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2026

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GLEN Working Paper No. 4

Cite as: Diekmann, A., Ries, F. & Behringer, T. (2026). Inequality of CO_2 Emissions. Carbon Footprint, Socioeconomic Correlates, and Adoption of E-Technology, GLEN Working Paper No.4.
https://doi.org/10.31235/osf.io/td4c3_v1

Inequality of CO_2 Emissions. Carbon Footprint, Socioeconomic Correlates, and Adoption of E-Technology

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Abstract

We estimate the carbon footprint of the German resident population from the first wave of the German Longitudinal Environmental Study (GLEN), a large register-based probability sample, using a comprehensive module that measures housing, mobility, diet, and consumption at the individual level. Emissions are strongly right-skewed, averaging 8.6 tons of CO_2 equivalents per capita (9.7 including public infrastructure), and roughly two-thirds of the population emit below the mean. A person at the 90^{th} percentile emits 3 times as much as one at the 10^{th}. The four sectors contribute to total emissions as follows: Mobility 3.6 tons, housing 2.2, diet 1.6, and consumption 1.2. A source decomposition shows that inequality is overwhelmingly driven by mobility. This sector accounts for more than 40 percent of emissions but nearly 80 percent of total footprint inequality. A large part of the amount and variance of mobility is due to flights. Emissions rise with income (elasticity 0.22) and education, while environmental concern and Green Party preference are associated with lower footprints net of sociodemographic characteristics. The adoption of low-carbon technologies, such as heat pumps, solar energy, and electric cars, increases with income and favors homeowners. Finally, we discuss the distributional implications for carbon pricing.

Keywords: Carbon footprint, environmental inequality, mobility, pro-environmental behavior, adoption of heat pumps, solar energy, electric cars

Highlights:

- New survey module measures carbon footprints in a large German panel study
- Mobility and housing account for 68 % of CO2 emissions and 92 % of inequality
- Footprints at the 90th percentile are three times as high as at the 10th
- Income elasticity of CO2 is 0.22; 1000 € rise in income results in +1108 kg CO2
- Income, ownership, green party preference increases the adoption of e-technologies

Funding sources

This work was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation), project number 533957184, as part of the German Longitudinal Environmental Study (GLEN).

Acknowledgements

We thank Henning Best and Nele König for their helpful comments and support in preparing this manuscript.

Data Availability

This study uses data from the first release of the German Longitudinal Environmental Study (GLEN). The main survey data are available for scientific use from the GESIS Data Archive (*https://doi.org/10.4232/1.14731*). The CO_2 module, including the derived sectoral emission estimates for housing, mobility, diet and consumption, is available at [GLEN Website TBA]. Flight-specific CO_2 emissions are not included in the published data files. The procedure for calculating them from the released variables is documented with the data.

Code availability. All R code required to construct the emission estimates, including the flight emission calculation, and to reproduce the analyses reported in this article is available at [REPOSITORY URL / DOI].

I. Introduction

Individuals differ enormously in how much CO_2[1] they emit. This individual impact, known as the carbon footprint, locates climate change at the level of individual behaviour and daily life, and understanding its distribution is a precondition for effective and equitable climate policy. It is also distributed highly unequally across the population. How large these emissions are, how they are distributed, and which social factors go along with them are therefore questions for both social inequality research and climate policy.

Much research in psychology and sociology has taken a different route. It has focused on activities that appear environmentally friendly, such as recycling glass and paper or shopping at organic stores, yet often have only a minor effect on actual emissions (for meta-analyses, see Hines et al. 1987; Bamberg and Möser 2007). In Stern's (2000) terms, this work is intent-oriented: it captures the intentions and motives behind action, usually through indices that aggregate many low-impact activities (see also Bruderer Enzler and Diekmann 2019). Inferring a person's environmental impact from such measures is precarious, because their link to actual emissions is weak. We instead take the impact-oriented route and work with estimated CO_2 emissions directly.

The factors that shape the footprint are largely structural. Regulations, institutions, and energy prices usually affect it more strongly than psychological influence techniques and nudging (Thaler and Sunstein 2008). Chater and Loewenstein (2022) contrast the individual i-frame with the structural s-frame and see the latter as far more relevant to decarbonization than small psychological tricks. Three decades ago, Bodenstein et al. (1997) pointed to the strategic, environmentally relevant decisions that effectively shape emissions. Anyone who lives in a large house, heats it with oil or gas, and commutes long distances by car leaves a heavy mark on the environment. No matter how environmentally conscious they try to be, through recycling, organic shopping, or biking to the store, these efforts offset only a small part of that footprint. In terms of the CO_2 footprint, the model household is not the high-

[1] Throughout, our carbon footprint measure incorporates all greenhouse gases, converted into CO_2 equivalents (CO_2e) by their global warming potential. For readability we write "CO_2" hereafter, but all figures refer to CO_2e.

income household in progressive circles but the retired couple in a small apartment (Diekmann and Jann 2000).

Accurately determining a carbon footprint involves complex calculations based on extensive data. This includes, for example, heating bills, electricity bills, annual gasoline consumption for cars, and so on. In addition, the "gray energy" associated with the production of goods must be factored into the calculation through "life-cycle assessments" (LCA). Survey data, on the other hand, will only yield relatively rough estimates. The accuracy of these estimates depends on the questionnaire used to determine CO_2 emissions and how that information is processed. A number of survey studies are now available that report on the carbon footprint and its distribution among the population and provide information on which factors influence emissions (see Section II). It can be noted that the distribution of carbon emissions is heavily right-skewed and that income generally has a stronger influence on the CO_2 footprint than attitudes or psychological characteristics (Bruderer Enzler and Diekmann 2019; Kaiser et al. 2026; see also Section II). The quality of CO_2 footprint estimates also depends on the data quality of the survey. The sample size, the sampling method, and the selection and number of indicators all play a role. We estimate the carbon footprint using the German Environmental Panel (GLEN), which is based on a random sample drawn from population registers and has a very large sample size. The estimate is based on a comprehensive CO_2 questionnaire module with a wide range of indicators in four areas: housing, mobility, diet, and consumption.

Section II reviews existing studies, describes how we measure the carbon footprint, and states our research questions. Section III presents the results for the GLEN data. Our aim throughout is descriptive and correlational: we document how emissions are distributed and how they covary with social position and attitudes, and we make no causal claims. Section III.1 reports the distribution of emissions overall and across the four sectors. Section III.2 examines how the footprint relates to sociodemographic characteristics, in particular income. Section III.3 turns to attitudes, asking what role environmental awareness, climate skepticism, and green party preference play. Section III.4 addresses investments in e-technologies. That heat pumps, electric cars, and solar panels improve the footprint is already built into our emission estimates; the question here is who invests in them. Do only affluent households adopt these technologies, or does adoption also depend on climate-friendly attitudes and environmental

awareness? The concluding Section IV discusses the results and their possible policy implications.

II. Measurement of Carbon Footprint and Research Questions

While early studies aggregated CO_2 emissions based on production location, the research field has focused more on consumption location for several years now (see, for example, Miehe et al., 2016). This sheds more light on consumers' environmental behavior and enables therefore more consumer-based policies to tackle the causes of high global carbon emission levels. Most studies in this research field are based on household expenditure data (e.g. Ivanova et al., 2017; Ivanova & Wood, 2020; Feng et al., 2021; Zheng et al., 2023), which comes with some inaccuracies. Household data does not differentiate which household member is responsible for the emissions, which can lead to biases, especially when focusing on the factors that explain individual CO_2 emissions.

Additionally, the calculation of CO_2 emissions from expenditure data assumes that an increase in spending always results in an increase in CO_2 emissions. This may be true in general for some concepts, such as heating fuels, electricity, and car fuels, but it is questionable for other concepts, such as diet and the consumption of goods like furnishings, electronic devices, and clothing (Girod & De Haan, 2010; André et al., 2024). Thus, the elasticity of expenditures and emissions is often overestimated. This leads to the emissions of richer households being overestimated and the emissions of poorer households being underestimated (Girod & De Haan, 2010; André et al., 2024). Moreover, there is a problem of over- and under-reporting of the consumption of socially (un-)desired and irregular purchased products in expenditure data (Girod & De Haan 2010). In contrast, individual behavioral data might improve the validity of the footprint computation (as e.g. in Notter et al. (2013), Bruderer Enzler & Diekmann (2019), Groß et al. (2022), Hadler et al. (2022), Gomm et al. (2023), Bohmann & Küçük (2024), Grothmann et al. (2024), Berland & Leroutier (2025)). This approach has only been pursued more strongly in recent years and has not been used in many other studies or national contexts.

As one might expect, average individual CO_2 emissions differ between countries (Chancel & Piketty 2015, Ivanova & Wood 2020, Zheng et al. 2023). However, results also differ between studies in the same national context. Depending on the study, the average individual CO_2 emission load of the German population is somewhere between 6.5 and 14 tons of CO_2

equivalents (Miehe et al. 2016, Kleinhückelkotten et al. 2016, Gill & Moeller 2018, Ivanova & Wood 2020, Groß et al. 2022, Brandenstein et al. 2023, Bohmann & Küçük 2024). This wide span is a consequence of the different methods that studies use for calculating the emission load and of the differences in considered measurement concepts. For example, some studies only consider housing, transportation, and diet (e.g. consumption of clothing and electronic devices are missing Schubert et al. (2013), Bohmann & Küçük (2024)), other studies lack emissions from cruise trips and pet keeping (Miehe et al. 2016, Gill & Moeller 2018)), and other sources. Nevertheless, all studies come to the result that the individual emission load is unequally distributed within countries and especially affected by income (Gough et al. 2011, Miehe et al. 2016, Ivanova et al. 2017, Gill & Moeller 2018, Bruderer Enzler & Diekmann 2019, Ivanova & Wood 2020, Brandenstein et al. 2023, Bohmann & Küçük 2024). Studies also concluded that individual CO_2 emissions on average decrease with the number of household members (Ivanova et al. 2017, Gomm et al. 2023, Bohmann & Küçük 2024). Other explanatory variables like age, gender, education, and urbanity have also been investigated in some studies, but have not led to clear and consistent results (Kleinhückelkotten et al. 2016, Miehe et al. 2016, Ivanova et al. 2017, Gill & Moeller 2018, Bruderer Enzler & Diekmann 2019, Gomm et al. 2023, Bohmann & Küçük 2024, Behringer 2027).

Here, we use data from the first wave of the German Environmental Panel (GLEN), which was collected in 2025. GLEN is a long-term panel study focusing on the environment and based on a relatively large sample. The sample was drawn at random from population registers. Data collection is conducted online and via written questionnaires; participants are offered incentives (for details on the data collection methodology, see Auspurg et al. 2024, 2026).

Building on previous research, we designed a comprehensive CO_2 questionnaire module for GLEN (Ries et al. 2026). Estimates rest on individual survey responses, supplemented by external data such as georeferenced weather to model heating demand. The module covers four sectors: housing captures heating, electricity, and the dwelling's embodied emissions; mobility covers private vehicles, public transport, flights, and cruises; diet reflects dietary composition scaled to individual energy needs; and consumption covers goods and appliances, clothing, pet keeping, and vacation travel. A list of indicators can be found in Table 1.

