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Carbon footprint inequality: A scaling decomposition across 165 countries (1980–2019)

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ABSTRACT

Individuals contribute to carbon emissions unequally. Yet, this inequality is often attributed solely to individual differences, overlooking the role of structural, societal-scale effects. Using a scaling framework, we analyze four decades of annual carbon footprint inequality data (1980–2019) across 165 countries. We uncover two distinct characteristics of high-emission groups: (i) Their emissions grow at a faster rate as population increases (societal-scale effects). (ii) They maintain higher emissions independent of population size (individual baseline). By proposing a counterfactual adjustment method, we reveal that baseline disparities are the dominant driver of inequality, while societal-scale effects also play a critical role. If all individuals shared the same return to scale as the bottom 10%, the global Gini index could be reduced by 18% and total emissions by 23%. Furthermore, we examine how these patterns vary across different economic contexts to inform more targeted policy. Our findings bridge individual and structural perspectives, advocating fairness-oriented climate policies that prioritize reducing baseline emissions while addressing the amplifying role of societal-scale effects.

1. Introduction

The Paris Agreement fosters a collective commitment among countries to mitigate climate change. Although greenhouse gas emission targets are set at the national level, the carbon footprints are not uniformly distributed within countries [1]. Certain groups

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contribute disproportionately to total emissions, leading to significant disparities [2,3]. For example, in 2019, China's average per-capita carbon footprint was 8 tonnes of carbon dioxide equivalent (tCO_2e), with the top 10% of emitters responsible for 33 tCO_2e, whereas the bottom 10% accounted for only 2 tCO_2e (source: https://wid.world/data/). Such inequality poses a serious challenge to climate justice, as those who emit the most are often not the ones who suffer the most from climate-related impacts [4–8]. Understanding carbon footprint inequality is therefore crucial for developing climate policies that are both effective and equitable.

Carbon footprint inequality is closely tied to economic disparities, primarily reflecting differences in personal consumption patterns [2,9–12]. High-income individuals typically have disproportionately large carbon footprints due to energy-intensive lifestyles, including frequent travel, larger living spaces, and higher consumption of goods and services. Empirical evidence across different regions, such as the USA [13], China [14,15], Japan [16], and Europe [17], supports this trend. Building on this economy-emissions link, recent studies have estimated individual-level carbon footprints for countries worldwide, offering a vivid picture of carbon footprint inequality [2].

However, most existing studies attribute carbon footprint inequality primarily to individual-level differences, overlooking the societal context in which these individuals are embedded. As populations grow, societies generate additional interaction opportunities through denser social networks, expanded infrastructure, and more complex economic activities [18]. Recent studies in economics suggest that these opportunities are not distributed evenly across population groups [19–21], leading to inequalities. Therefore, identifying the societal-scale influences that shape inequality, and comparing them with individual-level differences, is essential for more targeted mitigation strategies—ranging from systemic policy reforms to lifestyle interventions.

Carbon footprint inequality is a system-level outcome that reflects how socio-economic interactions and opportunities are organized within societies. Complex-systems and statistical-physics approaches provide a useful toolkit for studying such social systems and their emergent regularities [22]. In this view, macro-level patterns can arise from interaction structures, including higher-order group interactions beyond dyadic links [23], and can be characterized with network-based responses to shocks [24]. This perspective motivates a scaling-based, macro-level description of carbon footprint inequality.

To this end, we adopt the allometric scaling law—a core framework in complex systems theory. Empirically, scaling laws have been used to describe how various biological [25,26], socio-economic [27–29], and environmental [30–33] quantities (Y) scale systematically with size (S). This relationship generally follows a power-law form, $Y = Y_0 S^\beta$, where: (i) Y_0 is a normalization constant, which represents the baseline level. It captures inherent differences across systems independent of scale. (ii) β is the scaling exponent, which quantifies how sensitively the outcome responds to changes in system size. A well-known example is Kleiber's law, which suggests that the metabolic rate of organisms scales sub-linearly with body mass (approximately $\beta = 3/4$) [34]. In other words, while larger animals consume more energy than smaller ones, the increase in energy consumption is less than proportional to their body size. Moreover, differences in Y_0 distinguish species categories: (i) Warm-blooded organisms have higher Y_0. (ii) Cold-blooded organisms have intermediate values. (iii) Unicellular organisms have the lowest. This reflects baseline differences in metabolic rate across species [35]. This decomposition into scale effects and baseline levels makes the scaling law well-suited to our study, allowing us to separate population-driven responses from individual-level disparities in carbon footprints.

Here, we investigate the structural sources – societal-scale effects and individual baseline levels – that contribute to carbon footprint inequality through a scaling perspective. To this end, we use data from the World Inequality Database (see the 'Data' section of the Methods), which provides population sizes and carbon footprint data across various percentiles for 165 countries from 1980 to 2019 (see maps in Fig. 1). Specifically, we carry out the following steps to address the questions regarding carbon footprint inequality: (i) We measure the scaling patterns of emissions across different percentile groups, focusing on two scaling components—β, which reflects how individual emissions respond to increasing population size, and Y_0, which represents the baseline level of emissions regardless of population. This step aims to determine whether inequality arises from differentiated responses to societal-scale or from inherent differences in baseline levels. Variation in β across groups would suggest that individuals respond differently to increasing population size, while variation in Y_0 would indicate disparities in baseline emissions. (ii) We propose a scaling-based counterfactual method to assess the extent to which the observed differences in β and Y_0 contribute to overall inequality. This step allows us to isolate the roles of scale effects and baseline disparities, identifying which factor plays a more critical role in driving inequality, and thereby informing more targeted policy interventions. (iii) We examine how various economic factors influence these scaling components and their contributions to inequality. This step aims to offer a deeper insight into how inequality patterns are shaped under different economic conditions, offering insights for more flexible and context-specific policy design.

