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On the relationship between individual carbon literacy and carbon footprint components

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ABSTRACT

To mitigate climate change, individual greenhouse gas emissions need to decline substantially. This paper empirically explores the relationship between individual carbon footprints and carbon literacy as well as socio-economic and attitudinal factors. To operationalize carbon literacy, we distinguish between carbon knowledge and carbon engagement. Our econometric analysis uses widely representative survey data for 1000 individuals in Germany and distinguishes between components of an aggregate carbon footprint and of carbon footprints related with electricity consumption, heating, motorized individual transport, aviation, and dietary choices. We find a negative and sizeable correlation between carbon engagement and the aggregate footprint, as well as the footprints related to electricity consumption and diet. For example, a one-unit increase in our index reflecting carbon engagement corresponds to a decrease in the aggregate carbon footprint of about 4%. Furthermore, for carbon knowledge we find a negative correlation with the carbon footprint from diet. We also find significant correlations between the carbon footprints and gender, age, income, education, environmental preferences, and policy orientation, which generally exhibit the intuitively expected signs, but differ somewhat across activities. Overall, our findings support the notion that fostering carbon engagement represents a more effective strategy for reducing individuals' carbon footprints than enhancing carbon knowledge.

1. Introduction

To meet ambitious climate targets such as the European Union's (EU) target of reaching net zero greenhouse gas (GHG) emissions by 2050, emissions in all sectors need to be lowered drastically from current levels. For individuals, who account for about 40% of GHG emissions in the EU[1], this entails primarily reducing emissions related to electricity consumption, heating, transportation services, and dietary choices. A key approach to effectively manage GHG emissions involves empowering individuals with an understanding of the emissions associated with their activities, thereby enabling them to make informed decisions aimed at reducing their individual carbon footprint. Thus, individuals need to be knowledgeable about the topic. The literature has referred to this competency as carbon literacy (Whitmarsh et al., 2011; Howell, 2018).

'Literacy' is intended to measure the extent to which individuals have the knowledge to make informed choices in a particular domain (Howell, 2018). Originally, the term literacy referred to the ability to read and write or, more broadly, to engage with and use (written) language. Increasingly, the term has been employed to refer to competences and knowledge in a particular domain. For example, literacy as a concept has been widely used and refined in health education where it refers to the "cognitive and social skills which determine the motivation and ability of individuals to gain access to, understand and use information in ways which promote and maintain good health" (Nutbeam, 2000). Thus, the concept of literacy not only refers to available knowledge but also to behavioural consequences. It extends beyond the knowledge of specific facts, and encompasses a systemic understanding of an issue. As another application, financial literacy (Mason and Wilson, 2000) encompasses individuals' competence in understanding financial and economic matters. In the sustainability domain, literacy concepts refer to environmental literacy (Howell, 2018) and energy

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[1] Based on Eurostat data series env_ac_aigg_q. This figure is based on the territorial approach to attribute GHG emissions. Using the consumption-based approach, GHG emissions of EU households would be higher than under the territorial approach (e.g. Ivanova et al., 2016).

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literacy (e.g. Zografakis et al., 2008; DeWaters and Powers, 2011; Blasch et al., 2017; He et al., 2022). In particular, Blasch et al. (2017) define energy literacy as "an individual's ability to make informed and deliberate choices in the domain of household energy consumption". In their empirical specification, Blasch et al. (2017) construct a literacy index based on survey items eliciting individual knowledge about energy prices and energy consumption of different technologies. Hereby, energy consumption of particular technologies refers to typical or average energy consumption of these technologies at the national level. Empirical findings suggest that more energy literate individuals are more likely to have lower energy consumption levels (Blasch et al., 2017) and to be more likely to adopt energy efficient appliances (He et al., 2022).

Whitmarsh et al. (2011) transfer the concept of literacy to the domain of climate change. In their understanding, literacy is formed by a combination of knowledge, skills, and motivations.[2] Blasch et al. (2017) refer literacy to choices based on information and deliberation. Accordingly, we define carbon literacy as an individual's knowledge-based capacity to make informed and deliberate decisions aimed at lowering GHG emissions. In our understanding, this includes two components, knowledge and engagement. Knowledge refers to factual and systemic knowledge, e.g. about sources of carbon emissions, amounts of emissions by certain activities or sectors. Akin to the meaning of motivations in Whitmarsh et al. (2011), engagement refers to the willingness to update and extend this knowledge, e.g. by staying informed about ongoing climate-related topics.

While carbon literacy was introduced to the academic literature more than a decade ago (Whitmarsh et al., 2011), it has received relatively little attention in empirical studies. To our knowledge, no study has yet investigated empirically the relationship between carbon literacy and outcome indicators such as GHG emissions at the individual level. Few studies address the measurement of carbon literacy for selected sub-groups of the population. Howell (2018) considers carbon literacy to be a precondition to carbon management at the household level and therefore qualitatively analyse how carbon footprint statements, energy monitoring, and peer learning may enhance carbon literacy. Dósa and Russ (2020) examine how individual carbon literacy helps US-students to correctly interpret information about carbon footprints of exemplary industries. Horng et al. (2013) develop a carbon literacy scale geared for professionals in the Taiwanese tourism sector to measure the carbon footprint related to tourism. More recently, Huang and Gao (2021) find that carbon literacy among individuals in Shanghai (China) is correlated with commuters' intended mode of transportation. For the food domain, several studies investigate the relationship between dietary choices, carbon footprint, and healthiness (e.g. van Loo et al., 2017; van Dooren et al., 2018; Perino and Schwirplies, 2022; Righi et al., 2023).

In this paper, we attempt to close this gap by econometrically exploring the relationship between components of individuals' carbon footprints, their carbon literacy, and other individual characteristics. To this end, we use data from a widely representative survey among individuals in Germany. In particular, this survey included an original carbon footprint calculator to estimate individual emissions associated with electricity consumption, heating, transportation, and dietary choices. Following our definition of carbon literacy, we investigate two facets of literacy, namely carbon knowledge and carbon engagement. Carbon knowledge refers to factual understanding around (relative) amounts of GHG emissions associated with certain individual and societal activities. This approach to literacy rests on the basic assumption of the 'information deficit' model, which stipulates that lack of adequate knowledge is a barrier to a behavioural change towards a particular action (e.g. Suldovsky, 2017). Carbon engagement refers to individuals' willingness to engage with knowledge related to climate change and to update this knowledge in relation to societal developments such as political processes and new technologies. We therefore expect that higher levels of carbon knowledge and carbon engagement both result in a lower footprint at an aggregate level and at the level of different activities. In addition, the individual characteristics included in our empirical analyses comprise socio-economic characteristics and attitudes reflecting individuals' willingness and capability to lower emissions akin to previous studies on individual environmental impact (Moser and Kleinhückelkotten, 2017).

We organize the remainder of our paper as follows. Section 2 describes the survey and the carbon footprint calculator, Section 3 presents the econometric approaches and Section 4 displays the empirical results. Finally, Section 5 summarizes and discusses the main findings.

