Supplementary Materials for

New demand goals for energy and climate resilience

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Supplementary Text *(Methodological Issues on Energy Decomposition, Energy Use Differences, Energy Under- and Overconsumption.)*

Boxes

Materials and Methods *(Extended presentation of the analysis and results.)*

Figures and Tables

box S1. Energy Use Differences

Energy use varies widely as do indicators to measure it. Historically energy use has been measured by primary energy, i.e. the resource inputs (coal, oil, gas, hydropower, wind, solar) to the energy system. However, primary energy is affected by statistical conventions and upstream transformation losses that do not directly correspond to the energy services people use. In fact, renewable energy accounting remains inconsistent, with hydro counted by physical output (electricity generated) and other sources by the so-called substitution method (i.e., as the fossil fuel that would be required to produce an equivalent output of electricity) that inflates primary energy figures. With increasing shares of modern renewables growth trends in primary energy can thus increasingly decouple from the underlying trends in energy demand for services and the useful and final energy used to deliver those (GEA, 2012, Chapter 1 Figure A.1). In order to avoid these ambiguities and focus on energy end use final energy (e.g., delivered electricity, heat, fuels) offers a clearer, more consistent basis focused on the energy actually delivering energy services desired by end users

The traditional focus of differences in per capita energy use has been on differences across nations (fig. b1-1) where final energy use per capita varies between 3 to 300 GJ/capita for a global average of 53 GJ/capita in 2005), i.e. by a factor of 100. These differences between countries however ignore *within-country differences*, i.e. differences in energy use between rich and poor within a given country. There is increasing evidence that ignoring within-country differences in energy use results in an ever increasing omission bias when analyzing the true dispersion of per capita energy use. This has been highlighted in the recent literature on carbon inequality (differences in per capita CO2 emissions). Figure b1-2 from Chancel et al (2023) suggests that differences in carbon footprints between countries accounted for 62% of differences in global carbon footprints in 1990, whereas in 2019 64% of the global differences are accounted for by within-county differences.

Hence to answer the question of what constitutes possible under- and overconsumption of energy one needs to look at the distribution of per capita energy use including both across-country as well as within-country differences. While recent studies in carbon inequality have highlighted particularly the significant impact of high consumers (top 10%, 1%, and 0.1% which are estimated to account for 48%, 17% and 7% of global carbon emissions[1] respectively (Chancel, 2022), the existing literature on energy inequality is limited and due to data limitations and aggregation into broad income categories cannot capture the

[1] 50.5 GtCO2-equiv. in 2019. Emissions include those from final consumption (50% of total), as well as those embedded in investments as well as from international trade in products. These consumption based carbon emissions differ markedly from traditional national level reporting of "territorial" production based emissions.

top end of the distribution for energy footprints comparable to the carbon inequality literature.

An important study of energy use inequality was published by Oswald et al., 2020. The underlying empirical observations of the study are summarized in Figure b1-3. The sample estimated via I-O tables the direct and embodied energy in household consumption based on two samples: World Bank covering 4 income groups across 51 countries in the Global South, as well as Eurostat covering 5 income quintiles across 30 European countries. The data set covers 82% (5.4 Billion) of the global population, but only 38% (16.4 Trillion) of global expenditures, and 36% (141 EJ) of global final energy use (2015 data). It should be noted that the data set excludes prominent high income countries outside Europe such as Australia, Canada, Japan, or the United States or the oil exporting countries of the Middle East. Also, the World Bank data set with its (open ended) highest income category defined above a threshold of 23$/day (>8400 $/year) along with the use of income quintiles for European countries necessarily masks the significant dispersion of energy use at high incomes.

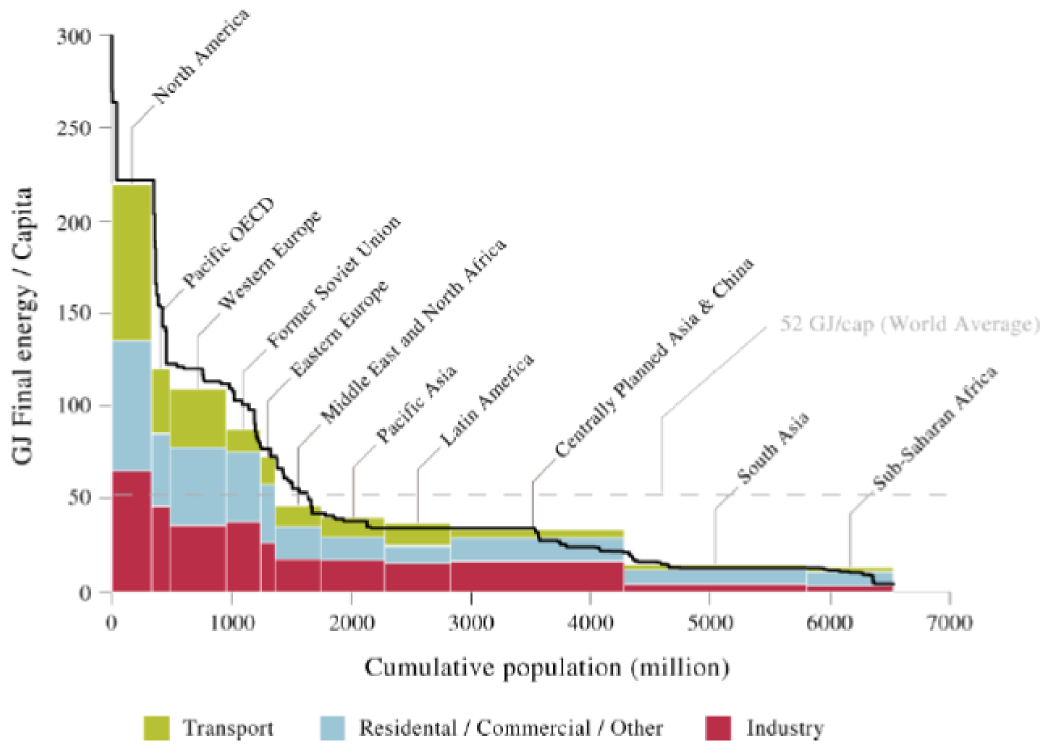


fig. b1-1. World per capita final energy use (GJ/capita) by sector and total vs cumulative population (million) for year 2005 for 11 world regions (colored bars) and 137 countries (black line). Source: GEA Energy Primer 2014.

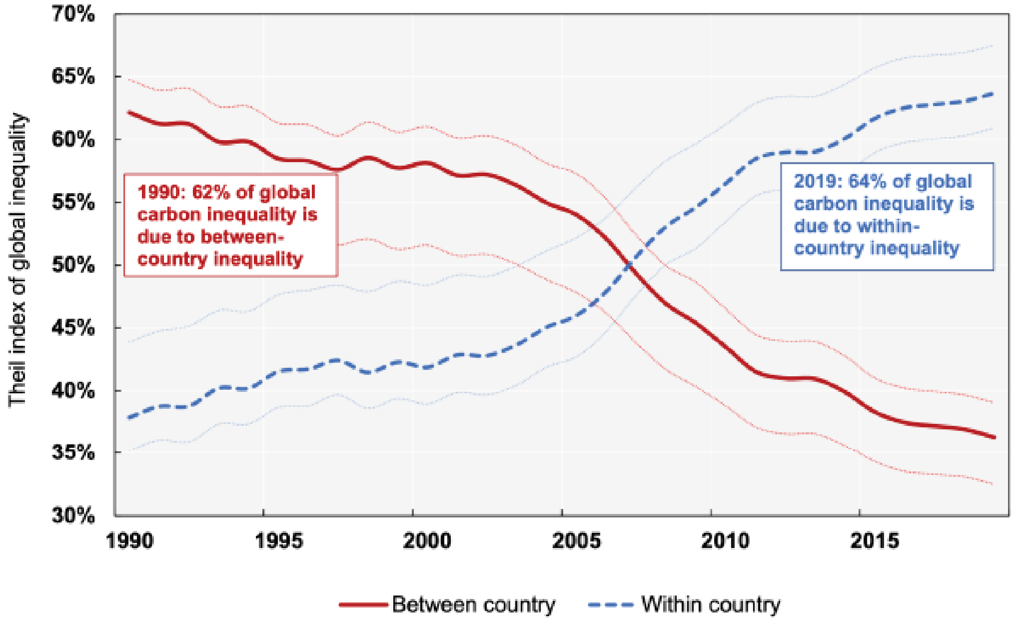


fig. b1-2. Explaining differences in per capita carbon emissions 1990-2019, due to variations across countries (blue) and within countries (red). Source: Chancel et al., 2023. CC BY 4.0

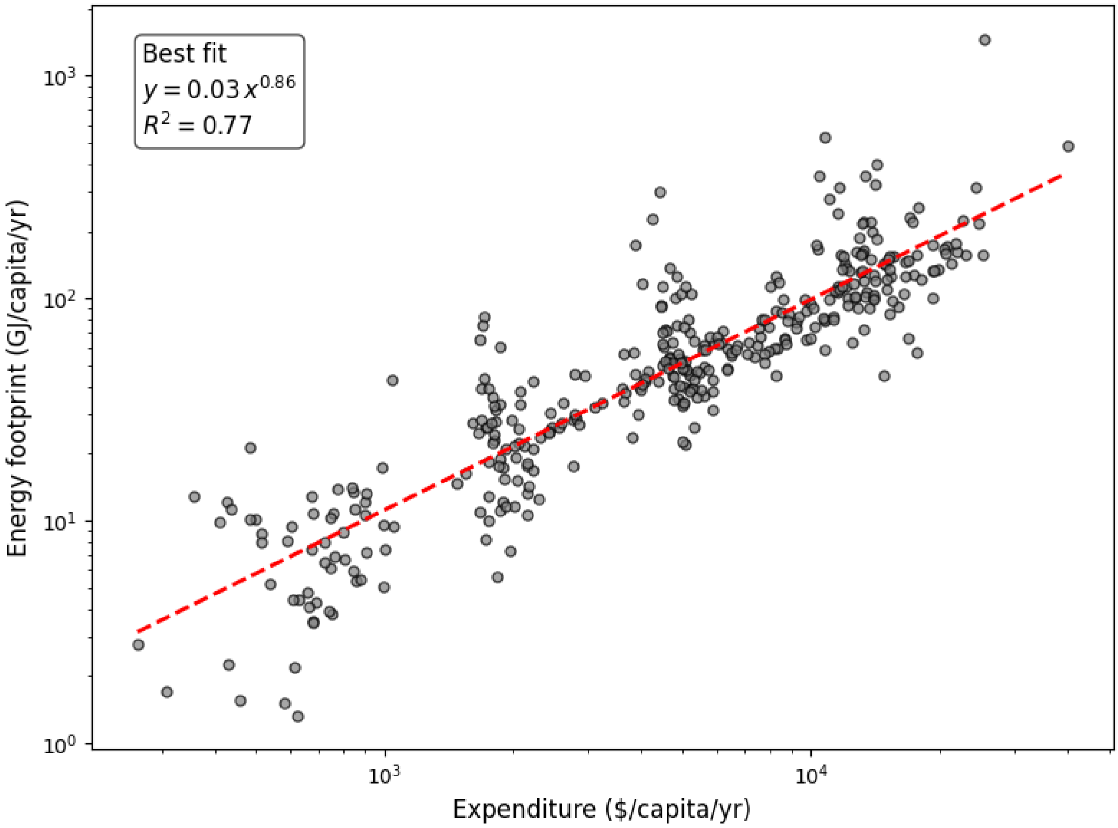


fig. b1-3. Energy footprints (final energy GJ/capita) variations for different income groups in the Global South (4 income categories) and in Europe (by income quintiles). The sample covers 5.4 billion people (82% of the globe), 16.4 Trillion $PPP expenditures (38% of the globe) and 141 EJ final energy (36% of the globe). The resulting energy use inequality has a Gini of 0.52 and a top-to-bottom-10% ratio of 20. The elasticity of final energy to expenditure is 0.86. Adapted based on original data from Oswald et al., 2020.

box S2. Estimating energy use of high consumers

To complement existing analyses of per capita energy use distributions we therefore need to consider especially the long tails of the distribution at high, and very high incomes for which only extremely limited data are available. Anecdotal evidence suggests that these can very high indeed. In 2007 there were press reports[2] about the residential energy bill of Al Gore amounting to 221,000 kWh per year, 20-times that of an average US home (equaling an energy footprint of 800 GJ, excluding transport energy and energy embodied in investments and products purchases). To put this number into perspective: using smart meter data from 8.6 million US households with identical heating systems (gas) OPOWER estimated for 2011 that the top 1% of US households consumed on average of close to 34,000 kWh/year (or 4% of total electricity use), with the top 10% consuming around 19,000 kWh/yr (20% of total electricity use) compared to the average of the bottom 90% of households with 7,200 kWh/yr (or 76% of total electricity use).