2. Methods

2.1. Data

In this study, we use total emission, percentile emission, population and per-capita GDP data. All data are collected from the World Inequality Database (https://wid.world/).

For emissions, the WID database integrates carbon footprint estimates originally sourced from the Global Carbon Project [36] and the EORA multi-region input–output database [37], covering all greenhouse gases except those from land-use change. Emissions are first estimated at the national level based on production and consumption activities, and then allocated across population percentiles using individual income distributions (for consumption emissions) and wealth distributions (for investment emissions) [2]. This process involves the concept of economic-emission *elasticity*, which is further detailed in Supplementary Information Text S1.4. Separate scaling analyses reveal that both consumption and investment emissions exhibit a clear relationship with national

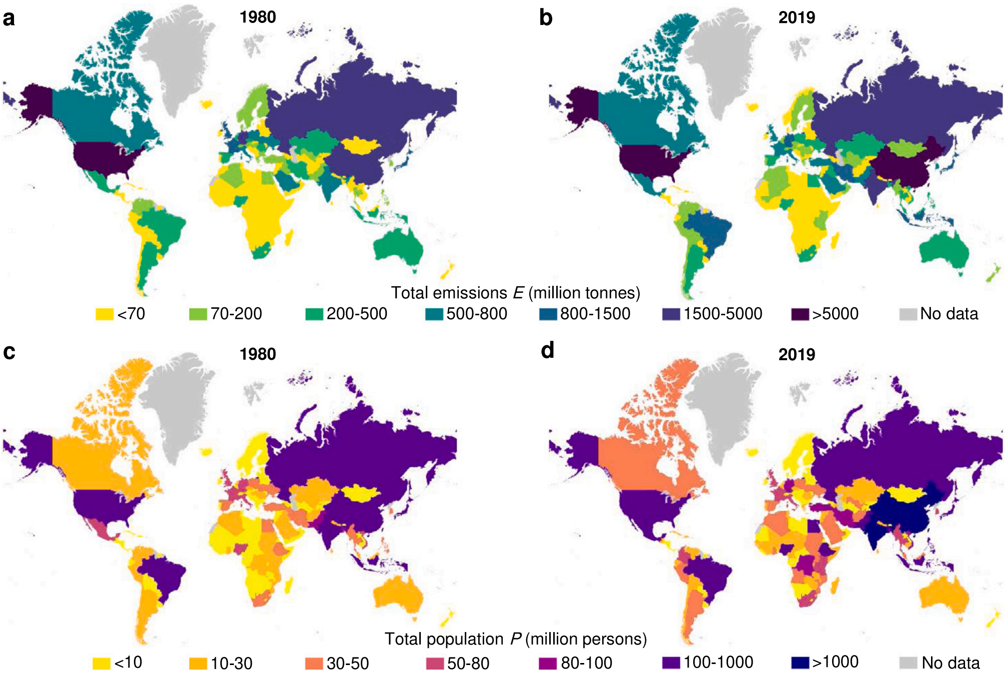

Fig. 1. Overview of the countries analyzed in this study and their emission and population scales. Maps of the 165 countries showing (a) total emissions (E) in 1980 (the first year of our data), (b) E in 2019 (the last year of our data), (c) national population size (P) in 1980, and (d) P in 2019.

population size (Supplementary Figure 9). Given this intrinsic linkage, we use the sum of both categories to allow for a broader quantification of human-induced carbon emissions.

Population data are originally sourced from the United Nations World Population Prospects [38]. GDP data are drawn from the World Bank [39]. Both datasets are integrated into WID to ensure consistency across variables.

The final dataset used in this study covers 165 countries over the period from 1980 to 2019, offering broad geographic and temporal representation. Fig. 1 shows the total carbon emissions and population sizes of these countries at the start and conclusion of the study period.

2.2. Scaling law

We begin by introducing the basic scaling model, which relates total emissions (E) to national population size (P) via a power-law function:

$$E = E_0 P^{\beta}, \tag{1}$$

where E_0 is a normalization constant representing the baseline level of emissions independent of population sizes, and β is the scaling exponent that measures the scale effect of population. Specifically: (i) $\beta > 1$ (super-linear) indicates that emissions grow faster than population. (ii) $\beta = 1$ (linear) indicates that emissions increase proportionally with population. (iii) $\beta < 1$ (sub-linear) indicates that emissions grow slower than population. Taking the natural logarithm of both sides yields a linearized form, which facilitates interpretation and empirical estimation (by the least square method):

$$\ln E = \underbrace{\ln E_0}_{\text{intercept}} + \underbrace{\beta \ln P}_{\text{scale-related}} . \tag{2}$$

This expression decomposes emissions into an intercept component (baseline emissions) and a scale-related component.

While most studies on scaling laws have focused on cities, emerging research suggests that extending these analyses to the national level could reveal new insights [40,41]. Indeed, the power-law distribution observed in broader network structures indicates that inequalities, which arise from the uneven distribution of individual opportunities, not only persist but also tend to intensify as scale increases [42]. Geographically, countries with their clearly established borders and governance structures shape individual mobility patterns [43], economic allocations [3,44], and climate policy implementation [45,46]. In this context, applying allometric scaling to countries offers a novel perspective to interpret intra-country carbon footprint inequality from a cross-country systems view.