2. Data and methods

We econometrically examine the relationship between components of individual carbon footprints, indicators of carbon literacy, and various other individual characteristics. To conduct these analyses, we rely on data from a survey that incorporates a carbon footprint calculator, as well as items reflecting carbon literacy and other individual characteristics. It is important to note that our data set is cross-sectional and non-experimental in nature. As a result, our findings can only be interpreted as correlations concerning the association between carbon footprints and literacy.[3]

In this section, we first provide a general overview of the survey. Then, we present the indicators used to empirically capture carbon knowledge, and carbon engagement, including results. Finally, we describe the carbon footprint calculator.

2.1. Description of the survey

We conducted an online survey using computer-assisted web interviews (CAWI) in September and October 2020, drawing on an existing individual panel by Psyma, a large private market research institute in Germany. Our original sample included 1005 participants who were selected via quota sampling to be representative of the adult population in Germany in terms of gender, age, education, and regional distribution (according to 16 federal states). Participants received a fee after completing the survey. The survey started with questions on socio-demographic characteristics to ensure that the quota criteria were met and with items on environmental and political attitudes. This was followed by a block of questions on climate change and carbon literacy (see Section 2.2). The core of the survey was the carbon footprint calculator (see Section 2.3). The survey concluded with additional questions on socio-economic characteristics (e.g. income classes). To control for the quality of the survey, we also included two screen-out questions. That is, participants were asked to indicate a particular response category within two blocks of survey items. Only participants who answered both screen-out questions correctly were retained in the sample. Furthermore, we conducted a pre-test with 46 participants to ensure that wording and instructions were comprehensible. The median time required to complete the survey was 15.4 min.

[2] Hereby, carbon motivation does not pertain to the motivation to change behaviours to reduce GHG emissions; rather, the emphasis is on literacy as a prerequisite for such change. To avoid misunderstandings, we use the term carbon engagement.

[3] In comparison, Enlund et al. (2023) use weekly panel data in a quasi-experimental approach, enabling them to analyse causal effects. Their study demonstrates that individuals who have access to a smartphone app, which provides information on carbon footprints derived from actual financial transactions across various domains (i.e. transportation, goods and services, food and beverages, and residential energy), reduce their carbon footprints within the initial four weeks.

Table 1
Measurement of carbon knowledge (1005 participants).

	Share of responses
(i) *Survey question: What causes the fewest greenhouse gas emissions in Germany on average?*	
Bringing one litre of water to boil in an electric kettle. (x)	57.21%
Bringing one litre of water to boil in a pot with lid on an electric oven.	23.28%
Bringing one litre of water to boil in a pot with lid in a microwave oven.	19.50%
(ii) *Survey question: Which of the following devices causes the most greenhouse gas emissions on average when used in Germany?*	
Refrigerator (x)	37.21%
Oven	17.11%
Computer	14.93%
Washing machine	14.03%
Light bulbs	8.66%
TV	6.57%
Telephone	1.49%
(iii) *Survey question: On average, what would save the most greenhouse gas emissions in Germany within one year?*	
Avoid a flight to the USA. (x)	49.95%
Use a hybrid vehicle instead of a car with a gasoline engine (petrol engine) for all journeys.	16.62%
Use an electric vehicle instead of a car with a gasoline engine (petrol engine) for all journeys.	33.43%
(iv) *Survey question: On average, what would save the most greenhouse gas emissions in Germany?*	
Switch to a plant-based (vegan) diet. (x)	21.89%
Reuse waste products (recycling).	45.27%
Switch the lighting to light emitting diodes / energy-saving lamps.	32.84%

Notes: Correct answers are indicated by '(x)'. The questions and answers are based on: (i) and (ii): Blasch et al. (2017), (iii) and (iv): Wynes and Nicholas (2017).

2.2. Carbon literacy

In this sub-section, we describe how we empirically measured carbon literacy. We thereby distinguish between carbon knowledge and carbon engagement.

2.2.1. Carbon knowledge

To capture carbon knowledge as a component of carbon literacy, we use the four survey questions shown in Table 1, thereby drawing on Blasch et al. (2017) and Wynes and Nicholas (2017). Table 1 suggests that most participants knew or guessed correctly that using an electric kettle to boil water causes fewer GHG emissions than using an electric oven or a microwave. In contrast, only about 37% of the participants correctly identified refrigerators to cause the most GHG emissions among the devices shown. About half of the participants knew that avoiding a flight to the US would save more emissions than using a hybrid or an electric vehicle instead of a car with a gasoline engine for all journeys. In contrast, only about 20% of the participants thought that switching to a plant-based diet would save more emissions than recycling or using energy-saving light bulbs such as light emitting diodes.

Thus, similar to previous studies, participants appear to overestimate the potential of recycling (e.g. Downing and Ballantyne, 2007) and to underestimate the significance of flying (e.g. Becken, 2007) and of meat-based diets (e.g. Attari et al., 2010; Truelove and Parks, 2012). On average, participants correctly answered about 42% of the individual questions used to measure carbon knowledge. In the empirical analysis, we use the dummy variable *carbon_knowledge*, assigned a value of one if the number of correct answers exceeds the sample median which is two. Thus, we apply equal weights to the four items, in line with Blasch et al. (2017) for example in the context of energy literacy. Approximately 23% of participants achieved three or four correct answers, resulting in the dummy variable having a value of one.

Table 2
Measurement of carbon engagement (1005 participants).

Survey question: Which, if any, of these things do you personally keep an eye on?[†]	Mean[a]
(i) Availability of more energy-efficient appliances for the home.	3.57
(ii) How the climate and seasons seem to be changing in Germany.	3.51
(iii) New scientific knowledge about climate change.	3.44
(iv) Debates about the future of energy provision (e.g. nuclear power, renewables, the future of coal).	3.31
(v) Measures to reduce greenhouse gas emissions.	3.30
(vi) German government policy on climate change.	3.27
(vii) New technologies to reduce greenhouse gas emissions.	3.27
(viii) Positions of the political parties on climate policy.	3.20
(ix) International agreements on climate change.	3.17
(x) Impact of climate change on developing countries.	3.11
(xi) Contributions by companies to reduce their greenhouse gas emissions.	3.07
(xii) Product labels for greenhouse gas emissions.	2.91

[†] Response categories: Not at all (1) - somewhat (2) - undecided (3) - rather strongly (4) - very strongly (5).
[a] To calculate the mean, we treated the ordered response categories as cardinal categories.

2.2.2. Carbon engagement

To capture carbon engagement, we drew on an item battery originally developed by Whitmarsh et al. (2011). Participants were shown a list of climate-related topics and they were asked to indicate on an ordered five-point Likert scale whether they personally keep an eye on them (see Table 2). We then calculated the mean of the scores of the twelve items.[4] In the empirical analysis we used the variable *carbon_engagement* which is the z-score of the mean of the individual scores.

