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Correcting Consumer Misperceptions about CO_2 Emissions

Abstract

Policy makers put great emphasis on the role of information about carbon emissions in achieving sustainable decisions by consumers. We conduct two studies to understand the optimal targeting of such information and its effects. First, we conduct an incentivized and representative survey among US consumers (N = 1, 022) to investigate awareness of climate impact and willingness to mitigate it. We find a large variation in the perceptions of the carbon emissions of different consumption behaviors, with an overall tendency to underestimate these emissions. We also find a positive but highly concave willingness to mitigate climate impact. We combine elicited misperceptions and willingness to mitigate in a structural model that delivers sharp predictions about where to best target information campaigns. In an experiment with actual consumption decisions (N = 2, 081), we then test for the effect of CO2 information on the demand for beef, a product predicted to be a productive target for information. Correcting misperceptions has no effect on the demand for beef, both in absolute terms and compared to a predictably less productive target of information, i.e. the demand for poultry. Our dataset allows us to hone in on the underlying reason for this null effect.

JEL-Codes: C810, C930, D840, Q540.

Keywords: climate change, carbon emissions, information provision, consumer behavior.

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1 Introduction

Reducing or reversing the emission of greenhouse gases is one of the most pressing challenges of our time. Unfortunately, some straightforward remedies like carbon pricing, are politically contentious. Instead, policy makers frequently stress the role of information to consumers and producers. For instance, the European Commission's "Farm to Fork Strategy," proposes an extensive carbon labeling strategy, while its "New Consumer Agenda" argues for "more reliable information on sustainability" (European Commission, 2020). In the US, the proposed (but ill-fated) American Clean Energy and Security Act of 2009 contained provisions to study and implement consumer carbon labels, while the Department of Agriculture and regulatory agencies like the EPA implement greenhouse gas labels for cars, beef, and other products. There is also a corporate interest in carbon labeling, as evidenced by carbon-labeling initiatives from several large European retail chains like TESCO, Casino, and E.Leclerc (Taufique et al., 2022).

In tandem with policy makers' enthusiasm about such information strategies, social scientists have been trying to understand their impact on consumer perceptions and behavior. Recent evidence indicates that consumers underestimate the carbon impact of various actions and products. In addition, a growing number of studies investigate the effect of carbon information labels in specific settings, like university canteens. These experiments, which we detail in the next section, typically show a small but discernible effect of carbon labels on emissions from food choices.

However, current research leaves open many important questions about the effects of information provision. For instance, it is not clear if information effects obtain in a more representative sample outside of a specific retail or university setting, or which products or actions policy makers should target for maximum effectiveness. We also know very little about the channels by which information transmission works. Current interventions are based on the application of carbon labels that provide information about impact, but also raise the salience of social norms about climate change, so the pure effect of changes in beliefs remains unclear.

In this paper, we address these issues through the lens of a structural economic decision making framework and an experiment involving real consumption choices. Our first objective is to improve the targeting information about CO_2 impact across products and people. To this end, we elicit existing beliefs and attitudes from a representative sample of US consumers ($N = 1,022$). In particular, we use incentive-compatible elicitation techniques to measure consumer beliefs about the climate impact of a number of products and actions. We elicit both point beliefs and belief distributions to capture consumer uncertainty about the impact. We then measure valuations of carbon emissions for the same consumers, using a willingness to pay for different amounts of carbon offsets, thus producing a "willingness to mitigate" function.

The survey confirms that consumers generally underestimate carbon impact, al-

though there is a large variation both across people and product categories. We find the largest underestimates for high-carbon-impact food categories such as beef and coffee. Valuations of carbon emission reductions are positive and relatively high, but marginal valuations decline strongly, leading to a concave willingness to mitigate function.

To make predictions about the impact of correcting consumer beliefs we use a structural model in which we combine each individual's subjective belief distributions about the consumer products with their elicited willingness to mitigate. We compare this expected willingness to mitigate with a counterfactual where subjective beliefs have collapsed to the true beliefs about carbon emissions, as measured by the latest scientific estimates. The resulting statistic describes the effect of an information campaign aimed at a particular product as the dollar-tax equivalent of correcting beliefs. For example, informing our participants of the carbon impact of 100 grams of dark chocolate is equivalent to raising the price of chocolate by 4.5 dollars.

Our model has advantages over using only misperceptions to target information campaigns. First, the model controls for a possible mismatch between who is optimistic about the carbon impact of a given product and who cares to mitigate carbon emissions. For example, if only people with no willingness to mitigate carbon emissions are optimistic about the carbon footprint of flying, then an information campaign aimed at flying would be impotent. Conversely, targeting groups with a high willingness to pay is ineffective if these groups are already well-informed. Second, our model explicitly accounts for the interaction of the shape of the subjective belief distributions and the willingness to mitigate curve. For instance, it predicts that information is much more effective when it shifts beliefs along the steep part of the concave willingness to mitigate curve than along the flat part of the curve.