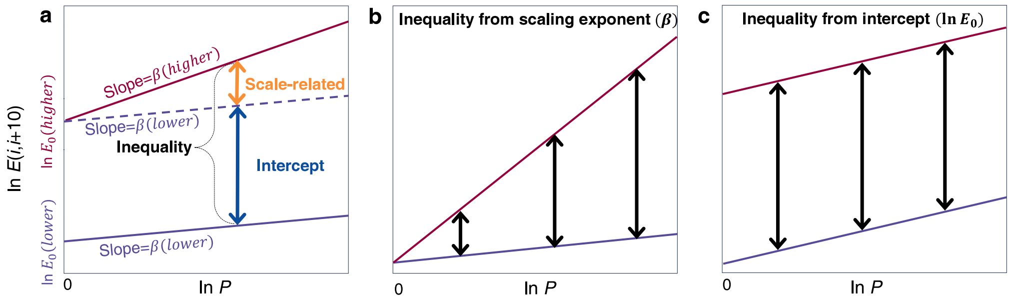

Fig. 2. Conceptual illustration of how inequality emerges from differences in scaling patterns. **a** An illustrative case where higher-percentile groups (red) have both a stronger scaling response ($\beta \ln P$) and higher baseline emissions (intercepts) than lower-percentile groups (blue), showing that inequality can arise when either parameter differs. **b** Inequality from differences in the intercept $\ln E_0$. Black arrows show how the emission gap widens with increasing population size, while $\ln E_0$ keeps constant. **c** Inequality from differences in the intercept $\ln E_0$, keeping β constant. In this case, emission gaps remain constant across country sizes. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

However, the total emissions model in Eq. (2) represents an aggregate scaling relationship that relies on the assumption of homogeneity, whereby each individual contributes equally to their country's total carbon footprint. Indeed, individual carbon footprints exhibit significant variation, and this aggregate perspective may obscure critical heterogeneity among population segments, as suggested in urban studies [19,20]. To this end, we extend the scaling framework via connecting the relationship between national population size and the emissions contributed by different percentile groups of individuals:

$$E(i, i+10) = E_0(i, i+10) P^{\beta(i,i+10)}, i \in \{0, 10, 20, \dots, 90\}, \tag{3}$$

where $E(i, i+10)$ represents the total emissions from individuals in the ith to $(i+10)$th population percentiles (exclusive of $i\%$, inclusive of $(i+10)\%$), $E_0(i, i+10)$ represents the baseline emissions for that group, and $\beta(i, i+10)$ is the corresponding scaling exponent.

Following this scaling formulation, inequality can arise from variations in both parameters – the societal-scale response (β) and the baseline emissions (E_0) – as illustrated in Fig. 2a. Specifically, differences in β imply that as population increases, emission gaps between percentile groups widen, since higher-percentile groups respond more strongly to population growth (Fig. 2b). In contrast, differences in E_0 indicate that emission gaps remain constant across population sizes, reflecting intrinsic disparities in baseline emissions independent of societal scale (Fig. 2c).

2.3. Theil index decomposition

To determine which component – intercept or scale-related – plays a more critical role in driving inequality, we employ the Theil index (T) [47]. Specifically, it allows us to decompose carbon footprint inequality into two components:

$$T_{emission} = T_{intercept} + T_{scale-related}, \tag{4}$$

where

$$T_{intercept} = \frac{1}{10} \sum_{i=0,10,\dots,90} \frac{\ln E_0(i, i+10)}{\overline{\ln E_0}} \ln\left(\frac{\ln E_0(i, i+10)}{\overline{\ln E_0}}\right), \tag{5}$$

and

$$T_{scale-related} = \frac{1}{10} \sum_{i=0,10,\dots,90} \frac{\beta(i, i+10)}{\overline{\beta}} \ln\left(\frac{\beta(i, i+10)}{\overline{\beta}}\right). \tag{6}$$

Note that in Eq. (6), the term $\ln P$ is eliminated because each percentile scaling model is based on the total country population.

2.4. Scaling decomposition

While the Theil index offers a decomposable measure of inequality, the scale-related term ($T_{scale-related}$) does not explicitly account for population size, which can amplify disparities. Moreover, the decomposition assumes that all countries well conform to the ideal scaling equation, neglecting deviations that reflect country-specific behaviors (Fig. 3a). To overcome these limitations, we propose a simulation-based adjustment framework that systematically isolates the contributions of the scaling exponent and intercept to overall inequality. Specifically, we construct two counterfactual scenarios by adjusting each percentile group's parameters to match those of the bottom 10%—a reference group characterized by the smallest scaling exponent and the lowest baseline emissions. This setup allows us to investigate the inequality consequences of removing either scale-related or intercept-related heterogeneity

