Polarized Plates: Climate Attitudes and the Effect of Carbon Emission Information on Food Choices

Dede Long, dlong@hmc.edu, Assistant Professor, Dept. of Social Sciences and Humanities, Harvey Mudd College

Hongxing Liu, liuho@lafayette.edu, Associate Professor, Dept. of Economics, Lafayette College

Liqing Li, liqing.li@ag.tamu.edu, Assistant Professor, Dept. of Agriculture Economics, Texas A&M University

Abstract

Carbon footprint labels are gaining traction as behavioral tools to promote low-carbon food choices. We use a randomized online experiment to examine how carbon emission information affects food choices and projected dietary emissions. On average, information treatments reduced projected emissions, but effects varied by climate attitudes. Climate-concerned individuals significantly reduced their emissions, while others showed little change. We find suggestive evidence that trust and information internalization drive this divergence. Trust mediates over half the effect of climate attitudes on internalization. Our findings emphasize the need to tailor labeling strategies with careful consideration of heterogeneity in individual attitudes and beliefs.

1. INTRODUCTION

Households are responsible for between 60% and 80% of global carbon emissions (Dubois et al., 2019; Wilson et al., 2013), with food consumption being a significant contributor. In particular, meat consumption alone accounts for approximately one-third of food-related carbon emissions in Western countries (Crippa et al., 2021). Despite the significant impact of reducing meat and dairy consumption and the urgency of climate change mitigation (Girod et al., 2014), many individuals remain unmotivated or lack the necessary knowledge to meaningfully change their dietary habits (Rose, 2018). Given these challenges, there is growing interest in designing strategies to incentive changes in consumption patterns. In the U.S., the absence of federal regulations and the political infeasibility of market-based policy instrument like meat taxes emphasize the need for behavioral interventions that can encourage pro-environmental actions without relying on economic incentives and government regulations (Funke et al., 2022). As an important form of behavioral interventions, environmental labels and information schemes such as environmental footprint labels are gaining traction (Camilleri et al., 2019).

However, the effectiveness of these information interventions on food choices remains unclear. Some studies show that improving consumer knowledge can indeed correct biases regarding food choices' environmental impact and leads to dietary changes (Camilleri et al., 2019; Panzone et al., 2024). In contrast, others argue environmental information provision is minimally effective, as it may be interpreted differently by groups with differing pre-existing beliefs, causing polarization and backfiring effects (Chapman & Lickel, 2016; Hornsey et al., 2016; Kahan et al., 2012; Leiserowitz, 2006; Long et al., 2021, 2023; Whitman et al., 2018). Additionally, previous work shows that framing and format can influence how information is perceived and processed (e.g., Spiegler, 2014).

To fill the gap in the literature, we provide causal evidence on how carbon emission information affects stated future food choices and carbon emissions through an online experiment. We investigate whether these effects vary depending on individuals' pre-existing beliefs about climate change, hypothesizing that divergent beliefs may lead to a polarization effect, where individuals change their behaviors in opposite directions. We also offer suggestive evidence on the underlying mechanisms driving these heterogeneous responses. In the experiment, participants first recall their food consumption from the previous week. They are then randomly assigned into three treatment groups or a control group. Treatment groups receive information about their carbon emissions based on their food choices (hereafter, we use "carbon foodprint" and food carbon emissions interchangeably), with varying formats (e.g., mean vs. range of emissions). After receiving the information, participants report their trust in it and provide self-assessed estimates of their weekly carbon foodprint. Lastly, they plan their food consumption for the following week.

We find that, on average, providing individuals with information about their past carbon emissions reduces their stated future emissions. However, this effect varies significantly with participants' climate attitudes. Those concerned about climate change reduce their emissions, while those who are not show no statistically significant change, though the effect is directionally negative. We further demonstrate that the total effect of climate attitudes can be decomposed into direct and indirect components. Climate attitudes can directly influence individuals' food choices due to motivating reasoning, that is, individuals are more likely to accept information that aligns with their pre-existing beliefs. Indirect effects operate through trust in the presented information as a mediator. Specifically, individuals who are less worried about climate change tend to place less trust in the carbon emission information, which in turn influences how they internalize it. These individuals report substantially lower self-assessed carbon foodprint than the displayed information they received, making them less likely to adjust their future food choices and carbon foodprint. Together, these mechanisms contribute to a polarization in responses to the information treatment.

Our study contributes to several strands of literature. First, we build on research examining how information aimed at promoting public goods provisions influences individual food choices. While extensive research has shown that health-related information such as nutrition or calorie content can shape dietary decisions (see Campos et al., 2011 for a systematic review; Dumoitier et al., 2019; Russell et al., 2017), fewer studies explore how information intended to promote public goods provision like climate change mitigation affects behavior. Some work has examined the impact of general climate-related information, such as offering a climate change script or adding carbon-friendly labels (e.g., Elofsson et al., 2016; Jalil et al., 2020; Visschers & Siegrist, 2015; Vlaeminck et al., 2014), but only a few have assessed the effect of direct carbon emissions information based on actual food choices. Among these, most focus on providing emissions data for specific items (e.g., carbon emissions from beef), demonstrating that individuals voluntarily substitute toward lower-emission alternatives (Lanz et al., 2018; Osman & Thornton, 2019; Perino et al., 2014).

A study that is most closely related to ours shows that presenting participants with the total carbon emissions of grocery purchases can be effective, but only with repeated exposure over multiple shopping trips (Fosgaard et al., 2024). Our study expands this literature by assessing the impact of providing individualized and direct carbon emissions information on food choices. We find that simply offering the total carbon emissions of a person's diet may be insufficient to change behavior, likely because many consumers lack the scientific knowledge about food items' carbon emissions. Instead, presenting information in accessible and actionable formats, such as carbon emission rankings the carbon footprint can offer clear guidance and encourage the adoption of low-carbon diets.

Second, we contribute to the emerging literature on the polarization effects of information treatments in the context of food choices. Prior work shows that people process information through the lens of their pre-existing beliefs (Chang et al., 2012; Glaeser & Sunstein, 2013). For instance, political biases shape how people interpret climate change information (Spiegler, 2014) and may lead to selective inattention to climate-related wording, exacerbating polarization (Whitman et al., 2018). Long et al. (2023) similarly find that presenting information on the connection between deforestation and climate change leads to polarized responses in donation behavior. However, there is limited evidence on whether such polarization extends to food choices. We find that it does. Climate-related information leads to significant emissions reductions among individuals concerned about climate change but has little effects among skeptics. This divergence might be partly due to motivated reasoning. Individuals tend to accept information that aligns with their beliefs and discount information that contradicts them (e.g., Epley & Gilovich, 2016). As a result, carbon emission feedback is processed differently depending on prior attitudes, reinforcing existing divisions.