2.3. Description of the carbon footprint calculator

For the purpose of this study, we integrated a carbon footprint calculator in the online survey. Our calculator accounts for GHG emissions related to electricity consumption, thermal heat demand, motorized individual transport, and dietary choices. These activities have the most significant impact on individual carbon footprints (e.g., as indicated by Jacksohn et al., 2023). Our carbon footprint calculator is similar to existing online carbon footprint calculators for individuals such as the one operated by the UNFCCC (https://offset.climateneutralnow.org/footprintcalc), the WWF (https://footprint.wwf.org.uk/#/), and the German Federal Environmental Agency Umweltbundesamt (https://uba.co2-rechner.de/en_GB/).[5]

In general, we asked participants to report single activities that refer to their electricity consumption, heat demand, motorized individual transport, and dietary choices. To obtain individual GHG emissions, we multiplied the corresponding consumption levels by specific GHG emissions factors for Germany. Table A1 in the Appendix documents the carbon emission factors used. To calculate the carbon footprint of electricity consumption, we considered indirect emissions from burning fossil fuel at the site of the power plant. For heating and motorized individual transport, we used direct emissions (i.e. from burning fossil fuel at the site or by the internal combustion engine vehicles), and indirect emissions when relevant such as for night storage heating and electric vehicle use. The values used to estimate the diet-related carbon footprint encompass direct and indirect energy-related emissions. In addition, they take into account methane emissions associated with livestock

[4] Cronbach's α is 0.94, suggesting high internal consistency of the 12 items.
[5] In a different context, this carbon footprint calculator has been used to study individuals' stated willingness to pay to offset their carbon footprint (Schleich and Alsheimer, 2022).

production. Similar to other carbon footprint calculators, ours does not include the full carbon footprint. For example, it does not encompass all GHG emissions generated both directly and indirectly by an activity, or accumulated throughout the various phases of a product's lifecycle (e.g. Wiedmann, 2009, p. 175). [6] Also, it is limited to certain activities. Hence, our carbon calculator covers components of carbon footprints only.

Data for all activities are for 2019, i.e. the last year before the Covid-19 pandemic. We used defaults when participants failed to report information and if the information provided failed plausibility checks. Data on emission factors, technologies, and default values was obtained from the most recent literature available for Germany.[7] For electricity consumption and heating, we asked for values at the household level. To obtain the individual carbon footprint for electricity consumption and heating, we divide the carbon footprint at the household level by the number of household members.

2.3.1. Electricity consumption

To estimate the individual carbon footprint for *electricity consumption*, we asked participants to report the electricity use (in kWh) in their household and their monthly or annual electricity bill (in Euro). If information on the electricity bill was available, but not on electricity use, we calculated electricity use by dividing the amount of the electricity bill by the average electricity price in 2019 for a private household using 3500 kWh per year, i.e. 0.304 Euro/kWh (BDEW, 2022). If there was no information on the electricity bill either, we used default values by household size (1, 2, 3, 4, 5, >6 persons) and building type (single family or multi-family buildings) to estimate electricity consumption.[8] Default values for electricity consumption ranged from 1500 kWh for a single-person household in a multi-family building to 5000 kWh for a five-person household in a single-family building. For larger households, we added 500 kWh per additional person in a single- and multi-family building. For households with an electric water heater, we added 700 kWh based on UBA (2020). To calculate the carbon footprint of electricity consumption, we multiplied household electricity use by the emission factor of the electricity mix in Germany in 2019 (i.e. 0.401 $kgCO_{2eq}$/kWh).[9] For households subscribing to a green tariff, we applied an emissions factor of zero.[10] Households with a rooftop photovoltaic (PV) system received a carbon credit, calculated as the product of the stated electricity generated by the PV system and the emission factor of the national electricity mix.[11] Thus, the carbon footprint of households with a PV system may be negative if their PV system generated more electricity than the household consumed and/or if the household also subscribed to a green tariff. Finally, we note that the carbon footprint related to electricity consumption does not include GHG emissions associated with transmission and distribution.

2.3.2. Heat demand

To estimate the individual carbon footprint for *heat demand*, we used default values for the dwelling.[12] To this end, the survey elicited information on the size of the dwelling (in m^2), the type of the building (single family, 2 family, 3–6 apartments, 7–12 apartments, ≥13 apartments), building age (before 1919, 1918–1948, 1949–1978, 1979–1990, 1991–2000, 2001–2008, after 2008), types of retrofitting measures implemented (insulation of roof, insulation of exterior walls, insulation of ceiling in cellar, exchange of majority of windows) and timing of retrofitting measures, the fuel used (natural gas, heating oil, district heat, hard coal, lignite, wood/biomass, electricity, green electricity), and how hot water was generated (via boiler or electricity). The final heat demand was then estimated based on standardized average data. Multiplying the final heat demand by average emissions factors (by fuel type) yields the carbon footprint for heat demand. For households who had a solar-thermal heating system installed, we applied a discount factor of 20% based on DENA (2015).

2.3.3. Transportation

To estimate the individual carbon footprint for *transportation,* we distinguish between different modes of transportation, i.e. private cars, motorcycles, cruise ships, and airplanes. For cars and motorcycles, we asked participants to report the total distances (in km) travelled alone and with other passengers. For the distances travelled with other passengers by car (motorcycle), we assumed an average rate of occupancy of 2.3 (2.0) based on the average rate of occupancy of all trips in Germany in 2019 (Forschungsinformationssystem Mobilität und Verkehr, 2019). If no information on distances travelled was available, we used a default of 13,727 km per person for cars based on Kraftfahrt-Bundesamt (2022) for 2018, and 2219 km for motorcycles.[13]

For the most frequently used car, participants also had to provide information on fuel consumption and the type of fuel used (gasoline, diesel, natural gas, liquefied petroleum gas, bio-diesel/ethanol, electricity and gasoline/diesel for hybrid cars[14], electricity). They also had to assign this car to a predefined set of vehicle categories (large cars/sports utility vehicles, midsize/compact cars, and small/sub-compact cars). Thereby, participants were given examples of the most popular models in each class. If information on fuel consumption was not available, we used default values based on the vehicle category of the car individuals used most often. If participants did not report fuel consumption for motorcycles, we applied 4.75 l/100 km.[15] Using information on distance travelled, fuel consumption, fuel type, and standard emission factors for each fuel[16], it was possible to calculate the individual carbon footprint for transportation by car and motorcycles. To

[6] To estimate the full carbon footprint, input-output analysis may be employed (e.g. Wiedmann, 2009; Heinonen et al., 2020).

[7] All technological aspects were discussed with sector and technology experts of Fraunhofer Institute for Systems and Innovation Research (Fraunhofer ISI).

[8] We thereby rely on co2online gemeinnützige GmbH, 2019. Stromspiegel für Deutschland 2019. (https://energieagenturen.de/wp-content/uploads/2019/02/Stromspiegel_2019_web_01.pdf).

[9] A more accurate calculation involves employing an emission factor of the electricity mix where the use of electricity from subscribers of green tariffs is factored out.

[10] The effectiveness of green electricity tariffs in reducing CO_2 emissions is a subject of debate. Firstly, from a physical perspective, unless the electricity consumed by a green tariff customer is sourced from a renewable energy plant at the time of use, it can lead to emissions. Secondly, the total emissions from facilities regulated by the EU Emissions Trading System (EU ETS) are predetermined. As a result, due to the "waterbed effect," any emission reductions achieved by a fossil-fuel power plant will be counterbalanced by an equivalent increase in emissions from other EU ETS-covered installations (e.g., as highlighted by Perino et al., 2019).

[11] For simplicity and in line with common practice in similar contexts, our carbon footprint calculator assumes zero greenhouse gas (GHG) emissions for renewable electricity generation. We acknowledge that when accounting for life-cycle emissions, GHG emissions from renewable energy technologies may not be negligible. However, they remain notably lower than those emitted by fossil fuel energy technologies (e.g. Amponsah et al., 2014).