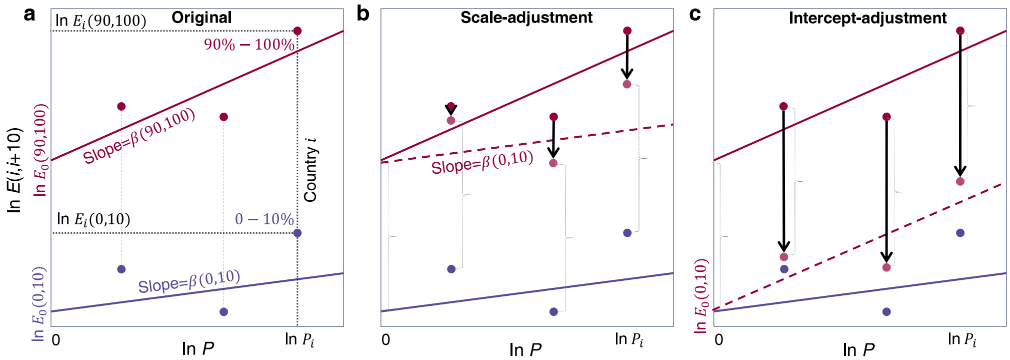

Fig. 3. Quantifying the contributions of scaling components via counterfactuals. **a** Original scaling patterns of top 10% (red) and bottom 10% (purple) emitters across countries. Solid lines represent the scaling relationships. For clarity, only the top 10% and bottom 10% (reference percentile) are displayed, but the same adjustment method applies to all percentiles. **b** Scale-adjustment: Higher-percentile groups adopt β of the bottom 10% group while retaining their original $\ln E_0$. Arrows indicate the shift from original to adjusted values, red dash lines represent the new scaling relationships for the adjusted higher-percentile groups. The brackets indicate the shift in intercepts, representing the difference between the original intercept of higher-percentile groups and that of the bottom 10% (here, $\ln E_0(90,100) - \ln E_0(0,10)$). **c** Intercept-adjustment: higher-percentile groups adopt $\ln E_0$ of the bottom 10% group while keeping original β constant. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

across groups. This approach is crucial because it demonstrates that imposing a universal cap on individual emissions ensures equitable treatment of higher emitters [48].

In the scale-adjustment, each higher-percentile group retains its original intercept while adopting the bottom 10%'s scaling exponent (Fig. 3b). On a natural logarithmic scale, this adjustment can be mathematically expressed as:

$$\ln E^S(i,i+10) = \ln E(0,10) + \ln E_0(i,i+10) - \ln E_0(0,10). \tag{7}$$

Then, the adjusted emissions follow the new scaling relation:

$$E^S(i,i+10) = E_0(i,i+10) P^{\beta(0,10)}. \tag{8}$$

In the intercept-adjustment, each higher-percentile group retains its original scaling exponent but adopts the bottom 10%'s intercept (Fig. 3c), which is expressed as:

$$\ln E^I(i,i+10) = \ln E(i,i+10) - \ln E_0(i,i+10) + \ln E_0(0,10). \tag{9}$$

The resulting emissions follow:

$$E^I(i,i+10) = E_0(0,10) P^{\beta(i,i+10)}. \tag{10}$$

Consequently, we compute the total emissions and Gini index (a standard measure of inequality ranging from 0 for perfect equality to 1 for maximum inequality [49,50]) for both adjustments. The adjustment that results in a larger reduction in inequality indicates which component – scale-related or intercept-related – plays a more dominant role.

3. Results

3.1. Uncovering carbon footprint inequality through percentile scaling

We begin by examining the scaling relationships between national population sizes (P) and emissions (E) across different percentile groups. Fig. 4a shows this relationship for the top 10% of emitters (90th–100th percentile) in 2019, where we find that: (i) The scaling exponent $\beta = 0.88 \pm 0.09$ (95% CI, $p < 0.01$), suggesting a sub-linear relationship—doubling a country's population results in less than a doubling of its top 10% emitters' emissions. (ii) The intercept $\ln E_0 = 2.21$, indicating the baseline emission level of the top 10% group—the emissions when population is held at the unit scale ($P = 1$).

For the bottom 10%, we observe a different scaling pattern, with a slightly lower $\beta = 0.85 \pm 0.10$ (95% CI, $p < 0.01$) and a much lower baseline level $\ln E_0 = 0.57$ (Fig. 4b). The contrast scaling patterns between the top and bottom 10% reveals inequality in two respects: (i) Each 1% increase in national population is associated with a 0.88% rise in the top 10% group's emissions, compared to only 0.85% for the bottom 10%. (ii) The top 10% group has a higher baseline emission level ($\ln E_0 = 2.21$) than the bottom 10% ($\ln E_0 = 0.57$), independent of population size. We extend this analysis to all percentile groups, visually revealing their different scaling patterns (Fig. 4c).

We extend the analysis to each year from 1980 to 2019 to assess how scaling patterns vary over time. For the scaling exponent β, we find that: (i) Before 1995, middle-percentile groups (roughly 10% to 90%) exhibit the highest β. (ii) After 1995, the top 10%