Table 1: Components and indicators of the carbon footprint module

Domain	Component	Indicators
Housing	Heating	Building type and age, modernization measures, usual indoor temperature, heating carriers, local weather, solar thermal system
	Electricity	Self-reported consumption, *or* number of large appliances, photovoltaic system
	Construction & maintenance	Living area, building type and age (embodied emissions)
	Second home	Indicator flag, adds 20% of housing emissions
	Overall	Living area and household members, to scale emissions
Transportation	Private transport	Size and fuel type of cars and motorcycles, mileage as driver or passenger, embodied emissions from vehicle construction and supply (incl. bicycles and scooters)
	Public transport	Frequency of short- and long-distance trips
	Flights	Number of private flights in four duration categories
	Cruises	Number of days on cruise ships
Diet	Energy requirement	Weight, sex, age, physical activity level
	Dietary composition	Consumption of: beef, other meat, fish, dairy and eggs, other food
Consumption	Household & individual goods	Furnishings (purchase preference, number of rooms), household appliances (count), consumer electronics (count), clothing (purchase preference)
	Pet keeping	Dogs, cats, horses, birds, aquaria and terraria, rabbits and other small animals
	Accommodation	Number of vacations in three length categories, length and type of accommodation for the longest vacation

See Ries et al. (2026) for a detailed report on the GLEN CO2 survey module.

Emissions are derived by converting reported quantities into physical consumption and then into emissions with survey-year emission factors, estimating consumption from dwelling and appliance characteristics where respondents cannot report it themselves. Embodied ("gray") emissions from producing durable goods and buildings are annualized via life-cycle assessment and added to the consumption-year emissions. The full estimation procedure is documented in Ries et al. (2026).

Unlike personal environmental behavior (PEB), which is strongly driven by beliefs and intentions (Stern 2000), the carbon footprint depends only in part on the goal-oriented actions

of respondents. Both individual and structural factors shape it, with the greater weight likely on structural conditions that are exogenous to the individual. We distinguish four categories that impact the footprint: (1) short-term behavioral changes, such as driving less or lowering the thermostat during the heating season; (2) long-term strategic investments in the household (Bodenstein et al. 1997), such as a heat pump or an electric car; (3) institutions, legal regulations, and relative energy prices, for example the EU emission allowances or rules on heating and vehicle propulsion systems; and (4) technological innovations, such as the falling costs of solar panels and battery storage or the rising share of renewables in electricity generation.

These categories sit at different levels, and our data speak to them unequally. A single national cross-section holds the macro conditions (3) and (4) effectively constant: respondents surveyed in 2025 face the same policy regime and the same technology prices, so we cannot identify how much these factors contribute to the footprint. What varies between individuals (within the same legal system) is (1) and (2), together with the resources and circumstances that enable or constrain them, and it is this variation our analysis describes. We take the structural conditions to be the more consequential lever for aggregate emissions over time and return to them in the discussion, but we do not estimate their effects. Citizens can press for such change through voting or protest, yet remain dependent on the regulations policymakers set. That about half of Germany's electricity now comes from renewable sources, a share legislated to reach 80 percent by 2030, illustrates the point: shifts at the societal macro level, not individual intent, are what can reduce the footprint substantially.

What varies across individuals is precisely what our data let us describe. We ask which characteristics of respondents align with with higher or lower emissions, focusing on resources, particularly income, but also on attitudes such as environmental awareness. In public discourse, party preferences are regularly tied to the carbon footprint. A recurring claim holds that Green Party voters fly and emit the most, supposedly because of higher incomes and greater mobility. Krämer and Trenkler (1996) have already noted that voters of the Green Party are not behaving in a way that is less environmentally friendly. The idea was popularized by a 2019 survey commissioned by the aviation industry association (Forschungsgruppe Wahlen 2019) and widely reported (e.g. Vogt 2019), though the reading was contested at the time (taz 2019). A scholarly version of this claim has empirical backing. Kleinhückelkotten et al. (2016) find that per-capita emissions rise steeply with income and education, and that the

milieus with the most pronounced environmental attitudes are not the low emitters, since those attitudes concentrate among high-status, high-consumption groups. Their result concerns attitudes confounded with status. We ask whether, net of income and other sociodemographic characteristics, environmental concern and Green Party preference still track lower emissions. First, however, we turn our attention to the descriptive question of the distribution of CO_2 emissions. A distribution that is heavily skewed to the right is to be expected. Furthermore, we will examine the distributions in the areas of housing, mobility, diet, and consumption. It is to be assumed that significant differences will be found across these areas. For example, the variance in mobility will be greater than that in diet (Bruderer Enzler and Diekmann 2019). We will compare these areas by calculating Lorenz curves, which can provide a clear picture of the differences.

Before turning to the results, a brief note on the analysis samples is in order. We mainly rely on the GLEN wave w1a from mid-2025, single items are used from different waves which is always indicated. The footprint regression analyses rest on a fixed estimation sample of n = 9,660, comprising those respondents for whom a complete carbon footprint could be estimated across all four sectors, held constant across the descriptive and regression analyses so that the reported figures refer to the same population. Case numbers nonetheless vary. Some descriptives are computed on pairwise or single-variable complete cases, but these do not differ meaningfully from the fixed-sample figures. Roughly 1.8 percent of respondents (178 of 9,660) report no mobility emissions at all. These are structural zeros: genuine non-participation in car use, flying and public transport, not missing data. Because the outcome enters in logs, these cases are undefined, and we estimate the mobility models on the 9,482 respondents with positive emissions. The restriction is minor. With participation close to 98 percent, the gradient among participants and the gradient across the full sample essentially coincide, so the complete-case log-log specification recovers the income elasticity without distortion. We prefer it to the usual alternatives: adding an arbitrary constant before logging makes the elasticity depend on that constant, while a two-part or Tobit model adds a participation equation that is weakly identified when so few respondents are zeros. Table A5 in the Appendix reports this participation model next to the intensity model. The covariates that predict any mobility emissions carry the same signs as in the intensity equation but are roughly an order of magnitude smaller, which confirms that the excluded cases are only weakly selected and that dropping them does not drive our estimates. The investment

analyses, by contrast, do not require a complete footprint and draw on a somewhat larger sample of n = 10,089. Throughout, we hold the sample fixed within each analysis rather than moving to model-wise complete cases, to avoid selectivity from shifting composition; robustness checks are reported in the appendix and supplement and referenced in the text or captions. The full sequence of selection steps is documented in Appendix Table A1, a correlation matrix of used variables can be found in Figure A1. Descriptive results are presented with survey weights (Leßner et al. 2026).

III. Results of the Analysis of the GLEN Data

1. Distribution of CO_2 emissions

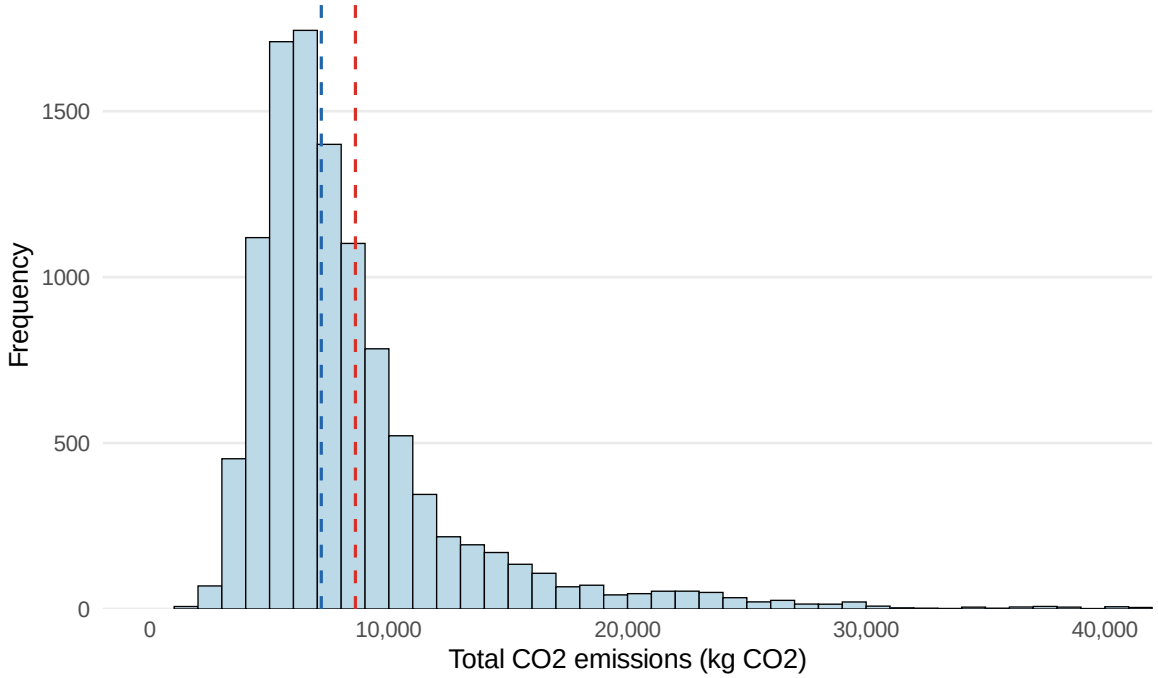
As can be seen, the distribution of CO_2 emissions is heavily right-skewed; accordingly, the median of the distribution lies below the mean. With a median of 7.2 tons and an arithmetic mean of 8.6 tons of CO_2 per year per capita, the estimate is higher than the officially reported emissions, which, however, are calculated on a production basis and do not take imported consumer goods into account. If we also add the base amount for public infrastructure, that is, for schools, bridges, etc., the mean per capita CO_2 emissions amount to 9.7 tons. A right-skewed distribution means that relatively few people have very high emissions, while almost two thirds of the population (65.4%) fall below the mean. Figure 1 shows the carbon footprint distribution.

Ten percent of respondents have a carbon footprint of 4.6 tons or less (10th percentile), while ten percent emit 13.8 tons or more (90th percentile). The footprint at the upper decile boundary is thus 3.02 times as high as at the lower one (P90/P10 ratio).

The distribution varies greatly depending on the specific areas considered. Mobility accounts for the largest share of CO_2 emissions, with an arithmetic mean of 3.6 tons, with air travel making the largest contribution (mean air travel = 1.98, mean other transportation = 1.63). This is followed by housing at 2.2 tons, diet at 1.6 tons, and consumption at 1.2 tons. A version of Figure 1b with uniform axis scaling can be found in the Appendix as Figure A2.