In 2021 researchers revealed the magnitude of CO2 emissions from mansions, yachts and private jets of 20 billionaires.[3] It is straightforward to calculate the associated energy use based on standard CO_2 emission factors (diesel and kerosene for yachts and jets, and assumed natural gas for residential buildings). On average these 20 super-rich used 121,000 GJ per year in 2018 (emitting 8,200 tons of CO_2), including some 4000 GJ for their dwellings, 77,000 GJ for their yachts, and 40,000 GJ for other modes of transport (private jets, regular air carriers, automobiles). The list is topped by Roman Abramovich with 460,000 GJ energy use per year. At the bottom of the list are Michael Bloomberg and Elon Musk with about 30,000 GJ/yr each (owning neither a private yacht or private jet results in their more “modest” energy and carbon footprints (some 2000 tons CO_2). Chancel (2022) estimates a comparable average carbon footprint of 2,332 tons CO_2-e for the 777,000 people that are the top 0.01% of emitters, accounting for 4% of global emissions.

[2]https://abcnews.go.com/Politics/GlobalWarming/story?id=2906888&page=1#:~:text=Armed%20with%20Gore%27s%20utility%20bills,average%20of%2010%2C656%20kilowatt%2Dhours.
[3] https://theconversation.com/private-planes-mansions-and-superyachts-what-gives-billionaires-like-musk-and-abramovich-such-a-massive-carbon-footprint-152514

box S3. Estimating global distributions of final energy use with explicit inclusion of high, and very high-income consumers

Extending the Oswald et al., 2020 study we first complemented the original data set with energy use data of high income developed countries not included in the Oswald et al. (2020) study, i.e. by countries outside Europe including: Australia, Canada, Japan, the USA (cf. below). We also augment the original Oswald et al. distribution by estimated energy footprints at the high end of income/expenditure distributions. To that end we use the estimated income distributions[4] of the top 1% of incomes, differentiated into two sub-segments of the top 0.1% and the remaining 0.9% within this category, representing Brazil, China, India, Russia and South Africa[5] as well as a residual "rest of world" (row) region that accounts for the difference between our augmented Oswald sample and the world total as estimated in the OXFAM carbon inequality study. For the four additional high income countries Australia, Canada, Japan and the USA we retain the original income categories of the underlying data set: bottom 50%, next 40%, top 9%, top 0.9% and 0.1% of incomes.

The energy footprint in each income category is then calculated using a method proposed by Spreng (2005) who suggested to determine deviations for the average energy footprint of a country using income differences combined with a constant energy elasticity term (0.86 derived from Oswald et al, cf. fig. b1-3, which is quite close to the original elasticity of 0.8 used by Spreng, 2005 and backed up by a literature synthesis in Spreng, 2005.). In a "high" variant of this calculation we also derive a distribution that considers a two-step approach to elasticities recognizing that at high incomes expenditures increasingly are dominated by transport energy use and other leisure- related activities which tend to be inelastic (elasticities >1) as demonstrated in Oswald et al. (2005), see fig. b3-1. For the top

[4] Data come from the online data base of the OXFAM Carbon Inequality Report hosted by the Stockholm Environmental Institute, see: https://emissions-inequality.org/

[5] Our estimated energy footprint of the top 1% of incomes is simply added to the original Oswald data sample to retain the integrity of the original data set and considering the likely high omission bias of energy use at very high incomes in the highest income category of the Oswald sample based on World Bank household expenditure data. For instance for India the Oswald sample's highest income group represents 246,282 people and a total income of 3.1 Billion $ (11604 $/capita, i.e. middle class levels). Conversely the Chancel data suggest that the top 1% of incomes in India comprise 13.8 Million people and an income of 1658 Billion $, 120,000 $/capita), a factor of 535 higher and thus a clear demonstration of the well-known omission bias of household surveys of high incomes. Adding thus the Chancel based energy footprint of the top 1% of incomes to the highest income group of Oswald corrects for this omission bias rather than representing double-counting. However, in some countries with extreme income inequality such as Russia and South Africa, the Chancel data top 1% of incomes are of the same order of magnitude as the top income categories in the Oswald sample, suggesting a certain potential of double counting of incomes and energy footprints, which also applies to our "rest of world" region. Note however, that any potential double counting does not apply to the top 0.1% and 0.9% of incomes and their associated energy footprint but rather to the highest income categories of the respective countries in the Oswald data sample, potentially overestimating the energy footprint of the upper-middle class. Note also that even in the extreme cases of Russia and South Africa the energy footprint of Oswald's highest income category (4) is with 200 GJ/cpita (Russia, RUS) and 163 GJ/capita (South Africa, ZAF) below the threshold of 300 GJ/capita propsed here to delineate "high" consumers, subject to the proposed alternative "overconsumption" taxation schemes and therefore not affected by any additional taxation scheme discussed.

1% of incomes, we assume an elasticity of 1.1 for the fraction of their incomes exceeding the value of the top 9% income category and retain the elasticity of 0.86 for their remaining incomes. Across all data points of the extended sample (without the original Oswald data) this approach yields an aggregate elasticity of 0.91 of final energy use versus income. The "high" variant in our view offers the best approximation of the global inequality of energy use based on available data und underlies also the quantitative results reported in the main paper.

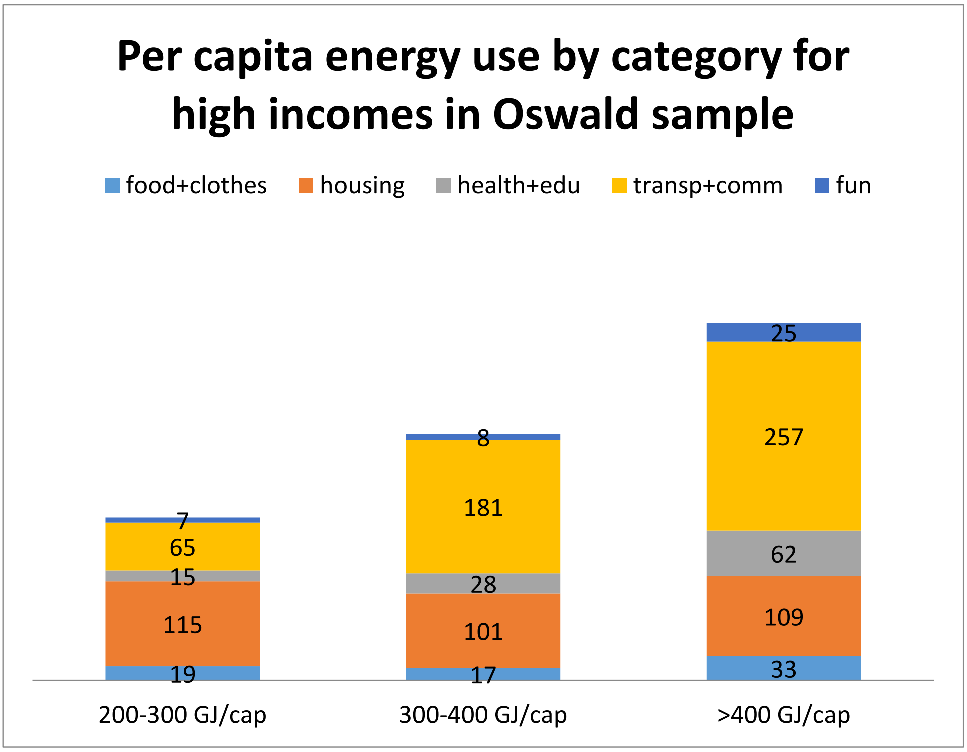
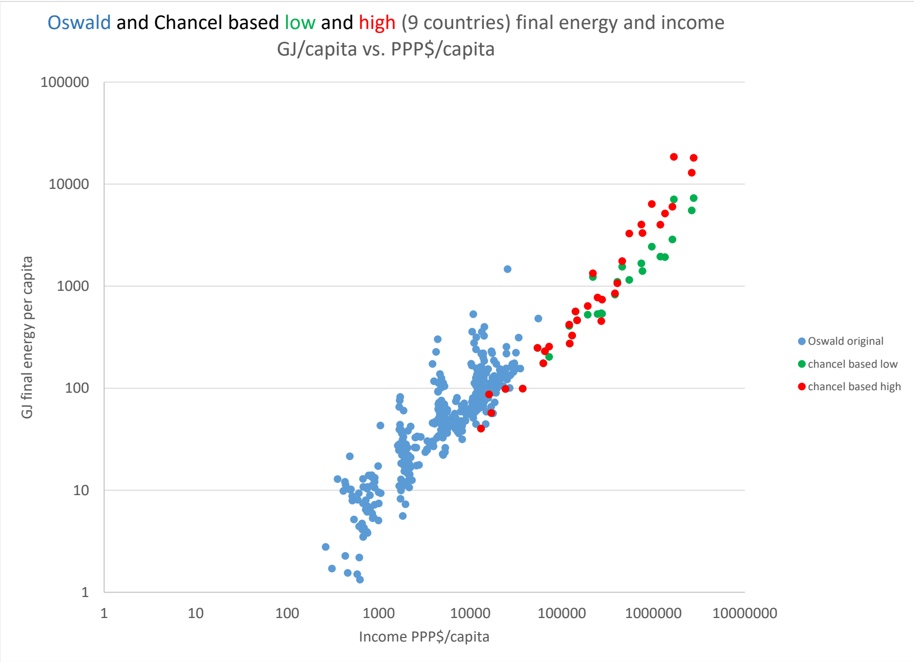


fig. b3-1. Per capita energy use by category of high income groups of Oswald et al sample (in GJ/capita by type of use). Data source: Oswald et al., 2005.

