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Abstract

This paper examines individuals' willingness to pay (WTP) to offset their carbon footprint in response to receiving information about (i) the size of their own carbon footprint, and (ii) further receiving in addition information about the difference between their carbon footprint and the target footprint, i.e. per-capita GHG emissions compatible with the 1.5°C target. The analysis employs a demographically representative survey among the adult population in Germany, which includes a comprehensive online carbon footprint calculator and randomized information treatments. The findings from estimating double hurdle models suggest that disclosing information about the size of the individual carbon footprint increases average WTP by about one third. Providing this information appears to affect the intensive margin but not the extensive margin. In comparison, providing information about the size of their carbon footprint together with information about the difference between their carbon footprint and the target footprint does not appear to affect individuals' WTP. Further, the WTP is related with income, gender, age, education, carbon literacy, the belief that carbon offsetting is effective, and with environmental preferences. In comparison, the findings provide no statistically significant evidence that the WTP is associated with the size of the individual carbon footprint, and whether participants consider their carbon footprint to be higher or lower than the carbon footprint of the average adult in the population.

Keywords: carbon footprint; willingness to pay; social norms; information disclosure

JEL Classification Codes : H41, Q54

Contents

1 Introduction

Pricing greenhouse gas (GHG) emissions is typically considered to be the first best approach to address climate change (e.g. High-Level Commission on Carbon Prices, 2017, Nordhaus, 2019). In practice, however, even in most OECD and G20 countries current carbon prices are much lower than the levels needed decarbonize these economies by mid-century (OECD, 2021) in order to limit global warming to no more than 1.5°C. Similarly, only about 4 percent of global greenhouse gas (GHG) emissions are currently subject to a carbon price, which is considered high enough to meet the 2°C target (World Bank, 2022). Some alternative approaches rely on individuals' social and environmental preferences (Andreoni, 1990; Kotchen and Moore, 2007) to voluntarily mitigate the negative effects of their consumption activities on the environment. Correspondingly, the market for voluntary GHG offsetting has strongly increased over the previous years. In Germany, for example, the volume of carbon credits has increased six-fold since 2016 (Umweltbundesamt, 2022). Yet, individuals typically lack information such as the magnitude of their carbon footprint. Likewise, they do not know how their own efforts to mitigate GHG emissions fare compared to the efforts needed to achieving the overall climate targets.

In this paper we examine individuals' willingness to pay (WTP) to offset their carbon footprint. In particular, we analyze the causal effect of individuals (i) receiving information about the size of their own carbon footprint, and (ii) further receiving in addition information about the difference between their carbon footprint and the target footprint, i.e. per-capita GHG emissions compatible with the 1.5°C target. We further relate individuals' WTP to offset their carbon footprint to a broad set of co-variates including attitudes, social comparisons, carbon literacy, the size of the individual carbon footprint, and socio-demographic characteristics. To this end, we conducted a demographically representative survey of the adult population in Germany. The core of the survey consisted of a carbon footprint calculator, which covers the main individual activities (i.e. electricity consumption, heating, transportation, and nutrition) causing individual greenhouse gas emissions in 2019.

We find that for these activities, individuals in our sample are willing to pay on average about 11 euros/t CO_2eq to offset their carbon footprint. Our findings from estimating double hurdle models suggest that disclosing information about the size of the individual carbon footprint increases average WTP by about one third. Providing this information appears to affect the intensive margin only, i.e. the WTP conditional on the WTP being positive, but not the extensive margin, i.e. the WTP some amount at all. In comparison, providing information about the size of their carbon footprint together with information about the gap between their carbon footprint and the target footprint does not appear to affect individuals' WTP. We further find that the WTP is related with income, gender, age, education, carbon literacy, the belief that carbon offsetting is effective, and with environmental preferences. In comparison, we fail to find a statistically significant relation between the WTP and the size of the individual carbon footprint, and social comparisons, i.e. whether participants consider their carbon footprint to be higher or lower than the carbon footprint of the average adult in the population.

These findings contribute to different streams of literature. First, offsetting greenhouse gas emissions essentially means a voluntary contribution to the public good climate protection. If there was a high potential for such voluntary contributions, this might alleviate the need for coercive emission reduction measures by governments (e.g. Diederich and Goeschl, 2014). Thus, estimating the WTP for such offsets and gaining a better understanding of the factors related to this WTP provide valuable insights for policy making. The extant literature to estimate individual WTP to lower or to offset greenhouse gas emissions yields a wide range of estimates spanning from zero (e.g. Diederich and Goeschl, 2014) to more than 100 euros per ton of CO_2eq (e.g. Alberini et al., 2018). To elicit WTP, most studies employ small and non-representative samples in laboratory experimental settings (e.g. in public goods games) or stated preferences methods such as discrete choice experiments. Exceptions include Löschel et al. (2013), Diederich and Goeschl (2014), and Bernard et al. (2022). These studies, however, do not relate participants' WTP to their actual carbon footprint. Few field experimental studies relate WTP to participants' actual footprint, yet these studies are limited to particular activities such as transportation (Kesternich et al., 2016) and electricity (Jacobsen et al., 2012). In addition, it is not clear to which extent findings from non-representative samples may be transferred to the general population.

Second, disclosing the carbon footprint to individuals addresses incomplete information, making individuals' contribution to climate change more salient and more concrete, and providing a direct link between their activities and the detrimental environmental effects associated with these activities. Thus, receiving information about their carbon footprint is expected to raise individuals' awareness of the environmental impact of their own activities. Usually, these activities reflect everyday routinized habitual behavior pertaining to energy consuming activities like using appliances, lighting, heating, commuting to work, and shopping (e.g. Verplanken and Whitmarsh, 2021). In addition, the carbon footprint associated with these activities is typically invisible and individuals would have to incur substantial efforts to estimate the associated carbon footprint. At the same time, individuals may perceive the information disclosed via a carbon footprint (in t of CO_2eq) as rather abstract, similar to receiving information about electricity consumption in kWh. Yet, the empirical literature has found that households tend to (somewhat) lower their electricity demand in response to receiving rather abstract information on their electricity consumption in kWh (e.g. Gans et al., 2013, Houde et al, 2013, Schleich et al., 2013, Asmare et al., 2021). Closer to the topic of our study, employing a randomized field experiment, Fosgaard et al. (2021) find that providing personalized information on the carbon footprint through a smartphone app affects grocery purchases in the short run. Similarly, according to Enlund et al. (2022) having access to a smartphone app, which displays the carbon footprint of individuals based on actual financial transactions for a broad set of activities (transportation, goods and serviced, food and beverages, and residential energy) lowers the carbon footprint during the first four weeks, but not in the longer run. Finally, the field experiments by Brunner et al. (2018) and Lohmann et al. (2022) in student cafeterias suggest that carbon footprint labels promote students switching from meals with a high carbon footprint to meals with a low carbon footprint.