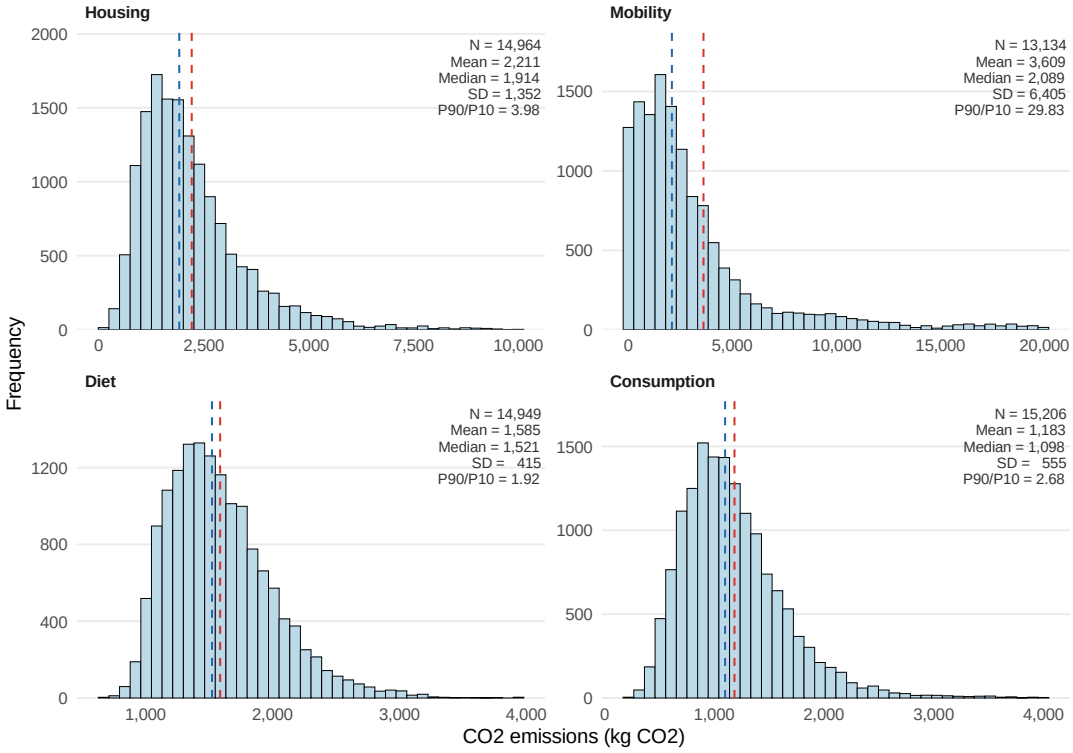
Figure 1: Distribution of CO_2 emissions

Figure 1a Total emissions



N = 10687, weighted | mean (red) = 8,596 | median (blue) = 7,166 | SD = 6,434 | P90/P10 = 3.02
52 cases > 40,000 not shown | P90/P10 = ratio of the 90th to the 10th percentile

Figure 1b Distributions of sector-specific emissions



Weighted. Mean (red) and median (blue) dashed. Statistics are computed on the full sector distribution; the display window is clipped.
P90/P10 is the ratio of the 90th to the 10th percentile

Concerning inequality, the Lorenz curves provide a first picture: the more pronounced the bulge, the more unequal the distribution. Figure 2 shows mobility as the most unequal and

diet as the most equally distributed sector, with housing and consumption in between. Table 2 decomposes how these sector differences aggregate into total footprint inequality, following Lerman and Yitzhaki (1985).

Figure 2: Lorenz curves of CO_2 emissions in the areas of housing, mobility, diet, and consumption

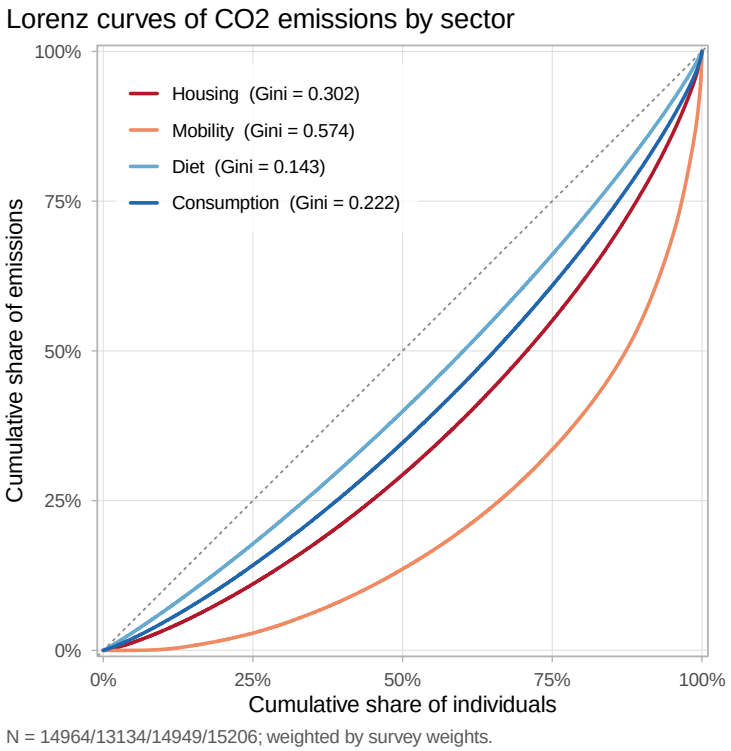


Table 2: Lerman-Yitzhaki (1985) decomposition, survey-weighted

Sector	Share of emissions (%)	Gini	Gini correlation	Contribution to inequality (%)	Elasticity
Housing	25.2	0.296	0.461	12.6 [11.5, 13.7]	-0.127
Mobility	42.3	0.555	0.923	79.2 [77.7, 80.5]	+0.369
Diet	18.5	0.142	0.263	2.5 [2.3, 2.8]	-0.160

Table 2: Lerman-Yitzhaki (1985) decomposition, survey-weighted

Sector	Share of emissions (%)	Gini	Gini correlation	Contribution to inequality (%)	Elasticity
Consumption	13.9	0.217	0.517	5.7 [5.3, 6.1]	-0.082

Contribution = share x Gini x Gini correlation, divided by the total Gini; contributions sum to 100%.

Elasticity = contribution minus emissions share. Brackets are 95% bootstrap intervals (500 replicates).

The result is stark: footprint inequality is overwhelmingly due to mobility. Mobility makes up 42 percent of emissions but 79.2 percent of total inequality, because it combines the highest own-Gini (0.555) with a Gini correlation of 0.923; those who emit most in total are, above all, those who fly and drive the most. The other sectors are close to distributionally neutral. Diet is the clearest contrast, contributing 18.5 percent of emissions but only 2.5 percent of inequality (Gini = 0.142, Gini correlation = 0.263). The elasticity column states this at the margin: a proportional increase in mobility emissions would widen the overall distribution (+0.369), whereas a proportional increase in any other sector would leave it flatter. To check whether the results depend on a few extreme values, we cap each sector's emissions at its 99.5th, 99th, 97.5th and 95th percentile, i.e. we set all values above the threshold to the threshold value (winsorising). Even at the strictest cap, the 95th percentile, the sectors' contributions to overall inequality and the overall Gini remain substantively unchanged (Table A4).

Correlations between sector emissions are weak to moderate (Table A2). The strongest associations involve consumption, which correlates with mobility (Pearson r = 0.18, Spearman ρ = 0.31) and with housing (r = 0.20, ρ = 0.20). Diet is positively associated with mobility (r = 0.12, ρ = 0.18), barely related to consumption, and slightly negatively related to housing (r = −0.07, ρ = −0.07). Mobility and housing, the two sectors with the highest mean emissions, are practically uncorrelated (r = 0.00, ρ = −0.03). Consistent with this, covariances between sectors account for only a small part of the variance in total emissions: 95.3 percent is within-sector variance. Emissions in one sector are therefore only a limited guide to emissions in another, and differences in total footprints stem mainly from differences within individual sectors rather than from high emissions across several sectors at once.

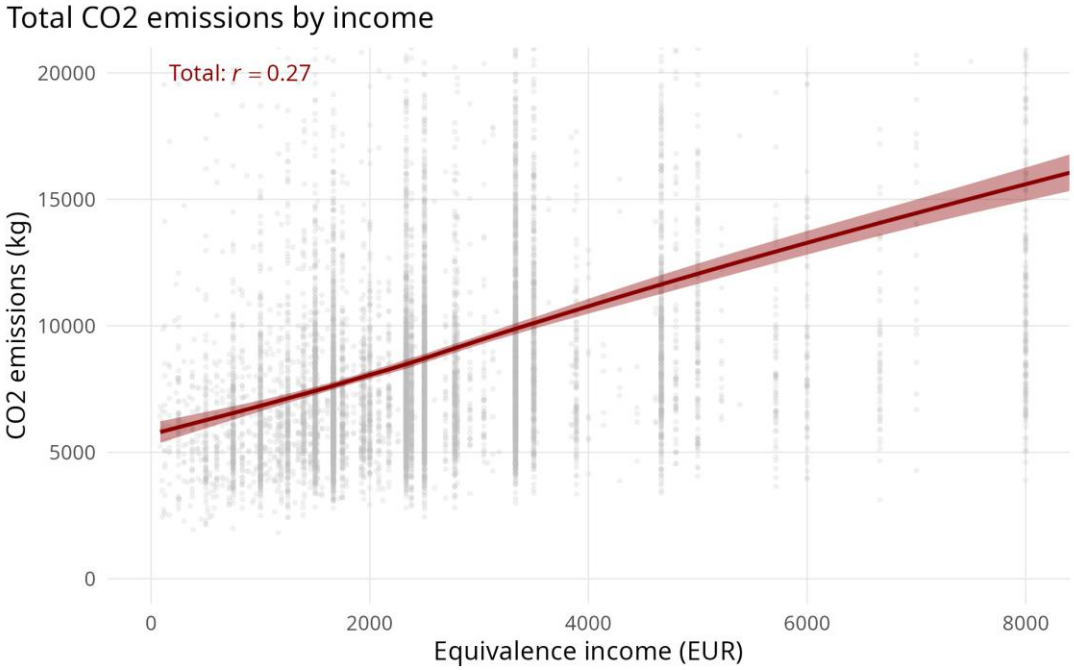
2. The income – footprint relation

We convert income at the individual level into household equivalence income. It is obvious that higher incomes are associated with greater consumption, mobility, and other expenditures, so that the level of CO_2 emissions will rise along with income. On the other hand, higher incomes create opportunities to invest in energy-saving and low-carbon technologies, as we will show below. Even though the positive correlation still holds true today, we should ask how strong the relationship between income and carbon footprint is, and how the strength of these relationships varies across different sectors. When we look at total emissions, the correlation becomes very clear (Figure 3a). In terms of the carbon emission distribution, the lowest decile (4.6 tons of CO_2) has an (log-log-)estimated income of €1,871, while the top emitters (the 9th decile, at 13.8 tons of CO_2) have an income of €3,109.

However, the strength of the correlations varies across different sectors: the income gradient is steepest for mobility and flattest for diet. Housing and consumption fall in between (Figure 3b).