This finding has important implications, particularly for carbon labeling efforts (Cohen & Vandenbergh, 2012; Lohmann et al., 2022). With the rise of climate labeling initiatives, such as those encouraged by the European Green (European Commission, 2021), our findings caution that these efforts may inadvertently lead to polarization. Given the current divergent opinions and beliefs regarding climate change in the U.S., careful consideration is needed to address belief-based resistance.

Finally, our findings further add to the literature on how framing and format of information affects perception and descision-making. Carbon emission is an abstract and complex concept, making it difficult for individuals to interpret and act on (Taufique et al., 2022). While some studies have examined the effectiveness of generic carbon emission information (Vanclay et al., 2011) and others explored the impact of personalized feedback (Luo et al., 2025), few directly compare different formats or test their efficacy across belief groups. Our results suggest that the specific format, whether a simple mean, a range, a ranking, or the combination of these, does not lead to significantly different behavior changes overall. However, presenting information in a clear and straightforward way, such as through emission rankings, is particularly effective in overcoming cognitive or motivational barriers to behavior change.

2. EXPERIMENTAL DESIGN AND DATA

We design an online experiment to examine whether carbon foodprint information influences respondents' future food choices and the associated carbon emissions, as well as whether these effects are heterogeneous based on prior climate attitudes. We also explore the underlying mechanism driving these differences by analyzing how pre-existing climate attitudes affect the internalization of information and the role of trust in the presented information in shaping responses.

2.1 Experimental Design

The experiment targeted the general adult population in the US and was administrated using the infrastructure of a major marketing research company between March 3 to May 8, 2023. The survey firm maintains a proprietary survey respondent pool by recruiting participants through websites and social medial. Note that participants do not contact the survey firm themselves. The initial screen introduced the main topic of the survey, informing respondents that we will inquire about their dietary choices. Following the consent question, we filter respondents to focus on US adult (above 18 years old) subjects. The full survey is presented in the Appendix C.

Following the screening questions and introduction page, all participants first answered questions eliciting their food choices in a typical week. The survey page displayed a food choice matrix with 12 rows, each representing a food category, as well as 5 columns representing consumption frequencies. The twelve food categories are constructed based on food categories used in Poore & Nemeceks (2018) and Heller et al. (2018), including cereals and grains, eggs, dairy, vegetables, fruits, fish, pork, beef, chicken, lamb (mutton, goad meat), tofu, and legumes and nuts. The consumption frequency ranges from zero time a week, 1-2 times a week, 3-5 times a week, once a day, to twice a day or more. The food consumption matrix page is available in Appendix Figure A1.

Next, we elicited respondents' attitudes toward climate change using the Six Americas Super Short Survey (SASSY!). The SASSY! climate survey consists of four questions representing a well-established segmentation of Americans based on their climate beliefs, attitudes, and behaviors. These four survey questions are identified from original 36 questions of the Global Warming's Six Americas survey, using analysis of 14 national samples and machine learning algorithms (Chryst et al., 2018). The survey segments the population into six distinct groups: alarmed, concerned, cautious, disengaged, doubtful, and dismissive, based on their attitudes toward climate change. We deliberately placed the climate attitude questions after the food choices to minimize potential salience effect (Barrera et al., 2020), which could influence recalling food choices by making climate change more salient.

After eliciting food choices and climate attitudes, we randomly assigned participants to one of four treatment categories or a baseline (control) group. Those in the treatment groups receive carbon foodprint information based on their past food consumption. A detailed discussion of the treatment types is in the next section. After receiving the information treatment, respondents in all groups, excluding the baseline group, are asked how much they trust the presented carbon emission information and to self-assess their carbon emissions from their diet.

Lastly, respondents express their future food choices through the food choice matrix. To mitigate hypothetical bias and encourage truthful answers, we implement a follow-up validation mechanism. At the end of the survey, participants are informed that there will be an opportunity to earn additional $20 compensation by submitting their future grocery shopping receipts within the next two weeks. By informing participants in advance that their reported future food choices may be verified through real transactions with real stake, it helps ensure truthfulness of their answers and reduces hypothetical bias (Harrison, 2007).

2.2 Information Treatments

In the baseline group, no carbon emission information was displayed, serving as a benchmark for measuring changes in carbon foodprint. In the treatment groups, we present respondents their food foodprint based on their past food choices in a typical week. The emission information, including the mean, minimum, and maximum, is calculated using emission data published in Poore & Nemeceks (2018) and Heller et al. (2018). We choose to use publicly available data from these two studies because they are both large scale meta-analysis and their categorization of food items is similar and comparable. Additionally, the carbon emissions for each food category vary slightly between the two studies due to the differences in methodologies, reflecting variances in scientific research while still allowing for a meaningful comparison. For simplicity, we refer to Poore & Nemeceks (2018) as study one and Heller et al. (2018) as study two hereafter.

In addition to examining the impact of carbon foodprint information on food choices, we are interested in evaluating the existence and extent of the framing effect. We construct four information treatment groups with four subgroups (Table 1). The corresponding carbon foodprint information is displayed when a respondent is randomly assigned into a specific treatment group. For instance, respondents in Treatment Category 1 Subgroup 1 receive information on their mean carbon foodprint, calculated based on their food choices using data from Study 1, while respondents in Treatment 2 Subgroup 3 receive information on the range (minimum and maximum) of their carbon foodprint, calculated using data from Study 2.

We hypothesize that, to motivate behavioral changes, it is crucial to offer participants guidance on how to adjust their dietary patterns based on their goals, whether that be reducing or increasing their carbon foodprint. Therefore, as shown in Table 1, we include the emission ranking for the twelve food items as a treatment group (Treatment 4) and combine different information format (i.e., mean and range of carbon emissions) with the emission rank in sub-treatment groups. This rank information can be essential in motivating behavioral changes, as past studies have shown individuals often lack the knowledge and information on how to reduce their food carbon emissions (Rose et al., 2019). Furthermore, when presenting means from two studies, we also randomized the display order.

[Table 1]

To help respondents better understand the measurement of carbon emissions, we provided two additional pieces of information: (1) the equivalent mileage for driving a typical gas-powered passenger vehicle, and (2) the percentile of participants' carbon emissions compared to the general population in the US.[1, 2] The information displayed to the respondents in each treatment category is available in Appendix B.

After viewing the carbon emission information, respondents in the treatment group are asked to indicate their level of trust in the study results using a slider, where 0% represents "not at all" and 100% represents "a great deal." They are then prompted to provide a numerical estimate of what they believe their actual weekly carbon emissions are. These responses allow us to explore potential mechanisms underlying behavioral change and examine heterogeneity in treatment effects.