Third, providing information about the size of the individual carbon footprint in relation to future targets speaks to the literature examining the role of social norms and of goal setting to nudge individuals to behave environmentally friendly. Social norms may be defined as the 'predominant behaviors, attitudes, beliefs, and codes of conduct of a group' (Cialdini and Jacobson, 2021). Empirical studies typically find that injunctive social norms (i.e. what others think one should do) and descriptive social norms (i.e. what others do) affect climate-relevant behaviors such as household electricity consumption and thermal heating demand (e.g. Allcott, 2011; Allcott and Rogers, 2014; Allcott and Kessler, 2019)[1]. Few studies have investigated the effects of social norms on individual WTP for carbon offsets. In particular, Bernard et al. (2022) find that providing information about climate-friendly activities by peers increases stated WTP to offset emissions for lighting. In this context, climate targets may be characterized as codified or explicit social norms (e.g. Bicchierei, 2017). Legislators typically express socially desirable behavior through laws (e.g. Rees-Jones and Rozema, 2020). For example, the amended German Federal Climate Change Act of 18 August 2021 posits climate targets for Germany considered to be in line with reaching the 1.5°C

[1] For recent overviews of the empirical findings see Farrow et al. (2017) and Cialdini and Jacobson (2021).

target. Relatedly, from the perspective of individuals, climate targets may be characterized as nonbinding nonmonetary relevant goals. Empirical studies have found that asking individuals to set energy savings goals and provide them with feedback may lead to lower energy consumption (e.g. Harding and Hsiaw, 2014; Brandsma and Blasch, 2022).

We organize the remainder of this paper as follows. Section 2 describes the survey and the experiment. Section 3 presents the empirical findings. The final section summarizes and discusses the key findings.

2 Methods

In this section, we describe the survey. In particular, we present the different experimental designs.

2.1 Survey

We conducted an online survey in October 2020 in Germany using an existing household panel of the market research institute Psyma. Panel members were invited by email to participate in the survey via a hypertext link. The welcome screen informed participants about the thematic focus of the survey and about the expected duration (15 minutes). At the start of the survey participants had to respond to screening questions to ensure that the sample was representative of the adult population in Germany in terms of age, gender, education and regional population dispersion (by 16 Federal States). The survey continued with a block of items on climate change, climate capability, carbon literacy, and environmental attitudes. The core of the survey consisted of a carbon footprint calculator which covers the main individual activities (i.e. electricity consumption, heating, transportation, and nutrition) causing individual greenhouse gas emissions in 2019, that is before the COVID 19 pandemic may have affected the pattern of individual greenhouse gas emissions. See A.1.1 for details on the carbon calculator. Participants then took part in a randomized experiment (see 2.2). The survey concluded with additional questions on socio-economic characteristics (e.g. income classes). To control for quality, the survey contained two screen out questions. In these questions, participants were asked to tick a particular answer category. Participants who failed to answer one of the two screen out questions were eliminated from the survey. Eventually, our sample included 1005 participants. Upon completion of the survey, participants received a fee coupon. Prior to fielding the survey, we ran a pre-test with 46 participants to make sure that wording and instructions were comprehensible. On average, participants took about 23 minutes to complete the final survey. The median time spent was about 15 minutes.

2.2 Experiment

The objective of our study was to analyse individuals' WTP to offset their carbon footprint. In particular, we wanted to quantify how this WTP changes in response to individuals receiving information about the size of their own carbon footprint, and receiving information about the difference between their carbon footprint and the per-capita carbon footprint compatible with the 1.5°C target (reflecting social norms). To this end, we randomly assigned participants into one control and two treatment groups. Individuals in the control group (T0) received no information about their carbon footprint. Individuals belonging to the disclosure group (T1) received the following information:

> *Based on your responses, it was calculated that you generated approximately x tons of greenhouse gas emissions in 2019.*

The value for x was calculated based on the procedure outlined in A.1.1, and reported in metric tons with one digit. Individuals in the social norm group (T2) received the same information as T1. In addition, they received the following information:

> *In order to meet international climate protection targets, the amount of greenhouse gas emissions in Germany would have to be no more than one ton per person per year in the long term.*
>
> *The greenhouse gas emissions you generated in 2019 are calculated to be about y metric tons* ***above*** *this maximum.*

The value for y was calculated as x-1, and displayed in metric tons with one digit.[2] Expressions shown in bold were also shown in bold in the original wording in German. In T2 we consider the long-term per-capita greenhouse gas emissions which are deemed to be consistent with long term climate targets. We decided to use a target of 1 ton for per-capita emissions based on Germany's commitment to become climate neutral by 2045 (BMU, 2021).

Participants in all three groups were then told that greenhouse gas emissions caused by human activity may be offset by activities elsewhere, such as building wind or solar power generation facilities, reforestation, or the like.

To elicit participants' willingness to pay for their carbon footprint we informed participants in all three groups that they could offset the greenhouse gas emissions they cause through providers of such offsetting services (e.g. atmosfair, myclimate) by paying a corresponding amount of money. We therefore posed the following question:

> *How many euros at most would you be willing to pay privately to offset the greenhouse gas emissions you caused in 2019?*

To limit hypothetical bias, we employed a strong cheap talk design. That is, prior to entering the amount, participants were told that in surveys, some respondents state that they want to pay a comparatively high amount of money for the reduction of greenhouse gas emissions. They were further told that, presumably, respondents do not take into account at this moment that they would have to do without other things if they actually had to pay this amount of money. We therefore asked them to indicate, if possible, only such an amount of money that they would actually be willing to pay in reality.

2 Had x-1 been negative, the participant would have seen the following information: *The greenhouse gas emissions you generated in 2019 are calculated to be about y metric tons* ***below*** *this maximum.* In our sample, x-1 was positive for all participants.

3 Results

We first report results of descriptive statistics pertaining to the balancing of the treatment groups. Then we compare findings on the willingness to pay per treatment group. The core of this section presents the results of estimating a double hurdle model relating the WTP first to treatment effects only, and then also to attitudes, social comparisons, carbon literacy, the size of the individual carbon footprint, and socio-demographic characteristics.

3.1 Descriptive statistics

Table 1 reports the means and in parentheses the standard deviations of the variables used as quota criteria in the sampling for the final sample. The last column reports the p-values of an F-test to the null hypotheses that the means are identical across the three treatments. Randomization of the treatments appeared to have been successful.