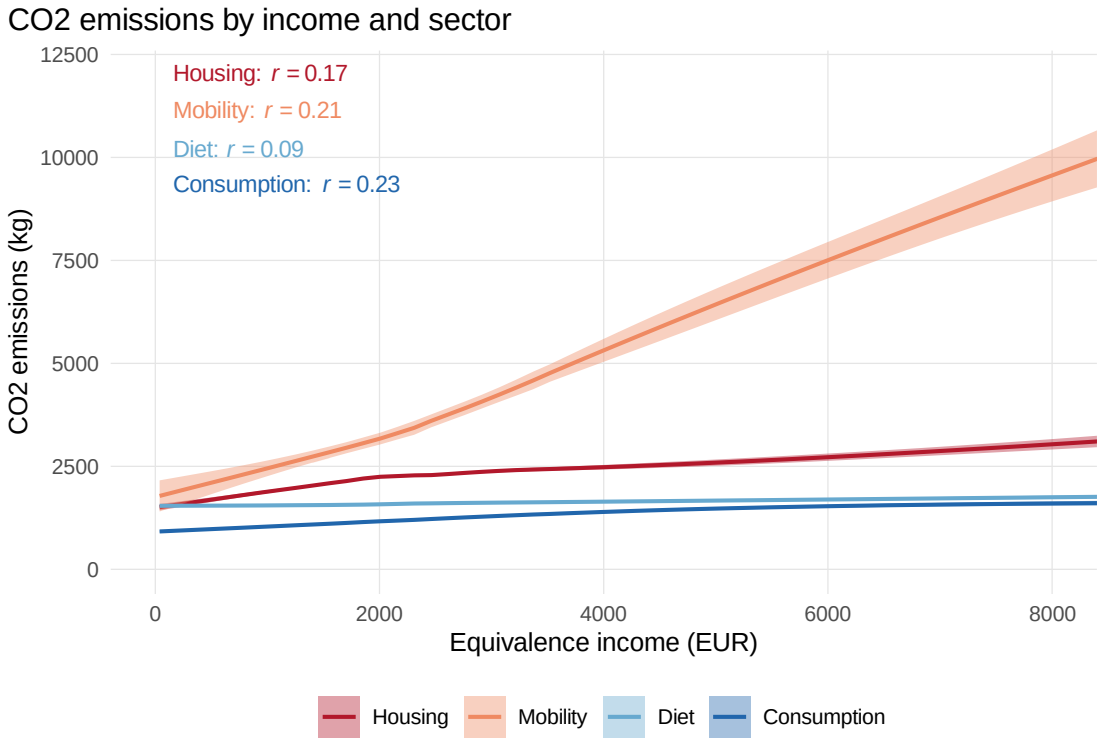
Figure 3: CO_2 emissions by income

Figure 3a Total emissions



Grey points: individual respondents. LOESS over weighted individual data, 95% CI. r: weighted Pearson.
Cases above the display limit are included in estimation but not shown.
LOESS (locally estimated scatterplot smoothing) is a non-parametric method that fits the trend line by running many loc regressions across the income range, letting the relationship bend freely instead of forcing it into a straight line.

Figure 3b Sector specific emissions



Weighted LOESS over individual data. Band: 95% CI. r: weighted Pearson.

It should also be noted, however, that the relationship between total income and the footprint is far from perfect. With a value of 0.27, the (Pearson) correlation is moderate (see Figure A1) and considerably lower than in previous studies for Germany, who use household expenditure data for calculating emissions (Gill & Möller 2018: 0.56, Hardadi et al. 2021: 0.58).

The correlation with income remains robust when other covariates are taken into account. Regression analysis yields an estimate of the income elasticity of CO_2 of 0.22. This means that a 1 percent increase in income is accompanied by a 0.22 percent increase in CO_2 emissions (Table 2). An estimate based on the absolute values for emissions and income yields a figure of 1108 kg of CO_2 per 1,000 € of income (Table A6 in Appendix). Accordingly, a person who earns €1,000 more than an otherwise comparable person has a carbon footprint that is approximately 1.1 tons higher. A closer look at the individual sectors reveals that the income relationship is primarily attributable to mobility (contributing 868 kg, elasticity is 0.52), with air travel accounting for the largest share (contributing 614 kg see A10). As already shown in Figure 3b, income plays only a very minor role in CO_2 emissions related to diet.

Considering the other sociodemographic characteristics. In both mobility and diet, emissions decrease steadily with age. Emissions are highest among those under 30 and lowest among

those aged 60 and older. For housing, the pattern is the opposite: the oldest group has the highest emissions. These findings are mostly in line with previous research (Schubert et al., 2013, Theine et al. 2022, Osorio et al. 2024), but some studies have also found an u-shaped association of age and emissions, that younger and older people have on average lower emissions than middle-aged people (Ottelin et al. 2019, Levay et al. 2021). The diet coefficients should not be read as purely behavioral: age enters our caloric estimation directly, assigning lower caloric requirements to older respondents, so part of the age gradient in dietary emissions is definitional rather than behavioral.

It is also noticeable that emissions increase with the level of education, with mobility again being the main contributor (as in Ivanova et al. 2017, Levay et al. 2021, Osorio et al. 2024). Thus, income and education, two dimensions of social status, are closely linked to the individual carbon footprint.

With regard to gender, men have on average a larger CO_2 footprint than women, driven by both greater mobility and a more carbon-intensive diet. The diet related gap has two sources. Part of it follows by definition from our footprint calculation, which assigns men more calories both by construction and because men in our sample are on average heavier, and body weight enters the calorie estimate directly (Ries et al. 2026). Beyond this definitional component, men in our sample also consume significantly more beef and meat than women,[2] consistent with the wider literature (Berland & Leroutier 2025).

In terms of urbanity, one might assume that city dwellers have lower mobility-related emissions than those living in suburban areas. However, this is not the case at all. CO_2 emissions are on average highest among the urban population. Descriptively, mobility emissions are somewhat higher in metropolitan areas (4.2t) than in peripheral rural areas (3.7t). This raw gap is compositional, reflecting the higher incomes, smaller household sizes, and younger age of urban residents. When controlling income, household size, age, and education, the log-log model places metropolitan residents proportionally below rural residents (Table 2). These compositional differences are also highlighted in Jones & Kammen (2014), Gill & Möller (2018), and Ottelin et al. (2019).

[2] Welch two-sample t-tests on the six-point frequency items (1 = almost daily to 6 = almost never) confirm both differences (beef and meat: both $p < .001$).

Table 2: Regression of log. CO_2 emissions on log. income and demographics

	Total	Housing	Mobility	Diet	Consumption
Log equivalence income	0.224***	0.133***	0.522***	0.030***	0.170***
	(0.009)	(0.009)	(0.025)	(0.004)	(0.008)
Household size	-0.044***	-0.224***	0.088***	0.014***	-0.045***
	(0.004)	(0.004)	(0.011)	(0.002)	(0.003)
Age 30-45 (ref. <30)	-0.078***	-0.020	-0.163***	-0.028***	-0.077***
	(0.019)	(0.018)	(0.045)	(0.008)	(0.014)
Age 45-60 (ref. <30)	-0.065***	0.101***	-0.215***	-0.042***	-0.020
	(0.018)	(0.018)	(0.045)	(0.008)	(0.014)
Age 60+ (ref. <30)	-0.141***	0.199***	-0.462***	-0.076***	-0.114***
	(0.018)	(0.017)	(0.044)	(0.007)	(0.014)
Male	0.106***	-0.019*	0.155***	0.317***	-0.081***
	(0.009)	(0.009)	(0.023)	(0.004)	(0.007)
Education: medium (ref. low)	0.063***	0.039*	0.192***	0.019**	0.065***
	(0.013)	(0.016)	(0.044)	(0.007)	(0.013)
Education: high (ref. low)	0.088***	0.057***	0.220***	-0.008	0.043**
	(0.015)	(0.017)	(0.047)	(0.007)	(0.014)
Metropol. city (ref. rural)	-0.049***	-0.094***	-0.105***	-0.007	-0.016
	(0.012)	(0.013)	(0.032)	(0.005)	(0.011)
Regiopol. city (ref. rural)	-0.053***	-0.043**	-0.150***	-0.008	-0.012
	(0.014)	(0.015)	(0.038)	(0.006)	(0.012)
Rural, close to city (ref. rural)	-0.004	0.000	-0.041	0.001	0.020
	(0.013)	(0.015)	(0.035)	(0.006)	(0.012)
Constant	7.358***	7.000***	3.545***	6.959***	5.914***
	(0.075)	(0.071)	(0.201)	(0.029)	(0.062)
N	9660	9660	9482	9660	9660
R2	0.144	0.393	0.111	0.436	0.124

Unweighted OLS on log CO_2 emissions, HC1 robust standard errors in parentheses. Income enters in logs, so its coefficient is an elasticity: a 1 percent higher equivalence income is associated with a b percent higher footprint. Remaining coefficients are approximate proportional differences. Cases with zero emissions in the mobility sector are excluded; see Appendix A5 for selection into 0. Reference categories: age under 30, female, low education, peripheral rural.

3. Environmental awareness, climate skepticism, green party preference: Is there a connection to the carbon footprint?

To measure environmental awareness, we use a composite index of six items based on the short scale proposed by Diekmann and Preisendörfer (2001). Climate skepticism is measured with an eight-item scale developed by Friedrich and Best (2025). Both scales use a five-point Likert response format ranging from "strongly disagree" (1) to "strongly agree" (5). Full item wordings for both scales are provided in the appendix (Table A7). Party preference was measured by asking which party the respondent would vote for if federal elections were held next Sunday and was sourced from the recruitment wave of GLEN from the end of 2024.

Environmental concern is negatively correlated with CO_2 emissions in all four areas: housing, mobility, diet, and consumption. Particularly, a significant reduction of approximately 15 percent per scale point is found in the area of mobility. Whether this reduction represents a causal effect of environmental awareness could be investigated in future studies using the GLEN panel data. Climate skepticism and environmental concern are strongly negatively correlated ($r \approx -0.65$) but are not interchangeable: they attach to different outcomes. For total emissions, environmental concern is the operative attitude (Table 3), while climate skepticism adds little once concern is held constant. This holds in the log-log specification, our primary model. In absolute terms, the skepticism coefficient is smaller and often not significant (Table A8). As with urbanity, the two specifications answer different questions: skepticism shifts emissions across the bulk of the distribution but has little influence on the small group of very high emitters that drives the arithmetic mean.