Both original and extended distributions of final energy use are summarized in Table b3-1 and in the Lorenz curves in fig. b3-2. By including the top 1% explicitly in the sample (and not simply in form of an aggregated high-income [read-middle class] category) global disparities increase substantially and follow more closely the pattern demonstrated by studies of carbon inequality, for which energy use is a major driver. It is also instructive to look at the energy use at the very top of the distribution function, which given the limited number of countries analyzed nonetheless provides some minima boundary values of characterizing very high energy consumers bridging to the anecdotal evidence of the energy and carbon footprint of billionaires referred to above. According to our preferred "high" scenario, the top 1% worldwide consume up to 80 EJ or some 20% of final energy with an average per capita footprint at or above some 500 EJ/capita. The top 0.1% have a footprint of above 3000 GJ/capita equaling up to 40 EJ or some 10% of world final energy use. Conversely, according to our analysis only 6-8% of the world population (of 6 billion covered in our sample) consume 50% of all final energy whereas the bottom 50% of the world's population only consume less than 10% of global final energy.

Table b3-1. Overview of energy footprints and defining per capita thresholds for global distributions with varying sample size and estimated per capita consumption. Source: see text.

	2019	Oswald et al	augmented Oswald base	augmented Oswald high
Population (10^9)	7.7	5.4	6.0	6.0
Final energy (EJ)	420	141	274	309
bottom 50% GJ/capita		<13	<21	<21
bottom 50% EJ		10	26	26
top 10% GJ/capita		>62	>98	>98
top 10% EJ		43	129	188
top 1% GJ/capita		>400	>480	>480
top 1% EJ		70	45	80



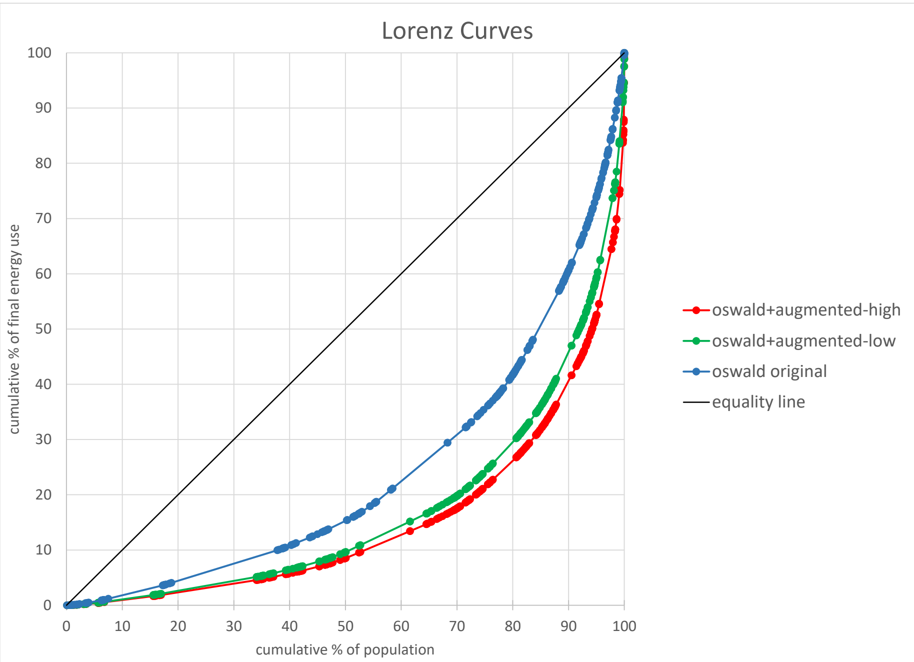


fig. b3-2.

Top: Summary of footprint sample data, final energy GJ/capita/year vs income PPP$/capita,

Original Oswald sample (blue), and Chancel income based low (green) and high (red) final energy use estimates used to augment the original Oswald sample.

Bottom: Lorenz curves of cumulative population vs cumulative final energy use for three data sets: original Oswald et al. 2020 study (Gini 0.52), augmented data set low (**Gini 0.63**), and augmented data set high (**Gini 0.67)**, with the latter retained as best estimate of current global disparities in final energy use for this study.

The corresponding thresholds in terms of per capita final energy use (GJ/capita) are also shown in figures S7 and b3-3. Our results suggest three classes of "high" energy use categories at: 100 GJ/capita (high consumption, top 10%), 500 GJ/capita (very high consumption, top 1%) and >1,500 GJ/capita (extremely high consumption, top 0.1%). These can be compared with existing thresholds of energy under-consumption, as defined by Decent Living Standards (DLS) and estimated to amount to between 13 to 18 GJ/capita (Rao and Min, 2018; Kikstra et al., 2021). Hence 50% of the global population covered in our sample distribution is at or below the DLS threshold. Elevating all those underserved (i.e. below DLS thresholds) would increase global final energy use by some 17% (68 EJ) which equals the energy use of the top 2% incomes in excess of a threshold of 300 GJ/capita. The thresholds shown in fig. b3-2 can also be compared to estimates of "energy sufficiency" thresholds, akin a definition of "overconsumption". The literature review given in Burke, 2020 summarizes such sufficiency thresholds to range between 60 GJ/capita[6] (83-87% of world population below this threshold in our sample) to 221 GJ/capita (threshold where the top 5-8% of the population consume almost 50% of global final energy).

Considering
A) the high end range from the sufficiency literature with
B) our estimate of "high" energy consumption derived from empirical distributions, and
C) normative thresholds as a suggested "solidarity" threshold of constraining personal energy use to allow providing decent standards of living for all
suggests a range of 100-500 GJ/capita to operationalize "high" energy use.

A pragmatic narrower range would suggest at values between 200-300 GJ/capita. We propose in this study a (generous) threshold of 300 GJ/capita/year to define excessive high energy consumption.

[6] Practically identical to the 63 GJ/capita upper floor suggested by the concept of a 2000 Watt society in view of social and ecological boundaries (cf. Spreng, 2005).

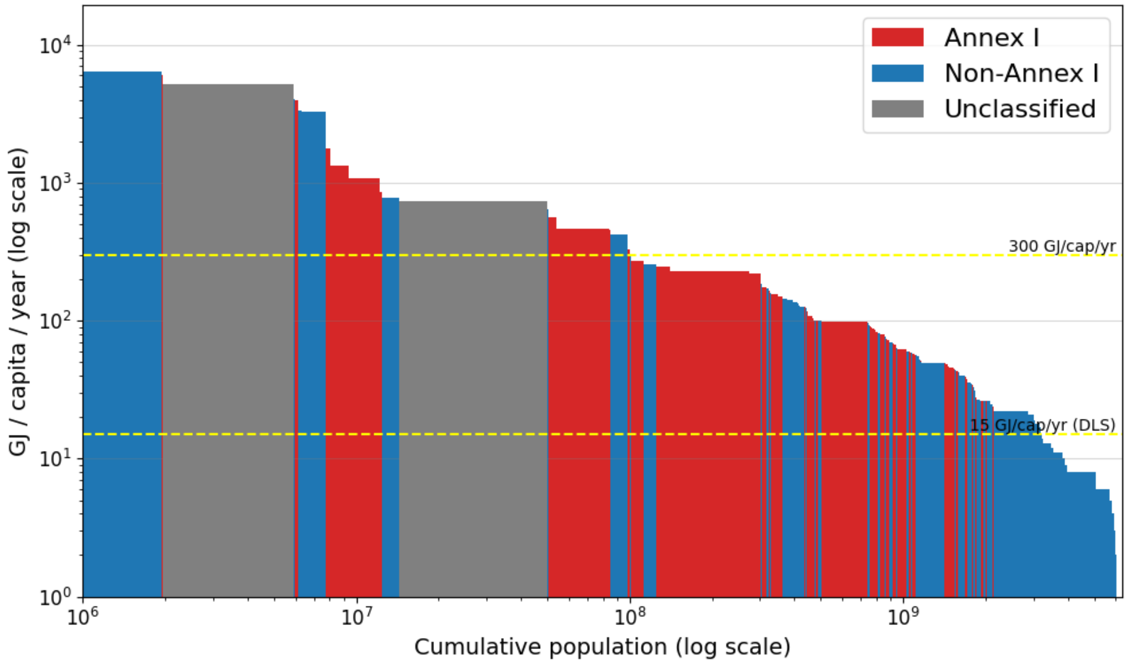


fig. b3-3. Rank-size distribution of per capita final energy use (GJ/capita/yr) versus cumulative number of people, augmented Oswald high sample, by region: UNFCC Annex-1 countries, Non-Annex-I countries, and “unclassified” all top 0.1% and 0.9% of incomes outside the nine countries estimated separately and the world total reported in Chancel, 2022. Note in particular the double logarithmic axes to be able to display the vast disparities. To improve readability the x-axis starts at 10^5. Our first observation is a high income population group comprising 145,000 people, consuming 18,505 GJ/capita/yr, out of which only 45,000 people are visible in above graph.

box S4. Energy taxes paid by high consumers and options to tax overconsumption

How much energy taxes are paid by high consumers and what could be alternative models to tax energy “overconsumption”?

The available literature of energy taxes is far from comprehensive and reported or estimated tax levels are available for only relatively few countries, predominantly OECD countries. The most comprehensive data set for energy taxes was developed by Ross et al., 2017 estimating gasoline taxes and subsidies for 153 countries for the years 2003 and 2015. Ross et al use the so-called price-gap model in determining de facto gasoline taxes/subsidies in which local gasoline prices are compared to a reference global market based reference gasoline price translated into local currencies considering purchasing power parities. Prices higher than the global reference price represent taxes; lower prices represent de-facto gasoline subsidies. Ross et al estimate that the global average (weighted by consumption volumes) gasoline tax in 2015 amounted to 24.2 cents/litre or some 8 $/GJ (a value we retain for our “rest of world” region and as a conservative assumption for countries with de facto gasoline subsidies (Kirgizstan and Egypt in our country sample). The estimated 2015 gasoline tax from the Ross et al. study is used here to derive a proxy estimate of the upper bound of energy taxes currently paid by high energy consumers. The estimate is an upper bound, as not all energy use is for transportation and consists of gasoline (e.g. including electricity and natural gas, generally taxed much lower) and even in the case of transport fuels high consumers consumption of kerosene for jet travel or diesel for yachts is generally taxed much lower than gasoline (if it is taxed at all as in the case of international aviation fuel). Yet, given the high share of transport fuels (incl. gasoline) in the energy budget of high energy consumers (cf. fig. b3-1) the use of gasoline taxes as a proxy for determining the upper bound of energy taxes paid by high consumers seems reasonable. The estimated tax levels vary significantly across countries from low values of 1.1. and 2.6 $/GJ for Russia and the USA respectively, all the way up to close to 27 $/GJ in Western Europe (Luxembourg). Applied to our sample of countries and income groups above a threshold of 300 GJ/capita energy consumption yields an estimate of 867 billion $ (0.9 Trillion) as upper bound of energy taxes currently paid by high consumers.

Given the typically low price elasticity of transport fuel demand (short term -0.3; long-term -0.6, see more details in Litman, 2025) energy taxes would have to rise significantly in order to yield a noticeable reduction effect on high consumers. We propose here two scenarios of energy taxation of high energy consumers. In both scenarios all energy use up to 300 GJ/capita would remain under their existing tax levels with the proposed “overconsumption” tax applied only to energy consumption above the 300 GJ threshold.

Scenario 1: linear overconsumption tax: This scenario assumes that each addition GJ of consumption above 300 GJ should be taxed at a rate of 40 $ per GJ which would translate to a maximum tax of some 700,000 $/capita for the highest consumers (the top 0.1% of incomes in Russia and Canada with over 18,000 GJ/capita). This additional “overconsumption” tax could raise potentially up to 3 Trillion $, tripling existing energy taxes for high consumers.