Table 1 Balance of treatment groups

	Full sample	Control T0	Disclosure T1	Social norm T2	p-value
Female (share)	0.53 (0.50)	0.51 (0.50)	0.50 (0.50)	0.56 (0.50)	0.23
Age (years)	50.43 (16.76)	51.72 (16.44)	49.11 (16.69)	50.47 (17.10)	0.14
Income (euro/month)	2503.85 (1678.56)	2464.40 (1561.96)	2597.99 (1796.17)	2449.70 (1670.30)	0.46
Above median education (share)	0.32 (0.47)	0.31 (0.46)	0.36 (0.48)	0.30 (0.46)	0.20
Eastern Germany (share)	0.19 (0.39)	0.17 (0.38)	0.19 (0.39)	0.21 (0.41)	0.54
N	975	323	324	328	

Prior to analyzing the results on WTP, we dropped all observations where the carbon footprint in 2019 exceeds 50 t, resulting in a loss of 5 observations.[3] Similarly, we capped the willingness to pay at 1000 euros which lead to a loss of 25 observations. The final data set therefore consists of 975 observations. Dropping these observations does not appear to systematically alter the composition of the three groups.

Table 2 displays the findings obtained for the share of participants willing to pay a positive amount to offset individual carbon emissions (WTP > 0, extensive margin), the conditional willingness to pay (i.e. WTP/WTP>0, intensive margin), and the average individual willingness to pay by treatment groups. We also report information on the size of the carbon footprint in Table 2.

[3] We suspect data entry errors to be the reason for high carbon footprints, notably when participants reported the number of flights. Several participants reported more than 100 private flights per year, which seems implausible.

Table 2 **Willingness to pay in euro (standard deviations in parentheses)**

	Full sample	Control (T0)	Disclosure (T1)	Social norm (T2)
WTP>0	0.66 (0.48)	0.65 (0.48)	0.65 (0.48)	0.67 (0.47)
N	975	323	324	328
WTP/WTP>0	84.99 (102.96)	79.13 (96.52)	90.83 (99.99)	84.94 (111.54)
N	640	209	212	219
Average WTP	55.79 (92.66)	51.20 (86.32)	59.44 (91.67)	56.71 (99.50)
Carbon footprint	6.30 (3.63)	6.15 (3.69)	6.23 (3.27)	6.52 (3.92)
N	975	323	324	328

Thus, participants in both treatment groups exhibit a higher average and conditional WTP than participants in the control group, but these differences are not statistically significant at conventional levels. Comparing conditional and average WTP for T1 versus T0, the associated p-values based on 2-sided z-tests are 0.24 and 0.22. For T2 versus T0, the corresponding p-values are 0.58 for the conditional WTP and 0.45 for the average WTP. Thus, based on simple comparisons of means, we find no evidence that disclosing information about the size of the individual carbon footprint and about social norms (i.e. distance to target carbon footprint) affects individual WTP or the propensity to offset carbon emissions. We also note that providing this information does not appear to lower the standard deviations of the conditional WTP and the average WTP compared to the control group. To further explore whether disclosing information about one's carbon footprint and the distance to the target carbon footprint reduce uncertainty pertaining to individuals' WTP to offset their carbon footprint, we asked participants once they had entered the amount how sure they were about the value of their WTP. Results are reported in Table 3. We note that for all experimental groups, about half the sample was either very certain or rather certain about their WTP. The last row reports the p-values of an F-test to the null hypothesis that the means are identical across the three treatments. We find no indication that the response shares differ across groups for any of the five response categories. Thus, we find no evidence that disclosing information about the size of individual carbon footprint and about the distance to the target carbon footprint affects uncertainty about individuals' WTP for their carbon footprint.

Table 3 **Certainty about willingness to pay to offset carbon footprint**

	Very uncertain	Rather uncertain	Indifferent	Rather certain	Very certain
Control (T0)	0.07	0.14	0.29	0.24	0.26
Disclosure (T1)	0.05	0.13	0.34	0.23	0.25
Social norm (T2)	0.08	0.11	0.32	0.25	0.23
P-value	0.17	0.53	0.44	0.93	0.74

Next, we turn to the findings for average WTP and conditional individual WTP per ton of CO_{2eq}. The figures displayed in Table 4 suggest that participants in our ample are willing to pay about 11 euros per ton of CO_{2eq}. The conditional WTP amounts to about 17 euros per ton of CO_{2eq}. Finally, we note that average and conditional WTP exhibit large standard deviations, suggesting substantial heterogeneity across individuals.

Table 4 **Average and conditional willingness to pay per ton of CO_{2eq} (in euro)**

	N	Mean	Std. Dev.	Min	Max.
Average WTP	975	10.90	19.62	0.00	177.07
WTP/WTP>0	640	16.61	22.18	0.07	177.07

3.2 Econometric analysis

Because under all experimental conditions, about one third of the sample stated that they would spend zero euros to offset their carbon footprint (i.e. WTP ≤ 0), estimating WTP via OLS would likely result in biased and inconsistent parameter estimates. We therefore employ a double-hurdle model which explicitly models the decision of whether to pay for the carbon footprint (first hurdle, extensive margin) separately from the decision of how much to pay (second hurdle, intensive margin). Double-hurdle models were originally developed by Cragg (1971). Accordingly, the first hurdle is modelled as a Probit model and the second hurdle as a Tobit (corner solution) model. Double-hurdle models imply less restrictive assumptions than Tobit models, which are also commonly used to analyse WTP decisions. Notably, unlike Tobit models, hurdle models allow the set of right-hand-side (RHS) variables to differ across both equations. In addition, the sign of the coefficient associated with a particular variable may vary across equations.

Formally, we model the first hurdle as

$$D_i = \begin{cases} 1 \; if \; D_i^* > 0 \\ 0 \;\; otherwise \end{cases} \quad (1)$$

$$D_i^* = x_i\beta + \varepsilon_{1,i} \quad (2)$$

where D_{it} is an indicator variable capturing whether individual *i* wants to pay for offsetting its carbon footprint or not. D_i^* reflects individual i's latent utility derived from offsetting her carbon footprint (such as "warm glow"), x_i is a vector of RHS-variables including attitudes and socio-demographic information, and. $\varepsilon_{1,i}$ is an idiosyncratic error term with $\varepsilon_{1,i} \sim N(0,1)$. The (conditional) probability that an individual is willing to pay for her carbon footprint is then

$$\Pr(D_i = 1 | x_i, \beta) = \Phi(x_i\beta + \varepsilon_{1,i}) \quad (3)$$

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

We model the second hurdle as

$$Y_i^* = max(Y_i^{**}, 0) \quad (4)$$

$$Y_i^{**} = x_i\delta + \varepsilon_{2,i} \quad (5)$$

where Y_{it}^{**} indicates individual i's desired WTP, and $\varepsilon_{2,i}$ is an idiosyncratic error term with $\varepsilon_{2,i} \sim N(0, \sigma_{\varepsilon 2}^2)$. Combining both hurdles, individual i's stated WTP to offset her carbon footprint is then