Table 3: CO_2 emissions, climate attitudes and green party preference (log-log)

	Total	Housing	Mobility	Diet	Consumption
Log equivalence income	0.216***	0.129***	0.503***	0.029***	0.166***
	(0.009)	(0.009)	(0.025)	(0.004)	(0.008)
Household size	-0.045***	-0.224***	0.088***	0.014***	-0.045***
	(0.004)	(0.004)	(0.011)	(0.002)	(0.003)
Age 30-45 (ref. <30)	-0.086***	-0.022	-0.177***	-0.033***	-0.078***
	(0.018)	(0.018)	(0.045)	(0.008)	(0.014)

Table 3: CO_2 emissions, climate attitudes and green party preference (log-log)

Age 45-60 (ref. <30)	-0.072***	0.100***	-0.228***	-0.047***	-0.022
	(0.018)	(0.018)	(0.044)	(0.008)	(0.014)
Age 60+ (ref. <30)	-0.141***	0.200***	-0.461***	-0.078***	-0.113***
	(0.018)	(0.017)	(0.044)	(0.007)	(0.014)
Male	0.086***	-0.027**	0.109***	0.309***	-0.089***
	(0.008)	(0.009)	(0.023)	(0.004)	(0.007)
Education: medium (ref. low)	0.069***	0.040*	0.202***	0.023***	0.067***
	(0.013)	(0.016)	(0.044)	(0.007)	(0.013)
Education: high (ref. low)	0.116***	0.066***	0.277***	0.006	0.050***
	(0.015)	(0.017)	(0.048)	(0.007)	(0.015)
Metropol. city (ref. rural)	-0.038**	-0.090***	-0.080*	-0.001	-0.013
	(0.012)	(0.013)	(0.031)	(0.005)	(0.011)
Regiopol. city (ref. rural)	-0.045***	-0.040**	-0.133***	-0.005	-0.010
	(0.014)	(0.015)	(0.038)	(0.006)	(0.012)
Rural, close to city (ref. rural)	0.002	0.003	-0.027	0.003	0.022
	(0.013)	(0.015)	(0.035)	(0.006)	(0.012)
Climate skepticism	-0.021**	-0.019**	-0.059**	0.002	-0.012*
	(0.007)	(0.007)	(0.019)	(0.003)	(0.006)
Environmental concern	-0.082***	-0.039***	-0.190***	-0.030***	-0.035***
	(0.007)	(0.007)	(0.020)	(0.003)	(0.006)
Green Party preference	-0.065***	-0.033**	-0.148***	-0.018***	-0.013
	(0.012)	(0.012)	(0.033)	(0.005)	(0.010)
Constant	7.753***	7.211***	4.501***	7.077***	6.091***
	(0.088)	(0.083)	(0.234)	(0.036)	(0.074)
N	9660	9660	9482	9660	9660
R2	0.168	0.396	0.128	0.450	0.128

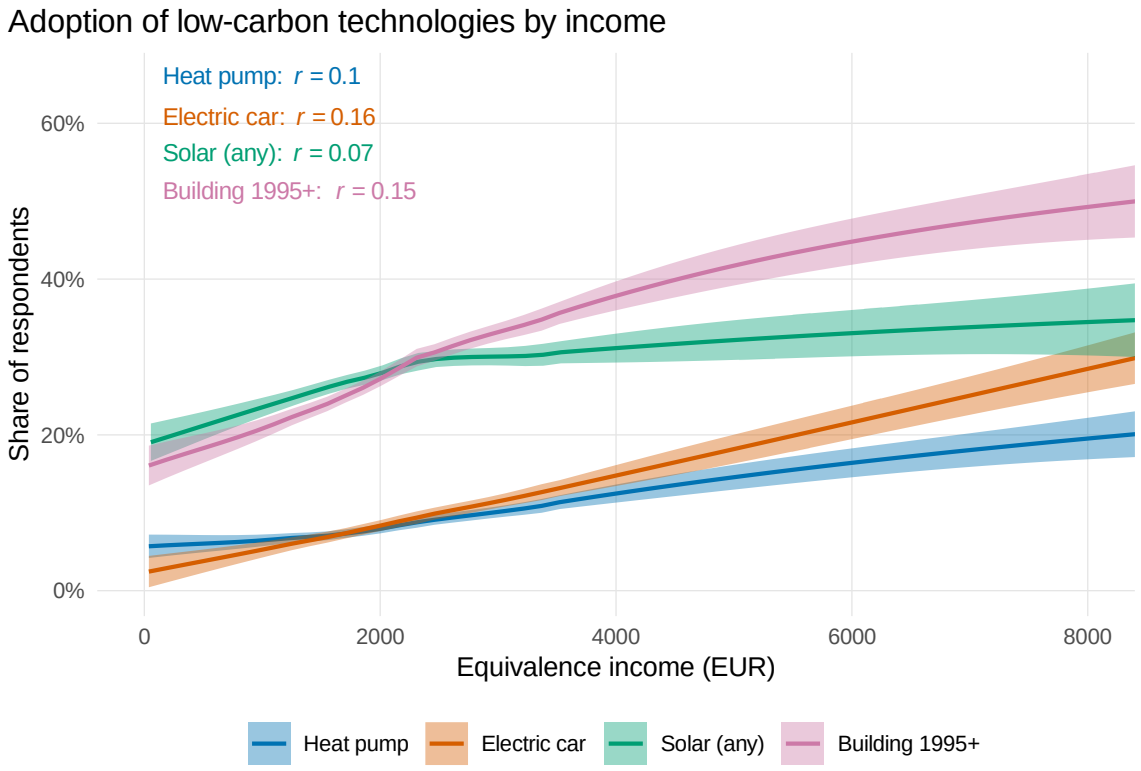
Unweighted OLS on log CO_2 emissions, HC1 robust standard errors in parentheses. Income enters in logs, so its coefficient is an elasticity: a 1 percent higher equivalence income is associated with a b percent higher footprint. Remaining coefficients are approximate proportional differences. Cases with zero emissions in the respective sector are excluded; see N. Reference categories: age under 30, female, low education, peripheral rural.

Climate skepticism and environmental concern are strongly negatively correlated (r = -0.65); read the coefficients jointly.

Is carbon footprint by Green Party preference positively correlated with CO_2 emissions as is often assumed? In fact, the opposite is true. The average carbon footprint for Green Party

voters is 8.3 tons while the number for voters with other party preferences (including non-voters) is 9.0 tons. Voters of the Green Party reduce their carbon footprint by 735 kg compared to voters of other parties. Mobility plays the main role here, with a reduced footprint of 482 kg (Table A11). Of course, this bivariate comparison needs to be supplemented, as the differences could be due to income disparities and other sociodemographic variables. We control for this and the other covariates. It turns out that voters of Green Parties do indeed have a below-average carbon footprint, even when environmental concern and income are taken into account. This correlation is particularly pronounced in the area of mobility (Table 3). The value of 6.5 percent reduction in the carbon footprint shown in Table 3 is actually an underestimate, as part of the association between "Green" and carbon footprint is attributable to environmental attitudes. If environmental attitudes are excluded, the percentage is -11.4 for Green Party voters when controlling for sociodemographic characteristics (Table A9). Regarding flights, it turns out that the belief that Green Party voters fly more often than supporters of other parties is a myth. Table A11 shows that a direct comparison between Green Party voters and others results in no difference in flight emissions or number of flights, yet controlled for other demographics like income and education, Green Party voters are more environmentally friendly in their mobility and do not show higher flight behavior.

Figure 4: Adoption of E-Technology and living in energy efficient buildings by income



Weighted LOESS over individual data. Band: 95% CI. r: weighted Pearson.

4. Investments in solar energy, heat pumps, and electric cars

Investments in green technologies are effective ways for households to reduce their carbon footprint. In addition, insulation and living in relatively new buildings help reduce carbon emissions. However, this always presents the problem that high upfront investments are required, which may not pay off until years later (Bruderer Enzler et al. 2019). Despite various incentive programs, income will still play a role. This is also evident in our data on investments in solar energy modules, heat pumps, electric cars, and living in energy-efficient buildings (Figure 4).

We will again take into account additional characteristics of the individual and the household. Even then, a clear correlation with income remains. For every €1,000 increase in income, the probability of installing a heat pump rises by 0.021 or 2.1 percentage points. For electric cars, the figure is 3.6 percent; for solar panels, 2.4 percent; and the probability of living in a newer home increases by 4.9 percentage points (Table 4). Household size now becomes a notable factor: larger households are more likely to make energy-saving investments. Age and education play a role when it comes to heat pumps. The propensity to invest increases with educational attainment and decreases with age. On the other hand, middle-aged and older people are more willing to drive electric cars than younger people. As expected, homeowners

are more likely to invest in electric technology than renters. A city-rural divide is also evident when it comes to solar energy and heat pumps. Investment is lower in cities than in rural areas. These estimates are based on the linear probability model; logistic regression yields robust results (Table A12).

Table 4: Adoption of E-Technology Linear Probability Models

	Heat pump	Electric car	Solar (any)	Building 1995+
Equivalence income (per 1,000 EUR)	0.021***	0.036***	0.024***	0.049***
	(0.003)	(0.003)	(0.003)	(0.004)
Home owner (ref. renter)	0.083***	0.076***	0.305***	0.067***
	(0.007)	(0.007)	(0.009)	(0.010)
Household size	0.020***	0.026***	0.063***	0.027***
	(0.003)	(0.003)	(0.004)	(0.004)
Age 30-45 (ref. <30)	0.026	0.023*	0.011	-0.026
	(0.014)	(0.012)	(0.017)	(0.019)
Age 45-60 (ref. <30)	-0.021	0.042***	0.035*	-0.014
	(0.013)	(0.012)	(0.017)	(0.019)
Age 60+ (ref. <30)	-0.040**	0.034**	0.031	-0.088***
	(0.013)	(0.011)	(0.017)	(0.019)
Male	0.012	0.006	0.004	-0.001
	(0.007)	(0.007)	(0.009)	(0.009)
Education: medium (ref. low)	0.021*	0.006	-0.010	0.035*
	(0.009)	(0.010)	(0.016)	(0.015)
Education: high (ref. low)	0.026*	0.008	-0.025	0.045**
	(0.011)	(0.011)	(0.017)	(0.017)
Metropol. city (ref. rural)	-0.021*	-0.006	-0.130***	-0.043**
	(0.009)	(0.009)	(0.013)	(0.013)
Regiopol. city (ref. rural)	-0.012	0.010	-0.079***	-0.028
	(0.011)	(0.011)	(0.015)	(0.015)
Rural, close to city (ref. rural)	0.008	0.005	-0.047***	-0.031*
	(0.010)	(0.010)	(0.014)	(0.014)
Climate skepticism	-0.009	-0.022***	-0.032***	0.005
	(0.005)	(0.005)	(0.007)	(0.007)
Environmental concern	-0.004	-0.001	-0.009	-0.002

Table 4: Adoption of E-Technology Linear Probability Models

	(0.006)	(0.006)	(0.008)	(0.008)
Green Party preference	0.043***	0.069***	0.078***	0.011
	(0.010)	(0.011)	(0.013)	(0.014)
Constant	-0.020	-0.093**	0.089	0.120*
	(0.034)	(0.034)	(0.048)	(0.050)
N	10089	10089	10089	10089
R2	0.046	0.065	0.157	0.043

Linear probability models (OLS), HC1 robust standard errors.

Coefficients are on the probability scale; multiply by 100 for percentage points.

Reference categories: age under 30, female, low education, peripheral rural, renter.

While environmental awareness is not associated with investments in electric technologies, climate skepticism reduces the likelihood of purchasing an electric car and installing a solar system. Finally, Green Party voters invest to a significantly greater extent in heat pumps, electric cars, and solar systems.

If we distinguish between rooftop solar systems and “balcony power plants” in the context of solar installations, no demonstrable correlation can be established between balcony power plants and income, whereas income does play a role again for rooftop systems and thermal solar systems (see A10). Balcony solar systems are energy-saving measures adopted by less affluent households.

IV. Discussion

We estimated the CO_2 emissions of a large sample of the German resident population from survey data using a complex measurement procedure. As expected, the distribution is strongly right-skewed: the median (7.2 tons) lies below the arithmetic mean (8.6 tons), and adding the per-capita share of public infrastructure such as roads and bridges raises the mean to 9.7 tons of CO_2 equivalents. The top decile emits about three times as much as the bottom. Decomposed by sector, inequality is by far highest in mobility, which is also the largest single source of emissions, followed by housing, consumption, and diet.