2.3 Data

Out of the 2,248 participants who initiated the survey, 2,104 consented, and 1,691 completed the main questions of interest, resulting in an 80% completion rate.[3] We implemented multiple measures to screen observations and ensure data quality. First, we removed observations where the same consumption frequency was chosen for all the food items for the past or future

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[1] To calculate each participant's emission percentile, we obtain dietary greenhouse gas emission data from O'Malley et al. (2023), which includes emissions for food items consumed by individuals in the National Health and Nutrition Examination Survey (NHANES) day one recall from 2005 to 2010. We then merge the food-level emission data with the NHANES data using food codes to calculate aggregated dietary carbon emissions at the individual level. Finally, we compare each survey participant's carbon emissions to those from individuals in the NHANES data to determine their corresponding percentile.

[2] The percentile information indicates how participants' carbon emissions compare to those of others, potentially serving as a form of social comparison that could influence their choices. The estimated average treatment effect therefore captures the combined impact of the carbon foodprint information and the social comparison. Since this information is provided to all participants in the treatment groups, it does not hinder comparisons of effect size across treatment groups.

[3] To test our hypotheses, the most important information is food carbon emissions, climate attitude, attitude towards science, and individual demographics. Therefore, we screened out those who did not complete these questions.

food matrix, as it is very unlikely a person consumes all food items with the same frequency within a week. Second, we measured the time respondents spent answering the climate attitude questions and removed observations where respondents spent less than 10 seconds on these questions. Similarly, we removed respondents who rushed through the food choice elicitation questions, spending less than the 10th percentile time. Lastly, we removed observations with extreme carbon emissions based on participants' past and projected food choices (above the 95th percentile and below the 5th percentile).[4] These steps left us with 1,220 observations. The number of observations within each treatment group is presented in the Appendix Table A1.

Table 2 presents summary statistics for the study sample, along with *p*-values from Welch's *t*-tests comparing mean differences between the treatment and control groups. Overall, our control and treatment groups are well-balanced. Respondents do not differ significantly across most observable demographic characteristics, with the exception that the control group includes a slightly higher proportion of low-income households and a lower proportion of middle-income households.

[Table 2]

3. Empirical Method

Given the randomized design of our experiment, our empirical strategy is straightforward. To examine whether the information treatment affects carbon foodprint, we compare the outcomes between respondents who received the treatment and those in the control group. Specifically, we estimate the following model using ordinary least squares (OLS) regression model:

[4] We experimented with different cutoffs (e.g., keeping observations between the 4th and 96th percentiles, 5th and 95th percentiles) as a robustness check, and the results remained unchanged.

$$EmissionChange_i = \alpha + \beta Treat_i + \boldsymbol{X_i} + \varepsilon_i \qquad (Eq. 1)$$

The dependent variable, $EmissionChange_i$, measures the change in respondent i's carbon foodprint, calculated as the difference between their average projected carbon emissions for the future food choices and those based on past consumption. A negative $EmissionChange_i$ represents a decline in emissions. As discussed in the Data section, carbon foodprint is calculated using data from two sources (Study one and Study two) and the emission change ($EmissionChange_i$) is the average change across both.

The treatment indicator, $Treat_i$, is defined in two ways: (1) To estimate the overall average treatment effect, $Treat_i$ is a dummy variable that equals 1 if respondent i receives any form of treatment, regardless of format. (2) When assessing differences in treatment effects across different information, $Treat_i$ is defined as a categorical variable representing assignment to specific treatment groups, as detailed in Table 1. In this specification, Equation (1) allows us to evaluate whether the framing of information leads to heterogeneous effects. ε_i is the error term.

Although the treatment and control groups are well balanced across observable demographics (see the Data section), we include a vector of respondent characteristics, $\boldsymbol{X_i}$, to improve the precision of the estimates, following recommendations in Angrist & Pischke (2009). These controls include age, gender, race, income, education, and political ideology.

To assess the heterogeneous effects by prior climate attitudes, we extend Equation (1) by interacting the treatment indicator $Treat_i$ with the respondent's pre-treatment attitudes toward climate change. Because these beliefs were measured before the treatment was administered, they are unaffected by the intervention and serve as a valid moderator in our analysis. The model is specified as follows:

$$EmissionChange_i = \alpha + \gamma Treat_i + \theta ClimateWorrier_i + \mu ClimateWorrier_i * Treat_i + \boldsymbol{X_i} + \varepsilon_i \qquad (Eq. 2)$$

where $ClimateWorrier_i$ is an indicator variable equal to 1 if respondent i is classified as "alarmed" and "concerned" about climate change, based on the SASSY! Segment, and 0 otherwise ("cautious", "disengaged", "doubtful", and "dismissive").[5] The coefficient on the interaction of climate attitude and the information treatment, μ, therefore quantifies the extent to which treatment effects vary based on respondents' pre-treatment attitude about climate change, providing evidence on the presence and magnitude of a polarization effect.

4. Results

4.1 Average Treatment Effects and Polarized Treatment Effects by Climate Attitude

In this section, we present results on the effects of receiving any carbon foodprint information on changes in food-related carbon emissions and explores whether these effects differ by respondents' climate attitudes. Table 3 reports estimates from Equations (1) and (2), respectively, where the treatment $Treat_i$ is defined as a dummy indicator equal to 1 if respondent i received any type of information treatment, regardless of format.

Column (1) reports the average treatment effect. The significantly negative coefficient indicates that, on average, respondents who received carbon emission information reduced their projected future carbon emissions by 1.451 kg/week compared to those in the control group (t = -1.994, $p < 0.10$). Column (2) incorporates the interaction between treatment status and climate

[5] As a robustness check, we redefine climate worriers to include individuals classified as "alarmed," "concerned," and "cautious." The results remain qualitatively unchanged under this alternative classification. We discuss this in the Result section.

attitudes to test for heterogeneous effects. The interaction term is negative and significant (-3.980 kg/week, t = -2.540, p < 0.05), indicating that treatment effects differ by respondents' prior belief about climate change. Specifically, climate worriers, defined as those classified as "alarmed" or "concerned", lowers their emissions by 3.047 kg/week (t = -3.174, p < 0.01),[6] while non-climate worriers exhibit no significant change. Among this latter group, the effect is directionally positive, suggesting a 0.933 kg/week increase in emissions, though this estimate is not statistically significant (t = 1.232, p > 0.10).

As a robustness check, we adopt an alternative definition of climate worriers by expanding the group to include individuals categorized as "alarmed," "concerned," and "cautious." The results remain qualitatively consistent under this alternative definition. In fact, the polarization effect becomes more pronounced: following the information treatment, climate worriers significantly reduce their projected emissions (-2.836, t = -3.590, p < 0.01), whereas the projected emissions on average show a statistically significant increase among non-worriers (3.652, t = 1.896, p < 0.10).

[Table 3]

These findings confirm the presence of a statistically significantly heterogeneous treatment effect. The contrasting responses between climate worriers and non-worriers, namely, reductions versus increases in emissions, suggesting a polarization effect. The overall reduction in emissions is primarily driven by individuals who are already concerned about climate change.