Next, we conduct an online experiment to test the impact of information provision on the demand for two meat products, beef and chicken. While these products are both parts of a more general food category (meat), beef has almost 10 times the carbon impact of poultry in CO_2 equivalents, mostly due to cow methane production and deforestation associated with the production of cattle feed. Our participants understand that beef is more polluting than poultry, but they think that the difference between them is much smaller than it actually is. In line with this, our structural model, applied to the representative survey data, predicts that while information on beef should have a large impact on demand, the impact on demand by providing information on chicken should be small or non-existent.

We recruited $N = 2,081$ subjects via an online platform and elicited their willingness to pay for a package of meat from a premium online butcher using incentive-compatible procedures. In four between-subject treatments, we varied the type of meat (beef vs. poultry) and whether we provide information about carbon emissions. All treatments feature prominent mentions of climate change impact. Unlike the introduction of climate change labels which mix information with increased salience about climate change, this

allows for the identification of the effect of information on behavior through its impact on beliefs.

Our intervention is successful in changing consumer perceptions related to the two products. However, we find no evidence that information is effective in changing the demand for either beef or chicken. This null result is true for all subgroups in our sample, and robust among those whose beliefs responded to the intervention. Moreover, we can rule out several explanations for the surprising null effect of information on beef consumption. It is not driven by the information making participants pessimistic about substitute products, by people not consuming much meat being the only ones with optimistic priors, by an overly noisy measure of demand, or by a non-replicable statistical fluke. We also rule out behavioral channels like an intention-action gap and are left to conclude that individuals' beef consumption simply does not seem to be subject to concerns about CO_2 emissions.

These results suggest that the current enthusiasm about labeling efforts should be tempered, as shifting beliefs may by itself not be effective in increasing voluntary mitigation. They also show the limits of standard economic decision making approaches to voluntary climate change mitigation. We find that economic primitives such as the valuation of carbon emissions and beliefs about their size, measured with state-of-the-art elicitation techniques from experimental economics, have little predictive power over consumer decisions in our experiment.

2 Literature Review

We elicit both beliefs about climate impact and their willingness to pay to offset it, combine these in a structural model and test the resulting predictions. To our knowledge, this is the first paper to take such an integrative approach. However, previous literature has investigated individual aspects of this exercise, namely the elicitation of beliefs about specific climate impacts, the elicitation of WTP to offset carbon emissions, and general tests of the impact of information about carbon emissions. We discuss these literatures in turn and highlight our contributions.

2.1 Eliciting Beliefs about Climate Impact

Closest to our paper is Camilleri et al. (2019), who elicit perceptions of energy consumption and Greenhouse Gas (GHG) emissions associated with the production and transportation of food (e.g., lamb, beef, rice, beans, tomato, orange) as well as the use of several electric appliances. Following the methodology in Attari et al. (2010), participants received information relative to the emissions of an incandescent lightbulb. Participants showed a substantial underestimation of GHG emissions both in the domain of electric appliances and in the food domain. This confirms results in Attari et al.

(2010), who elicited perceptions about energy use, where participants underestimated energy use and savings by a factor of 2.8 on average.[1]

Another strand of the literature has elicited broader knowledge of the climate change phenomenon and linked it to measures of concern and policy support (Tobler, Visschers and Siegrist, 2012; Klenert et al., 2018; Dechezleprêtre et al., 2022; Fairbrother, 2022). For instance, Shi et al. (2016) find that knowledge about the causes or consequences of climate change, but not knowledge about the physical aspects of climate change (e.g., that it is caused by greenhouse gasses), is associated with more concern about the phenomenon.

Our study confirms the result in Camilleri et al. (2019) that consumers underestimate carbon impact. However, unlike Camilleri et al. (2019), we do not find that correction of such underestimation translates into changes in behavior.

2.2 Willingness to Pay

There is a large literature on willingness to pay to reduce climate impact, often using unincentivized surveys and contingent valuation methods. A review by Nemet and Johnson (2010) finds a stated WTP between $22 and $437 per household annually. This wide range is echoed by literature on willingness to pay to reduce emissions from specific sources like car transport (Hulshof and Mulder, 2020) or flights (Bernard, Tzamourani and Weber, 2022), and may be partially explained by the hypothetical nature of the questions (see also Streimikiene et al. (2019) for an overview of methods). Several recent studies use incentivized revealed preference techniques to elicit WTP. Löschel, Sturm and Vogt (2013) find an average WTP to buy emissions offsets for one ton of CO_2 of 12€. Diederich and Goeschl (2014) find a mean of 6.30€. Both of these studies elicit the WTP to offset a single CO_2 amount.