[12] In a pre-test we asked participants to provide information on their heating costs and heating consumption, leading to a high share of missing values and implausible responses. Also, the heating bill does not necessarily coincide with the calendar year. For these reasons we decided to use default values to estimate heat demand.

[13] https://de.statista.com/statistik/daten/studie/468850/umfrage/kraftrad-bestand-in-deutschland-nach-kraftstoffarten/.

[14] We assume that for hybrid cars 60% of the distance is travelled using the combustion engine according to Plötz et al. (2020).

[15] https://www.adac.de/rund-ums-fahrzeug/zweirad/motorrad-roller/fahrberichte/bmw-r-1250-gs/. This figure stands for gasoline because >99% of the motorcycles registered in Germany run on gasoline.

[16] https://www.co2online.de/klima-schuetzen/mobilitaet/auto-co2-ausstoss/, https://www.spritmonitor.de/de/uebersicht/0-Alle_Hersteller/0-Alle_Modelle.html?fueltype=10&powerunit=2 (for hybrid and electric vehicles).

calculate aviation-related emissions, we asked participants to report the number of flights for non-professional purposes (excluding flights in sports planes), distinguishing four categories (by length/duration of flights). Akin to the UN carbon calculator[17], participants were asked to distinguish between short flights (3000 km; up to 6 h duration), medium-long flights (between 3000 km and 6000 km; between 6 and 8 h duration), long flights (between 6000 km and 12,000 km; between 8 and 14 h duration), and very long flights (with >12,000 km; longer than 14 h duration). Participants were asked to count roundtrips as two flights and flights with stop-overs as one flight. When calculating flight-related GHG emissions, we used a standard emission factor of 369 $kgCO_{2eq}$/1000 km.[18] This factor takes into account that CO_2 from burning fossil fuels in aircrafts is generally emitted into the high atmosphere, which has a greater greenhouse effect than CO_2 released at the sea level. Finally, to calculate the individual carbon footprint of ship cruises, we asked for the total duration of all cruises undertaken for private purposes in the reference period and multiplied this figure by a standard emission factor of 214 $kgCO_{2eq}$/day.[19]

2.3.4. Dietary choices

To estimate the individual carbon footprint for *diet*, we asked participants to characterize their diet based on five categories: meat-based (2100 $kgCO_{2eq}$) balanced/mixed (1600 $kgCO_{2eq}$), low-meat (1300 $kgCO_2$), vegetarian (1100 $kgCO_{2eq}$) and vegan (900 $kgCO_{2eq}$) diets. The GHG emission factors were based on information available from the carbon footprint calculators by Naturefund (https://www.naturefund.de/en/information/co2_calculator#calc-food) and Umweltbundesamt (https://uba.co2-rechner.de/de_DE/). We introduced certain simplifying assumptions in order to streamline the questionnaire and given that the impact on emissions is relatively minor based on whether individuals primarily shop at local markets or supermarkets, and whether they predominantly choose organic produce or not. In particular, we assumed that vegan diets were typically prepared from local and organic production, and that meat-based diets are non-organic and were purchased at supermarkets.

To mitigate input data errors, we excluded unrealistic values for several items. For example, household electricity consumption was required to range between 500 kWh and 50.000 kWh, electricity generated from renewable energy sources had to lie between 0 kWh and 20.000 kWh, and values for apartment size had to range between 10 m^2 and 3000 m^2. Furthermore, for distances travelled by car in 2019 we allowed values between 0 and 200,000 km, fuel consumption for gasoline and diesel cars had to be between 3 l/100 km and 32 l/100 km, and the number of flights had to be at most 500.[20]

Table 3 reports some descriptive statistics for the carbon footprint related to the individual activities and for the aggregate carbon footprint, calculated as the sum of the footprints of the individual activities. We distinguish explicitly between the aggregate footprint with and without aviation because for those participants who fly (i.e. around 23% of our sample) the aviation-related GHG emissions account for almost 9 t CO_{2eq} on average, i.e. almost twice the average GHG emissions related to the other activities considered.

Similarly, for participants who took a cruise in 2019 (i.e. about 2.3% of our sample), the average carbon footprint related to those cruises amounts to about 2.4 t CO_{2eq}. The aggregate footprint (without aviation and ship cruises) ranges between 0.9 t CO_{2eq} and about 31 t CO_{2eq}. The minimum value corresponds to a participant who in 2019 subscribed to a green tariff, lived in a building that is heated by renewable energies, did not use a car, and lived on a vegan diet.

Table 3
Descriptive statistics on individual carbon footprint (in t CO_{2eq}) (1005 participants).

Variable	Mean	Standard deviation	Minimum	Maximum
Aggregate footprint	7.05	27.88	0.90	836.88
Aggregate footprint (without aviation and cruises)	4.94	2.33	0.90	30.73
Electricity	0.45	0.47	−1.78	4.46
Heating	1.46	1.42	0.00	14.04
Motorized individual transport	1.43	1.65	0.00	27.08
Aviation	2.02	27.72	0.00	830.25
Cruises	0.09	0.57	0.00	6.42
Diet	1.59	0.30	0.90	2.10

3. Econometric models

In our econometric analysis we examine the effect of the indicators of carbon knowledge and carbon engagement and of other individual characteristics on the individual carbon footprint. We estimate separate econometric models for the aggregate carbon footprint (without emissions related to aviation and ship cruises), and also for the footprints related to electricity consumption, heating, motorized individual transport (i.e. the use of cars and motorcycles), aviation, and dietary choices.[21]

3.1. Linear regression models

For the econometric analysis of the aggregate carbon footprint (without aviation and cruises) and for the carbon footprints related with electricity consumption, heating, and motorized individual transport, we consider linear regression models with

$$Y_{ij} = \beta_j x_i + \varepsilon_{ij} \tag{1}$$

where Y_{ij} reflects individual i's carbon footprint associated with activity j (j = aggregate, electricity, heating, motorized individual transport, dietary choices), β_j is the vector of parameters, x_i denotes the vector of explanatory variables including our indicators of carbon literacy and of individual characteristics, and ε_{ij} is an idiosyncratic error term. We use ordinary least squares (OLS) to estimate the linear regression models.

3.2. Double-hurdle model

Analysing emissions related to aviation is more challenging because about 77% of participants in our sample did not fly in 2019. Therefore, the aviation-related carbon footprint is zero for a large share of the sample. Hence, the OLS estimation of a linear regression model could lead to biased and inconsistent parameter estimates.[22] Double-hurdle models allow separating the decision of whether to take a plane at all (first hurdle) from the decision of how often to take a plane on aviation-related GHG emissions (second hurdle). The first hurdle is modelled as a binary probit model with

[17] https://offset.climateneutralnow.org/footprintcalc.
[18] https://www.naturefund.de/wissen/co2_rechner/daten.
[19] We used data from https://co2.myclimate.org/en/cruise_calculators/new, assuming a cruise ship for 2000–3000 passengers and a standard cabin for two persons.
[20] These ranges were discussed with sector and technology experts from Fraunhofer Institute for Systems and Innovation Research.
[21] Because only 39 participants in our sample reported to have been on a cruise in 2019, we did not conduct an individual econometric analysis for cruise ship-related emissions.
[22] It is important to note that for participants who engaged in air travel, aviation-related emissions constitute a significant proportion of the overall carbon footprint attributed to transportation (and to the aggregate carbon footprint in general).