Figure 1 plots the past and future carbon foodprint by climate attitude and treatment status. Across all respondents, emissions generally decline over time. However, the steeper slope

[6] The reported estimate of the treatment effect for climate worriers ($\gamma + \mu$), along with its statistical significance, is obtained by estimating the full marginal effects model, which directly recovers the treatment effect for this subgroup.

for climate worriers in the treatment group shows that the change in their behavioral response is much more noticeable, while the slope for non-worriers remains flatter.

[Figure 1]

4.2 Heterogeneous Treatment Effects by Information Format

Next, we assess whether the effectiveness of information varies by how the carbon foodprint is presented. We hypothesize that differences in framing and format may influence future food choices by shaping how information is processed and interpreted. Identifying such differences can provide important insight into the design and implementation of more effective policies tools aimed at reducing carbon emissions. Our experimental design enables comparisons across several treatment variations: 1) Receiving a single average carbon foodprint from one study versus two separate averages from two different studies, 2) The order in which averages from the two studies are presented,[7] 3) Point estimates versus emission ranges, and 4) Inclusion versus omission of emission rank information. Appendix Table A2 presents linear hypothesis tests comparing these subgroups. Across all four comparisons, we find no statistically significant differences in effects between subgroups. As a result, we aggregate the subgroups into broader treatment categories, as defined in Table 1.

Table 4 reports the estimated treatment effects by format. Column (1) presents the average effects across the full sample. Two formats stand out as particularly effective: presenting only the emission rank of foods and providing a single average carbon foodprint. These treatments reduce weekly carbon foodprint by 2.970 kg and 2.390 kg, respectively. The ranking format appears especially effective by offering participants clear, actionable guidance on which

[7] The carbon foodprint calculated based on study 1 are generally higher than those derived from study 2.

foods to consume less frequently, reducing ambiguity and cognitive burden. Similarly, the simplicity of a single-source average may make it easier to interpret the information, compared to more complex or conflicting information. Overall, these findings suggest that simpler, less complicated information may facilitate greater behavior change. However, most treatment formats do not produce statistically significant reductions in emissions when averaged across all participants, consistent with prior findings that information-based interventions often have limited behavioral impact (Long et al., 2023; Mertens et al., 2022; Sunstein, 2015).

Columns (2) and (3) of Table 4 disaggregate results by climate attitude, presenting estimates separately for climate worriers and non-climate worriers. This breakdown reveals substantial heterogeneity in treatment effects. While many of the average treatment effects reported in column (1) are not statistically significant across the full sample, disaggregated results show that nearly all treatments significantly reduce future carbon foodprint among climate worriers. In contrast, non-climate worriers do not exhibit statistically significant responses to any of the treatments. For example, the "Rank Only" treatment reduces emissions by 3.880 kg/week among climate worriers, while non-worriers show no meaningful response. This pattern of divergence is consistent across nearly all other treatment formats.

[Table 4]

Taken together, these findings demonstrate that polarization exists across treatment formats. The behavioral changes among climate worriers are offset by the lack of response among non-worriers. As a result, some treatments show little or no effect on average, despite being highly effective for a particular subgroup. This suggests that individuals process new information in a self-serving manner, readily accepting reaffirming evidence while critically scrutinizing disconfirming evidence, a pattern consistent with theories of motivated reasoning

(Epley & Gilovich, 2016). This divergence in responses also suggests that ignoring subgroup differences may lead to misleading conclusions about the overall effectiveness of information interventions.

4.3 Mechanisms

Our main findings show that providing carbon foodprint information leads to a reduction in future carbon emissions on average. However, this overall effect masks substantial variation across climate attitudes. Non-worriers, those who are less concerned about climate change, exhibit no statistically significant change (though the effect is directionally negative), whereas climate worriers exhibit significant reductions in future carbon foodprint. While our experiment is not designed to causally identify mechanisms, we provide suggestive evidence that these divergent responses are driven by differences in how the information is internalized, differences that appear closely linked to individuals' pre-existing climate attitudes and their level of trust in the presented information.

Polarized Internalization of Information

Motivated reasoning theory (Druckman & McGrath, 2019; Epley & Gilovich, 2016; Kashner & Stalinski, 2024) suggests that individuals interpret new information in ways that conform to their pre-existing beliefs and experiences to avoid cognitive dissonance (Birch, 2020; Kashner & Stalinski, 2024). Our findings are consistent with this framework: climate worriers appear more receptive to the carbon foodprint information and adjust their behavior accordingly. Non-worriers, on the other hand, appear to discount or dismiss the same information and exhibit no change in their food choices.

To assess whether and to what extent participants internalized the information, we asked them to provide their self-assessed weekly carbon foodprint after receiving the treatment. These self-assessments provide insight into whether participants accepted and incorporated information into their beliefs. Figure 2 graphically presents the average self-assessed emissions by treatment groups and climate attitudes.[8] Note that participants in the control group and the "Rank Only" treatment group, a total of 191 individuals, did not receive carbon foodprint information and are therefore excluded from the analysis in this section. The figure clearly shows that, on average, self-assessed emissions are about 30% lower among non-climate worriers compared to worriers across all treatments. A one-tailed Wilcoxon signed-rank test confirms the distributions differ significantly ($W = 99{,}277$, $p < 0.001$).

To rule out the possibility that this discrepancy is not simply due to differences in actual food choices and the associated carbon emissions, we compare the actual emissions between the two groups. The Wilcoxon signed-rank test reveals no statistically significant difference in actual emissions ($W = 138{,}855$, $p = 0.2205$), implying that both groups' food choices produced comparable emissions. The lower self-assessed emissions among non-worriers, therefore, suggest that they internalized the information to a lesser extent than climate worriers, or they appear to have rejected or discounted the carbon foodprint information.

[Figure 2]

Figure 3 provides additional evidence by showing the unconditional means of the difference between self-assessed and displayed emissions across treatments and climate attitude.

[8] As shown in Table 1, individuals in some sub-groups receive the emission rank information. The rank information was displayed only after participants provided their self-assessed carbon foodprint. Therefore, whether receiving the rank information or not does not affect the self-assessed emissions. Therefore, the subgroups that receive rank information are aggregated with the sub-group without rank information. This leaves us with three treatment groups: one mean, two means, and range.

These results reinforce the earlier finding: Climate worriers' self-assessments are generally close to the values shown during the treatment, while non-worriers consistently report values well below the displayed information. Moreover, when presented with a range, climate worriers' self-assessed emissions are, on average, near the midpoint, whereas non-worriers are well below the midpoint and skew toward the lower end.

These patterns indicate that participants' responses to carbon foodprint information are shaped not just by the content of the information, but by how much of it they accept and integrate. Climate worriers appear to treat the information as credible and relevant, resulting in more accurate self-assessments and stronger behavioral responses. Non-worriers, by contrast, appear to discount or disregard the information, leading to underestimation and limited behavioral change. This variation in internalization is a key driver of the observed polarization in outcomes.