Andre et al. (2021) look at the willingness to donate to fight climate change by asking subjects to divide $450 between themselves and an organization that fights climate change. They investigate the role of social preferences and perceptions of social norms and find that correcting underestimations about the willingness of other people to combat global warming raises donations to charity.

The novelty of our study is to elicit WTP for a range of emission sizes, using incentivized elicitation techniques, and find that CO_2 emissions are increasing but not very responsive to the size of the emissions. This finding mirrors results in Pace and van der Weele (2020), by a subset of the co-authors, which uses slightly different elicitation methods and a non-representative sample. Similar concavity in WTP has been found in other prosocial decisions, like the number of beneficiaries of a costly prosocial action

[1]Results about the absolute values of estimations have been shown to be sensitive to the numeric referent used to elicit beliefs (Frederick, Meyer and Mochon, 2011), although the rankings of different products are largely preserved.

(Schumacher et al., 2017) or the number of measles vaccinations (Ziegler, Romagnoli and Offerman, 2020).

2.3 Information Provision and Labeling

A rapidly increasing number of studies test the effects of emission information on consumer behavior. Most of these studies focus on climate labels, that code high and low impact in an easily digestible way. The literature on labeling is large and summarized in Taufique et al. (2022), but most studies focus on hypothetical consumer choices, as opposed to actual ones. In the latter category, several studies have conducted interventions with labels in restaurants or university canteens, sometimes in combination with another information transmission like lectures, or posters (e.g., Spaargaren et al., 2013; Visschers and Siegrist, 2015; Brunner et al., 2018; Jalil, Tasoff and Bustamante, 2020; Soregaroli et al., 2021; Lohmann et al., 2022). Most of these studies find intervention effects of a few percentage points on emissions, but these effects tend to decrease over time.

Similarly, researchers have provided shoppers in (online) supermarkets with informative labels about specific products or shopping baskets (Vlaeminck, Jiang and Vranken, 2014; Elofsson et al., 2016; Perino, Panzone and Swanson, 2014; Kanay et al., 2021; Bilén, 2022), or informed them via a cell phone app (Fosgaard, Pizzo and Sadoff, 2021). In line with the restaurant studies, most of the papers find a small and short-lived effect of interventions on emission sizes. However, null results have been reported for specific products like detergents (Kortelainen, Raychaudhuri and Roussillon, 2016).

Dechezleprêtre et al. (2022) conduct a large multi-country survey of climate change beliefs, and find that information that simply providing information about the effects of climate change does not increase support for climate policy. However, targeted interventions to address concerns about the effectiveness or distributional impact of policies have a substantial effect.

Finally, some studies have looked specifically at meat consumption, which is the focus of our experiment in Section 5. Carlsson, Kataria and Lampi (2022) finds substantial resistance to switching away from meat among Swedish consumers. A review by Bianchi et al. (2018) finds that information can affect intentions but laments a lack of evidence on actual consumption. Jalil, Tasoff and Bustamante (2020) show that a 50-minute lecture on meat consumption reduces purchases of the meat-based meal at the university canteen by 4.6 percentage points, although the effect declines over time. Camilleri et al. (2019) conducts an experiment where participants were asked to purchase a can of soup. Participants were less likely to buy high-impact beef soup when a GHG impact label was present, and an increase in knowledge mediated the effect. Bilén (2022) finds that when carbon labels are introduced in a supermarket, customers reduce their purchases of beef.

While these results are encouraging, these studies leave open the possibility that the effect of the intervention stems in part from increasing the salience of climate change, a change in the perceived social norms, or even the outcome of discussions or conversations among consumers, something we can rule out in our study. Our study also considers a representative sample of US consumers, whereas most previous studies consider student populations. In addition, our study features a random assignment of treatments, whereas some labeling studies document sorting of consumers in and out of treated stores (Bilén, 2022).

2.4 Structural Modeling

A small number of studies use structural models to evaluate the welfare impact of information and price interventions. Lanz et al. (2018) use a structural model to quantify the welfare effects of different pricing and tax policies, based on data from a field experiment in Perino, Panzone and Swanson (2014). Rodemeier and Löschel (2020) assess the welfare effects of information and taxes in the context of a structural model. In a field experiment, they find that consumers overestimate energy savings and that full information disclosure, therefore, reduces demand for energy saving and decreases welfare. Finally, Espinosa and Stoop (2021) also present a framework to evaluate the impact of information campaigns, based on seven belief types, including those who are resistant to information.

These approaches collect data on consumption and consumer beliefs, and use them to infer consumer preferences and welfare impact. By contrast, since we collect data on both the input (preferences, beliefs) and the output (consumption choices) of the decision process, we can test a basic economic model of voluntary climate mitigation.