Scenario 2: progressive overconsumption tax: This scenario is inspired by the typical income elasticity of transportation fuels of +1.1, aiming to compensate ever increasing energy consumption with rising incomes. The proposed progressive “overconsumption” tax scenario is determined by taxing each *x* GJ consumption above the 300 GJ threshold by $ = $0.01x^{1.1}$. The maximum tax could reach in this scenario a prohibitive level of over 8 Million $ per capita for our highest income groups (top 0.1% incomes in Russia and Canada), exceeding their respective income levels (>2.5 Million $).[7] The progressive tax scenario could yield a potential revenue of up to 7 Trillion $.

The implementation of such “overconsumption” taxes could be rather straightforward at the beginning by first taxing fuels characteristic for high consumption such as for private yachts (diesel) and airplanes (kerosene) as well as all utility billed fuels such as electricity and natural gas above specified household consumption thresholds (e.g. 20,000 kWh electricity and 100 GJ natural gas). Alternatively, “citizen credit cards” for energy purchases could be established to make energy consumption expenditures and associated tax levies both transparent and operable.

[7] See the discussion on the associated demand response below where a constraint limits the impacts of such rather unrealistically high tax levels.

box S5. Demand response to taxation of high consumers

Given the proposed taxation of excess consumption (>300 GJ/capita) there will be likely a demand response (i.e. reduction). As the largest fraction of the excess consumption is in transportation fuels, the demand response primarily depends on the price elasticity of transport fuels for which there is a large body of literature (see the comprehensive review and meta study of Brons et al., 2008 and Litman, 2025). Brons et al synthesize the literature concluding that gasoline demand price elasticity is inelastic (i.e., <1, declining disproportionally to price increases) giving a mean price elasticity for gasoline demand of -0.34 (with a range of -0 to -1.0) in the short-term and of -0.84 (range of -0.15 to -1.5) in the long-term. The Litmann (2025) review concurs with this synthesis (-0.3 short-term price elasticity), with the mean long-term elasticity however being somewhat lower -0.6 vs -0.84). However, these syntheses based on both macro- as well as micro-level studies do not answer the question of what the price elasticity at very high incomes could be, as the corresponding literature is extremely sparse.

Even the most detailed study of price elasticities across different income groups performed for Germany by Priesmann & Praktiknjo (2024 and 2025) ends at an income category of 80,000 Euros per year—a value substantially lower than for the incomes of typical high energy consumers (>300 GJ/capita) that ranges from 10^5 to several 10^6 US$)—for which the authors give a mean price elasticity of -0.14. Priesmann & Praktiknjo (2024 and 2025) also observe a non-linear pattern in the price elasticity versus income that declines linearly with high income levels (fig. b5-1) suggesting that, by extrapolating their trends, the price elasticity of motor fuels could ultimately approach zero at income levels above some 160,000 Euros per year. The effect of the demand response to our suggested two taxation scenarios remains therefore uncertain as robust price elasticities for very high-income groups remain elusive in the literature.

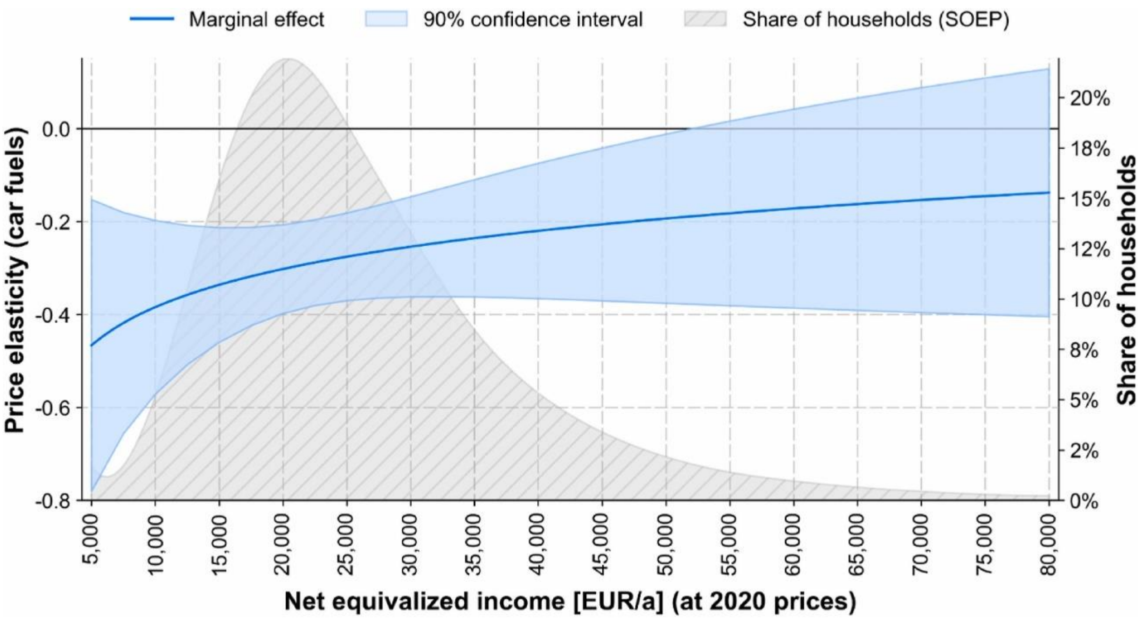


fig. b5-1. Price elasticities of automotive fuel demand for Germany versus incomes. The mean price elasticity for the entire sample population is -0.29, in good agreement with the mean short-term elasticity of -0.34 synthesized from 221 studies by Brons et al. (2008). Source: Priesmann & Praktiknjo (2024 SSRN pre-print, open content).

For the potential (short-term) impacts on demand of high energy consumers, we thus provide a range anchored in the available literature using values between -0.14 to -0.34.

Combining the two price elasticities with the two proposed taxation schemes of excess energy consumption, we determine a possible demand response (reduction) of between -21 EJ (linear taxation model with low elasticity of -0.14) to -53 EJ (exponential taxation model with high price elasticity of -0.34).[8] (For comparison: the estimated energy use of high consumers above 300 GJ/capita is some 70 EJ).

Such a demand response would evidently reduce the potential revenues from taxing excessive consumption. We estimate the resulting ultimate global tax revenues to range between 0.2 to 2 Trillion US$ per year after taking the 2x2 demand response (reduction) and taxation scenarios into account. There is thus an inherent tradeoff between the twin objectives of reducing overconsumption and the possible tax revenues from levies on overconsumption.

Nonetheless, both impacts are notably large and can contribute substantially towards the energy goals proposed here. A demand reduction between 21 to 53 EJ/yr can reduce pressures on energy supply (mostly oil), dampen price volatility as well as making much needed energy available for addressing energy poverty. (Recall here that the energy required to bring everyone globally to decent standards of living is estimated to require some 68 EJ). And potential tax revenues between 0.2 to 2 Trillion US$ can go a long way to invest in addressing energy poverty as well as to finance the transition towards higher efficiency and electrification (see table S5-1 for a synthesis table).

[8] Given the extreme high taxation levels at very high consumption levels the demand response estimates were constrained to not exceed the level of energy overconsumption above 300 GJ/capita for reasons of consistency (stated objective of the proposed tax is to reduce overconsumption >300 GJ/capita). This constraint affects the demand response of high energy consumers under the progressive tax model at levels above 3700 GJ/capita (-0.34 elasticity scenario) to 12700 GJ/capita (-0.14 elasticity scenario) respectively. The constraint is not binding in the linear taxation cases. Relaxing this constraint in the progressive tax scenario would increase the demand response to 45 EJ (compared to 34 EJ in the constrained case) for the -0.14 elasticity scenario and to 109 EJ (compared to 54 EJ in the constrained case) for the -0.34 elasticity scenario.

table S5-1 Estimated demand response and tax revenues under excess consumption taxation

Price Elasticity (short-term)	Taxation Model	Estimated Demand Reduction (EJ/yr)	Share of Excess Use (70 EJ)	Estimated Annual Revenues (Trillion US$)	Notes
–0.14 (low, high-income extrapolation; Priesmann & Praktiknjo 2024/25)	Linear	–21 EJ	~30%	~2.0 T$	Elasticity derived at ~80k € income level; extrapolation to higher incomes uncertain
–0.14	Exponential	–50 EJ	~70%	~1.5 T$	Same elasticity, stronger taxation response
–0.34 (mean short-term, Brons et al. 2008; Litman 2025)	Linear	–34 EJ	~50%	~0.8 T$	Literature synthesis across 221 studies; broadly applicable to general population
–0.34	Exponential	–53 EJ	~75%	~0.2 T$	Upper-bound estimate; assumes high responsiveness to taxation

box S6. Accounting Activity, Intensity and Structure Effects

The traditional approach to calculating structure (or structural) change effects in energy demand decomposes total energy consumption into three key factors (Koomey, 2019):

- **Activity Effect**: Changes in the level of activity (e.g., production, transport volume).
- **Intensity Effect**: Changes in the energy intensity (efficiency) of an activity.
- **Structure Effect**: Changes in the composition of energy demand across different sectors or technologies.

The conventional decomposition method applies percentage changes either multiplicatively or additively (Ang, 2015) and ensures that their aggregation matches the total observed energy change, without residuals. This explains its wide utilization to decompose energy demand and CO_2 emissions (Koomey, 2019; IEA, 2015). Particularly, it relies on the logarithmic mean Divisia index (LMDI) framework (Ang, 2004a), which relies on logarithmic averages to avoid problems with the mathematical treatment of zero and negative values.

Despite its wide use, the traditional approaches present several limitations in capturing the full scope of structural change (including within sectors or categories), are complex (8 distinct models depending on the weighting scheme (LMDI I or II) Ang (2015)) and are not straightforward to implement.

To show the importance of structure effects and their relation to activity and intensity effects, we develop a simple method for computing this important component, often overlooked. This approach is based on a simple two-factor version adapted from the generalized Fisher equation (Ang et al., 2004b). It leverages the multiplicative nature of the residual when decomposing final energy consumption into activity and intensity. These interaction effects reveal unobserved technological changes that simultaneously affect the activity and intensity of service delivery at category and aggregated levels.

1) Structure change at category level

Suppose that for each line item *i* we have the following values for the two years:

- **Activity:**
  - A_{0i} for 2020
  - A_{1i} for 2050
- **Intensity:**
  - I_{0i} for 2020
  - I_{1i} for 2050
- **Final Energy:**

- E_{0i} for 2020
- E_{1i} for 2050

In practice, E_{0i} (and E_{1i}) is obtained by multiplying activity and intensity (with the same conversion factor in both years), so that:

$$E_{1i} / E_{0i} = (A_{1i} / A_{0i}) * (I_{1i} / I_{0i})$$

Define the multipliers for each effect as follows:

- **Activity multiplier:**
  $M_{(A,i)} = A_{1i} / A_{0i}$
- **Intensity multiplier:**
  $M_{(I,i)} = I_{1i} / I_{0i}$

In terms of percentage changes (expressed as deviations from 1), we can define:

$\Delta A_i = M_{(A,i)} - 1$ and $\Delta I_i = M_{(I,i)} - 1$

The total multiplier for the final energy of line item *i* then becomes:

$$M_{(E,i)} = E_{1i} / E_{0i} = M_{(A,i)} * M_{(I,i)} = (1 + \Delta A_i)*(1 + \Delta I_i)$$

Expanding this product gives:

$$(1 + \Delta A_i)*(1 + \Delta I_i) = 1 + \Delta A_i + \Delta I_i + (\Delta A_i * \Delta I_i)$$

Thus, if we define the "structure effect" for line item *i* as:

$$\Delta S_i = \Delta A_i * \Delta I_i$$

then the total predicted percentage change for that line is:

$$\Delta T_i = \Delta A_i + \Delta I_i + \Delta S_i$$

or, in multiplicative terms,

$$1 + \Delta T_i = (1 + \Delta A_i)*(1 + \Delta I_i) = M_{(E,i)}$$

Illustrative example

For a given line item, let $M_{(A,i)} = 1.12$ (i.e., $\Delta A_i = 0.12$) and $M_{(I,i)} = 0.51$ (i.e., $\Delta I_i = -0.49$), then:

- The structure effect is
  $\Delta S_i = 0.12 * (-0.49) \approx -0.0588$.
- The sum of the effects (the total percentage change) would be:
  $\Delta T_i = 0.12 + (-0.49) + (-0.0588) \approx -0.4288$.
- The total multiplier is:
  $1 + \Delta T_i \approx 0.5712$.