$$Y_i = D_i Y_i^* \quad (6)$$

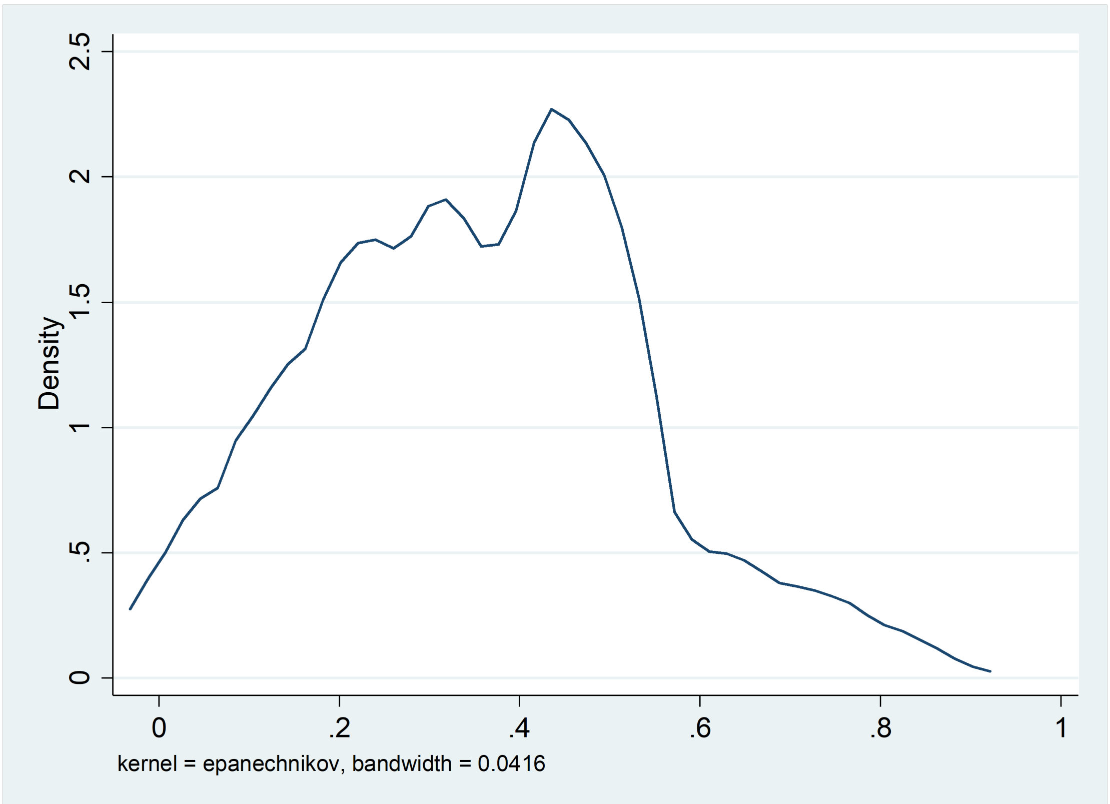
We estimate the double-hurdle model via the *churdle* command implemented in Stata. In doing so, we estimate two types of models. The *simple model* includes dummies reflecting treatment effects for disclosure and social norms only. To more precisely estimate the effects of disclosure and social norms treatments and to gain further insights into the factors related with individuals' WTP to offset their carbon footprint we also estimate a *full model* which includes covariates reflecting, for example, individual attitudes and socio-demographic characteristics.

3.2.1 Variables

The dependent variable is individuals' stated willingness to pay to offset their carbon footprint. Our set of RHS-variables includes dummies reflecting the treatments, i.e. disclosure (T1) and social norms (T2).

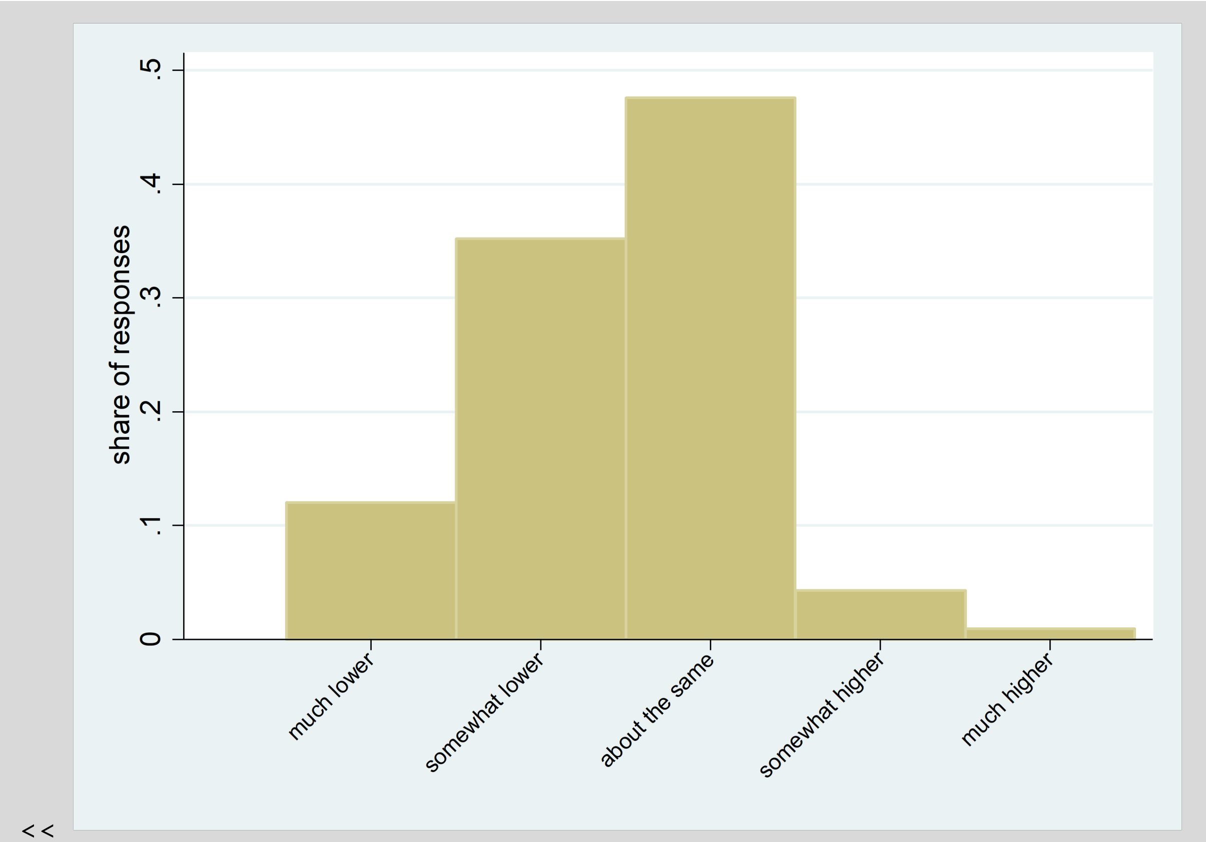
In addition, we consider as RHS-variables two variables capturing the effects of social comparison on individuals' WTP to offset their carbon footprint. Both these variables refer to individuals' perception to which extent their carbon footprint exceeds the carbon footprint of others. First, we asked participants to indicate what proportion (in %) of adults in Germany produced fewer or more greenhouse gas emissions than themselves for the activities included in the carbon calculator (*share_GHG_lower*). Because this question may be difficult to comprehend, we included detailed explanations, graphical tools (slider), a follow-up question to ensure that the response given corresponded to the participant's assessment, and a second follow-up question asking participants how sure they were that their assessment was correct (see A.1.2 for details). In addition, we incentivized this item for one half of the participants. Participants which were subject to the incentive treatment and belonged to the 10% with the most accurate assessments among all participants of the survey, received 10 euros after the fielding of the survey was completed. Figure 1 shows that the distribution of *share_GHG_low* is positively skewed. This illustrates that participants tend to underestimate the share of individuals with a lower carbon footprint than their own.