[Figure 3]

Trust as a Mediator

A substantial body of research has shown that trust in scientific or environmental information is shaped by their prior attitudes toward the issue at hand (e.g., Dries et al., 2025; Metzger et al., 2020). In our context, we hypothesize that trust acts as a mediating variable linking climate attitudes to how participants internalize the carbon foodprint information they receive. To measure this, participants in the treatment groups reported how much they trusted the carbon foodprint information, using a slider scale ranging from 0% ("not at all") to 100% ("a great deal"). As shown in Figure 4, across all treatments, climate worriers consistently express higher trust, averaging 50–59%, while non-worriers reported substantially lower trust, in the range of 30–37%. A Wilcoxon signed-rank test confirms this gap is statistically significant (W = 82,224, $p < 0.001$).

[Figure 4]

To formally test whether climate attitudes are associated with trust, we estimate the following regression model:

$$Trust_i = \alpha_0 + \alpha_1 ClimateWorrier_i + \alpha_2 \boldsymbol{X_i} + \varepsilon_i, \qquad (Eq. 3)$$

where $Trust_i$ measures the reported level of trust individual i has in the displayed foodprint information, ranging from 0% to 100%. $ClimateAttitude_i$ measures respondent i's climate attitude, ranging from 1 ("dismissive") to 5 ("alarmed") based on the SASSY! climate attitude survey, and $\boldsymbol{X_i}$ is a vector of individual-level controls, including age, gender, education, income, political beliefs, and trust in science.

Results presented in Table 5 support our hypothesis. After controlling for demographics, we find that climate attitude is significantly and positively associated with trust in the presented information. Additionally, younger respondents tend to report higher trust levels, while none of the other individual-level controls are statistically significant. These findings are in line with a large literature showing that trust in science and environmental data is shaped by pre-existing beliefs (Hornsey et al., 2016; Gao et al., 2022).

[Table 5]

We next test whether trust mediates the relationship between climate attitudes and how information is internalized. Our model is specified as follows

$$AssessedAbove_i = \beta_0 + \beta_1 ClimateAttitude_i + \beta_2 Trust_i + \beta_3 \boldsymbol{X_i} + \varepsilon_i \qquad (Eq. 4)$$

Here, the dependent variable $AssessedAbove_i$ is a binary indicator equal to 1 if respondent i's self-assessed carbon foodprint is greater than or equal to the displayed value, and 0 otherwise.

This serves as a proxy of whether the participant internalized and accepted the information. In the sample, 735 participants (71.4%) reported self-assessed emissions below the displayed value, while 294 participants (28.6%) reported values at or above it.

We interpret this model by comparing two specifications to decompose the effect of climate attitude. If we omit $Trust_i$ from Equation (4) , the coefficient on $ClimateAttitude_i$ would capture the *total effect* of climate attitudes, this includes both the direct effect of climate attitude on information internalization and the indirect effect mediated through trust. By including $Trust_i$, we are able to decompose this total effect into direct and indirect effect: β_1 now represents the direct effect, whereas β_2 captures the indirect effect channeled through trust. A significant estimate of β_2 would suggest that trust is a key channel through which prior climate attitudes shape to what extent the presented information is internalized. We include the same set of individual-level controls as in Equation (3), and ε_i is the error term.

Table 6 presents the estimation results. Column (1) reports the specification without controlling for $Trust_i$, identifying the total effect of climate attitude on the probability that a respondent reports a self-assessed carbon foodprint greater than or equal to the displayed value. Column (2) adds $Trust_i$, allowing us to isolate the indirect effect from the total effect. To interpret the magnitude of the total effect of climate attitude, as shown in column (1), a one-unit increase in climate attitude score boosts the likelihood of internalizing the carbon foodprint information (i.e., reporting emissions at or above the displayed value) by 5 percentage points. When $Trust_i$ is included, the coefficient on climate attitude decreases but remains positive and statistically significant, suggesting a persistent direct effect. The coefficient on $Trust_i$ is also positive and highly significant, confirming its role as a mediating channel. That is, individuals who are more concerned about climate change are more likely to trust the information, and this trust is in turn associated with greater internalization of the carbon foodprint data.

[Table 6]

To assess the relative magnitude of the direct and indirect pathways, we follow Kim & Long (2024) and calculate the proportion of the total effect that is mediated by trust using the following formula:

$$\Phi \equiv \frac{\Delta ClimateAttitude \times \alpha_1 \times \beta_2}{\Delta ClimateAttitude \times \widetilde{\beta_1}} \qquad (Eq. 5)$$

Here, $\widetilde{\beta_1}$ is the coefficient of $ClimateAttitude_i$ from the model without trust (i.e., column (1) of Table 6), which reflects the total effect. The denominator thus reflects the expected change in the likelihood that a participant reports self-assessed emissions equal to or above the presented value, associated with a one-unit change in climate attitude. The numerator represents the indirect effect via trust, where α_1 is the effect of climate attitude on trust (from Table 5), and β_2 captures the effect of trust on the internalization of information (from column (2) of Table 6). Since $\Delta ClimateAttitude$ appears in both the numerator and denominator, it cancels out, making the ratio independent of its scale, though this simplification only holds when effects are assumed to be homogeneous.

Using our estimates (α_1 from Table 5, $\widetilde{\beta_1}$ from Table 6 column (1), and β_2 from Table 6 column (2)), we calculate $\Phi = 0.53$. This indicates that 53% of the total effect of climate attitude on information internalization is mediated through trust in the presented information, while the remaining 47% reflects a direct effect.[9] This decomposition reinforces the mechanism we

[9] An alternative way to express the proportion of the total effect is mediated by trust is to use the direct effect estimate from Equation (4). In this specification, where $\Delta Trust$ is included, the direct effect of climate attitude is captured by β_1. The total effect can then be defined as: $\Delta Climate\ Attitude \times (\alpha_1\beta_2 + \beta_1)$. Accordingly, the proportion of the total effect that is attributable to the indirect pathway through trust is: $\alpha_1\beta_2/(\alpha_1\beta_2 + \beta_1)$. From the

propose: individuals' climate attitudes shape their level of trust in the carbon foodprint information, which in turn influences how they internalize and act upon that information. Understanding this interplay between belief systems and trust is critical for designing effective climate communication strategies.

Conclusions

This study examines how direct and individualized carbon foodprint information influences stated future food choices and associated carbon emissions. Using an online experiment, we find that providing the emissions information can reduce projected food-related emissions on average. However, responses vary widely by participants' climate attitudes. Individuals more concerned about climate change are significantly more likely to internalize the information and adjust their future food choices, while those less concerned exhibit limited trust and little behavioral change. We show that these differences are driven both by a direct effect of climate attitudes and an indirect effect operating through trust in the information.