This is a reduction in energy demand of 43%. It is worthwhile noting that there can be small differences between the results from the simple procedure shown in this example and other disaggregation methods such as the LMDI. The differences often arise from the fact that the effects are not simply additive in an unweighted manner when aggregating several items and different aggregation methods (e.g., using weights or logarithmic means) are possible, as shown next.

2) Aggregated structure effect versus interaction effects at the category level (or why category-level interaction is different than aggregate interaction and why structure is not a mere residual)

For two years $t \in 0{,}1$ (e.g., 2020, 2050), let activity A_{ti}, intensity I_{ti}, and final energy E_{ti} satisfy

$$E_{ti} = A_{ti}\, I_{ti} \Rightarrow E_{1i}/E_{0i} = A_{1i}/A_{0i} \cdot I_{1i}/I_{0i} = (1+\Delta A_i)(1+\Delta I_i),$$

with $A_{1i}/A_{0i} = M_{A,i}$, $I_{1i}/I_{0i} = M_{I,i}$, $\Delta Ai = M_{A,i} - 1$ and $\Delta Ii = M_{I,i} - 1$.

Let base-year energy shares be $\alpha_i \equiv E_{0i} / \sum j\, E_{0j}$ $(\sum i\, \alpha_i = 1)$.

Aggregate energy change (energy-weighted expansion):

$$E_1/E_0 = \sum i\, \alpha_i(1+\Delta A_i)(1+\Delta I_i) = 1 + \sum i\, \alpha_i \Delta A_i + \sum i\, \alpha_i \Delta I_i + \sum i\, \alpha_i \Delta A_i \Delta I_i\, . \qquad (1)$$

with $\sum i\, \alpha_i \Delta A_i = \langle \Delta A \rangle_\alpha$, $\sum i\, \alpha_i \Delta I_i = \langle \Delta I \rangle_\alpha$, $\sum i\, \alpha_i \Delta A_i \Delta I_i = \langle \Delta A \Delta I \rangle_\alpha$.

Aggregate activity & intensity (true aggregates):

$A_t \equiv \sum i\, A_{ti}$, $\bar{I}_t \equiv E_t / A_t$ (so $E_t = A_t \bar{I}_t$).

Hence

$$E_1/E_0 = A_1/A_0 \cdot \bar{I}_1/\bar{I}_0 = 1+\Delta\bar{A}+\Delta\bar{I}+\Delta\bar{A}\,\Delta\bar{I} \qquad (2)$$

with $A_1/A_0 = 1 + \Delta\bar{A}$ and $\cdot \bar{I}_1/\bar{I}_0 = 1 + \Delta\bar{I}$.

Bridge identity (why they differ): equating (1) and (2) yields

$$\Delta\bar{A}\,\Delta\bar{I} = \langle \Delta A \Delta I \rangle_\alpha + (\langle \Delta A \rangle_\alpha - \Delta\bar{A}) + (\langle \Delta I \rangle_\alpha - \Delta\bar{I}) \qquad (3)$$

The aggregate interaction equals the energy-weighted sum of item interactions plus two reweighting terms that arise because:

1. energy vs. activity weights differ, and
2. the mix of activity across categories changes between years (a between-category structural effect).

Therefore, simply summing item-level interaction terms $\sum i\ \alpha_i \Delta A_i \Delta I_i$ **does not** recover the aggregate interaction $\Delta\bar{A}\,\Delta\bar{I}$. In practice, the item-level sum is often lower under decarbonization (decreasing A, falling I, plus mix shifts toward low-intensity categories)—though this is not always the case as we show with a quantitative example.

Numeric illustration (two categories)

Base (2020):
$A_{01}=100,\ I_{01}=2.0 \Rightarrow E_{01}=200$
$A_{02}=100,\ I_{02}=0.5 \Rightarrow E_{02}=50 \Rightarrow\ \alpha 1 = 0.8,\ \ \alpha 2 = 0.2$.

Change to 2050:
$\Delta A_1=-0.20,\ \ \Delta I_1=-0.30 \Rightarrow \Delta E_1=\ 112$
$\Delta A_2 = +0.10, \Delta I_2 = -0.10 \Rightarrow \Delta E_1 = 49.5$

Category interaction (energy-weighted):
$\langle\Delta A \Delta I\rangle_\alpha = 0.8(-0.20 \cdot x -0.30) + 0.2(0.10\, x \cdot -0.10) = 0.046$.

Aggregate quantities:
$A_0 = 200 \rightarrow A_1 = 190 \Rightarrow\ \Delta\bar{A} = -0.05$.
$E_0 = 250 \rightarrow E_1 = 161.5$ and $\bar{I}_0 = E_0/A_0 = 1.25 \rightarrow \bar{I}_1 = 0.85 \Rightarrow \Delta\bar{I} = 0.85/1.25-1=-0.32$.

Aggregate interaction:

$\Delta\bar{A}\,\Delta\bar{I} = (-0.05)\times(-0.32) = 0.016$.

Hence, the item-level interactions generally are different from the aggregate interactions – in this case it is relatively larger because mix shifts (activity and weighting changes) reduce its magnitude. This illustrates again that category-level interaction terms are not the same as the aggregate interaction—the gap is exactly the reweighting terms.

Therefore, *structure is not a residual*: it includes cross-category shifts (e.g., modal change in transport) and weight dynamics—drivers that are missed by within-category interactions alone. Thus, there is a need for a dedicated structure goal (e.g., pace of electrification) that targets these cross-category shifts directly, complementing activity and intensity goals.

box S7. ASI(F) decomposition of CO_2 emissions and energy consumption

Building on the foundational concepts of Ehrlich & Holdren (1971), who linked environmental impact to population, affluence, and technology (IPAT), and on Kaya (1997) and Schipper et al. (2000), who recast IPAT in terms of activity, structure, and intensity (ASI)—see box S6 for its operationalization—we decompose changes in economy-wide CO_2 emissions—associated with the transformations in final energy (FE) consistent with net zero by 2050—and compare the resulting contributions in the decarbonization scenarios with the effects of the proposed goals.

This expanded IPAT identity is mathematically identical to the well-known Kaya identity used in climate analysis, but the ASI framework makes the structural and intensity factors explicit rather than lumping them under a broad "Technology" term. The new ASIF has further the advantage of explicitly showing the electrification ratio.

This Kaya-ASIF formulation decomposes the changes in CO_2 emissions including a carbon content factor, as following:

$$CO_2 = GDP \times \left(\frac{FE}{GDP}\right) \times \left(\frac{Elec}{FE}\right) \times \left[EF_{elec} + \left(\frac{1-S}{S}\right) \cdot EF_{non}\right]$$

where (in order of appearance):

GDP: economic activity (A)

$\frac{FE}{GDP}$: energy intensity (I)

$\frac{Elec}{FE}$: electrication ratio (electricity share of final energy) as a focal point of the energy structure (S)

$\left[EF_{elec} + \left(\frac{1-S}{S}\right) \cdot EF_{non}\right]$: Composite emissions factor anchored to electricity (F)

$EF_{elec} = CO_2/FE_{elec}$: Power-sector emission factor per unit electric final energy;

$EF_{non} = CO_2/FE_{non}$: Emission factor per unit non-electric final energy.

As the system becomes fully electrified (S tends to 1), the bracketed factor F tends to $EF_{elec} = CO_2/FE_{elec}$. As a result: $CO_2 = GDP \times \left(\frac{FE}{GDP}\right) \times \left(\frac{CO_2}{FE_{elec}}\right)$.

As the system is still starting the electrification (S is close to 0), the identity reduces to the non-electric pathway $EF_{non} = CO_2/FE_{non}$. As a result: $CO_2 = GDP \times \left(\frac{FE}{GDP}\right) \times \left(\frac{CO_2}{FE_{non}}\right)$.

This equation allows us to examine whether CO_2 emissions fell mainly due to lower economic activity (A), versus a more efficient (better energy vector, i.e., electricity vs fuels or heat) structure (S), versus better energy intensity of the economy (I), versus a cleaner energy with low-carbon composition factor (F).

Electricity and heat as zero emission fuels at the point of end-use appear often together in the scenarios. Hence, we operationalize the ASIF identity with the electrification ratio fixed as S=Elec/FE and lump electricity + district heat only inside the composition factor. The identity reads:

$$CO2 = GDP \times \frac{FE}{GDP} \times \frac{Elec}{FE} \times \left[\frac{Elec + Heat}{Elec} \cdot \frac{CO2(Elec + Heat)}{Elec + Heat} + \frac{(1 - Elec/FE - Heat/FE)}{Elec/FE} \cdot \frac{CO2(FinalCons)}{FE - (Elec + Heat)}\right]$$

so that ***A*** is **activity** (*GDP*), ***I*** is energy **intensity** (*FE/GDP*), ***S*** is the **electrification ratio** (*Elec/FE*), and ***F*** is a **composition factor** that (i) uses utility emissions per unit utility energy or $CO_2(Elec+Heat)/(Elec+Heat)$ and (ii) non-utility emissions per unit non-utility energy or $CO_2(FinalCons)/(FE-(Elec+Heat)$. This isolates *S=Elec/FE* while aligning numerators and denominators inside *F*; expanding the brackets recovers $CO_2 =(Elec+Heat)EF_{utility}+(FE-Elec-Heat)\ EF_{non\text{-}utility}$.

Note that the coefficients inside *F* are not normalized; convex weights emerge *SxF*, yielding a standard structure-weighted average of intensities.

Table b7-1 presents per-year growth factors and compound average growth rates (CAGR) for the world. In particular, it reports the growth-factor decomposition of economy-wide CO_2 activity, intensity, structure and composition factor. In discrete time, per-year growth factors multiply, so the compound annual growth rate (CAGR) of CO_2 satisfies:

$$1 + CAGR_{CO_2} = (1 + CAGR_A)\,(1 + CAGR_I)\,(1 + CAGR_S)\,(1 + CAGR_F)$$

Equivalently, log changes (not shown) are additive: $\Delta\ln CO_2 = \Delta\ln A + \Delta\ln I + \Delta\ln S + \Delta\ln F$. Minor rounding can cause ≈±0.01 differences. For an explanation of the deduction of the formula, see the methodological note at the end of table b7-1.

Please note that the values for the structure effect shown in this table may not match exactly those in table S2, as they are derived using different methods (electrification shares in table S2 versus CO_2 disaggregation here). In addition, the base year differs for the LED scenario: 2020 is used here, consistent with the original scenario definition, whereas table S2 uses 2023, the last year with available historical data.