Figure 1 Kernel density estimation for share of adults in population believed to have a lower carbon footprint (*share_GHG_lower*)



Second, and after the previous item, we asked participants to rate their carbon footprint for the activities included in the carbon footprint calculator compared to the footprint of the average adult person in Germany. Results are displayed in Figure 2. Similar to Figure 1, Figure 2 confirms that participants tend to underestimate their own carbon footprint compared to others. Almost half the participants conjecture that their carbon footprint is lower or somewhat lower than the carbon footprint of the average adult person in Germany, while only about 5% believe that it is somewhat higher or much higher. Thus, in addition to T2, which allows for a causal interpretation of the effects of social norms on individual WTP to offset their carbon footprint, the findings for *share_GHG_lower* and *GHG_lower* are correlational.

Figure 2 **Perceived relative position in terms of carbon footprint (*GHG_lower)***



Our set of RHS-variables further includes participant *carbon footprint* as estimated by the carbon calculator described in A.1.1. Because our outcome variable relates to the offsetting of GHG emissions, we asked participants to rate on a five-point Likert scale the effectiveness of such offsets in protecting the climate and include the dummy variable *offsetting_effective* as a RHS-variable in the analysis. The extent to which offsetting measures actually lead to lower GHG emissions is contested.[4] We further include standard socio-demographic variables, i.e. participant age, gender, income, and level of education (see Table 5 for details). Because offsetting GHG emissions would likely be irrelevant for individuals who do not believe in climate change, our set of RHS-variables comprises the dummy *cc_deny*. In addition, we include *cc_literacy* to control for participant information about climate change. To this end, we use the scale proposed by Whitmarsh et al. (2011). Finally, to account for environmental preferences, we rely on the New Environmental Paradigm (NEP) scale originally developed by Dunlap et al. (2000). Following Whitmarsh (2008), we use the six-item NEP.

[4] McAfee (2022) provides a recent overview of arguments casting doubt on the effectiveness of offsetting.

Table 5 Description of covariates

Variable	Description	Mean	SD
share_GHG_lower	Share of adult persons in Germany believed to have a lower carbon footprint than participant.	0.36	0.18
GHG_lower	Dummy equal to 1 if participant believes that her carbon footprint is lower or much lower than the carbon footprint of the average adult person in Germany.	0.47	0.50
age	Participant age in years.	50.43	16.76
female	Dummy equal to 1 if participant is female, 0 otherwise.	0.53	0.50
income	Monthly household net income in 2019 in 1000 euro.	2.504	1.679
high_educ	Dummy equal to 1 if participant has at least advanced technical college entrance qualification	0.32	0.47
carbon footprint	Greenhouse gas emissions according to carbon footprint calculator (in tons of CO_{2eq}).	6.30	3.63
offsetting_effective	Dummy equal to 1 if participant considers carbon offsetting to be effective or very effective.	0.53	0.50
cc_deny	Dummy equal to 1 if participant believes that climate change does not exist.	0.04	0.20
cc_literacy	Dummy equal to 1 if sum of positive response to the items below is above the median. Which, if any, of these things do you personally keep an eye on?[5] (i) How the climate and seasons seem to be changing in Germany. (ii) Availability of more energy-efficient appliances for the home. (iii) Debates about the future of energy provision (e.g. nuclear power, renewables, the future of coal). (iv) Measures to reduce carbon emissions. (v) New technologies to reduce carbon emissions. (vi) German government policy on climate change. (vii) New scientific knowledge about climate change. (viii) Impact of climate change on developing countries. (ix) International agreements on climate change. (x) Positions of the political parties on climate policy. (xi) Contributions by companies to reducing their GHG emissions. (xii) Product labels for GHG emissions.	0.48	0.50
high_NEP	Dummy equal to 1, if the NEP score is higher than the median NEP score in the sample (i.e. 4). The NEP score is calculated as the sum of the scores from individual responses to the following six-item scale[6]	0.54	0.50

[5] Cronbach's alpha is 0.9439 for the final sample, suggesting excellent internal consistency of these items.

[6] Cronbach's alpha is 0.7588 for the final sample (and after recoding reversed items), suggesting satisfactory internal consistency of these items.

Variable	Description	Mean	SD
	How strongly do you agree with the following statements? (very weakly (1) - rather weakly (2) - neither weakly nor strongly (3) - rather strongly (4) - very strongly (5)) (i) "humans have the right to modify the natural environment to suit their needs" (ii) "humans are severely abusing the planet" (iii) "plants and animals have the same right to exist as humans" (iv) "nature is strong enough to cope with the impacts of modern industrial nations" (v) "humans were meant to rule over the rest of nature" (vi) "the balance of nature is very delicate and easily upset" Prior to calculating the sum of the scores, we recoded the negatively keyed items (i), (iv) and (v).		

3.2.2 Results of double hurdle model

Our results of estimating the double hurdle model appear in Table 6. The first column of results displays the findings of the *simple model*, which includes the treatment dummies and a constant only. In addition to these variables, the *full model* also contains the covariates described in Table 5. Finally, the models reported in the two final columns include either *share_ghg_lower* (see Figure 1*)* or *ghg_lower (see* Figure 2) in addition to those covariates.

To facilitate the interpretation of the findings we report in the marginal effects and - for dummy variables - the discrete probability effects for the *simple model* and the *full model*. We thereby distinguish between the effects on the extensive margin, intensive margin, and the average WTP.