With growing concerns of the environmental impacts of dietary choices, particularly on climate change, carbon labeling is gaining growing and significant interest from policymakers, researchers, and the public. Pilot programs are currently being implemented in countries such as the United Kingdom, Switzerland, and Japan (Vandenbroele et al., 2020). Under this context, our findings carry important policy implications. our results suggest that one-size-fits-all information interventions may have uneven effects. To maximize impact, labeling strategies should consider how information is framed and whom it is targeting. Building trust, particularly among skeptical

same estimates applied in the earlier calculation of Φ, we find that this value to be approximately 0.58, which is consistent with our estimate of 0.53 in the main text.

groups, may be just as critical as improving informational content. Tailored communication and credible messengers may help increase the effectiveness of carbon labeling as a behavioral tool for climate mitigation.

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Table 1. Treatment Groups and Subgroups

Treatment Category	Treatment 1 One Mean	Treatment 2 Range	Treatment 3 Two Means	Treatment 4 Emission Ranking
Subgroup 1	Mean from Study 1	Range from Study 1	Mean from Study 1 then Study 2	Emission Rank Only
Subgroup 2	Mean from Study 1 & Emission Rank	Range from Study 1 & Emission Rank	Mean from Study 1 then Study 2 & Emission Rank	
Subgroup 3	Mean from Study 2	Range from Study 2	Mean from Study 2 then Study 1	
Subgroup 4	Mean from Study 2 & Emission Rank	Range from Study 2 & Emission Rank	Mean from Study 2 then Study 1 & Emission Rank	

***Notes*:** This table presents the treatment groups and sub-treatment groups. Each cell describes the specific format of carbon footprint information shown to participants, depending on their assigned group. Information formats include the mean, range, and rank of carbon emissions from one or two studies.

Table 2. Summary Statistics

Variable	Control (N=96)	Treated (N=1202)	Diff. in Means (SE)
Age	53.56 (17.34)	52.00 (16.44)	-1.56 (1.83)
Female	0.45 (0.50)	0.51 (0.50)	0.05 (0.05)
Asian	0.05 (0.23)	0.07 (0.25)	0.02 (0.02)
Black	0.17 (0.38)	0.12 (0.32)	-0.05 (0.04)
White	0.62 (0.49)	0.65 (0.48)	0.03 (0.05)
Other	0.16 (0.36)	0.16 (0.37)	0.00 (0.04)
Low Income (<$40k)	0.36 (0.48)	0.23 (0.42)	-0.13** (0.05)
Mid Income ($40k - $99,999)	0.38 (0.49)	0.48 (0.50)	0.10* (0.05)
High Income (>$100k)	0.26 (0.44)	0.29 (0.45)	0.02 (0.05)
Conservative	0.30 (0.46)	0.25 (0.43)	-0.05 (0.05)
Liberal	0.25 (0.44)	0.26 (0.44)	0.01 (0.05)
High Education (4-year college or higher)	0.54 (0.50)	0.55 (0.50)	0.01 (0.05)
Trust Science Index	10.99 (2.65)	10.88 (2.52)	-0.11 (0.28)
Climate Attitude Score	4.41 (1.74)	4.47 (1.64)	0.06 (0.18)

Notes: This table presents the summary statistics of respondent characteristics by treatment status. Standard deviations and standard error are in parentheses. *P*-values and significance levels are based on differences in means, using Welch's *t*-test. The Trust Science Index is constructed based on responses to three 5-point Likert questions, where respondents indicate their attitude toward science by selecting between options ranging from "strongly agree" to "strongly disagree". The three statements are: 1. "Information provided by scientific research is very important in guiding our daily life decisions." 2. "My daily life decisions are informed by scientific research." 3. "I don't understand the point of all the scientific research being done today." The climate Attitude Score is measured by the SASSY! Segment, ranging from 1 to 6, representing "doubtful", "dismissive", "disengaged", "concerned", "cautious", and "alarmed". No participants in our sample fell into the "disengaged" category. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Average and Heterogeneous Effect of Receiving a Treatment on Changes in Carbon Foodprint

	Receive Any Treatment	
	(1)	(2)
Average treatment effect (β, Eq. 1)	−1.451*	
	(0.763)	
Effect on non-climate worriers		0.933
(γ, Eq. 2)		(1.232)
Effect on climate-worriers		−3.047***
($\gamma + \mu$, Eq. 2)		(0.960)
Polarization effect: Difference between		−3.980**
worriers and non-worriers (μ, Eq. 2)		(1.567)
Constant	−3.019**	−4.003**
	(1.514)	(1.909)
Demographics Controls	Yes	Yes
Observations	1,148	1,148
Adjusted R-squared	0.010	0.015

***Notes*:** Dependent variable in Columns (1) and (2) is the change in carbon foodprint, calculated as the difference between future and past carbon foodprint. Column (1) represents estimates from estimating Equation (1), while Column (2) represents estimates from estimating Equation (2). The treatment indicator in these specifications is a dummy variable indicating if a respondent has received any information treatment. Robust standard errors are reported in parentheses. Individual demographics include age, White, female, income, education, and political affiliation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Effects of Information Treatment Formats on Changes in Carbon Foodprint: Average and by Climate Attitude

	(1)	(2) Non-Climate Worriers	(3) Climate Worriers
One Mean + Rank	-1.153 (1.108)	0.860 (1.528)	-2.541* (1.535)
Two Means + Rank	-0.757 (1.118)	2.631 (1.679)	-3.068** (1.476)
Range	-1.121 (1.030)	0.791 (1.524)	-2.411* (1.402)
Range + Rank	-1.873 (1.185)	1.137 (1.740)	-3.963** (1.594)
Rank Only	-2.970** (1.513)	-0.039 (1.903)	-3.880*** (1.484)
One Mean	-2.390** (1.187)	-1.344 (1.944)	-4.043* (2.130)
Two Means	-0.633 (1.064)	1.181 (1.558)	-1.833 (1.438)
Constant	−2.901*(1.512)	−3.885** (1.895)	
Observations	1,148	1,148	
Adjusted R-squared	0.009	0.010	

***Notes*:** Dependent variable in all columns are the change in carbon foodprint, calculated as the difference between future and past carbon foodprint. Column (1) reports estimates from Equation (1). Columns (2) and (3) present results from Equation (2), where average effects are shown separately for non-climate worriers and climate-worriers. $Treat_i$ in both equations is defined as a categorical variable representing if a respondent has received a specific type of information treatment, as described in the experimental design section and detailed in Table 1. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Determinants of Trust in Carbon Foodprint Information.