Also note that NZE scenario includes captured and removed CO_2 (negative emissions technologies), while these are by design excluded in the LED scenario.

table b7-1. Absolute decomposition of changes in CO_2 emissions under the proposed goals (GOALS), with demand-side levers fixed at I=−4%/yr and S=+4%/yr. Activity (A) and composition factor (F) parameters are calculated using the growth assumptions from LED and NZE, reported as GOALS–LED–anchored and GOALS–NZE–anchored cases, respectively. See more details in the text. Note: LED uses 2020 as the base year; NZE includes CO_2 capture and removal.

	GOALS (A & F = NZE)		**GOALS (A & F = LED)**	
	Values (CO_2 Gt)	**CAGR (%)**	**Values (CO_2 Gt)**	**CAGR (%)**
2023	35.9	-	35.9	-
Change (2023-2035)				
ΔA	7.9	3.0%	12.4	3.3%
ΔI	-10.9	-4.0%	-15.6	-4.0%
ΔS	10.4	4.0%	14.9	4.0%
ΔF	-30.7	-10.9%	-35.1	-8.8%
ΔCO_2	-23.4	-8.4%	-18.6	-5.9%
2035	12.5	-	17.2	-
Change (2035-2050)				
ΔA	1.5	2.4%	3.9	2.3%
ΔI	-2.6	-4.0%	-6.9	-4.0%
ΔS	2.5	4.0%	6.7	4.0%
ΔF	-13.2	-18.6%	-13.8	-7.8%
ΔCO_2	-11.7	-16.7%	-10.2	-5.8%
2050	0.8	-	7.0	-

Methodological note on table b7-1: We decompose economy-wide CO_2 (C) using an adapted ASIF identity in multiplicative form, applied over each window (2023-2035, 2035-2050). For a window of *N* years with component growth rates g_A, g_I, g_S, g_F,

$$\frac{C_{t_1}}{C_{t_0}} = (1+g_A)^N(1+g_I)^N(1+g_S)^N(1+g_F)^N \ , \ \ \Delta ln\ C = \sum_{X\in\{A,I,S,F\}} \Delta ln\ X \ ,$$

$$\Delta ln\ X \equiv N ln\ (1+g_X) \ .$$

We first compute the CO_2 level at the end of the window, $C_{t_1} = C_{t_0} exp(\Delta ln C)$. To express contributions in absolute units (Gt) that sum exactly to $\Delta C = C_{t_1} - C_{t_0}$, we use the standard log-mean scaling:

$$\Delta C_X = L\ \Delta ln\ X \ , \quad L = \frac{C_{t_1} - C_{t_0}}{ln(C_{t_1}/C_{t_0})} \ , \qquad \sum_X \Delta C_X = \Delta C \ .$$

This yields the component ΔC_A, ΔC_I, ΔC_S, ΔC_F per window, and we report CO_2 CAGRs as $(C_{t_1}/C_{t_0})^{1/N} - 1$. For GOALS, we fix the demand-side levers at *I=−4%/yr* and *S=+4%/yr*, and consider two anchors for the remaining drivers: GOALS–NZE-anchored (take A and F growth from NZE) and GOALS–LED-anchored (take A and F from LED), always over *identical windows*. All contributions are computed from rates within each scenario/window—we never transfer absolute Gt values across scenarios—ensuring numerical closure and comparability.

Finally, table b7-2 compares the three pathways side by side. For GOALS, table b7-2 compiles the GOALS results from table b7-1 and reports them as ranges by adopting A and F growth from the NZE and LED scenarios over identical time windows (2023–2035 and 2035–2050), while fixing the demand-side levers at I = −4%/yr and S = +4%/yr, consistent with the proposed goals. Overall, this comparison shows that the GOALS pathway yields emissions trajectories that are consistent (i.e., broadly in line) with the two established decarbonization scenarios NZE and LED.

table b7-2. Decomposition of the absolute change in CO_2 and the compound annual growth rate (CAGR) under the proposed goals, compared with the Low Energy Demand (LED) and Net Zero Emissions (NZE) scenarios. Results use the adapted ASIF framework—ΔA activity, ΔI intensity, ΔS structure (electrification as the key structural driver), and ΔF composition of final energy. CO_2 levels for 2023, 2035, and 2050 are reported. GOALS values are shown as ranges [shown within square brackets] by adopting A and F growth from the NZE/LED scenarios over identical time windows (2023–2035, 2035–2050), while fixing demand-side levers at I = −4%/yr and S = +4%/yr reflecting the proposed goals. Note: the detailed decompositions for GOALS–NZE–anchored and GOALS–LED–anchored cases are provided in table S7-1; LED uses 2020 as the base year, consistent with its original definition; NZE includes CO_2 capture and removals, reflected in a more negative ΔF.

	LED		**NZE**		**GOALS**	
	Values (CO_2 Gt)	**CAGR (%)**	**Values (CO_2 Gt)**	**CAGR (%)**	**Values (CO_2 Gt)**	**CAGR (%)**
2023	35.2	-	35.9	-	35.9	-
Change (2023-2035)						
ΔA	10.7	3.3%	8.1	3.0%	[7.9; 12.4]	[3.0%; 3.3%]
ΔI	-18.4	-5.4%	-11.5	-4.1%	[-15.6; -10.9]	-4.0%
ΔS	15.5	4.8%	12.6	4.7%	[10.4; 14.9]	4.0%
ΔF	-30.3	-8.8%	-31.6	-10.9%	[-35.1; -30.7]	[-10.9%; -8.8%]
$\Delta C0_2$	-22.6	-6.6%	-22.5	-7.9%	[-23.4; -18.6]	[-8.4%; -5.9%]
2035	12.6	-	13.4	-	[12.5; 17.2]	-
Change (2035-2050)						
ΔA	2.7	2.3%	1.6	2.4%	[1.5; 3.9]	[2.3%; 2.4%]
ΔI	-3.9	-3.3%	-2.1	-3.0%	[-6.9; -2.6]	-4.0%
ΔS	2.6	2.3%	1.9	2.9%	[2.5; 6.7]	4.0%
ΔF	-9.5	-7.8%	-14.0	-18.6%	[-13.8; -13.2]	[-18.6%; -7.8%]
$\Delta C0_2$	-8.1	-6.7%	-12.5	-16.8%	[-11.7; -10.2]	[-16.7%; -5.8%]
2050	4.4	-	0.9	-	[0.8; 7]	-

As for the previous table, note that all contributions are computed from rates within each window, ensuring exact closure; consequently, absolute values can differ even when a rate is fixed because end-year emissions vary. Additionally, the structural effect (ΔS) can appear positive because electrification increases electricity demand, which still carries emissions if the mix is not fully carbon-free. Moreover, ΔS should be read together with the composition factor (ΔF), which captures structural shifts through both electricity and other fuel vectors.

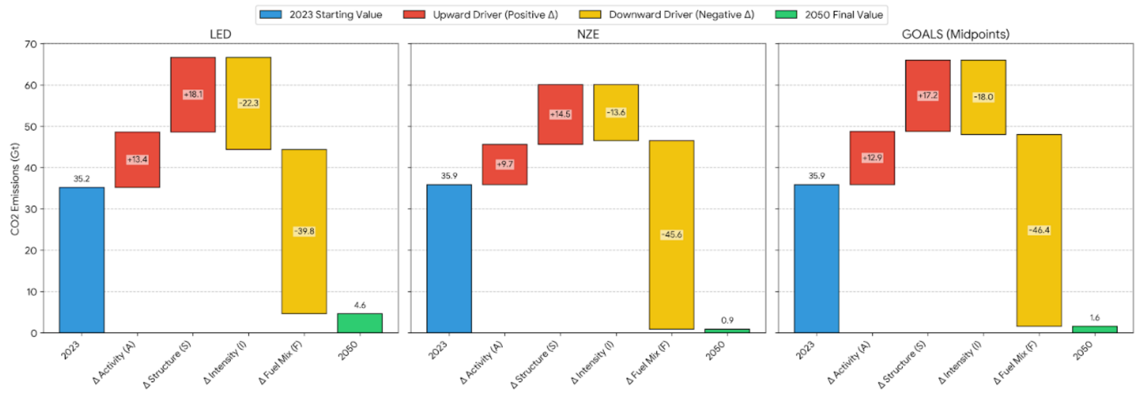


fig. b7-1. Comparison of the proposed goals with the Low Energy Demand (LED) and Net Zero Emissions (NZE) scenarios, with the total change decomposed into activity, structure, and intensity effects. See table b7-2 for the underlying values.

FIGURES and Tables

Goal 1 *Tripling the long-term rate of energy intensity improvements to at least 3% per year, aiming for an average rate of 4% annually through 2035*.

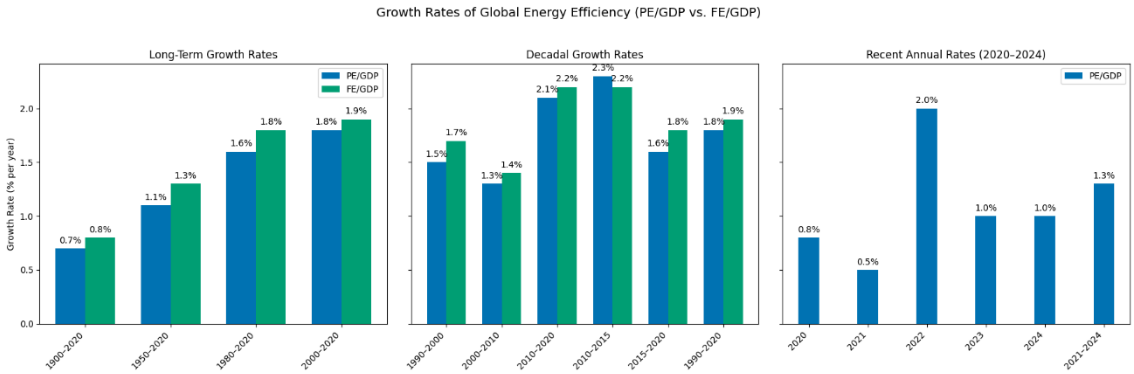


fig. S1. Long-term (left), decadal (center) and recent (right) growth rates of energy-intensity improvements—i.e., annual percentage reductions in global primary-energy intensity (PE/GDP) and final-energy intensity (FE/GDP). Source: De Stercke (2025); (2020-2024) IEA (2024b).