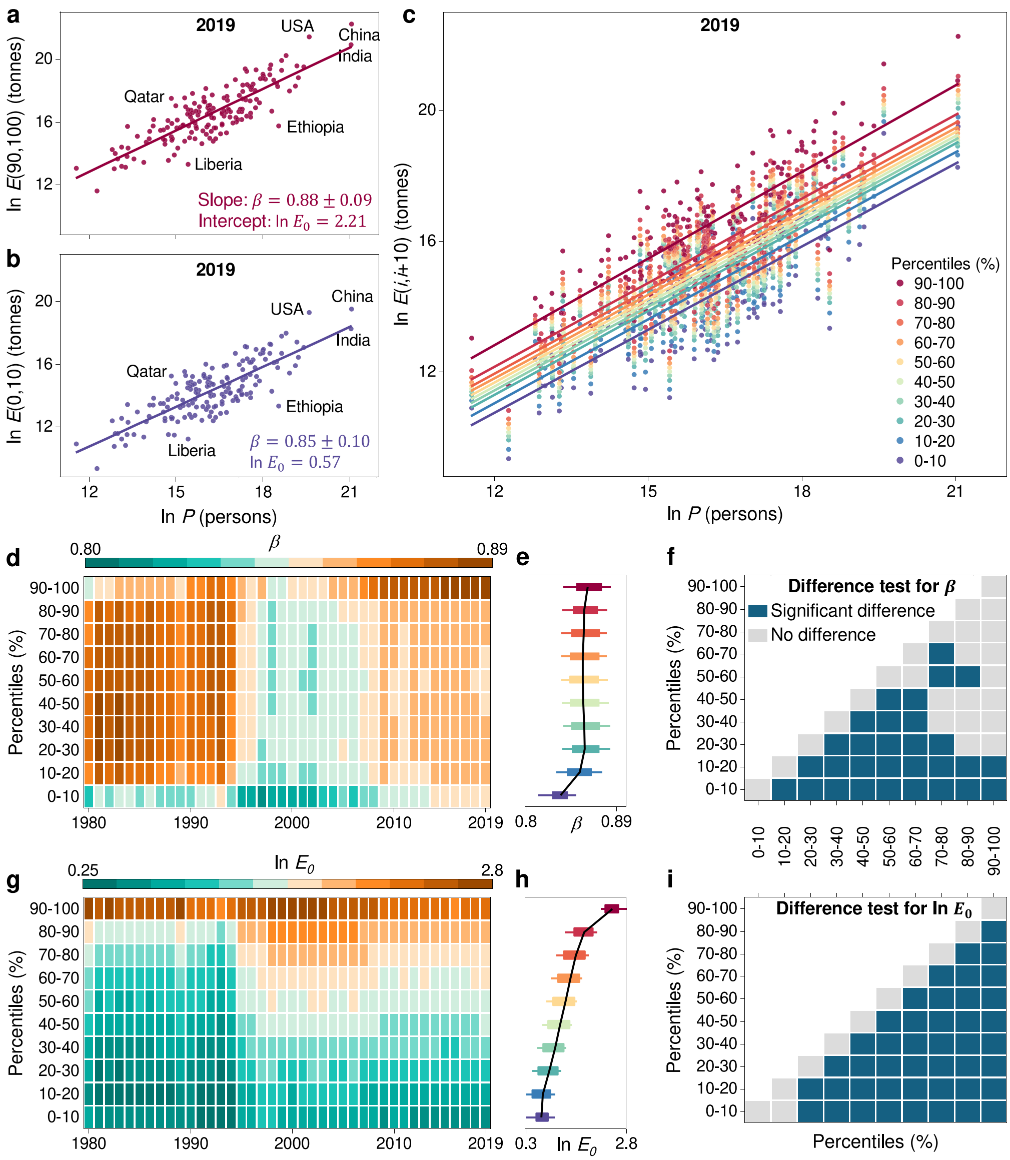

Fig. 4. Scaling of percentile emissions reveals distinct baseline levels and scale effects across population groups. Scaling relationships (the fit lines, where the slope is β and the intercept is $\ln E_0$) in 2019 between national population size and total emissions from the top 10% (a), bottom 10% (b), and all percentiles groups (c). Temporal evolution of the scaling exponent β and intercept $\ln E_0$ from 1980 to 2019 across percentiles is shown in (d) and (g), respectively. All values are statistically significant ($p < 0.01$). Distributions of these parameters over time are summarized in (e) and (h), where boxes indicate interquartile ranges, whiskers span the full data range, and the black line connects the average. The Mann–Whitney test is used to check pairwise differences in β (f) and $\ln E_0$ (i) across percentile groups over years, with significance set at $p < 0.01$.

began to lead. (iii) On average, higher-percentile groups show larger β than the bottom 10% (Fig. 4d,e). For the intercept $\ln E_0$, we observe that: (i) The top 10% consistently rank highest. (ii) Overall, $\ln E_0$ increase with percentile rank, with the top 10% group standing ahead of all others (Fig. 4g,h).

Next, we employ the Mann–Whitney test [51] to statistically check whether β (Fig. 4f) and $\ln E_0$ (Fig. 4i) differ significantly across percentile groups. For β, significant differences ($p < 0.01$) are primarily observed between higher-percentile groups (20%–100%) and the lower percentile group (0%–20%). For $\ln E_0$, nearly all pairwise comparisons between groups show statistically significant differences. The observed differences are robust through a number of robustness tests: (i) Using per-capita emissions instead of total emissions (Supplementary Information Text S1.1). (ii) Excluding outliers (Supplementary Information Text S1.2). (iii) Using finer 1% percentile resolution data (Supplementary Information Text S1.3).

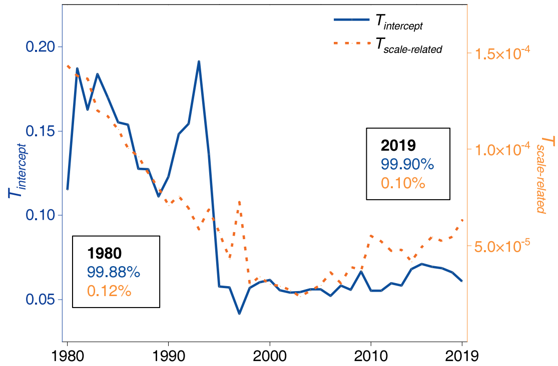

Fig. 5. Theil index decomposition reveals the dominant contribution of baseline differences to inequality. Theil index decomposition of inequality into scale-related (orange) and intercept (blue) components from 1980 to 2019. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Taken together, these findings suggest that carbon footprint inequality emerges through two distinct mechanisms: (i) Individuals respond disproportionately to increasing societal population (differences in β). (ii) Individuals exhibit inherent baseline differences in their emissions (differences in E_0).