The findings for the *simple model* shown in Table 7 suggest that providing information about the carbon footprint (T1) increases the average WTP pay by almost 21 euros, and the intensive margin by about 30 euros. In comparison, disclosing information about the carbon footprint does not appear to affect the extensive margin. We further find that our social norm treatment (T2) increases the average WTP by about 10 euros, and the intensive margin by about 12 euros, yet the coefficients are not statistically significant. Further, we find no evidence that T2 has an effect on the extensive margin.[7]

For the *full model* the findings for T1 and T2 are very similar to the *simple model*. In addition, several of the covariates in Table 6 are related with the extensive and intensive margins. Younger participants, women, individuals believing that offsetting is an effective means to protect the climate, and participants with a higher climate change literacy are more likely to state a positive WTP. Conditional on paying a positive amount, participants who are male, richer, better educated, believe that offsetting is an effective means to protect the climate, exhibit a higher climate change literacy, and who have stronger environmental preferences are associated with a higher stated WTP. Surprisingly, we find no statistically significant evidence that the level of the carbon footprint is related with the extensive margin, intensive margin, or the average WTP.

[7] We also note that the difference between T1 and T2 is not statistically significant (p = 0.719 for the extensive margin, p = 0.166 for the intensive margin).

Table 6 **Results for simple and full models†**

	Simple model	*Full model*	*Social norm share_ghg_lower*	*Social norm ghg_lower*
Intensive margin (WTP/WTP>0)				
T1 (information)	0.287**	0.248**	0.246**	0.251**
	(0.132)	(0.124)	(0.124)	(0.124)
T2 (target) t	0.111	0.163	0.163	0.164
	(0.134)	(0.126)	(0.126)	(0.126)
age		-0.004	-0.004	-0.004
		(0.003)	(0.003)	(0.003)
female		-0.263**	-0.261**	-0.271***
		(0.104)	(0.103)	(0.104)
income		0.135***	0.136***	0.131***
		(0.032)	(0.032)	(0.032)
high_educ		0.315***	0.313***	0.330***
		(0.112)	(0.112)	(0.113)
carbon_footprint		0.015	0.015	0.014
		(0.012)	(0.012)	(0.012)
offsetting_effective		0.290***	0.287***	0.298***
		(0.109)	(0.109)	(0.109)
cc_deny		-0.999***	-1.009***	-0.992***
		(0.360)	(0.362)	(0.356)
cc_literacy		0.364***	0.366***	0.368***
		(0.106)	(0.106)	(0.106)
high_NEP		0.300***	0.293***	0.312***
		(0.106)	(0.106)	(0.107)
share_GHG_lower			-0.162	
			(0.302)	
ghg_low				-0.128
				(0.103)
constant	3.608***	2.857***	2.919***	2.918***
	(0.098)	(0.249)	(0.270)	(0.255)
Extensive margin (WTP>0)				
T1_info	0.020	0.010	0.010	0.010
	(0.101)	(0.105)	(0.105)	(0.105)
T2_target	0.056	0.057	0.057	0.057
	(0.101)	(0.107)	(0.107)	(0.107)
age		-0.013***	-0.013***	-0.013***
		(0.003)	(0.003)	(0.003)
female		0.301***	0.301***	0.301***
		(0.088)	(0.088)	(0.088)
income		0.030	0.030	0.030
		(0.027)	(0.028)	(0.028)
high_educ		0.130	0.130	0.130
		(0.100)	(0.100)	(0.100)
carbon_footprint		0.007	0.007	0.007

	Simple model	*Full model*	*Social norm share_ghg_lower*	*Social norm ghg_lower*
		(0.013)	(0.013)	(0.013)
offsetting_effective		0.441***	0.441***	0.441***
		(0.090)	(0.090)	(0.090)
cc_deny		-0.500**	-0.499**	-0.499**
		(0.225)	(0.225)	(0.225)
cc_literacy		0.501***	0.501***	0.501***
		(0.094)	(0.094)	(0.094)
high_NEP		-0.044	-0.044	-0.044
		(0.092)	(0.093)	(0.092)
share_GHG_lower			0.009	
			(0.238)	
ghg_low				-0.005
				(0.088)
constant	0.377***	0.347*	0.344	0.350*
	(0.072)	(0.205)	(0.224)	(0.210)
LL0	-3533.992	-3429.641	-3429.471	-3428.839
AIC	7116.161	7031.343	7044.767	7043.504
N	975	975	975	975

[†] Robust standard errors are shown in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01

Results for the socio-demographic characteristics in Table 7 imply than additional ten years of age are associated with a decrease in the average WTP of about 7 euros. Further, women are about 10% points more likely to pay for their carbon footprint than men, yet their intensive margin is almost 26 euros lower. An increase in income by 1000 euros is associated with an increase in the average WTP by 10 euros and the conditional WTP by about 13 euros. Finally, the average WTP of participants with at least an advanced technical college entrance qualification is about 27 euros higher than of participants with a lower qualification.

Last but not least, Table 7 illustrates that the size effects of perceptions about the effectiveness of offsetting, believing in climate change, climate change literacy, and environmental preferences are typically large.

Table 7 Average marginal effects

	Simple model			**Full model**		
	extensive margin	intensive margin	average	extensive margin	intensive margin	average
T1_info	0.007	30.220**	20.607**	0.003	25.213**	18.242*
	(0.037)	(14.079)	(10.083)	(0.035)	(13.210)	(10.037)
T2_target	0.021	11.728	9.888	0.018	16.379	13.456
	(0.037)	(14.105)	(10.077)	(0.035)	(13.072)	(9.974)
age				-0.004***	-0.360	-0.663***
				(0.001)	(0.300)	(0.232)
female				0.100***	-25.576**	-9.017
				(0.029)	(10.291)	(7.696)

	Simple model			Full model		
income				0.010	13.150***	10.234***
				(0.009)	(3.344)	(2.506)
high_educ				0.43	32.112***	27.015***
				(0.033)	(12.121)	(9.322)
carbon_footprint				0.002	1.425	1.236
				(0.004)	(1.199)	(0.953)
offsetting_effective				0.150***	27.544***	32.879***
				(0.031)	(10.107)	(7.576)
cc_deny				-0.177**	-62.585***	-50.760***
				(0.082)	(13.909)	(8.485)
cc_literacy				0.169***	34.911***	40.025***
				(0.017)	(10.180)	(7.889)
high_NEP				-0.015	28.640***	18.921**
				(0.030)	(10.103)	(7.733)
N	975	640	975	975	640	975

† Robust standard errors are shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4 Conclusions