Emissions rise with income. The estimated income elasticity of the total footprint is 0.22: a one-percent higher income is associated with roughly a 0.22 percent higher footprint. In

absolute terms, €1,000 of additional equivalence income corresponds to about 1,108 kg more CO_2 per year. Mobility carries most of this relationship, with an elasticity of 0.52 and about 868 kg per €1,000. The link is far from deterministic, however: explained variance is low, so at any given income the room for variation is wide. Someone who rarely flies, relies on public transport, and drives an electric car emits far less than an equally affluent person who flies several times a year and commutes by a large petrol SUV. Even high earners can therefore run a low-carbon household, above all through the energy-saving investments we examine below.

These patterns relate to the distinction between intent- and impact-oriented behavior and to the i-frame/s-frame contrast drawn in the introduction (Stern 2000; Chater and Loewenstein 2022). Individual characteristics explain only a limited part of the footprint. In our primary specification, income and sociodemographic position together account for about 14 percent of the variation in total emissions ($R^2 = 0.144$), and adding environmental attitudes raises this only slightly ($R^2 = 0.17$, Table 3). The sector structure fits this picture. Correlations between sector emissions are weak to moderate (Pearson r between −0.07 and 0.20, Table A2), so emissions in one sector are only a limited guide to emissions in another. Total emissions are closely tied to mobility emissions ($r = 0.97$), which reflects mobility's large share of the variance of the total, even though observed characteristics explain mobility least ($R^2 = 0.11$). One possible reading is that footprints depend less on a general environmental orientation than on the conditions under which emissions arise in each sector, such as the housing stock and tenure, settlement structure and transport supply, energy prices, and available technologies. We cannot test this, since these conditions are not measured directly, and the large unexplained share is equally consistent with unobserved individual circumstances or with measurement error in the footprint itself. What the data do show is that environmental attitudes account for only a small part of the variation in footprints, even though environmental concern shows a robust association of its own (Section III.3).

Attitudes are not irrelevant, though. As expected for intent-oriented behavior, pro-environmental attitudes correlate strongly with self-reported environmental action (Hines et al. 1987; Bamberg and Möser 2007); the more demanding question is whether they track the impact measure. They do: environmental awareness remains negatively associated with the footprint net of sociodemographic factors, and climate skepticism is associated with lower adoption of green technologies such as solar panels, heat pumps, and electric cars. Consistent

with this, and contrary to a frequently repeated claim (e.g., Krämer and Trenkler 1996), Green Party preference is negatively, not positively, correlated with emissions: Green voters emit more than 700 kg less than others, chiefly through lower-carbon mobility, and invest more in solar, heat pumps, and electric cars. These associations only suggest an effect reaching beyond low-impact action; whether any is causal can be established only with longitudinal data (Andersen and Mayerl 2022).

A few limitations should be noted. Footprint regressions are exposed to what Brandenstein et al. (2025) call tautological predictors: variables that enter the footprint calculation and are then used to predict it, inflating explained variance while obscuring the social factors upstream. Our specification largely avoids this problem. Income, our main focus, is not part of the footprint by definition: it does not enter the calculation of any sector's emissions. Its relationship with the footprint is therefore not mechanical, and the same holds for education, urbanity, and the attitude and party measures. The modest R^2 therefore reflects the deliberate exclusion of such proxies, not weak measurement, and is not comparable to studies that regress footprints on their own inputs. Three controls are partial exceptions: household size enters the housing and consumption footprints by per-capita construction, and age and sex enter diet through calorie assumptions. The latter is no artifact, since higher dietary emissions among younger respondents and men track documented differences in energy needs and intake (Li et al. 2026; Taherzadeh et al. 2026), but we do not read these coefficients as independent behavioral effects. Two further caveats apply. First, characteristics such as income, education, or attitudes do not produce emissions directly. Rather, they stand for a range of behaviors and circumstances that our models do not capture individually. Second, our data are a single cross-section. Disentangling these links, and the causal roles of the four categories discussed in Section II, requires the longitudinal GLEN waves, which will allow us to observe changes within the same individuals over time. The estimation sample is also mildly selective, since requiring a complete footprint across all four sectors (n = 9,660) introduces some item-driven attrition (Appendix Table A1).

The findings carry distributional implications for climate policy. First, transportation accounts for a large portion of CO2 emissions from private households and is also the sector where the greatest inequality in emissions can be observed. Furthermore, income elasticity of CO2 emissions is much higher in this sector than in all other sectors. Interventions that impose

costs on individual transportation, such as road pricing or an air travel tax, align with distributional policy goals. Secondly, because emissions are right-skewed, nearly two-thirds of the population emit below the mean (Figure 1a). A flat CO_2 levy is regressive, since lower-income households spend a larger income share on housing, transport, food, and consumption. Redistributing the revenue per capita as an eco-bonus reverses this: everyone emitting below the mean gains on net, so the levy plus refund is effectively progressive, and by our estimates a large majority would benefit even if it covered only fossil fuels for transport and heating, as planned under ETS II (see also Diekmann and Bruderer Enzler 2019). Yet the scheme, agreed in the last German government coalition contract but never implemented, remains unpopular: only a minority supports raising the CO_2 price with redistribution. Our investment results sharpen the design problem. Adoption of solar panels, heat pumps, and electric cars rises with income and favors homeowners, so subsidies risk flowing disproportionately to affluent households and, over time, eroding the progressivity of the eco-bonus as wealthier households cut their taxable emissions. Balcony power plants are the exception, adopted independently of income, and raising their output limit would widen low-cost access. Two levers follow: adjust purchase subsidies by income while improving conditions for renters and landlords, and, as Frondel (2024) proposes, use levy revenue to lower electricity prices for all households rather than industry alone. Cheaper electricity alongside a higher carbon price would make heat pumps and electric cars doubly attractive and could accelerate the transition, provided the distributional safeguards are in place to sustain public support.

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Appendix

Table A1: Waterfall selection of cases for the analyse sample

Requirement	Dropped at this step	Remaining	Recovered if dropped	Sole blocking reason
CO_2 housing	1,655	14,964	636	636
CO_2 mobility	2,784	12,180	1,677	1,677
CO_2 diet	1,017	11,163	704	704
CO_2 consumption	476	10,687	402	402
Equivalence income	620	10,067	564	564
Education	282	9,785	270	270
RegioStaR	12	9,773	12	12
Climate skepticism	50	9,723	44	44
Environmental concern	13	9,710	12	12
Green Party preference	50	9,660	50	50

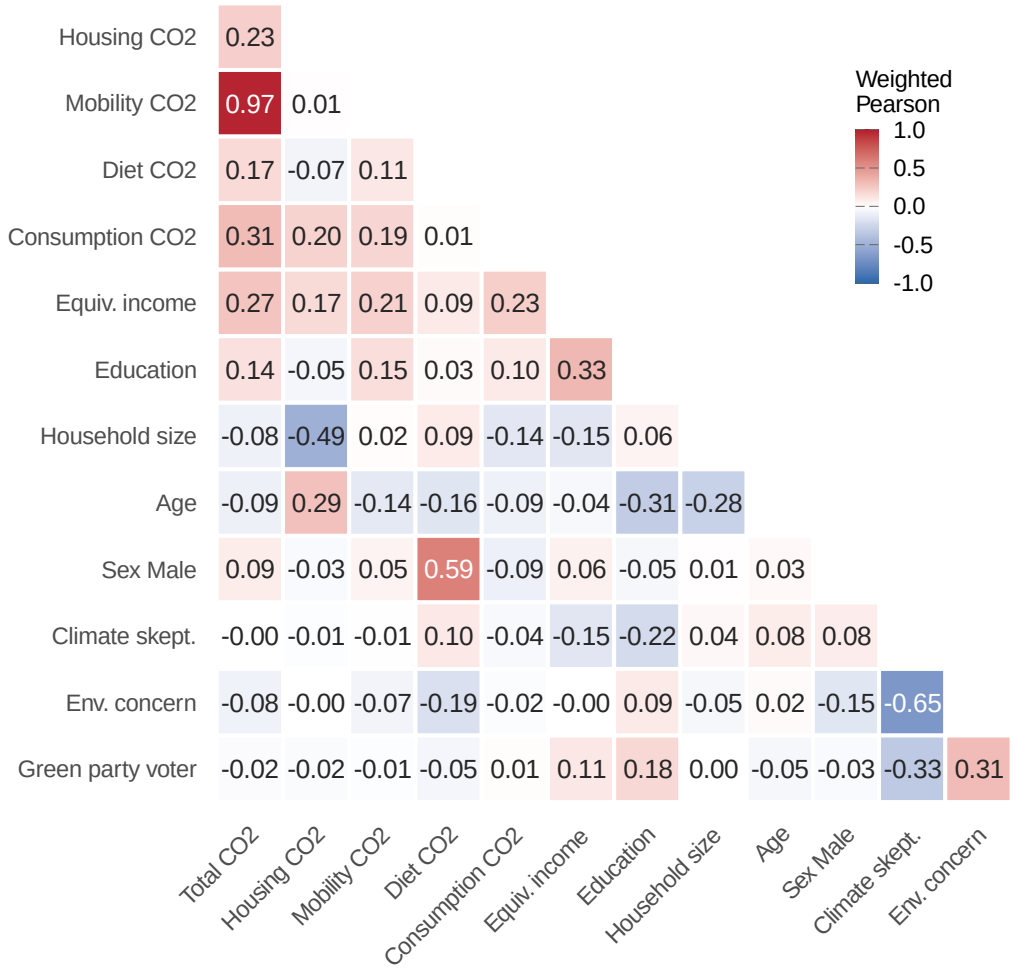
Column 2 is order dependent. Column 4: cases that would re-enter if this single requirement were removed.

Column 5 counts cases failing this requirement and no other (order-independent partition).

9,660 cases meet all requirements; 2,588 fail more than one.

Omitted because they never bind: Household size, Age group, Sex, Positive survey weight.

