre-tax bottom 50% income share** (compare with table 4 in main paper)

Pre-tax income (log)	0.115***
	(0.000)
Low-income * mean of bottom 50% share	-7.794***
	(1.053)
Lower-middle-income * mean of bottom 50% share	-2.481***
	(0.526)
Upper-middle-income * mean of bottom 50% share	-0.558
	(0.327)
High-income * mean of bottom 50% share	-4.685***
	(0.193)
Low-income * yearly deviation of bottom 50% share	5.053**
	(1.935)
Lower-middle-income * yearly deviation of bottom 50% share	0.662
	(1.412)
Upper-middle-income * yearly deviation of bottom 50% share	-3.665
	(2.274)
High-income * yearly deviation of bottom 50% share	0.597
	(0.992)
Obs.	296,948
R2	0.750

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Robustness tests: **Middle 40% income share** (compare with table 3 in main paper)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Personal carbon footprint (log)						
Pre-tax income (log)	0.171***	0.116***	0.116***	0.116***	0.116***	0.115***	0.114***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Middle 40% share: mean	6.250***	-0.849***	-0.746***	-0.965***	-1.413***	-2.306***	-1.551***
	(0.097)	(0.129)	(0.134)	(0.192)	(0.127)	(0.115)	(0.176)
Middle 40% share: dev.	0.615	0.782***	0.742***	0.935***	0.761	0.690	0.443
	(1.586)	(0.224)	(0.241)	(0.164)	(0.571)	(0.689)	(1.082)
GDP per capita (log)		0.598***	0.866***	0.650***	0.886***	0.838***	0.561***
		(0.011)	(0.026)	(0.030)	(0.028)	(0.029)	(0.029)
GDP per capita (log)^2			-0.016***	-0.004**	-0.017***	-0.016***	-0.005***
			(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Renewable energy				-0.003***			-0.002***
				(0.000)			(0.000)
Tropical nights					-0.001***		
					(0.000)		
Temperate days						-0.001***	-0.001***
						(0.000)	(0.000)
Urban population							0.003***
							(0.000)
Industry share							0.008***
							(0.001)
Services share							0.002
							(0.002)
Agricultural share							-0.002
							(0.001)
Constant	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes
Obs.	327,948	321,248	321,248	318,348	309,348	309,348	297,648
R^2	0.328	0.710	0.711	0.716	0.714	0.722	0.737

Standard errors (Driskoll-Kraay) in parentheses. Constants and year dummies not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness test: **pre-tax middle 40% income share** (compare with table 4 in main paper)

Pre-tax income (log)	0.114***
	(0.000)
Low-income * mean of middle 40% share	-4.965***
	(0.971)
Lower-middle-income * mean of middle 40% share	-1.628**
	(0.578)
Upper-middle-income * mean of middle 40% share	0.507***
	(0.119)
High-income * mean of middle 40% share	-3.162***
	(0.156)
Low-income * yearly deviation of middle 40% share	-0.088
	(1.725)
Lower-middle-income * yearly deviation of middle 40% share	1.912**
	(0.871)
Upper-middle-income * yearly deviation of middle 40% share	-0.679
	(2.705)
High-income * yearly deviation of middle 40% share	0.924
	(1.023)
Obs.	296,948
R2	0.745

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Robustness tests: **Top 10% income share** (compare with table 3 in main paper)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Personal carbon footprint (log)						
Pre-tax income (log)	0.170***	0.117***	0.117***	0.116***	0.117***	0.116***	0.114***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top 10% share: mean	-3.346***	0.524***	0.443***	0.604***	0.985***	1.635***	1.256***
	(0.056)	(0.047)	(0.051)	(0.073)	(0.036)	(0.038)	(0.148)
Top 10% share: dev.	-0.665	-0.833***	-0.808***	-0.788***	-0.844*	-0.786*	-0.573
	(0.974)	(0.185)	(0.200)	(0.132)	(0.417)	(0.453)	(0.601)
GDP per capita (log)		0.600***	0.842***	0.612***	0.825***	0.730***	0.490***
		(0.010)	(0.028)	(0.032)	(0.031)	(0.033)	(0.034)
GDP per capita (log)^2			-0.014***	-0.001	-0.014***	-0.010***	-0.000
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Renewable energy				-0.003***			-0.002***
				(0.000)			(0.000)
Tropical nights					-0.001***		
					(0.000)		
Temperate days						-0.002***	-0.002***
						(0.000)	(0.000)
Urban population							0.002***
							(0.000)
Industry share							0.008***
							(0.001)
Services share							0.001
							(0.002)
Agricultural share							-0.002
							(0.001)
Constant	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes
Obs.	327,948	321,248	321,248	318,348	309,348	309,348	297,648
R^2	0.327	0.711	0.711	0.717	0.715	0.724	0.739