In this paper, we employ a demographically representative survey among the adult population in Germany to examine the causal effect of informing individuals about the size of their carbon footprint on their WTP to offset the associated GHG emissions. We found that providing information about participants' carbon footprint increased their WTP for offsetting by about one third. At a general level, this result corroborates the introduction of carbon footprint labels to address incomplete information. Such labels may help shift consumer choices from high-carbon impact products and services to low-carbon impact alternatives and thus better align consumer preferences and actions, similar to Lohmann et al. (2022) in the context of meals for example. On average, participants in our sample were willing to pay about 11 euros/t CO_{2eq}. This value is at the lower end of estimates typically found in related studies (see Nemet and Johnson, 2010). Thus, even though our WTP elicitation was not incentivized, hypothetical bias appears to be low. Our point estimate for the WTP/t CO_{2eq} is in the range of values found in field experiments on voluntary offsetting of flight-related emissions (e.g. Berger et al., 2022) and providers of offsets such as atmosfair (https://www.atmosfair.de/en) and myclimate (https://co2.myclimate.org/en). Possibly, WTP to offset carbon emissions is low because participants' demand for climate policy is already met by existing policies. In fact, Germany is among the set of countries with the highest implicit carbon price (OECD, 2021). The average WTP to offset GHG emissions observed in our study, however, is much lower than the price levels typically deemed to be consistent with meeting ambitious climate targets (World Bank, 2022). Thus, relying on individuals to voluntarily lower their GHG emissions will unlikely be sufficient to meet the 1.5°C target. Providing information on the size of the carbon footprint appears to affect the intensive margin but not the extensive margin. Hence, for about one third of our sample displaying the size of their carbon footprint was not found to be effective.

In comparison, providing information about the size of the carbon footprint together with the distance to the target carbon footprint does not appear to affect individuals' WTP to offset their own carbon footprint. Thus, unlike in related research (e.g. Bernard et al., 2022) coupling information with a behavioral nudge (here an explicit social norm) was not associated with a higher WTP. Of course, we can only speculate about the underlying reasons. Drawing on the literature on goal setting and individual norms suggest that the target footprint may have discouraged participants, because they perceived the target footprint as too ambitious to achieve or as too distant from their own social norms, similar to Loock et al. (2013) and Hille et al. (2016) in related contexts. In addition, in our case, it is governments rather than individuals themselves who set the target, potentially undermining intrinsic motivation towards goal attainment (Ryan and Deci, 2000).

We further find that individuals' WTP to offset their carbon footprint is related with income, gender, age, education, carbon literacy, the belief that carbon offsetting is effective, and with environmental preferences. While our results for these covariates are rather intuitive, we failed to find a statistically significant relation between the WTP and the size of the individual carbon footprint. The latter finding is unexpected, yet it is in line with Pace and Weele (2020) and Lohmann et al. (2022), for example. Possibly we found this no result because the statistical power is too low. Alternatively, and similar to decision-making in other domains (see for example Thaler, 1999), participants may mentally allocate a fixed financial budget to offset their carbon emissions, which is unrelated to actual emissions (and damage). Finally, and somewhat surprisingly - yet in line with our finding for the social norm treatment - individuals' WTP to offset their GHG emissions was not found to be related with social comparisons, i.e. whether participants consider their carbon footprint to be higher or lower than the carbon footprint of the average adult in the population. Our (non) findings on the role of social norms for individual' WTP to compensate their carbon footprint raises questions on the transferability of findings from related domains on the effectiveness of nudging via social norms to individuals' WTP to offset their carbon footprint. Future research could look at this issue in more depth.

5 List of Figures

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7 References

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A.1 Appendices

A.1.1 Appendix A: Carbon footprint calculator[8]

Our carbon footprint calculator estimates per-capita greenhouse gas emissions related to electricity consumption, thermal heating, transportation and diet in 2019. Calculations are based on 27 items included in the survey. The calculator is similar to existing online carbon footprint calculators for individuals such as those available from 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/).

Electricity

Participants were asked to report (or estimate as precisely as possible) household electricity consumption in 2019 in kWh. If participants did not know their electricity consumption, we asked them for their annual or monthly electricity bill in 2019. In this case, electricity consumption was estimated by dividing electricity costs by the average household electricity price in 2019 for a private household using 3500 kWh per year, i.e. 0.304 Euro/kWh (BDEW 2022).

For participants who neither knew their electricity consumption nor their electricity costs we used default values distinguishing by household size (1, 2, 3, 4, 5 >6 persons), building type (single family or multi-family buildings). Data for default values were taken from Stromspiegel Deutschland (2019)[9] and ranged from 1500 kWh for a single person household in a multi-family building to 5000 kWh in a five-person household in a single-family building. For households with more than five household members we used 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 information provided by the Federal Environment Agency (UBA, 2020).

To calculate CO_2-emissions pertaining to electricity use, we took into account whether households subscribed to a green electricity tariff and whether they generated electricity from a rooftop PV installation. For households who had subscribed to a green electricity tariff, electricity-related CO_2-emissions were set to zero.[10] We asked households who indicated that they generated electricity from renewable energy sources to report (or make the best guess of) the electricity generated from these sources in 2019. To calculate electricity-related CO_2-emissions for these households we used the net electricity consumption, i.e. electricity consumption minus electricity generated from renewable energy sources.

[8] All values used in the carbon footprint calculator were discussed with technology and sector experts of Fraunhofer Institute for Systems and Innovation Research.

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

[10] Whether green electricity tariffs actually lead to lower CO_2 emissions is contested. First, in terms of physical flows, unless the power plants that are producing electricity on the grid at the time electricity is used happens to be a renewable plant, electricity demand of a green tariff customer causes emissions. Second, total emissions of installations governed by the EU Emissions Trading System (EU ETS) are fixed. Hence, because of the so-called waterbed effect, any emission reductions by a fossil-fuelled power plant will be offset by an increase in emissions of equivalent magnitude by other installations covered by the EU ETS (e.g. Perino et al. 2019).

We then calculated electricity-related CO_2-emissions per household by multiplying (net) electricity consumption by 0.401 kg/kWh, i.e. the CO_2-emissions for the electricity mix in Germany in 2019 (Statistisches Bundesamt 2020).[11]

Finally, we calculated per-capita electricity consumption by dividing electricity-related CO_2-emissions per household by the number of household members. We thereby apply OECD weights and weight the first adult in the household with the factor one, each other adult household member with the factor 0.5, and each child younger than 14 years with the factor 0.3.

Heating

Heating-related CO_2-emissions are calculated based on estimated heating demand and fuel type.[12] Heating demand is estimated based on the size of the dwelling in m^2 and default values for final energy demand per m^2 which account for building type (single family, 2 family, 3-6 apartments, 7-12 apartments, ≥13 apartments), building age (built before 1919, 1918-1948, 1949-1978, 1979-1990, 1991-2000, 2001-2008, built 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.

Heating-related CO_2-emissions are then estimated using standard emissions factors per fuel type for the main heating system (natural gas, heating oil, district heat, hard coal, lignite, wood/biomass, electricity, green electricity). These factors were based on UBA (2018). For wood/biomass, we used a value of 0.1. For households who used solar-thermal heat, we applied a discount factor of 20%, i.e. the mid-range documented in the literature (DENA, 2015).