2026-2035 (scenario 4%/year)

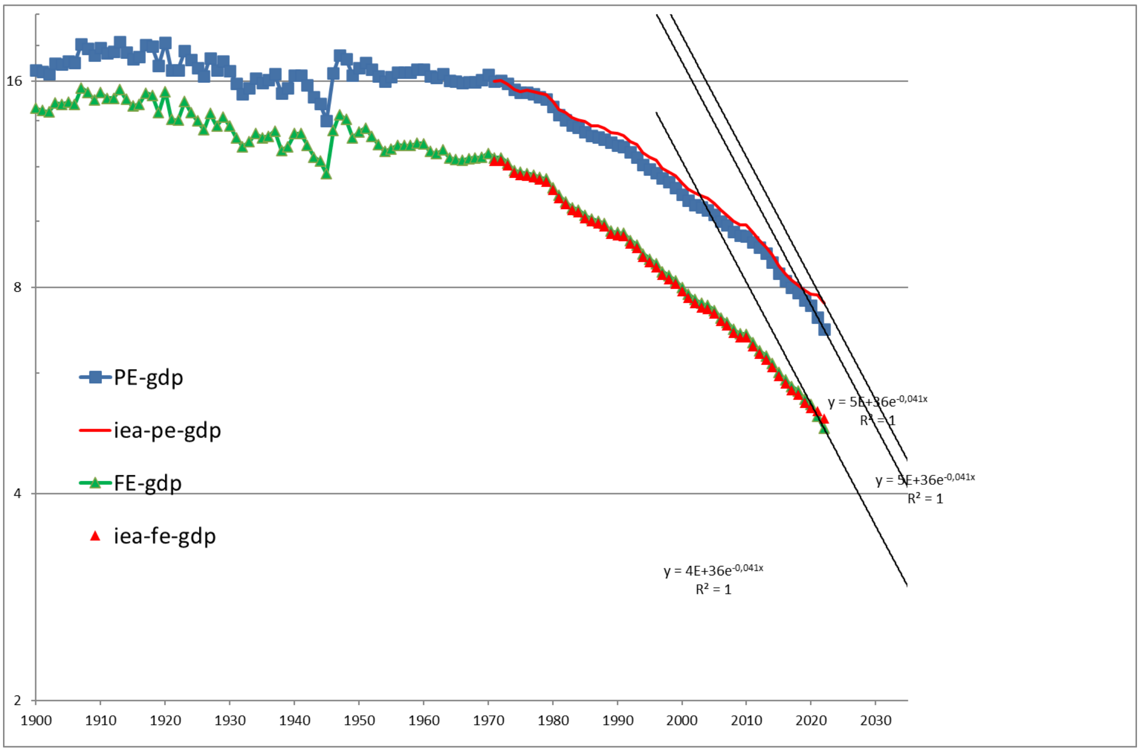


fig. S2. Historical evolution of energy intensity (energy per unit of GDP) for primary and final energy from IEA (2024a) and PFUDB (De Stercke, 2025): data since 1900 and a scenario trend assuming a 4% annual decline from 2026 to 2035.

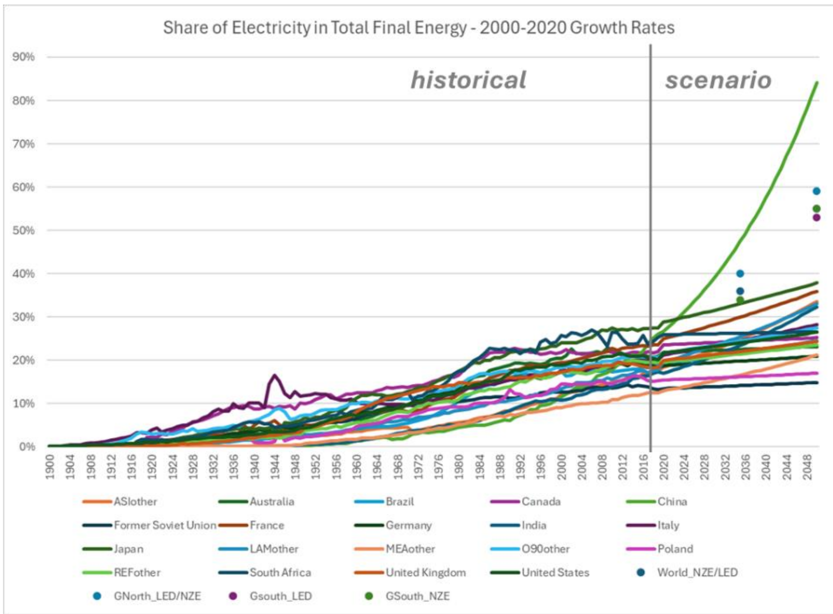
Goal 2 ***Tripling the rate of growth of the share of electricity in final energy consumption to 4% annually through 2035.***

table S1. Historical annual growth rates of electrification for the world. Sources: IEA (2024a).

Indicator	Historical (EJ)				Shares (%)				CAAGR (Shares) (%)
	2000	**2010**	**2022**	**2023**	**2000**	**2010**	**2022**	**2023**	**2010-2023**
Total final consumption	289	377	437	445	100	100	100	100	-
Electricity	56	64	88	91	19	17	20	20	**1.3**

table S2. Projected annual growth rates for electrification in the Low Energy Demand (LED) scenarios and the IEA's New Zero Emissions (NZE). Sources: (NZE) IEA (2024a); (LED) Grubler et al. (2018) and Low Energy Demand (LED) Database (Version 1.0.5) https://db1.ene.iiasa.ac.at/LEDDB .

Indicator	Scenario (EJ)				Shares (%)				CAAGR (Shares) '23 to:		
	2023	**2030**	**2035**	**2050**	**2023**	**2030**	**2035**	**2050**	**2030**	**2035**	**2050**
World											
LED											
Total final consumption	445	309	288	245	100	100	100	100	-	-	-
Electricity	91	99	111	132	20	32	**39**	54	6.9	**5.6**	**3.7**
NZE											
Total final consumption	445	415	382	344	100	100	100	100	-	-	-
Electricity	91	116	136	188	20	28	**36**	55	4.9	**4.9**	**3.8**
Global North											
LED											
Total final consumption	157	125	111	82	100	100	100	100	-	-	-
Electricity	35	41	44	49	22	33	**40**	59	5.7	**4.8**	**3.6**
NZE											
Total final consumption	157	135	114	93	100	100	100	100	-	-	-
Electricity	35	41	45	55	22	30	**40**	59	4.3	**4.9**	**3.6**
Global South											
LED											
Total final consumption	272	175	167	153	100	100	100	100	-	-	-
Electricity	55	58	67	84	20	33	**40**	55	7.1	**5.8**	**3.7**
NZE											
Total final consumption	272	280	268	251	100	100	100	100	-	-	-
Electricity	55	75	91	133	20	27	**34**	53	4.0	**4.3**	**3.6**



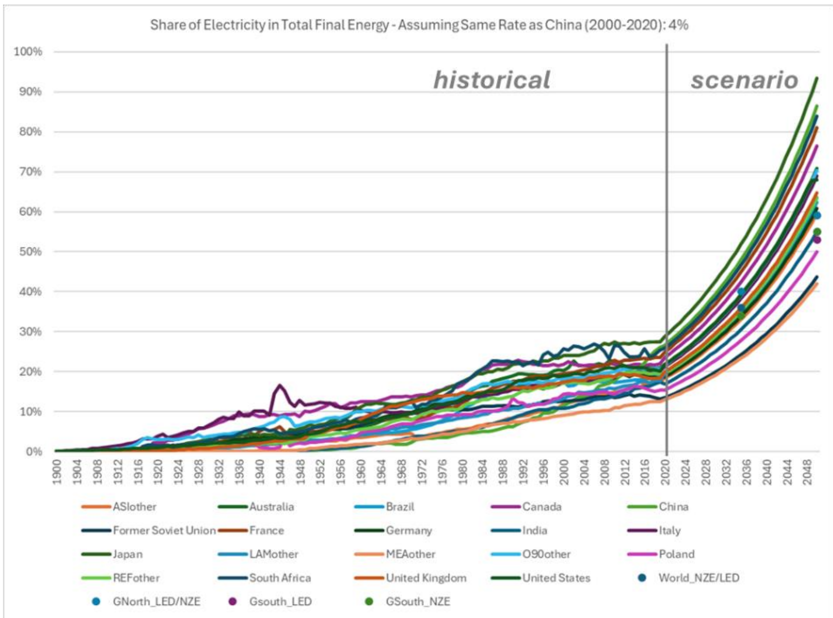


fig. S3. Historical data and projections for electrification rates in selected countries and regions (1900-2050), comparing current trends (bottom) with a 4%/year growth rate (top) equivalent to China's rate between 2000 and 2020. Data source: PFUDB (de Sterke 2025).

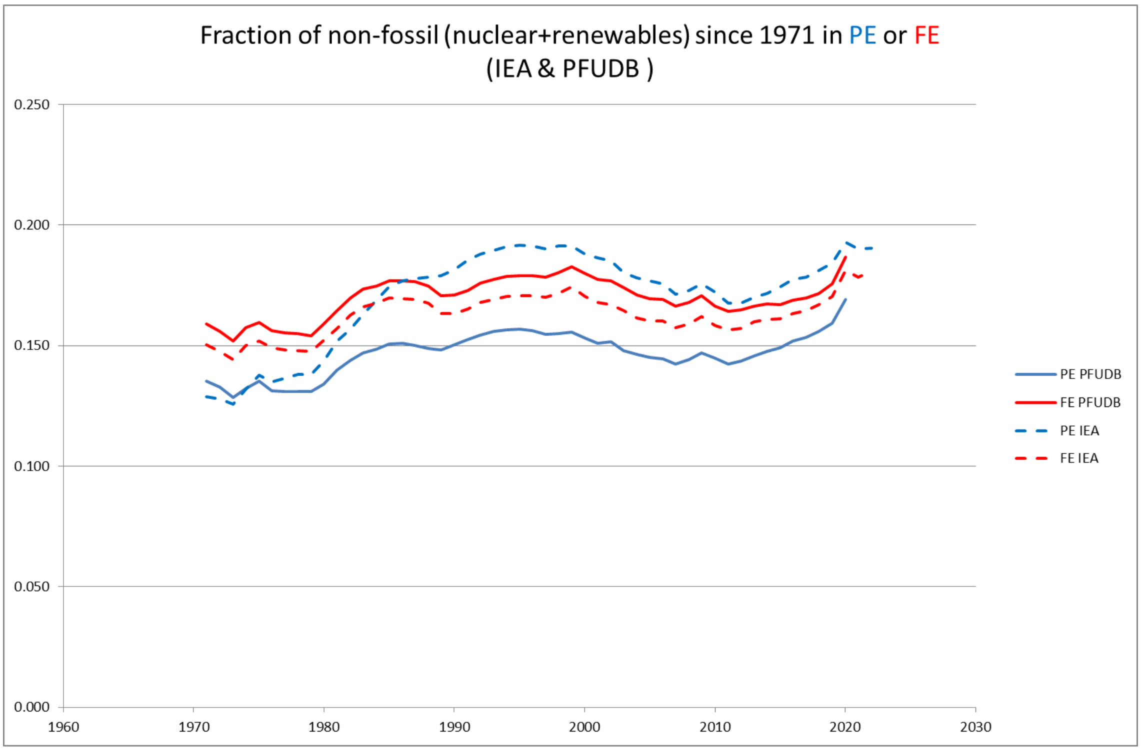


fig. S4. Comparison of the share of non-fossil energy sources (nuclear and renewables) in primary and final energy since 1971 from two statistical sources (IEA and PFUDB).