	Coefficient
Climate Attitude	6.623***
	(0.589)
Age	-0.270***
	(0.055)
Constant	25.057***
	(4.490)
Additional Demographic Controls	Yes
N	1148
R2 Adj.	0.092

Notes: This table presents the correlation between climate attitude and subjects' trust in presented carbon emission information. Trust in carbon foodprint information, ranging from 0% to 100%, is the dependent variable. Climate Attitude is measured by SASSY! climate attitude survey, ranging from 1 ("dismissive") to 5 ("alarmed"). Additional demographic controls include race, gender, income, education, political inclination, and trust in science. Robust standard errors are presented in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6. Determinants of the gap between self-assessed and actual emissions

	(1)	(2)
Climate Attitude	0.050***	0.019**
	(0.008)	(0.009)
Trust		0.004***
		(0.001)
Constant	0.107	-0.020
	(0.074)	(0.073)
Demographic Controls	Yes	Yes
N	966	966
R2 Adj.	0.033	0.080

Notes: The reported level of trust for the presented information is the dependent variable. Climate attitude is defined by the segments is the SASSY! climate attitude survey, ranging from ranging from 1 (“dismissive”) to 5 (“alarmed”). Robust standard errors are presented in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

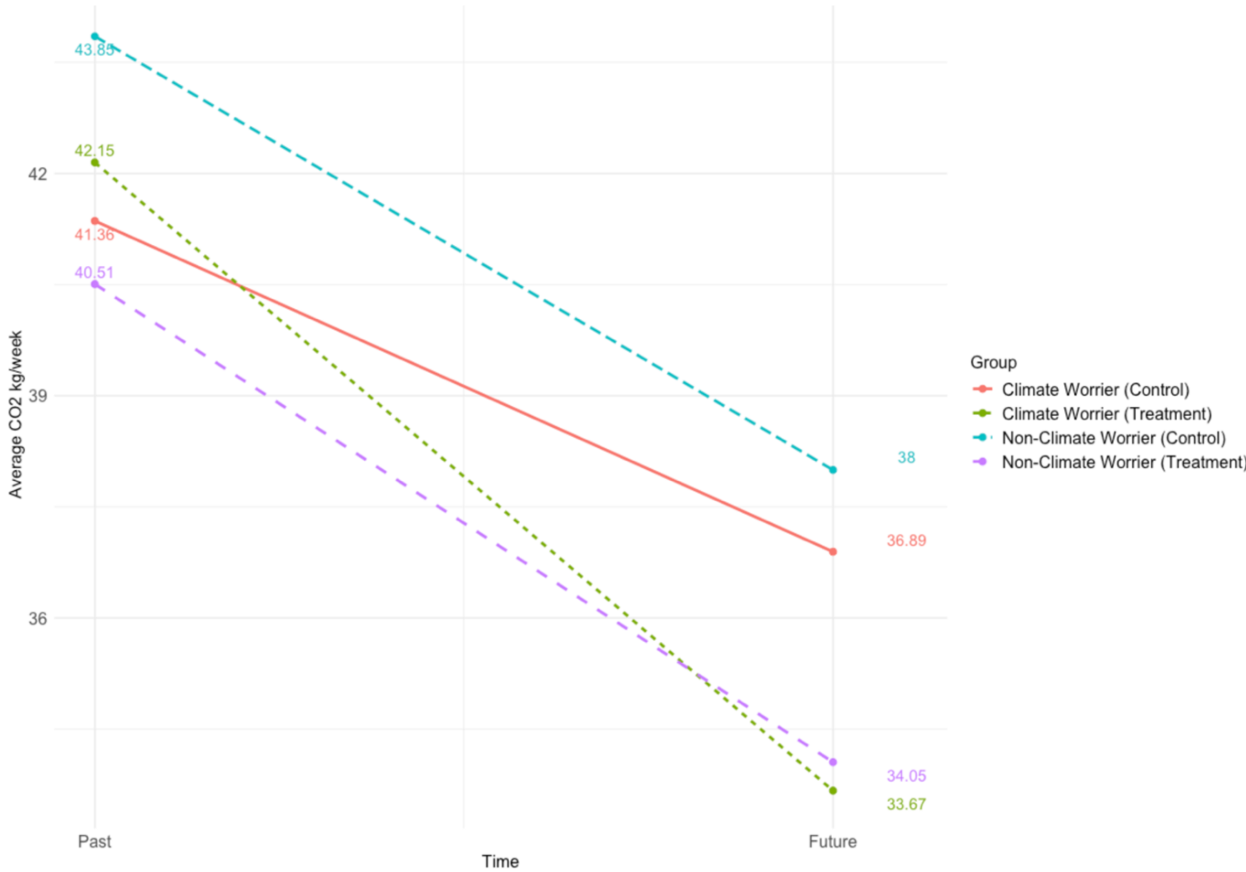

Figure 1. Past and Future Carbon Footprints Across Treatment Groups and Climate Attitude Combinations

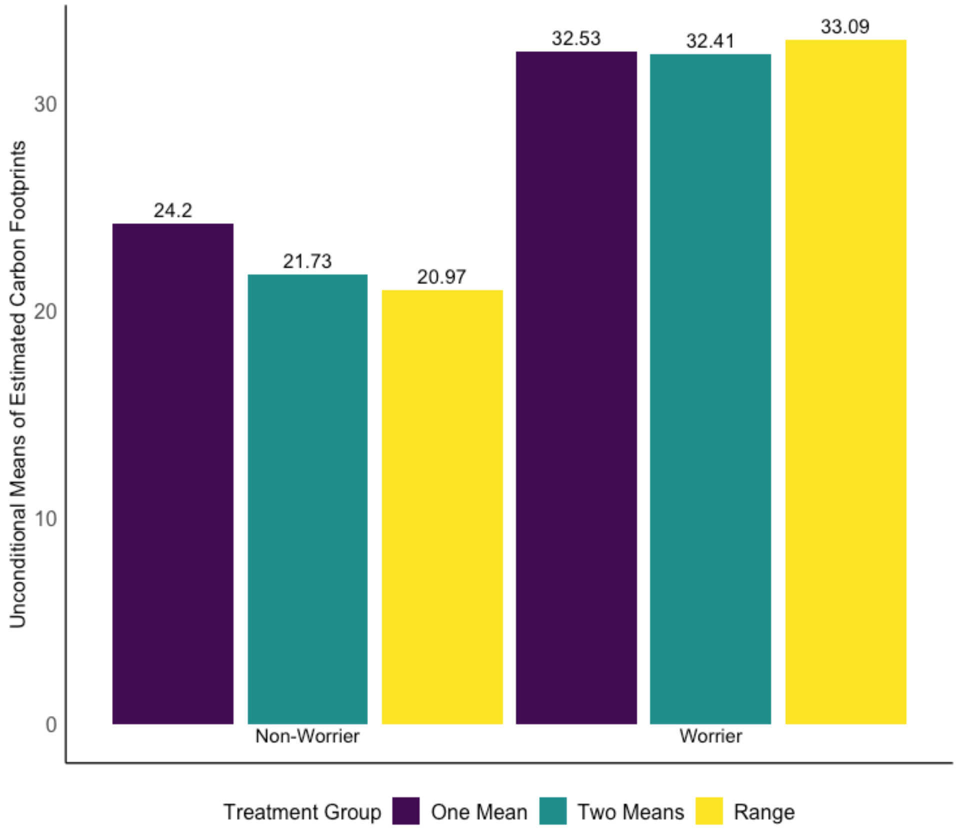

Figure 2. Unconditional Means of Estimated Carbon Foodprint Across Treatment Groups and Climate Attitude Combinations