Figure A1: Pairwise complete correlations between used variables



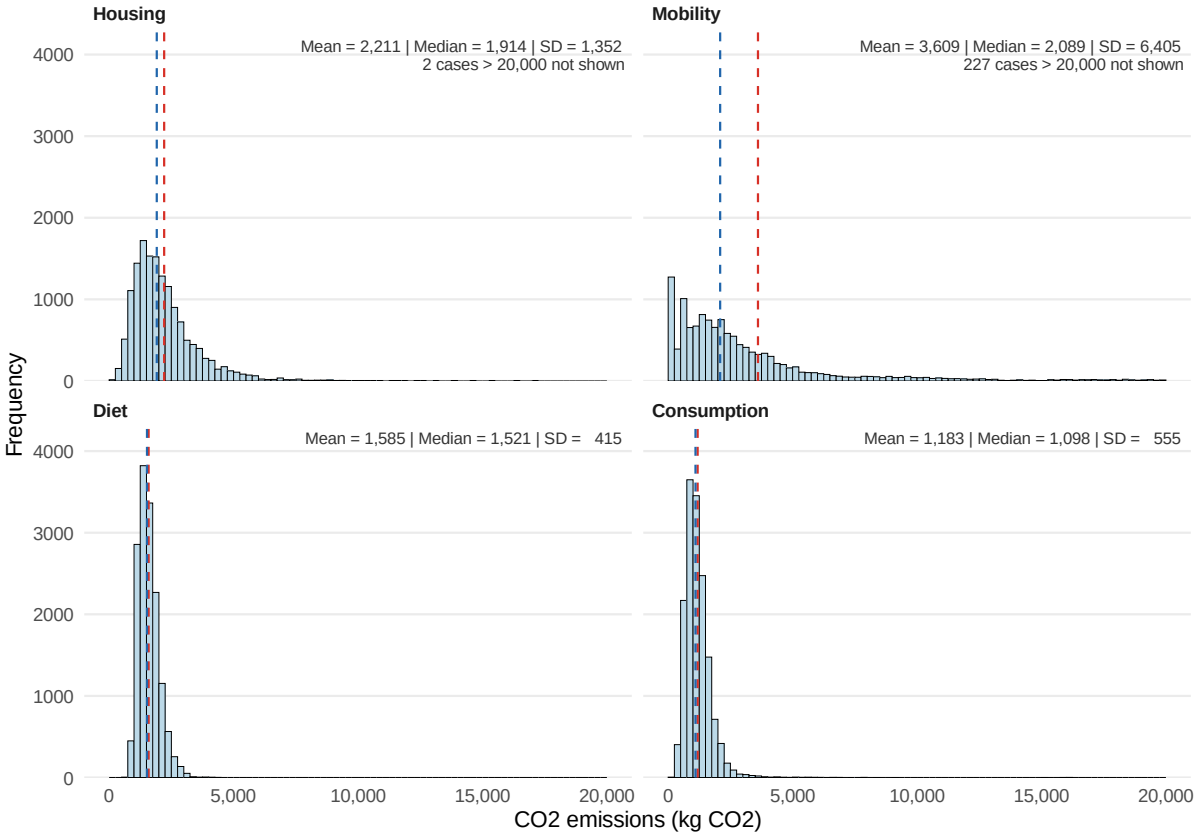
Weighted Pearson correlations. Education ordinal (low < medium < high); sex binary, male = 1. Pairwise complete cases.

Table A2: Weighted correlations between sector emissions

Sector	Housing	Mobility	Diet	Consumption
Housing	-	-0.0009	-0.0675	0.2013
Mobility	-0.0332	-	0.1169	0.1843
Diet	-0.0716	0.1840	-	0.0050
Consumption	0.2026	0.3084	0.0029	-

Estimation sample, n = 9,660, survey-weighted. Upper triangle: Pearson; lower triangle: Spearman on weighted mid-ranks. Within-sector share of total variance: 95.3 percent.

Figure A2: Version of Figure 1b with uniform axis scaling



Identical x and y scales across panels; bin width 250 kg. Weighted by survey weights. Mean (red) and median (blue) dashed. Statistics are computed on the full sector distribution.

Table A4: Winsorisation robustness of gini and sector decomposition

p	mean_total	gini	p90_p10	Housing	Mobility	Diet	Consumption
1.000	8,662.806	0.274	2.976	12.6	79.2	2.5	5.7
0.995	8,541.682	0.264	2.952	12.8	78.8	2.6	5.7
0.990	8,453.277	0.257	2.939	12.9	78.6	2.7	5.8
0.975	8,326.005	0.248	2.909	12.5	78.9	2.8	5.8
0.950	8,072.436	0.229	2.894	12.7	78.1	3.0	6.2

Each row winsorises all four sectors at the stated percentile and re-runs the decomposition. Housing to Consumption are contributions in percent.

Table A5: Selection into positive mobility emissions: participation and intensity

	Participation (LPM)		Intensity (log-log)	
	P(any), socdem	P(any), full	log kg, socdem	log kg, full
Log equivalence income	0.013***	0.012***	0.522***	0.503***
	(0.003)	(0.003)	(0.025)	(0.025)
Household size	0.005***	0.005***	0.088***	0.088***
	(0.001)	(0.001)	(0.011)	(0.011)
Age 30-45 (ref. <30)	-0.006	-0.004	-0.163***	-0.177***
	(0.005)	(0.005)	(0.045)	(0.045)
Age 45-60 (ref. <30)	-0.005	-0.004	-0.215***	-0.228***
	(0.005)	(0.005)	(0.045)	(0.044)
Age 60+ (ref. <30)	-0.012**	-0.011*	-0.462***	-0.461***
	(0.005)	(0.005)	(0.044)	(0.044)
Male	0.006*	0.006*	0.155***	0.109***
	(0.003)	(0.003)	(0.023)	(0.023)
Education: medium (ref. low)	0.020**	0.019**	0.192***	0.202***
	(0.007)	(0.007)	(0.044)	(0.044)

Table A5: Selection into positive mobility emissions: participation and intensity

	Participation (LPM)		Intensity (log-log)	
Education: high (ref. low)	0.028***	0.024***	0.220***	0.277***
	(0.007)	(0.007)	(0.047)	(0.048)
Metropol. city (ref. rural)	0.005	0.004	-0.105***	-0.080*
	(0.004)	(0.004)	(0.032)	(0.031)
Regiopol. city (ref. rural)	0.001	0.001	-0.150***	-0.133***
	(0.005)	(0.005)	(0.038)	(0.038)
Rural, close to city (ref. rural)	-0.004	-0.005	-0.041	-0.027
	(0.005)	(0.005)	(0.035)	(0.035)
Climate skepticism		-0.005*		-0.059**
		(0.003)		(0.019)
Environmental concern		-0.004		-0.190***
		(0.003)		(0.020)
Green Party preference		0.009***		-0.148***
		(0.003)		(0.033)
Constant	0.850***	0.882***	3.545***	4.501***
	(0.023)	(0.030)	(0.201)	(0.234)
N	9660	9660	9482	9482
R2	0.014	0.016	0.111	0.128
Fitted outside [0,1]	0.111	0.131		

Participation columns: linear probability that mobility emissions are positive, full estimation sample (N = 9,660).

Intensity columns: log-log OLS among respondents with positive mobility emissions (Mobility columns of Tables 2 and 3).

Scales differ: participation coefficients are probability changes, intensity coefficients proportional differences. The log income term is an elasticity in both.

HC1 robust standard errors. Reference categories as in Table 2.

Table A6: CO2 emissions on sociodemographic characteristics (levels, kg)

	Total	Housing	Mobility	Diet	Consumption
Equivalence income (per 1,000 EUR)	1108***	137***	868***	22***	81***
	(54)	(8)	(52)	(2)	(4)
Household size	-353***	-428***	118	21***	-63***
	(63)	(10)	(61)	(3)	(5)
Age 30-45 (ref. <30)	-793**	-25	-634*	-51***	-83***
	(279)	(42)	(270)	(12)	(21)
Age 45-60 (ref. <30)	-752**	232***	-896***	-77***	-11
	(276)	(42)	(267)	(12)	(21)
Age 60+ (ref. <30)	-1538***	516***	-1793***	-135***	-125***
	(272)	(41)	(263)	(12)	(20)
Male	1029***	-47*	682***	502***	-108***
	(146)	(22)	(141)	(7)	(11)
Education: medium (ref. low)	457	58	292	32**	74***
	(254)	(39)	(245)	(11)	(19)
Education: high (ref. low)	590*	84*	477	-17	47*
	(274)	(42)	(264)	(12)	(20)
Metropol. city (ref. rural)	-418*	-307***	-60	-8	-43**
	(209)	(32)	(202)	(9)	(16)
Regiopol. city (ref. rural)	-572*	-156***	-383	-12	-21
	(243)	(37)	(234)	(11)	(18)
Rural, close to city (ref. rural)	-168	-19	-178	3	26

Table A6: CO2 emissions on sociodemographic characteristics (levels, kg)

	(233)	(35)	(225)	(10)	(17)
Constant	7196***	2781***	1831***	1313***	1271***
	(425)	(65)	(410)	(19)	(32)
N	9660	9660	9660	9660	9660
R2	0.069	0.289	0.049	0.400	0.087

Unweighted OLS, standard errors in parentheses. Reference categories: age under 30, female, low education, peripheral rural. Outcome in kg CO2 equivalents per year. Weighted and unweighted estimates are substantively identical; survey weights are applied to the descriptive quantities only.

Table A7: Items for Environmental awareness index (Diekmann and Preisendörfer 2001) and for Climate skepticism index (Friedrich and Best 2025)

Env. Awareness	***What about environmental issues in general? To what extent do you agree with the following statements?***
Item	**Wording**
env4i1	It worries me to think about the environmental conditions that our children and grandchildren will likely live in.
env4i2	If we carry on as we are, we are heading for an environmental disaster.
env4i3	The industrialized world has already exceeded or will soon reach the limits of growth.
env4i4	Many environmental problems are greatly exaggerated. (reverse-coded)
env4i5	Politicians are doing far too little to protect the environment.
env4i6	For the sake of the environment, we should all be willing to reduce our standard of living.
Climate skepticism	***People have different views on climate change. We are interested in your opinion. To what extent do you agree with the following statements?***
Item	**Wording**
att4i1	The evidence for climate change is unreliable.
att4i2	Climate change is just a natural fluctuation in the earth's temperatures.
att4i3	Too much fuss is being made about climate change.
att4i4	Attempts to solve climate change are a waste of time.
att4i6	I am uncertain about whether climate change is really happening.
att4i7	Claims that human activities are changing the climate are exaggerated.
att4i8	It is too early to say whether climate change is really a problem.
att4i9	Human behavior has little effect on climate change.

Response scale (both indices): five-point Likert, 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree. Each index is the mean of its items, returned to the original 1–5 scale; env4i4 is reverse-coded prior to indexing.

Table A8: Unweighted OLS Regression on CO_2 emissions on level

	Total	Housing	Mobility	Diet	Consumption
Equivalence income (per 1,000 EUR)	1081***	133***	849***	20***	79***
	(55)	(8)	(53)	(2)	(4)
Household size	-356***	-428***	115	20***	-63***
	(63)	(10)	(61)	(3)	(5)
Age 30-45 (ref. <30)	-901**	-30	-722**	-61***	-88***
	(279)	(43)	(270)	(12)	(21)
Age 45-60 (ref. <30)	-849**	227***	-975***	-86***	-15
	(276)	(42)	(267)	(12)	(21)
Age 60+ (ref. <30)	-1573***	516***	-1824***	-139***	-127***
	(271)	(41)	(262)	(12)	(20)
Male	840***	-67**	536***	488***	-117***
	(147)	(22)	(142)	(6)	(11)
Education: medium (ref. low)	534*	63	356	38***	78***
	(253)	(39)	(245)	(11)	(19)
Education: high (ref. low)	920***	110**	742**	7	61**
	(277)	(42)	(268)	(12)	(21)
Metropol. city (ref. rural)	-291	-296***	41	2	-38*
	(209)	(32)	(202)	(9)	(16)
Regiopol. city (ref. rural)	-494*	-149***	-321	-7	-18
	(242)	(37)	(234)	(11)	(18)
Rural, close to city (ref. rural)	-103	-12	-126	7	29
	(232)	(35)	(225)	(10)	(17)
Climate skepticism	-64	-36*	-30	3	-2
	(116)	(18)	(113)	(5)	(9)
Environmental concern	-706***	-86***	-533***	-51***	-37***
	(124)	(19)	(120)	(5)	(9)
Green Party preference	-652**	-88**	-521**	-28**	-15
	(207)	(32)	(201)	(9)	(16)
Constant	9966***	3176***	3882***	1497***	1411***

Table A8: Unweighted OLS Regression on CO_2 emissions on level

	(770)	(117)	(745)	(34)	(58)
N	9660	9660	9660	9660	9660
R2	0.077	0.292	0.055	0.415	0.091

Unweighted OLS, standard errors in parentheses. Reference categories: age under 30, female, low education, peripheral rural. Outcome in kg CO2 equivalents per year. Weighted and unweighted estimates are substantively identical; survey weights are applied to the descriptive quantities only.