3.2. Decomposing inequality

To inform effective mitigation strategies, it is critical to identify which of these components plays a more dominant role in driving inequality. This distinction clarifies whether policy efforts should focus on managing population-driven scaling effects (social fairness) or on reducing inefficiencies stemming from individual baseline emissions (individual fairness).

First, we test this idea using the Theil index decomposition. In this decomposition, each component reflects its proportional contribution to overall inequality—the larger the value, the greater the share of inequality attributable to that component. As shown in Fig. 5, we find that the intercept component overwhelmingly dominates the index compared to the scale-related component, indicating that individual baseline levels are the dominant source of inequality. Nevertheless, the societal-scale effect remains non-negligible, suggesting its important role in shaping carbon inequality.

Next, to better understand the country-specific inequality composition, we employ scaling decomposition.

Using China, the USA, and India in 2019 as examples, we illustrate how the scale- and intercept-adjustments reshape the emissions across percentiles (Fig. 6a–c) and their corresponding cumulative population-emission distributions (Fig. 6d–f). Both adjustments lead to reductions in total emissions and inequality (measured by the Gini index), with the intercept-adjustment showing a more substantial impact in each case.

To quantify the overall impacts, we aggregate the results of the two adjustments across all countries in 2019. The findings consistently show that the intercept-adjustment achieves stronger mitigation: (i) It reduces total emissions by 63%, compared to an 18% reduction under the scale-adjustment (Fig. 6g). (ii) It lowers the average Gini index by 75%, while the scale-adjustment achieves only a 23% reduction (Fig. 6h).

Extending the analysis over time confirms the persistence of this pattern from 1980 to 2019: (i) The average reduction in total emissions from 1980 to 2019 is 55% under the intercept-adjustment, compared to 30% under the scale-adjustment (Fig. 6i). (ii) The average Gini index reduction reaches 75% under the intercept-adjustment, while the scale-adjustment achieves only a 5% reduction (Fig. 6j). We find analogous results (baseline emissions dominate inequality) when: (i) Using per-capita emissions instead of total emissions (Supplementary Information Text S1.1). (ii) Excluding outliers (Supplementary Information Text S1.2). (iii) Using finer 1% percentile resolution data (Supplementary Information Text S1.3).

As a result, these findings underscore that targeting baseline emissions is a more effective approach for simultaneously mitigating both total emissions and inequality, reflecting the dominant role of individual differences. Nevertheless, inequality arising from variations in societal-scale effects also remains an important factor.

A closer look at individual countries reveals systematic variation in the composition of inequality. While intercept-adjustment consistently leads to larger reductions across all countries—supporting the overall dominance of baseline disparities, countries with higher original Gini indices tend to exhibit relatively greater reductions from scale-adjustment (Fig. 7). This suggests that societal-scale effects differences play a more substantial role in these more unequal countries. In contrast, inequality in more equal countries is shaped almost entirely by baseline differences.

3.3. Associations with economic contexts

Economics represent another critical societal characteristic, which is closely linked to emissions [52–54]. Here, we investigate how economic factors are associated with the scaling of carbon footprint inequality.