Table 4
Description of explanatory variables (1005 participants).

Variable	Description	Mean	Standard deviation
Carbon_knowledge	Dummy variable equal to 1 if number of correct answers >2.	0.21	0.41
Carbon_engagement	*Z*-score of means of individual scores of 12 items listed in Table 2.	0	1
Female	Dummy variable equal to 1 if female.	0.52	0.50
Age	Age in years.	50.05	16.86
Income	Equivalized monthly net income in 2019 in 1000 Euro.	2.53	1.71
High_education	Dummy variable equal to 1 if at least advanced technical college entrance qualification.	0.33	0.47
NEP	The NEP scale is calculated as the sum of the scores from individual responses to the following six items.[a]		
	Survey question: Please indicate to what extent you agree with the following statements[†]		
	(i) "Humans have the right to modify the natural environment to suit their needs."	2.42	1.1
	(ii) "Humans are severely abusing the planet."	4.29	0.85
	(iii) "Plants and animals have the same right to exist as humans."	4.46	0.83
	(iv) "Nature is strong enough to cope with the impacts of modern industrial nations."	2.11	1.04
	(v) "Humans were meant to rule over the rest of nature."	1.98	1.08
	(vi) "The balance of nature is very delicate and easily upset."	4.25	0.85
Pol_conservative	Dummy variable equal to 1 if full agreement to the following statement: "I identify myself with conservatively oriented policy".[†]	0.04	0.20
Pol_liberal	Dummy variable equal to 1 if full agreement to the following statement: "I identify myself with liberally oriented policy". [†]	0.06	0.24
Pol_social	Dummy variable equal to 1 if full agreement to the following statement: I identify myself with socially oriented policy".[†]	0.19	0.39
Pol_environmental	Dummy variable equal to 1 if full agreement to the following statement: I identify myself with environmentally oriented policy".[†]	0.15	0.36

[†] Response categories: Fully disagree (1) - rather disagree (2) - undecided (3) - rather agree (4) - fully agree (5)].
[a] Cronbach's alpha is 0.7569 suggesting satisfactory internal consistency of these items. Prior to calculating Cronbach's alpha and the sum of the scores, we recoded the negatively keyed items (i), (iv), and (v). In the econometric specifications we use the z-score.

$$D_i = \begin{cases} 1 \text{ } if \text{ } D_i^* > 0 \\ 0 \text{ } otherwise \end{cases} \tag{2}$$

$$D_i^* = \gamma x_i + \mu_{1,i} \tag{3}$$

where $D_i$is an dummy variable which is equal to the value of one if individual i takes a plane at all and thus causes aviation-related emissions. D_i^* reflects individual i's unobservable latent utility associated with taking a plane at all, x_i is again a vector of explanatory variables, $\mu_{1,i}$ is an idiosyncratic error term that is standard normally distributed and γ is a vector of parameters. The (conditional) probability that an individual takes a plane at all and thus causes aviation-related GHG emissions is then

$$Pr(D_i = 1|\gamma x_i) = \Phi(\gamma x_i + \mu_{1,i}) \tag{4}$$

where $\Phi()$ reflects the cumulative density function of the standard normal distribution.

The second hurdle is modelled as a Tobit model with

$$Y_i^* = max(Y_i^{**}, 0) \tag{5}$$

$$Y_i^{**} = \delta x_i + \mu_{2,i} \tag{6}$$

where Y_{it}^{**}indicates the GHG emissions associated with individual i's number of flights, $\mu_{2,i}$ is an idiosyncratic normally distributed error term with $\mu_{2,i} \sim N\left(0, \sigma_{\mu 2}^2\right)$, and δ is a (row) vector of parameters. Combining both hurdles, the aviation-related carbon footprint of individual i' is then

$$Y_i = D_i Y_i^* \tag{7}$$

To estimate the parameters of the double-hurdle model, we use the maximum likelihood (ML) method. Specifically, we utilize the "churdle" command implemented in Stata.[23]

3.3. Individual characteristics

The individual characteristics considered in all models include the socio-economic characteristics and attitudes as described in Table 4. These variables have typically been found in the empirical literature to be related with individuals' carbon-related behaviours such as adopting energy efficient technologies (e.g. Schleich et al., 2019), taking up energy conservation measures (e.g. Mills and Schleich, 2012), implementing renewable energy technologies (e.g. Ameli and Brandt, 2015), subscribing to green electricity tariffs (e.g. Ziegler, 2020), and purchasing electric and hybrid vehicles (e.g. Plötz et al., 2014).

To capture the effects of gender on the carbon footprints, we include the dummy variable *female* which is equal to the value of one if the participant is a woman. The variable *age* is recorded in years and varies between 18 and 81. To calculate *income,* we use the midpoint of 19 categories for monthly net income, the upper bound for the lowest category (< 500 Euro) and the lower bound for the highest category (≥ 10,000 Euro). In our empirical analysis, we use the OECD-modified equivalence scale to adjust household income. This scale assigns a value of 1 to the household head, of 0.5 to each additional adult member, and of 0.3 to each child.[24] The dummy variable *high_education* is equal to the value of one if the participant is qualified to at least enter a technical college. We further consider the New Environmental Paradigm (NEP) scale which was originally developed by Dunlap et al. (2000). More specifically, we follow Whitmarsh (2008) and use a six-item NEP scale. In the empirical analysis, we use the z-score of the sum of the scores of the six items which are based on an ordered five-point Likert scale. In addition, we incorporate policy orientation, distinguishing between conservative, liberal, socially, and environmentally oriented policy. Previous empirical studies analysing individual environmental and climate protection activities for Germany imply that it is important to distinguish between policy identification (especially environmental policy identification) and environmental awareness measured by a NEP scale (e.g. Ziegler, 2020, 2021). Finally, to capture regional effects on personal GHG emissions, we include 15 dummy variables for the German federal states using one state, Baden-Wuerttemberg, as the base category.

[23] We note that the double hurdle model is (weakly) identified if the set of covariates is identical across both equations (e.g. García, 2013).

[24] Our results are not sensitive to using OECD weights. Findings from econometric analyses where we did not use these weights are available upon request.

Table 5
OLS estimation results in linear regression models on the aggregate carbon footprint and the carbon footprints related to individual activities.