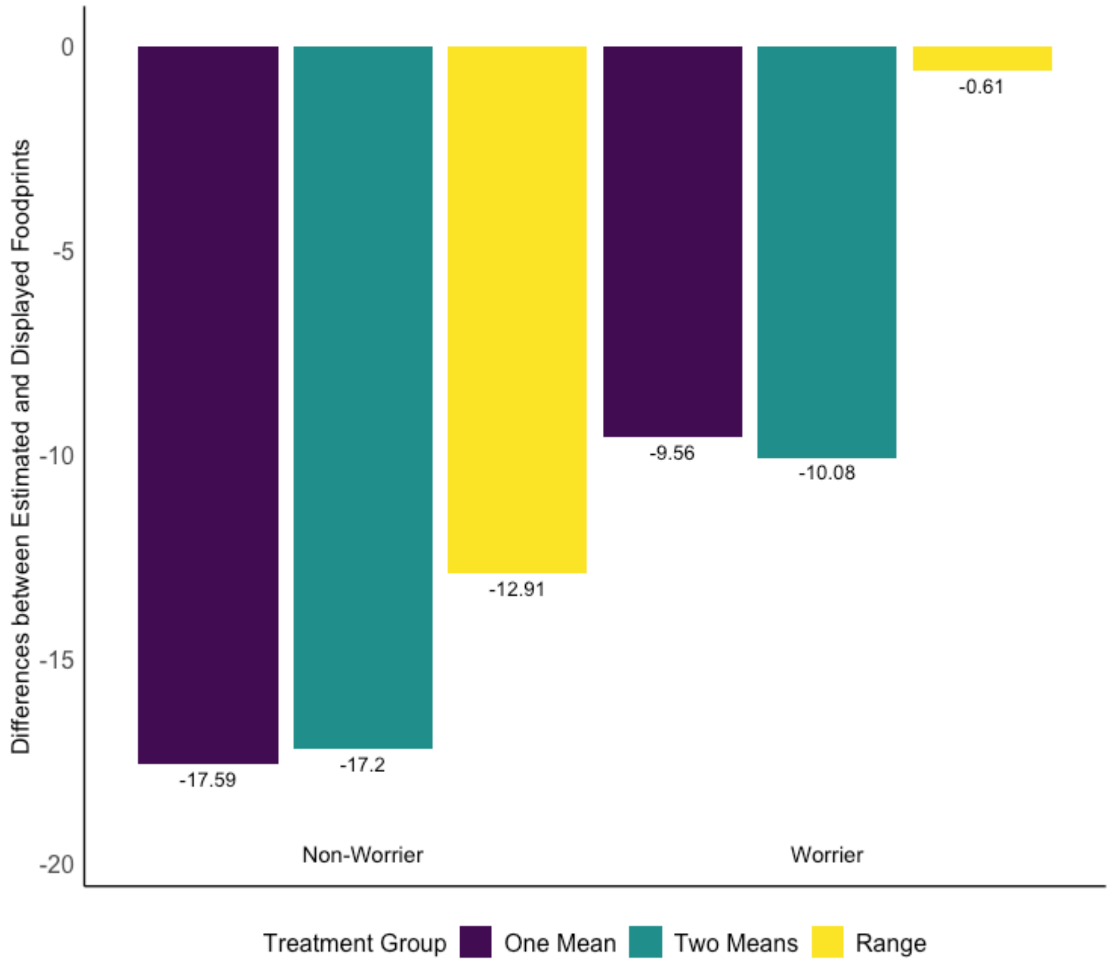

Figure 3. Unconditional Means of Differences between Estimated and Displayed Carbon Foodprint Across Treatment Groups and Climate Attitude Combinations

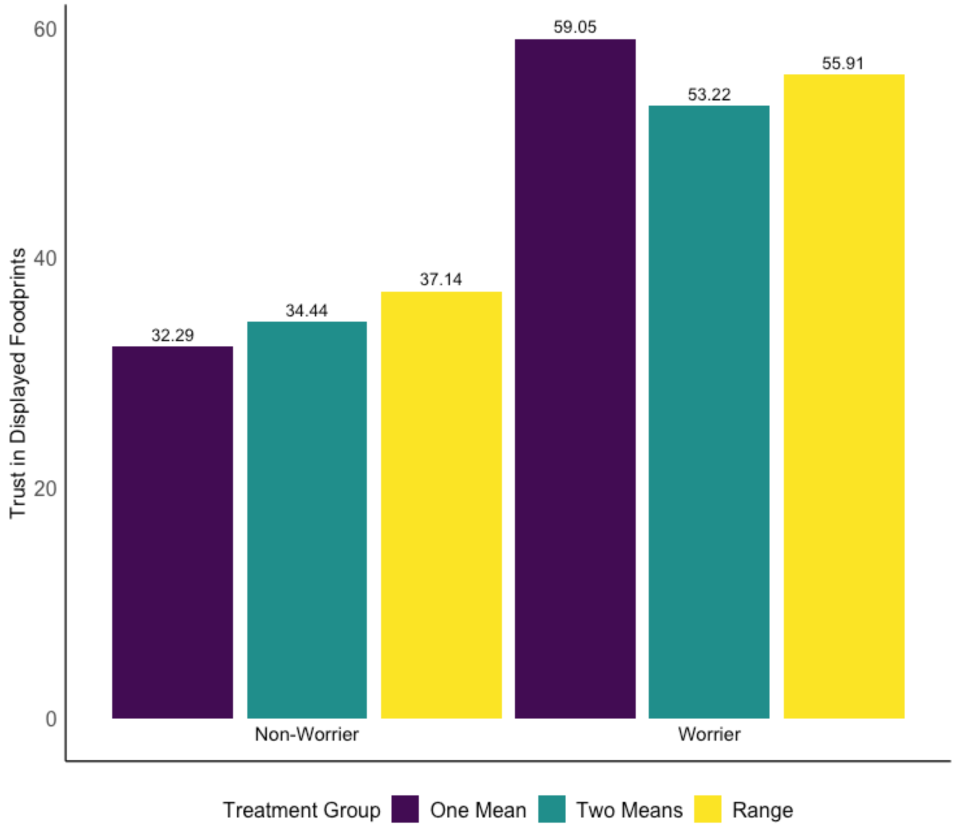

Figure 4. Unconditional Means of Trust in Displayed Carbon Foodprint Across Treatment Groups and Climate Attitude Combinations