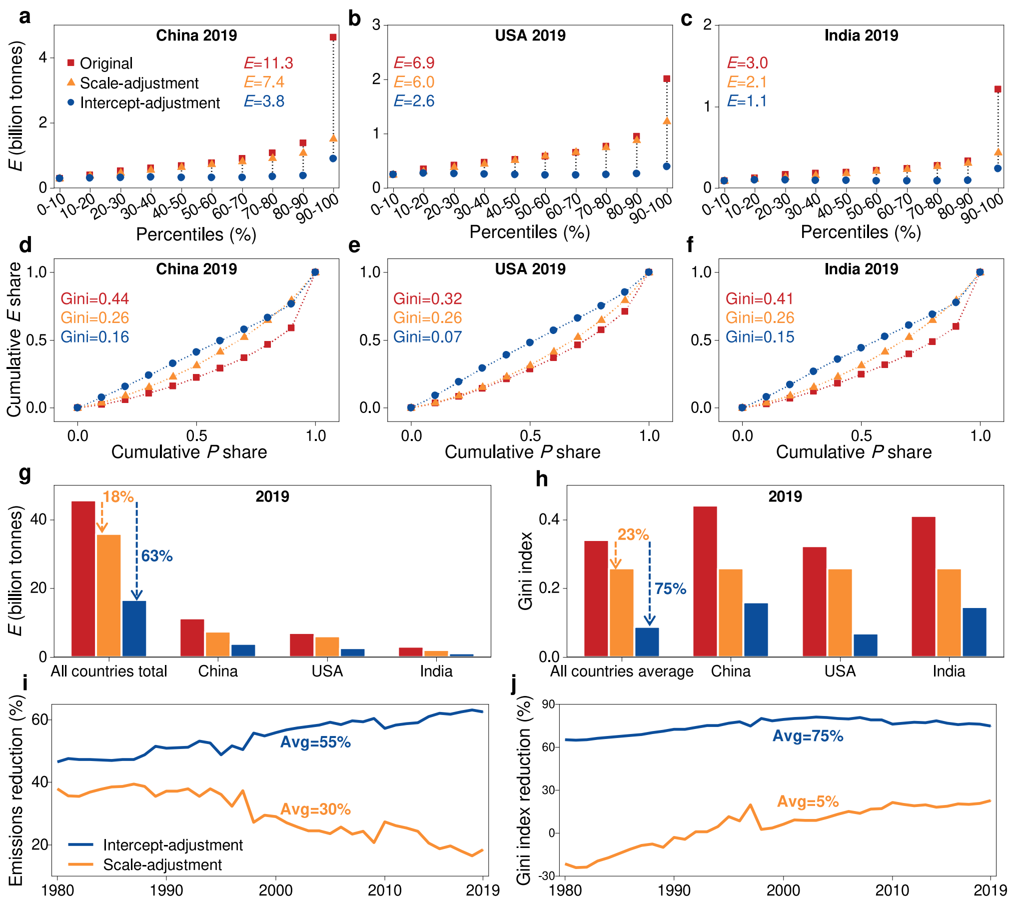

Fig. 6. Counterfactual scaling adjustments show baseline differences dominate inequality and emission gaps. (a)–(c) Emissions by population percentiles for China, the USA, and India under the original, scale-adjusted, and intercept-adjusted scenarios in 2019. (d)–(f) Corresponding Lorenz curves showing cumulative emissions versus cumulative population share. The space between the Lorenz curve and the line of equality ($Y = X$) indicates the Gini index [50]. (g) Total emissions and (h) Gini index under each scenario in 2019, with arrows indicating the percentage reduction relative to the original scenario. (i)–(j) Temporal evolution of the reduction in total emissions (i) and average Gini index (j) across all countries from 1980 to 2019.

We first examine the income-emission *elasticity* (α), which measures the relationship between individual income and carbon footprint. A higher α indicates that higher-income individuals are allocated a disproportionately larger share of emissions, while total national emissions remain constant (Supplementary Information Text S1.4). We find that: (i) Increasing α is associated with greater carbon footprint inequality (Supplementary Figure 10c,d,h). (ii) The scaling patterns shift accordingly—larger α widen the gap between the top 10% and bottom 10% groups in both scaling exponent β and baseline emissions $\ln E_0$ (Supplementary Figure 10e,f). (iii) Despite these changes, baseline emissions remain the dominant contributor to both overall inequality and total emissions (Supplementary Figure 10 g,h).

Next, we consider the heterogeneity in countries' development levels (Supplementary Figure 11; Supplementary Information Text S1.5). The results reveal that: (i) Developed and developing countries show higher β values across all percentiles (Supplementary Figure 12a), suggesting that increasing population is associated with larger emission increments in these countries. (ii) Developed countries show the highest $\ln E_0$ (Supplementary Figure 12b), reflecting higher baseline emissions regardless of population size. (iii) While baseline emissions remain the dominant driver of inequality, β plays a more substantial role in least developed countries (Supplementary Figure 12d), indicating different inequality patterns across development levels.

4. Discussion and conclusions

This study introduces a scaling framework to investigate the roles of societal-scale and baseline emissions in shaping inequality.

(i) Economies of scale exist in emissions, but targeted strategies are needed across groups. Our results consistently reveal sublinear scaling with population ($\beta < 1$)—whether based on total national scaling (Supplementary Figure 11), 1% percentile resolution (Supplementary Figure 6), or 10% resolution (Fig. 4). This implies that per-capita emissions tend to decrease as population increases,

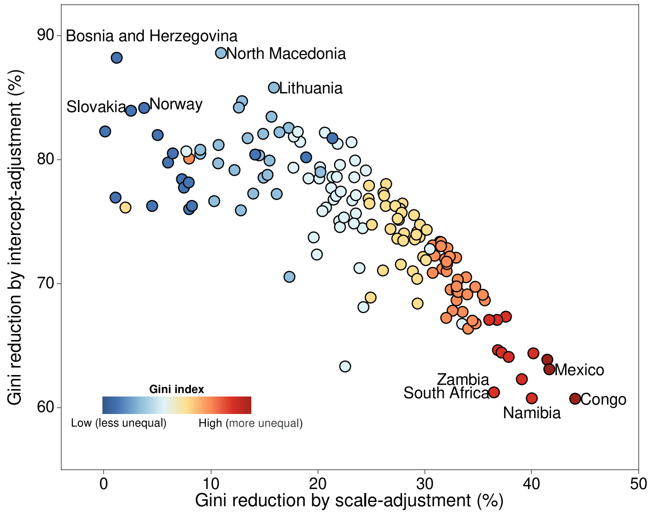

Fig. 7. Country-specific Gini reduction reveals that scale-driven inequality is stronger in more unequal countries. Scatter plot showing the reduction in Gini index by scale-adjustment (x-axis) and intercept-adjustment (y-axis) across countries in 2019. Each scatter represents a country, colored by its original Gini index. Cross-country correlations reveal that countries with higher original inequality experience larger reductions from scale-adjustment ($r = 0.92$, $p < 0.01$), but smaller reductions from intercept-adjustment ($r = -0.64$, $p < 0.01$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

reflecting economies of scale. In dense environments, shared infrastructure such as public transportation or high-density housing can improve energy efficiency and reduce per-capita emissions [18]. This highlights the importance of population concentration strategies, such as promoting urbanization, especially given that the global population is projected to rise from 8 billion in 2024 to 10 billion by the mid-2080s [55]. However, the benefits of scale are not equally distributed. Higher-income groups exhibit larger scaling exponents. Notably, the extreme top 0.001% shows near-linear scaling with $\beta = 0.96$ (Supplementary Figure 8), compared to $\beta = 0.85$ for the bottom 10% (Fig. 4). This suggests potential deviations from typical scale efficiencies, possibly due to lifestyles characterized by spacious residences and private transport [12,56]. Raising the cost of private luxury consumption while improving the quality and accessibility of shared public infrastructure may help shift preferences toward more sustainable and equitable options.