	Aggregate (without aviation and cruises)	Electricity consumption	Heating	Motorized individual transport	Diet
Carbon_knowledge	*0.021*	*−0.008*	*0.204*	*−0.106*	*−0.069******
	(0.170)	*(0.039)*	*(0.129)*	*(0.098)*	*(0.022)*
Carbon_engagement	−0.197**	−0.037**	−0.027	−0.079	−0.054***
	(0.084)	(0.014)	(0.050)	(0.056)	(0.010)
Female	−0.487***	0.009	−0.062	−0.304***	−0.129***
	(0.153)	(0.029)	(0.095)	(0.108)	(0.019)
Age	0.011**	0.001	0.019***	−0.011***	0.002***
	(0.005)	(0.001)	(0.003)	(0.004)	(0.001)
Income	0.308***	−0.009	0.050	0.255***	0.012
	(0.089)	(0.016)	(0.055)	(0.057)	(0.010)
High_educ	−0.173	−0.057*	0.045	−0.120	−0.042**
	(0.151)	(0.033)	(0.099)	(0.102)	(0.020)
NEP	0.005	0.012	0.057	−0.010	−0.055***
	(0.080)	(0.016)	(0.056)	(0.048)	(0.011)
Pol_conservative	0.368	−0.076	0.382	0.074	−0.012
	(0.452)	(0.079)	(0.286)	(0.234)	(0.057)
Pol_liberal	0.013	0.160*	−0.157	0.061	−0.051
	(0.227)	(0.093)	(0.160)	(0.161)	(0.036)
Pol_social	−0.355**	0.020	−0.297***	−0.089	0.012
	(0.175)	(0.053)	(0.108)	(0.119)	(0.025)
Pol_environmental	−0.626***	−0.147***	−0.111	−0.284**	−0.084***
	(0.192)	(0.050)	(0.126)	(0.137)	(0.028)
Constant	4.625***	0.473***	0.426**	2.103***	1.623***
	(0.430)	(0.068)	(0.209)	(0.325)	(0.043)
Dummy variables for federal states	YES	YES	YES	YES	YES
Number of participants	1000	1000	1000	1000	1000
R-squared	0.099	0.048	0.103	0.074	0.198

The table reports the estimated parameters and the corresponding robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Our final sample includes 1000 participants. We excluded five observations with an annual carbon footprint of >50 t because they were flagged as outliers. These exceptionally high carbon footprint levels were primarily associated with reported responses on the number of flights. For instance, three participants indicated that they had taken more than one hundred flights in 2019. The descriptive statistics shown in Tables 1, 2, 3, and 4 for the original sample of 1005 participants are virtually identical to those for the final sample of 1000 participants used in the econometric analysis.

4. Results

We first present the results for our main model specification. Then, we examine the robustness of our findings with respect to alternative assumptions regarding a logarithmic transformation of the dependent variables and allowing for correlations between the carbon footprints associated with the different activities.

4.1. Main model specification

The results of the OLS estimation of the linear regression models for the aggregate carbon footprint (without emissions related to aviation and ship cruises) and for the carbon footprints related to electricity consumption, heating, motorized individual transport, and dietary choices are reported in Table 5. In Table 6, we show the findings of the ML estimation of a double hurdle model for the carbon footprint related to aviation.[25] To facilitate the interpretation of the findings, Table 6 shows the marginal effects and for dummy variables the discrete effects. We thereby distinguish between the effects on the share of participants flying (first hurdle, extensive margin), and the effects on the aviation-related GHG emissions for those participants that fly (second hurdle, intensive margin). Combining the effects on both hurdles, yields the change in the average GHG emissions related to aviation in response to a one-unit change in the respective covariate.

First and foremost, we consider the estimation results for the two indicators of carbon literacy, i.e. *carbon_knowledge* and *carbon_engagement*. Carbon knowledge is significantly negatively correlated with the carbon footprint related to dietary choices. According to the point estimate, high carbon knowledge is linked to an average reduction of about 69 kg in the carbon footprint associated with diet, while controlling for all other explanatory variables (ceteris paribus). Hence, the estimated effect size of *carbon-knowledge* appears to be rather small. For the aggregate carbon footprint and the footprints of the other activities, we do not find a significant correlation with *carbon_knowledge*. In contrast, our findings for *carbon_engagement* suggest that carbon engagement is negatively correlated with the aggregate carbon footprint and with the footprints related to electricity consumption and to dietary choices. On average, a one-unit increase in *carbon_engagement*, which corresponds to an increase of one standard deviation due to the variable being z-scored, is associated with an estimated decrease of about 197 kg in the aggregate carbon footprint, ceteris paribus. Using the data on means provided in Table 3, this corresponds to a reduction in the aggregate carbon footprint (without aviation and cruises) of about 4%. Similarly, our findings indicate that a one standard deviation increase in *carbon_engagement* is linked to a reduction in the carbon footprint attributed to electricity consumption of about 37 kg, and a decrease in the carbon footprint related to dietary choices of about 54 kg. For heating and motorized individual transport, the associated estimated parameters also exhibit the expected negative sign, but they are not different from zero at common significance levels. Likewise, we find no significant correlation between *carbon_knowledge* and *carbon_engagement* with aviation-related emissions.

The estimation results for the socio-economic characteristics suggest that *female* is associated with a lower aggregate carbon footprint and with lower footprints related to motorized individual transport, and to

[25] The average variance inflation factor is 1.27 and variance inflation factors for the explanatory variables range from 1.04 to 2.08. Hence, these findings provide no indication that our results may suffer from collinearity problems.

Table 6
ML estimation results in a double hurdle model on aviation-related carbon footprint.

	Extensive margin (first hurdle)	Intensive margin (second hurdle)	Average emissions (combining both hurdles)
Carbon_knowledge	*−0.014*	*−0.170*	*−0.094*
	(0.030)	*(0.405)*	*(0.147)*
Carbon_engagement	0.008	0.203	0.079
	(0.014)	(0.205)	(0.073)
Female	0.061**	−0.495	0.121
	(0.026)	(0.372)	(0.131)
Age	−0.002*	0.000	−0.006
	(0.000)	(0.000)	(0.004)
Income	0.096***	0.252*	0.431***
	(0.012)	(0.138)	(0.066)
High_educ	0.082***	−0.171	0.273*
	(0.030)	(0.369)	(0.149)
NEP	−0.029**	−0.222	−0.166**
	(0.014)	(0.199)	(0.073)
Pol_conservative	0.014	0.802	0.253
	(0.066)	(1.109)	(0.409)
Pol_liberal	0.044	−0.143	0.130
	(0.059)	(0.704)	(0.292)
Pol_social	−0.003	−0.223	−0.062
	(0.036)	(0.528)	(0.183)
Pol_environmental	−0.072**	0.073	−0.267
	(0.037)	(0.675)	(0.191)
Number of participants	1000	1000	1000

The table reports the estimated average marginal and average discrete probability effects as well as the corresponding robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

dietary choices. The estimated effect size of *female* is rather large and amounts to about 0.5 t CO_{2equ} for the aggregate carbon footprint. For the other activities, we find no significant correlations, except for the extensive margin for the aviation-related carbon footprint. Accordingly, women are about 6.1 percentage points less likely to fly than men (Table 6). For *age*, the significance and direction of the estimated correlation with the carbon footprints depend on the type of activity. For *income*, we find a significantly positive correlation with the aggregate carbon footprint. This result appears to be due to the estimated positive correlation between *income* and the footprint related to motorized individual transport. We further find that for the aviation-related carbon footprint, an increase in monthly net income (in OECD equivalents) is linked with a significantly higher probability to take a plane (extensive margin) of about 9.6 percentage points per 1000 Euro, a significant intensive margin of about 0.25 t CO_{2eq} per 1000 Euro, and significant increase in the average footprint of about 0.42 t CO_{2eq} per 1000 Euro. For the other activities, we do not find a significant correlation between the carbon footprint and income. Next, our estimation results for *high_education* imply that individuals with at least an advanced technical college entrance qualification are associated with a lower carbon footprint at the aggregate level and for electricity consumption and dietary choices. Furthermore, their estimated probability of taking a plane is about 8.2 percentage points higher, and their estimated average aviation-related footprint is about 277 kg higher.