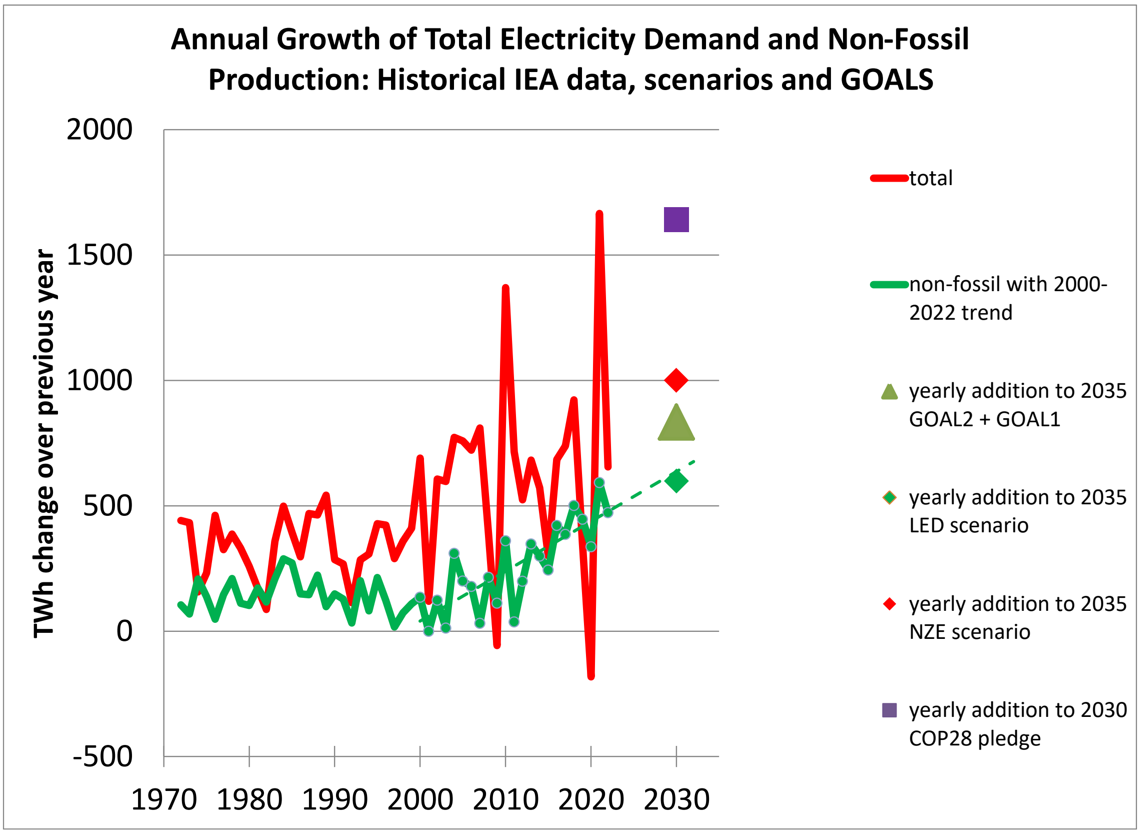


fig. S5. Annual growth of total electricity demand and non-fossil electricity generation since the early 1970s, with projections to 2035. Required annual growth to 2035 for the combined GOAL1 and GOAL2 proposed here in comparison to the LED scenario (Grubler et al., 2018), the NZE scenario (IEA, 2024a) which both reach net-zero by 2050. For comparison also the required annual growth to reach the COP28 pledge of increasing installed renewable electric capacity to 11,000 GW by 2030 (2022: 3,324 GW), which assuming current typical load factors would generate some 1600 TWh, is also shown. Sources: Historical data: IEA *World Energy Balances Highlights* (September 2024) and De Stercke, 2025 (PFUDB).

Goal 3 ***Tripling taxation of excessive energy consumption***

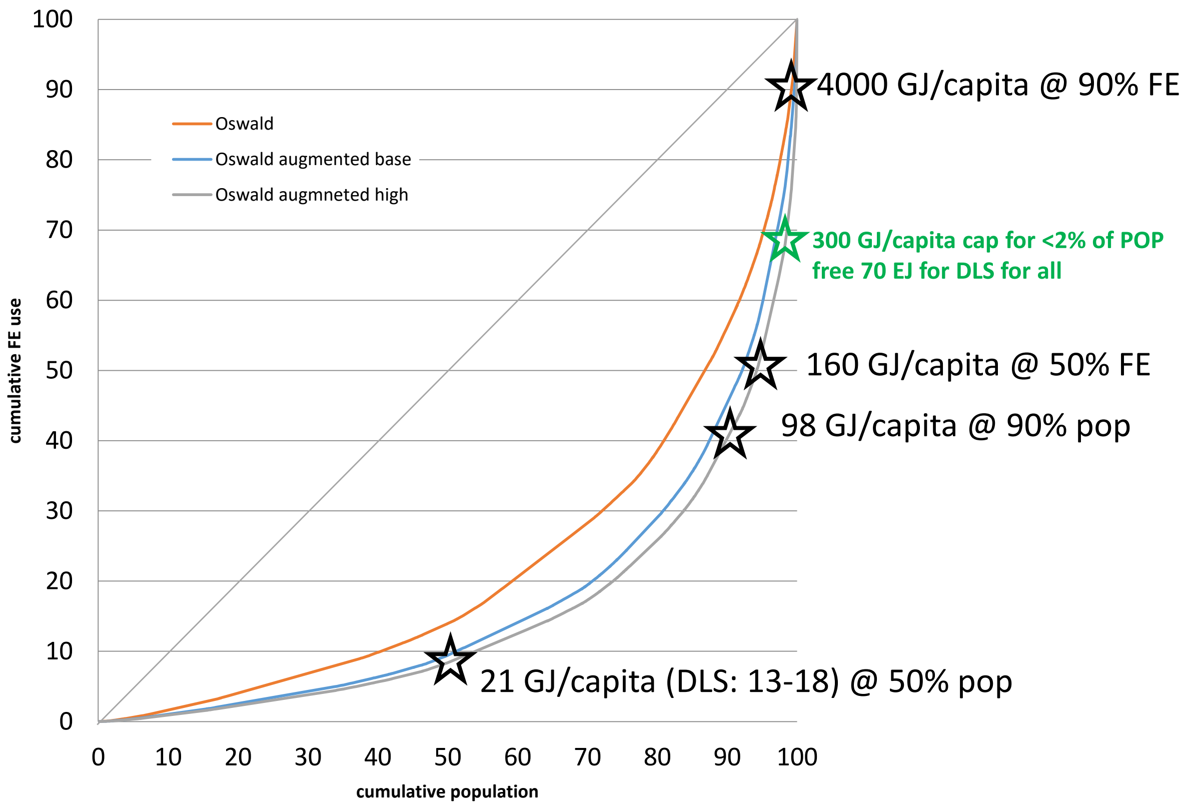


fig. S6. Global Lorenz curves of cumulative population vs cumulative final energy sorted by increasing per capita consumption based on three data samples: red, original sample from Oswald et al (2020) covering 5.4 billion people (82% of globe) and 141 EJ (36% of globe) final energy; blue; augmented Oswald sample by selected missing high income OECD countries and by high income groups (above top 1% of incomes) from Chancel (2022) with estimated associated energy footprints covering 6.1 billion people and 282 EJ final energy (67% of 2020 final energy use of 420 EJ); and grey: high variant of the augmented sample considering the effects of ever increasing shares of inelastic (elasticity above 1) luxury consumption such as personal transportation and leisure vacation for incomes above a threshold of some 100,000 $/year. The inequality index Gini of 0.52 associated to the original Lorenz curve in Oswald et al (2020) compare with 0.648 (+25%) for the augmented base, and 0.698 (+34%) in the augmented high case which we adopt as best estimate to represent global inequalities in final energy use. Stars denote significant parts of the Lorenz curve distribution with associated per capita final energy thresholds (see more details in box S3).

REFERENCES

Ang, B. W. (2015). LMDI decomposition approach: A guide for implementation. *Energy Policy*, *86*, 233-238.

Ang, B. W. (2004a). Decomposition analysis for policymaking in energy: which is the preferred method?. Energy Policy, 32(9), 1131-1139.

Ang, B. W., Liu, F. L., & Chung, H. S. (2004b). A generalized Fisher index approach to energy decomposition analysis. *Energy Economics*, *26*(5), 757-763.

Brons, M., Nijkamp, P., Pels, E., & Rietveld, P. (2008). A meta-analysis of the price elasticity of gasoline demand. A SUR approach. Energy Economics, 30(5), 2105-2122.

Burke MJ, 2020, Energy-Sufficiency for a Just Transition: A Systematic Review, Energies 2020, 13, 2444; doi:10.3390/en13102444

Chancel L., 2022, Global carbon inequality 1990-2019, Nature Sustainability 5 (Nov.2022): 931–938. https://doi.org/10.1038/s41893-022-00955-z

Chancel, L., Bothe, P., Voituriez, T. (2023). Climate Inequality Report 2023, World Inequality Lab Study 2023.

De Stercke S. (2025). Primary, Final and Useful Energy Database (PFUDB)", (IIASA Models and Databases, 2025); https://iiasa.ac.at/models-tools-data/pfudb. (for historical data prior to 1970)

GEA (2012). *Global Energy Assessment: Toward a Sustainable Future*. Cambridge University Press.

Grubler, A., Wilson, C., Bento, N., Boza-Kiss, B., Krey, V., McCollum, D. L., ... & Valin, H. (2018). A low energy demand scenario for meeting the 1.5 C target and sustainable development goals without negative emission technologies. *Nature Energy*, *3*(6), 515-527.

IEA (2024a). World Energy Balances Highlight September 2024. https://www.iea.org/data-and-statistics/data-product/world-energy-balances-highlights /last access 5/5/2025).

IEA (2024b). Global annual improvement in primary energy intensity, 2000-2024, and by IEA scenario, 2022-2030, IEA, Paris https://www.iea.org/data-and-statistics/charts/global-annual-improvement-in-primary-energy-intensity-2000-2024-and-by-iea-scenario-2022-2030 (for more recent data since 2020).

Kaya, Y. (1997). *Impact of Carbon Dioxide Emission Control on GNP Growth: Interpretation of Proposed Scenarios.* Paper presented at the IPCC/OECD joint meeting, Paris.

Kikstra J, Mastrucci A, Min J, Riahi K and Rao ND, 2021, Decent living gaps and energy needs around the world, Environ. Res. Lett. 16 (2021) 095006 https://doi.org/10.1088/1748-9326/ac1c27

Litman, T. (2025). Understanding transport demands and elasticities. Victoria, BC, Canada: Victoria Transport Policy Institute. 18 August 2025 https://www.vtpi.org/elasticities.pdf

National Geographic (2013). Is energy use distributed as unequally as our wealth? March 12, 2013. *https://www.nationalgeographic.com/environment/article/is-energy-use-distributed-as-unequally-as-our-wealth*

Oswald, Y, Owen, A and Steinberger, JK (2020) Large inequality in international and intranational energy footprints between income groups and across consumption categories. Nature Energy, 5. pp. 231-239.

Priesmann, J and Praktiknjo, A. (2024) Estimating Short- and Long-Run Price and Income Elasticities of Final Energy Demand as a Function of Household Income. SSRN preprint (open content) https://ssrn.com/abstract=4924764

Priesmann, J., & Praktiknjo, A. (2025). Estimating short-and long-run price and income elasticities of final energy demand as a function of household income. Energy Policy, 207, 114850.

Rao N D and Min J 2018 Decent living standards: material prerequisites for human wellbeing Soc. Indic. Res. 138 225–44.

Ross, M.L., Hazlett, C., & Mahdavi, P. (2017). Global progress and backsliding on gasoline taxes and subsidies. Nature Energy 2, 16201. Doi: 10.1038/nenergy.2016.201

Schipper, L., Marie-Lilliu, C., & Gorham, R. (2000). *Flexing the Link between Transport and Greenhouse Gas Emissions: A Path for the World Bank.* International Energy Agency (IEA).

Spreng, D., 2005, Distribution of Energy Consumption and the 2000 W/capita target, *Energy Policy* 33:1905-1911.