(ii) Targeting baseline emissions offers a more effective strategy for mitigating inequality. We find that disparities in baseline emissions ($\ln E_0$) are the dominant driver of inequality (Fig. 6), suggesting that wealthier individuals maintain higher emission levels regardless of population size. Addressing this requires promoting low-carbon alternatives that fulfill basic needs, such as shifting to sustainable diets [57,58], improving building efficiency [59], and enabling clean household energy [60,61].

(iii) High emitters should be prioritized in mitigation efforts. Recent work has shown that high-income individuals contribute disproportionately to climate change, while low-income populations bear the brunt of its impacts [8]. This imbalance strengthens the case for requiring high emitters to take greater responsibility in mitigation. Our analysis reinforces this conclusion by considering the income-emission *elasticity*, showing that inequality intensifies when greater wealth translates into disproportionately higher emissions. This highlights the importance of encouraging high emitters to transition toward more sustainable behaviors. To better target both scale-related and baseline emissions, broader policy may be necessary, such as implementing carbon tax [62,63] or promoting public awareness [64].

(iv) Country-specific strategies. We uncover that countries with higher original carbon inequality tend to experience greater Gini reductions from scale-adjustment (e.g., Mexico, Congo), while more equal countries (e.g., Norway, Slovakia) show that most of their inequality stems from baseline differences (Fig. 7). This suggests that unequal countries can learn from equal ones in managing scaling disparities, i.e., promoting more uniform emission returns across population groups. In contrast, relatively equal countries should focus on lowering baseline emissions to further enhance equity. Moreover, we show that while developed and developing countries should prioritize addressing baseline emissions, least developed countries would benefit from also targeting disparities in scaling exponents across percentiles (Supplementary Figure 12). We also note that technological innovation and energy system structure also influence emissions levels [65]. How these factors interact with the observed scaling patterns remains an important avenue for future research.

However, this study has limitations. One challenge is distinguishing between sectoral emissions that are baseline-related versus those that are scale-related. In this context, it is reassuring that, in our dataset, emissions are categorized into consumption and investment components. We find that consumption emissions are more closely linked to population size, as indicated by a higher R^2 value compared to investment emissions (Supplementary Figure 9). This suggests that consumption-related emissions are more likely to be scale-related, while investment emissions may be more indicative of baseline components. Our analysis aggregates consumption and investment emissions, potentially obscuring sector-specific dynamics (e.g., industrial vs. residential emissions). Disaggregated data would clarify how manufacturing or transportation sectors contribute to inequality in large countries like China or the USA.

Additionally, our understanding of different percentile groups is currently limited to their emissions. To obtain a more comprehensive picture of inequality, it would be valuable to consider additional factors such as geographic location (e.g., whether individuals reside in cities and which cities matter [15]), employment status (e.g., whether individuals work in carbon-intensive industries [66]) and demographic characteristics (e.g., smaller or aging households tend to have higher emissions [67]). Such information could further illuminate intra-country inequality and provide a more nuanced understanding of emissions distribution. Finally, our adjustments estimate the potential reductions in emissions and inequality based solely on emission-related scaling exponents. However, given the strong link between economic activity and emissions [68–74], it is crucial to consider the potential economic losses associated with these reductions. Balancing emission reductions with economic growth remains a central challenge for policymakers.

Despite such constraints, our work enhances understanding of carbon footprint inequality by decomposing its structural origins—highlighting the distinct contributions of societal-scale effects and individual baseline emissions. This has been largely overlooked but is essential for designing more equitable and effective climate strategies. Our framework provides a systematic, cross-national lens to quantify inequality mechanisms and can be extended to explore other domains, such as economic or environmental disparities. Furthermore, the counterfactual adjustment method we propose offers a novel analytical tool for simulating inequality under different policy scenarios, thereby informing more targeted and fairness-oriented interventions.

CRediT authorship contribution statement

Peiran Zhang: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Liang Gao:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Formal analysis, Data curation, Supervision, Conceptualization. **Yunfei Li:** Writing – review & editing, Supervision. **Chaoyang Zhang:** Writing – review & editing. **Xiqun (Michael) Chen:** Writing – review & editing, Supervision. **Jingfang Fan:** Writing – review & editing, Supervision. **Daqing Li:** Writing – review & editing, Supervision. **Bin Jia:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Ziyou Gao:** Writing – review & editing, Funding acquisition, Supervision, Conceptualization. **Jürgen Kurths:** Writing – review & editing, Supervision, Conceptualization. **Jose F.F. Mendes:** Writing – review & editing, Supervision, Conceptualization.

Data, materials, and software availability

Data and codes for this analysis are publicly available at figshare (https://figshare.com/s/834bd2931c1950b76c6b).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.chaos.2026.118215.

Data availability

Data and codes for this analysis are publicly available at figshare (https://figshare.com/s/834bd2931c1950b76c6b).

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