Finally, we turn to the results on attitudes. We find that individuals with a higher NEP scale have a significantly lower footprint. An increase in the NEP scale by one standard deviation leads to an estimated decrease in the diet-related footprint by about 55 kg and an estimated decrease of the probability to take the plane by about 2.9 percentage points. Yet, we do not find a significant correlation between *NEP* and the footprints of the other activities, between *NEP* and the aggregate footprint, and - for aviation - between NEP and the intensive margin and average aviation-related emissions. In contrast, individuals with a strong environmental policy orientation *(pol_environmental)* have significantly lower carbon footprints than individuals who identify less strongly with environmentally oriented policy. For this variable, only the estimated parameter associated with the footprint for heating is not significant at common significance levels. The estimated size effect of *pol_environmental* corresponds to about 0.6 t CO_{2eq} for the aggregate footprint, and hence is substantial.

For aviation-related emissions, our findings for *pol_environmental* are qualitatively similar as for *NEP*. Individuals who fully identify with a socially oriented policy have a significantly lower aggregate carbon footprint. This findings appears to be primarily driven by the estimated negative correlation between *pol_social* and the carbon footprint related with heating. Individuals who fully identify with liberally oriented policy have a significantly higher carbon footprint related with electricity use. *Pol_liberal* is not significantly correlated with the carbon footprints of the other activities and not with the aggregate carbon footprint. Similarly, we do not find a significant correlation between *pol_conservative* and any of the carbon footprints.

4.2. Robustness checks

To examine the robustness of our findings, we conduct two types of robustness checks. First, to address outliers and skewness of the carbon footprints, we use the logarithmic transformation of the dependent variables. We add the value of one to each value prior to applying the logarithmic transformation to address the presence of zeros in the dependent variable, in particular for the aviation-related footprint. The estimation results for this log-level model are reported in Table A2 for the linear regression models and Table A3 for the double hurdle model. The findings reported in Table A2 suggest that estimating a log-level specification for the aggregate carbon footprint and the individual carbon footprints related to electricity consumption, heating, motorized individual transport, and dietary choices are very similar to those reported in Table 5 in terms of signs and significance of the estimated parameters. Similarly, the findings for the aviation-related carbon footprint in Table A3 are qualitatively very similar to those shown in Table 6. The only differences pertain to the aggregate carbon footprint, where the estimated parameters associated with *age* and *pol_environmental* are significantly different from zero for the log-level specification.

Second, we consider the carbon footprint equations for the five activities as a system of seemingly unrelated equations, allowing for correlation in the error terms across these equations. Thereby, we assume the standard errors to be clustered at the individual level. We use the 'suest' command implemented in Stata. By definition, the parameter estimates obtained from considering the system are identical to those derived from estimating the equations individually because we always include the same explanatory variables. More interestingly, the standard errors obtained from estimating the system exhibit remarkable similarity to those reported in Tables 5 and 6. Thus, our findings appear to be robust to the introduction of correlated error terms across the equations.[26]

5. Discussion and conclusions

This study empirically links individual carbon footprints with carbon literacy. Relying on data from a large widely representative sample among adults in Germany, and distinguishing between two components of carbon literacy - engagement and knowledge - we find that engagement is significantly negatively correlated with the aggregate carbon footprint, and with the footprints related to electricity consumption and to dietary choices. Thus, our findings provide suggestive empirical evidence that individuals with higher carbon engagement, i.e. people with

[26] To save space, we do not include the findings from estimating the system. They are available upon request.

a higher willingness to engage with information on this topic, indeed have smaller carbon footprints, ceteris paribus. In contrast, carbon knowledge is significantly correlated with the footprint of dietary choices only. Hence, we find little evidence for the notion that enhancing carbon knowledge through information provision only will lead to significant reductions in individual carbon footprints. In this sense, and in line with previous studies, our findings on carbon knowledge add to the doubts on the simplistic 'information deficit' model (e.g. Whitmarsh et al., 2011; Suldovsky, 2017). Therefore, policies which focus on improving carbon knowledge only might not be effective. Instead, we expect that fostering individuals' willingness to actively engage with the topic are more promising.

Furthermore, we do not find a significant correlation between either component of carbon literacy and the footprints of heating and mobility (motorized individual transport, aviation). Possibly, individual behaviour in these domains is more strongly shaped by structural factors such as the place of living, broader institutional relationships, or by domain-specific carbon literacy not covered by our measures. This also aligns with research findings indicating that the so-called awareness-attitude action gap varies across behavioural domains (Kaiser et al., 2021). In the context of our findings, making individual adjustments such as altering dietary choices (e.g. reducing meat consumption) may prove more feasible given an individual's actual circumstances compared to the substantial investments required to reduce emissions related to heating or to the dependence on available mobility options when adjusting mobility habits.

Our findings further suggest that carbon footprints are generally correlated with socio-economic variables (gender, age, income, and education). Only for the carbon footprint of electricity consumption we do not find significant correlations with any of the socio-economic variables. Similarly, the carbon footprint of heating is significantly correlated with age only. The findings for electricity consumption and heating may be explained by how we calculate the individual carbon footprints for these activities. Because for both activities we derive individual-level figures from information at the household level, the link with individual characteristics may be weak. In addition, to calculate the carbon footprint of electricity consumption we take into account whether households subscribe to a green electricity tariff and whether they produce electricity from a private photovoltaic plant. As a result, individuals with a high level of electricity consumption may still have a low carbon footprint of electricity. For example, because in our sample high income households are more likely to have higher electricity consumption (similar, for example, to Krishnamurthy and Kriström, 2015) but are also more likely to subscribe to a green tariff (similar, for example, to Ziegler, 2020), the average effect of income on the carbon footprint of electricity may be insignificant.[27] Finally, in line with studies in related contexts (e.g. Costa and Kahn, 2013; Ziegler, 2020), we find that an environmental policy orientation is significantly negatively correlated with the carbon footprints examined in this study.

In sum, our findings suggest that measures aimed at improving individual carbon engagement may contribute to lowering the aggregate carbon footprint, in particular by lowering the carbon footprints related to electricity consumption and dietary choices. Therefore, fostering carbon engagement seems to be a more promising strategy towards lowering individuals' carbon footprints than strengthening carbon knowledge. This highlights the importance of keeping climate change and mitigation efforts in the wider societal discourse, enabling individuals to actively participate in acquiring new knowledge and sustaining their interest.

When interpreting these results it is important to bear in mind that our correlational findings may be subject to omitted variable bias. That is, there may exist unobserved factors that are correlated with both carbon footprints and (some of) the covariates considered. Despite our efforts to alleviate such bias by incorporating a comprehensive set of covariates, we must acknowledge that such bias may pose a potential challenge to our findings. Further, our calculations of carbon footprints rely on stated information provided by individuals. Hence, they may be subject to recall inaccuracy and social desirability. Future studies could rely on metered data using information from smart electricity meters, and on information from actual electricity and heating bills which are uploaded on the survey platform. While data from such sources would be more reliable, collecting this data will increase survey duration and depend on the willingness of participants to go through additional troubles. For motorized individual transport and dietary choices, gathering observed rather than stated data for a representative sample would likely be even more challenging. Depending on data availability, future research may also examine whether the relations identified in this study for carbon footprint components also hold for more comprehensive measures of carbon footprints, taking into account life-cycle emissions and including activities not considered by our study. Future work could also explore the relationship between the carbon footprints related to particular activities and the carbon knowledge and carbon engagement specific to these activities. In this regard, future studies may account for differences across activities in the difficulty to change behaviour, as well as differences in the range of available options for behaviour adjustments. The findings of these analyses are expected to provide more fine-grained insights into the relationship between carbon literacy and the carbon footprints of particular activities, and hence also allow for more detailed policy recommendations. Furthermore, the focus of our study is on carbon literacy and how it relates to carbon footprints, but neglects how carbon literacy may affect behavioural intentions and behaviour. More comprehensive studies could investigate the mechanisms through which carbon literacy leads to specific results and under what circumstances. For example, future studies may examine whether carbon literacy enhances awareness of alternative options or increases self-efficacy for implementing behavioural changes.