Table A9: Unweighted OLS Regression on CO_2 emissions excluding attitudes

	Total	**Housing**	**Mobility**	**Diet**	**Consumption**
Log equivalence income	0.226***	0.134***	0.526***	0.031***	0.170***
	(0.009)	(0.009)	(0.025)	(0.004)	(0.008)
Household size	-0.044***	-0.223***	0.090***	0.014***	-0.045***
	(0.004)	(0.004)	(0.011)	(0.002)	(0.003)
Age 30-45 (ref. <30)	-0.083***	-0.022	-0.173***	-0.030***	-0.078***
	(0.019)	(0.018)	(0.045)	(0.008)	(0.014)
Age 45-60 (ref. <30)	-0.069***	0.099***	-0.224***	-0.043***	-0.021
	(0.018)	(0.018)	(0.044)	(0.008)	(0.014)
Age 60+ (ref. <30)	-0.144***	0.197***	-0.470***	-0.077***	-0.114***
	(0.018)	(0.017)	(0.044)	(0.007)	(0.014)
Male	0.101***	-0.021*	0.145***	0.315***	-0.082***
	(0.008)	(0.009)	(0.023)	(0.004)	(0.007)
Education: medium (ref. low)	0.068***	0.041**	0.203***	0.021**	0.067***
	(0.013)	(0.016)	(0.044)	(0.007)	(0.013)
Education: high (ref. low)	0.110***	0.067***	0.270***	0.000	0.049***
	(0.015)	(0.017)	(0.048)	(0.007)	(0.014)
Metropol. city (ref. rural)	-0.042***	-0.091***	-0.089**	-0.004	-0.014
	(0.012)	(0.013)	(0.032)	(0.005)	(0.011)
Regiopol. city (ref. rural)	-0.047***	-0.041**	-0.137***	-0.006	-0.011
	(0.014)	(0.015)	(0.038)	(0.006)	(0.012)
Rural, close to city (ref. rural)	0.000	0.002	-0.031	0.002	0.021

Table A9: Unweighted OLS Regression on CO_2 emissions excluding attitudes

	(0.013)	(0.015)	(0.035)	(0.006)	(0.012)
Green Party preference	-0.114***	-0.050***	-0.253***	-0.043***	-0.031**
	(0.011)	(0.011)	(0.031)	(0.005)	(0.009)
Constant	7.352***	6.997***	3.535***	6.956***	5.912***
	(0.075)	(0.071)	(0.202)	(0.029)	(0.062)
N	9660	9660	9482	9660	9660
R2	0.153	0.394	0.117	0.440	0.125

Unweighted OLS on log CO_2 emissions, HC1 robust standard errors in parentheses. Income enters in logs, so its coefficient is an elasticity: a 1 percent higher equivalence income is associated with a b percent higher footprint. Remaining coefficients are approximate proportional differences. Cases with zero emissions in the respective sector are excluded; see N. Reference categories: age under 30, female, low education, peripheral rural.

The party coefficient is larger than in the full model because the omitted attitude scales absorb part of it.

Table A10: Unweighted OLS Regression on CO_2 emissions of mobility with decomposition regarding flight emissions

	Mobility (total)	**Excl. flights**	**Flights only**
Equivalence income (per 1,000 EUR)	849***	235***	614***
	(53)	(12)	(50)
Household size	115	192***	-77
	(61)	(14)	(58)
Age 30-45 (ref. <30)	-722**	5	-727**
	(270)	(64)	(258)
Age 45-60 (ref. <30)	-975***	51	-1025***
	(267)	(63)	(255)
Age 60+ (ref. <30)	-1824***	-284***	-1540***
	(262)	(62)	(251)
Male	536***	306***	231
	(142)	(34)	(136)
Education: medium (ref. low)	356	205***	151
	(245)	(58)	(234)
Education: high (ref. low)	742**	129*	612*

Table A10: Unweighted OLS Regression on CO_2 emissions of mobility with decomposition regarding flight emissions

	(268)	(63)	(257)
Metropol. city (ref. rural)	41	-374***	415*
	(202)	(48)	(193)
Regiopol. city (ref. rural)	-321	-278***	-43
	(234)	(55)	(224)
Rural, close to city (ref. rural)	-126	7	-134
	(225)	(53)	(215)
Climate skepticism	-30	-4	-25
	(113)	(27)	(108)
Environmental concern	-533***	-289***	-243*
	(120)	(28)	(115)
Green Party preference	-521**	-201***	-319
	(201)	(47)	(192)
Constant	3882***	2169***	1714*
	(745)	(176)	(712)
N	9660	9660	9660
R2	0.055	0.124	0.033

Unweighted OLS, standard errors in parentheses. Reference categories: age under 30, female, low education, peripheral rural. Outcome in kg CO_2 equivalents per year. Weighted and unweighted estimates are substantively identical; survey weights are applied to the descriptive quantities only.

Columns decompose mobility emissions additively: total = excluding flights + flights only.

Table A11: Weighted flight emission and numbers by Green Party preference

Outcome	green_voters	non_green_voters	diff	p
CO_2 Mobility	3,498.006	3,980.025	-482.020	0.001
CO_2 wo/flights	1,888.305	2,283.643	-395.337	0.000
CO_2 flights	1,609.700	1,696.383	-86.683	0.528
Num. of flights	0.877	0.866	0.010	0.841

Estimation sample, n = 9,660, survey-weighted. Differences tested with t-test.

Table A12: Adaption of E-Technologies logit models

	Heat pump	Electric car	Solar (any)	Building 1995+
Equivalence income (per 1,000 EUR)	1.19***	1.32***	1.13***	1.24***
	(0.03)	(0.03)	(0.02)	(0.02)
Home owner (ref. renter)	2.64***	2.52***	5.07***	1.38***
	(0.22)	(0.22)	(0.30)	(0.07)
Household size	1.19***	1.26***	1.37***	1.13***
	(0.03)	(0.04)	(0.03)	(0.02)
Age 30-45 (ref. <30)	1.24	1.40*	1.07	0.89
	(0.15)	(0.21)	(0.10)	(0.08)
Age 45-60 (ref. <30)	0.81	1.59**	1.20	0.94
	(0.10)	(0.23)	(0.11)	(0.08)
Age 60+ (ref. <30)	0.65***	1.49**	1.21*	0.66***
	(0.08)	(0.22)	(0.12)	(0.06)
Male	1.14*	1.06	1.02	1.00
	(0.07)	(0.07)	(0.05)	(0.04)
Education: medium (ref. low)	1.37*	1.11	0.95	1.21*
	(0.18)	(0.14)	(0.07)	(0.10)
Education: high (ref. low)	1.43**	1.13	0.88	1.27**
	(0.20)	(0.15)	(0.07)	(0.11)

Table A12: Adaption of E-Technologies logit models

Metropol. city (ref. rural)	0.80*	0.93	0.52***	0.82***
	(0.07)	(0.08)	(0.03)	(0.05)
Regiopol. city (ref. rural)	0.89	1.10	0.69***	0.88
	(0.09)	(0.11)	(0.05)	(0.06)
Rural, close to city (ref. rural)	1.06	1.05	0.80***	0.86*
	(0.10)	(0.10)	(0.05)	(0.06)
Climate skepticism	0.90*	0.75***	0.85***	1.02
	(0.05)	(0.04)	(0.03)	(0.04)
Environmental concern	0.95	0.96	0.96	0.99
	(0.05)	(0.05)	(0.04)	(0.04)
Green Party preference	1.45***	1.67***	1.47***	1.05
	(0.12)	(0.13)	(0.09)	(0.07)
Constant	0.03***	0.02***	0.11***	0.18***
	(0.01)	(0.01)	(0.03)	(0.04)
N	10089	10089	10089	10089
AIC	7093.00	7101.00	11710.00	12445.00
Pseudo R2 (McFadden)	0.06	0.09	0.13	0.03

Unweighted logistic regression. Odds ratios, standard errors in parentheses. Reference categories: age under 30, female, low education, peripheral rural, renter.

Party coefficient estimated net of attitudes, as in the emissions models.

Table A13: Linear probability models on specific solar investments

	Roof PV	Balcony PV	Solar thermal
Equivalence income (per 1,000 EUR)	0.026***	-0.002	0.007**
	(0.003)	(0.002)	(0.003)
Home owner (ref. renter)	0.211***	0.082***	0.103***
	(0.008)	(0.006)	(0.007)
Household size	0.052***	0.003	0.032***
	(0.004)	(0.003)	(0.003)
Age 30-45 (ref. <30)	0.010	0.033**	-0.013
	(0.015)	(0.010)	(0.013)
Age 45-60 (ref. <30)	0.019	0.025*	0.034**
	(0.015)	(0.010)	(0.013)
Age 60+ (ref. <30)	0.028	0.021*	0.031*
	(0.015)	(0.010)	(0.013)
Male	0.010	0.004	0.001
	(0.008)	(0.006)	(0.007)
Education: medium (ref. low)	0.012	-0.010	-0.019
	(0.013)	(0.011)	(0.012)
Education: high (ref. low)	0.003	-0.020	-0.019
	(0.015)	(0.011)	(0.013)
Metropol. city (ref. rural)	-0.116***	0.012	-0.100***
	(0.012)	(0.008)	(0.010)
Regiopol. city (ref. rural)	-0.068***	0.012	-0.070***
	(0.014)	(0.010)	(0.012)
Rural, close to city (ref. rural)	-0.038**	0.006	-0.037**
	(0.013)	(0.009)	(0.012)
Climate skepticism	-0.028***	-0.004	-0.011*
	(0.006)	(0.004)	(0.005)
Environmental concern	-0.006	0.000	-0.004
	(0.007)	(0.005)	(0.006)

Table A13: Linear probability models on specific solar investments

Green Party preference	0.071***	0.020*	0.026*
	(0.012)	(0.009)	(0.010)
Constant	-0.024	0.016	0.058
	(0.043)	(0.031)	(0.037)
N	9992	9992	9992
R2	0.121	0.019	0.058
Adj. R2	0.120	0.018	0.057
Fitted p outside [0,1]	0.088	0.002	0.061

Linear probability models (OLS). Coefficients are changes in the adoption probability; HC1 robust standard errors in parentheses. Reference categories: age under 30, female, low education, peripheral rural, renter.

Respondents reporting solar of unknown type are missing on specific technologies and are excluded, so N is lower than in the aggregate solar models.