To calculate per-capita heating-related CO_2-emissions we divide household heating- related CO_2-emissions by the number of household members thereby again applying OECD weights.

Transport

For transport-related emissions, we distinguish between distances travelled by private cars, motorcycles, cruise-ships, and airplanes.

For *private cars* we asked participants to report (or estimate as precisely as possible) the total km travelled in 2019 distinguishing between distances travelled alone and with others. For the latter we assume an average rate of occupancy of 2.3 based on the average rate of occupancy of all trips in Germany in 2019 (Forschungsinformationssystem Mobilität und Verkehr, 2019). If participants did not know the distances travelled by car, we used a default of 13,727 km per person relying on data provided by Kraftfahrt-Bundesamt (2018) for 2018. We further asked for fuel consumption and fuel type of the car respondents used the most. We thereby distinguished between gasoline, diesel, natural gas, liquefied petroleum gas, bio-diesel/ethanol, electricity and gasoline/diesel for hybrid cars[13], and electricity. For participants who failed to report fuel consumption, we used default values distinguishing between large cars (including SUVs), midsize/compact cars, and small/sub-compact cars, and fuel types.[14] Multiplying fuel consumption and distance travelled per capita yields our

[11] Thus, for households generating electricity from renewable energy sources, electricity-related emissions may be below zero, especially if they subscribe to a green tariff.

[12] In a pre-test we also asked for heating costs/heating consumption, leading to a high share of missing and implausible responses. In addition, the heating bill does not necessarily coincide with the calendar year. For these reasons, we decided to use proxies based on technological information.

[13] We assume 60% of distance is travelled using diesel/gasoline based on Plötz et al. (2020).

[14] In the survey, we provided examples of the most popular models in each class.

estimate for the per-capita fuel consumption. Multiplying this figure by standard emission factors of fuels yields per capita CO_2 emissions related with private car use.[15]

To calculate the CO_2 emissions related with *motorcycle* use we apply the same logic as for private car use. For occupancy, we use a factor of 2 for trips with additional passengers. If participants did not report the distance travelled by motorcycle we used 2219 km as the default.[17] For fuel types we distinguish between gasoline, diesel and electricity. If participants failed to report fuel consumption, we used 4.75 l/100 km.[16] This value corresponds to gasoline because more than 99% of the motorcycles registered in Germany use gasoline.[17]

To estimate the CO_2 emissions pertaining to *ship cruises* we multiply the number of days participants travelled on a cruise-ship in 2019 with a standard default factor of 214 $kgCO_2$/day.[18]

To calculate the CO_2 emissions related to *aviation*, we asked participants to report the number of flights they took in 2019 for private purposes (e.g. for vacation, but not business trips or trips with a sporting airplane). Following the set-up of the UN carbon calculator[19], participants were asked to distinguish between short flights (3000 km; up to 6 hours duration), medium-long flights (between 3000 km and 6000 km; between 6 and 8 hours duration), long flights (between 6000 km and 12,000 km; between 8 and 14 hours duration), and very long flights (with more than 12,000 km; longer than 14 hours duration). We asked participants to count flights with stop-overs as one flight and to count outbound and return flights as two separate flights. We then calculated the aviation-related CO_2 emissions as the product of the number of flights per category and a standard emission factor of 369 $kgCO_2$/1000 km.[20] This value accounts for the fact that when CO_2 emissions reach higher layers of the atmosphere, they have a much greater impact on the climate there than when they are emitted close to the ground.

Diet

Finally, to calculate the nutrition-related greenhouse gas emissions, we asked participants to best characterize their typical diet distinguishing between meat-based (2100 $kgCO_2$) balanced/mixed (1600 $kgCO_2$), low-meat (1300 $kgCO_2$), vegetarian (1100 $kgCO_2$) and vegan (900 $kgCO_2$) diets. The associated greenhouse gas emission factors were taken from information available from the carbon footprint calculators available from Naturefund (https://www.naturefund.de/en/information/co2_calculator#calc-food) and Umweltbundesamt (https://uba.co2-rechner.de/de_DE/). To limit the number of items we made plausible assumptions. For example, we assumed that vegan diets were prepared from local and organic produce, and that meat-based diets are non-organic and purchased at supermarkets.

To mitigate input data errors, several items included plausibility checks. For example, household electricity consumption was forced to range between 500 kwh and 50,000 kWh, electricity generated from renewable energy sources had to be between 0 kWh and 20,000 kWh, values for apartment size were required to range between 1 m^2 and 3000 m^2, for distance travelled by car we allowed values between 0 and 200,000 km only, fuel consumption for gasoline and diesel cars had to lie between 3 l/100km and 32 l/100 km, and the maximum number of flights allowed was 500.

15 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).

16 https://www.adac.de/rund-ums-fahrzeug/zweirad/motorrad-roller/fahrberichte/bmw-r-1250-gs/

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

18 We used data provided by https://co2.myclimate.org/en/cruise_calculators/new, assuming a cruise ship for 2000-3000 passengers and a standard cabin for 2 persons.

19 https://offset.climateneutralnow.org/footprintcalc

20 https://www.naturefund.de/wissen/co2_rechner/daten.

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A.1.2 Appendix B: Details on construction of *share_GHG_lower*

Now we would like to know in more detail how you rank the greenhouse gas emissions caused by you in comparison to other people.

Please indicate what proportion (in %) of adults in Germany you estimate to have caused fewer or more greenhouse gas emissions than yourself in 2019?

In doing so, please provide as accurate an assessment as possible.

Please mark your position on the slider that represents all adult persons in Germany in 2019 ordered by the greenhouse gas emissions they caused. The area to the ***left*** *of your mark is the proportion of adults in Germany who caused* ***fewer*** *greenhouse gas emissions than you in 2019. The area to the* ***right*** *of your mark is the proportion of adults in Germany who caused* ***more*** *greenhouse gas emissions than you in 2019.*

Now please mark your position on the slider:[21]

<--- *Proportion of adults with lower greenhouse gas emissions in %.*

Proportion of adults with higher greenhouse gas emissions in %. % --->

33%	67%

This was followed by the subsequent question:

Here is your assessment in words again:

[33%] of adults in Germany caused fewer greenhouse gas emissions than you in 2019, and [67%] of adults in Germany caused more greenhouse gas emissions than you in 2019.

Is your assessment reflected correctly?

☐ No

☐ Yes[22]

[21] A mark appeared at the position where participants clicked on the scale. The proportions to the left and right of the mark were displayed in percent within the horizontal bar. E.g. for a participant who believed that one third of adults in Germany in 2019 caused fewer GHG emissions than herself would see 33% to the left of the mark and 67% to the right.

[22] Participants who clicked 'No' were sent back to the slider and saw an error message: Please adjust your marker to correctly reflect your assessment.