Finally, our study is among the first empirical analyses applying the concept of literacy to the field of climate change mitigation efforts. Thereby, our distinction between two facets of literacy proved valuable. In a similar vein, to gain even more nuanced insights, future conceptual and empirical work on carbon literacy could consider additional facets, thereby making more extensive use of the existing research from the health literature, for example.

CRediT authorship contribution statement

Joachim Schleich: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Elisabeth Dütschke:** Conceptualization, Funding acquisition, Methodology, Writing – original draft, Writing – review & editing. **Elke Kanberger:** Data curation, Project administration, Writing – original draft. **Andreas Ziegler:** Funding acquisition, Methodology, Project administration, Writing – original draft.

Declaration of Competing Interest

The authors confirm that they have no competing interests to declare.

Data availability

Data will be made available on request.

[27] Estimating the relationship between whether a household subscribed to a green tariff in 2019 or not and socio-economic variables with a binary probit model yields a significant correlation with *income*. Likewise, regressing electricity consumption on socio-economic variables with a linear regression model yields a significant correlation with *income*.

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Appendix A. Emission factors used by the carbon calculator and results of robustness checks

Table A1
Emission factors used by the carbon calculator.

Activity	Value	Unit
Electricity consumption		
Electricity mix	0.401	$kgCO_{2eq}/kWh$
Renewable energy technologies	0	$kgCO_{2eq}/kWh$
Heat demand		
Natural gas	0.24	$kgCO_{2eq}/kWh$
Oil	0.3	$kgCO_{2eq}/kWh$
District heating	0.13	$kgCO_{2eq}/kWh$
Hard coal	0.47	$kgCO_{2eq}/kWh$
Lignite	0.51	$kgCO_{2eq}/kWh$
Wood biomass	0.1	$kgCO_{2eq}/kWh$
Transportation		
Cars and motorcycles		
Gasoline	2.35	$kgCO_{2eq}/l$
Diesel	2.65	$kgCO_{2eq}/l$
Natural gas	2.74	$kgCO_{2eq}/kg$
Liquefied natural gas	1.65	$kgCO_{2eq}/l$
Bio diesel/ethanol	0.9	$kgCO_{2eq}/l$
Hybrid without plug-in functions	0.125	$kgCO_{2eq}/km$
Electricity	0.0948	$kgCO_{2eq}/km$
Airplanes	0.369	$kgCO_{2eq}/km$
Ship cruises	214	$kgCO_{2eq}/day$
Dietary choices		
Meat-based	2100	$kgCO_{2eq}/year$
Balanced/mixed	1600	$kgCO_{2eq}/year$
Low-meat	1300	$kgCO_{2eq}/year$
Vegetarian	1100	$kgCO_{2eq}/year$
Vegan	900	$kgCO_{2eq}/year$

Table A2
OLS estimation results in log-level regression models on the aggregate carbon footprint and the carbon footprints related to individual activities.

Explanatory variables	Aggregate (without aviation and cruises)	Electricity consumption	Heating	Motorized individual transport	Diet
Carbon_knowledge	0.008	−0.001	0.056	0.012	−0.028***
	(0.025)	(0.022)	(0.037)	(0.037)	(0.008)
Carbon_engagement	−0.032***	−0.030***	−0.009	−0.036*	−0.020***
	(0.012)	(0.009)	(0.016)	(0.019)	(0.004)
Female	−0.068***	0.002	−0.008	−0.083**	−0.050***
	(0.022)	(0.019)	(0.030)	(0.034)	(0.007)
Age	0.002***	0.000	0.007***	−0.004***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Income	0.050***	−0.003	0.012	0.111***	0.004
	(0.012)	(0.009)	(0.016)	(0.021)	(0.004)
High_educ	−0.026	−0.022	−0.002	−0.017	−0.016**
	(0.023)	(0.021)	(0.032)	(0.036)	(0.008)
NEP	−0.009	0.009	0.005	−0.008	−0.021***
	(0.012)	(0.010)	(0.017)	(0.019)	(0.004)
Pol_conservative	0.002	−0.017	0.078	0.011	−0.006
	(0.068)	(0.046)	(0.087)	(0.086)	(0.022)
Pol_liberal	0.020	0.061	−0.075	0.058	−0.018
	(0.039)	(0.047)	(0.064)	(0.063)	(0.014)
Pol_social	−0.052*	0.032	−0.089**	−0.055	0.004
	(0.028)	(0.027)	(0.037)	(0.044)	(0.010)
Pol_environmental	−0.105***	−0.106***	0.000	−0.136***	−0.035***
	(0.033)	(0.029)	(0.044)	(0.053)	(0.011)
Constant	1.639***	0.353***	0.415***	0.840***	0.956***

(*continued on next page*)

Table A2 (*continued*)

Explanatory variables	Aggregate (without aviation and cruises)	Electricity consumption	Heating	Motorized individual transport	Diet
	(0.058)	(0.042)	(0.070)	(0.094)	(0.016)
Dummies for federal states	YES	YES	YES	YES	YES
Number of participants	1000	994	1000	1000	1000
R-squared	0.116	0.060	0.116	0.112	0.204

The table reports the estimated parameters and the corresponding robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A3
ML estimation results in a double hurdle model on aviation-related carbon footprint for the log-level specification.

	Extensive margin (first hurdle)	Intensive margin (second hurdle)	Average emissions (combining both hurdles)
Carbon_knowledge	−0.014	−0.037	−0.032
	(0.030)	(0.065)	(0.052)
Carbon_engagement	0.008	0.031	0.020
	(0.014)	(0.033)	(0.025)
Female	0.061**	−0.079	0.084*
	(0.026)	(0.060)	(0.045)
Age	−0.002*	0.000	−0.002*
	(0.000)	(0.002)	(0.001)
Income	0.096***	0.042*	0.170***
	(0.012)	(0.022)	(0.022)
High_educ	0.082***	−0.028	0.130**
	(0.030)	(0.060)	(0.052)
NEP	−0.029**	−0.034	−0.057**
	(0.014)	(0.032)	(0.025)
Pol_conservative	0.014	0.138	0.057
	(0.066)	(0.171)	(0.125)
Pol_liberal	0.044	−0.023	0.067
	(0.059)	(0.115)	(0.102)
Pol_social	−0.003	−0.032	−0.012
	(0.036)	(0.087)	(0.064)
Pol_environmental	−0.072**	−0.002	−0.121*
	(0.037)	(0.106)	(0.065)
Number of participants	1000	1000	1000

The table reports the estimated average marginal and average discrete probability effects as well as the corresponding robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

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