Standard errors (Driskoll-Kraay) in parentheses. Constants and year dummies not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness test: **pre-tax top 10% income share** (compare with table 4 in main paper)

Pre-tax income (log)	0.114***
	(0.000)
Low-income * mean of top 10% share	3.356***
	(0.431)
Lower-middle-income * mean of top 10% share	1.165***
	(0.337)
Upper-middle-income * mean of top 10% share	-0.001
	(0.090)
High-income * mean of top 10% share	2.206***
	(0.077)
Low-income * yearly deviation of top 10% share	-1.034
	(0.978)
Lower-middle-income * yearly deviation of top 10% share	-0.981*
	(0.509)
Upper-middle-income * yearly deviation of top 10% share	1.117
	(1.664)
High-income * yearly deviation of top 10% share	-0.644
	(0.707)
Obs.	296,948
R2	0.748

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Robustness tests: **Top 1% income share** (compare with table 3 in main paper)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Personal carbon footprint (log)						
Pre-tax income (log)	0.178***	0.117***	0.117***	0.116***	0.116***	0.116***	0.114***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top 1% share: mean	-3.804***	1.114***	0.999***	1.189***	1.883***	2.603***	1.730***
	(0.108)	(0.110)	(0.117)	(0.157)	(0.121)	(0.111)	(0.241)
Top 1% share: dev.	-0.566	-0.628**	-0.594**	-0.645***	-0.730	-0.676	-0.559
	(1.398)	(0.241)	(0.255)	(0.184)	(0.730)	(0.699)	(0.847)
GDP per capita (log)		0.597***	0.841***	0.621***	0.848***	0.794***	0.529***
		(0.010)	(0.027)	(0.031)	(0.029)	(0.031)	(0.031)
GDP per capita $(\log)^2$			-0.014***	-0.002	-0.015***	-0.014***	-0.003*
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Renewable energy				-0.003***			-0.002***
				(0.000)			(0.000)
Tropical nights					-0.001***		
					(0.000)		
Temperate days						-0.001***	-0.001***
						(0.000)	(0.000)
Urban population							0.003***
							(0.000)
Industry share							0.008***
							(0.001)
Services share							0.002
							(0.002)
Agricultural share							-0.001
							(0.001)
Constant	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes
Obs.	327,948	321,248	321,248	318,348	309,348	309,348	297,648
R^2	0.293	0.711	0.711	0.717	0.715	0.723	0.738

Standard errors (Driskoll-Kraay) in parentheses. Constants and year dummies not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness test: **pre-tax top 1% income share** (compare with table 4 in main paper)

Pre-tax income (log)	0.114***
	(0.000)
Low-income * mean of top 1% share	2.764***
	(0.444)
Lower-middle-income * mean of top 1% share	1.536**
	(0.678)
Upper-middle-income * mean of top 1% share	-0.272*
	(0.150)
High-income * mean of top 1% share	3.577***
	(0.141)
Low-income * yearly deviation of top 1% share	-0.357
	(1.454)
Lower-middle-income * yearly deviation of top 1% share	-1.834***
	(0.534)
Upper-middle-income * yearly deviation of top 1% share	0.841
	(1.670)
High-income * yearly deviation of top 1% share	-1.232
	(1.120)
Obs.	296,948
R2	0.744

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$