3 Climate Survey

Our initial survey measures consumers' existing beliefs about CO_2 emissions generated in the production of common consumer goods, as well as their willingness to pay (WTP) to avoid CO_2 emissions. These quantities subsequently serve as inputs for a structural model that allows us to make predictions about the provision of information, as we explain in Section 4. Figure 1 shows the four tasks that constitute the survey. The first task asked general questions about climate change facts and the social cost of carbon. The next two tasks focused on eliciting beliefs, where we collect both point beliefs and belief distributions of CO_2 emissions from several common consumer products and activities. The last task elicited willingness to pay for mitigating CO_2 emissions.[2] After

[2]The survey had one additional part that we analyze in a separate paper. At the end of the survey, we provided subjects with information about the actual impact of a subset of the product list (three or six randomly selected products). We then re-invited the subjects two weeks later to test their

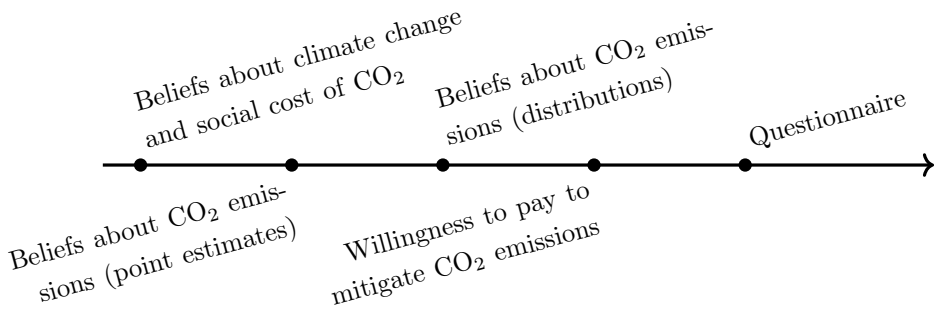

Figure 1: Timeline of the climate survey.

participants completed all four tasks, we asked them about their demographics and revisited the products and activities from tasks two and three to ask them about their consumption frequency in these categories.

Our elicitation methods used incentive-compatible payment schemes developed in the experimental economics literature, while keeping the instructions and the interface as simple and participant-friendly as possible to allow for a representative sample to take part. Below we elaborate on each of the elicitation procedures in more detail. Online Appendix A.1.2 contains additional information about the steps we took to maximize the data quality.

Belief elicitation

At the start of the survey, we elicited participants' beliefs about the CO_2 emissions generated by driving one mile by car. We then elicited beliefs about 12 common consumer products and activities listed in Table 1. We included food items, the use of household appliances, and transportation. We provided participants with information about the product specification and the type of emissions we considered. Table 1 presents the scientific estimates we used to incentivize the guesses together with their source.[3] We took these estimates from top-tier academic journals or from the estimates the UK government uses for its environmental regulations. We disclose these scientific sources only at the end of the experiment.

To make the answers more meaningful to subjects, we did not elicit emissions in grams, but asked about the number of miles by car one needs to drive to emit as much CO_2 as the product in question, an approach in line with previous studies (Camilleri et al., 2019). Since we also elicited the conversion from a mile driven by a car to grams of CO_2, we can convert all measures to the perceived grams equivalent (see Table A.3 and Figure A.6 in the Online Appendix). Moreover, the model we describe in Section 4 further mitigates any concern that systematic misperceptions about the CO_2

recollection of this information.

[3]Participants could learn the detail of what the scientific source took into account in calculating the size of CO_2 emissions. See Table A.1 in the Online Appendix.

Table 1: List of consumer products and actions.

		Emission size		
	Quantity	Estimate	Unit	Source
Beer	12 fl oz	1.46	mile	Poore and Nemecek (2018)
Phone call	1 hour	1.55	mile	Smith et al. (2013)
Microwave	1000W, 2 hour	1.76	mile	UK BEIS†
Milk	1 cup	2.60	mile	Poore and Nemecek (2018)
Egg	6 eggs	4.81	mile	Poore and Nemecek (2018)
Poultry meat	7 oz	6.78	mile	Poore and Nemecek (2018)
Shower	Average usage	3.90	mile	Hackett and Gray (2009)
Dark chocolate	100g	16.03	mile	Poore and Nemecek (2018)
Coffee beans	1 lb	44.41	mile	Poore and Nemecek (2018)
Beef	7 oz	68.39	mile	Poore and Nemecek (2018)
Flight	SFO to LAX	304.60	mile	UK BEIS†
Gas heating	One month	606.68	mile	Padgett et al. (2008)
Car	drive 1 mile	291.00	gram	UK BEIS†

Notes: † UK Department for Business, Energy & Industrial Strategy (`https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2019`).

emissions associated with driving bias our predictions, because these predictions will be independent of the denomination of CO_2 emissions.

We divided the belief elicitation into two parts. We first elicited a point estimate for the modal value of the emissions. Participants indicated how much CO_2 each of the 12 products in Table 1 emitted relative to driving one mile by car. Participants answered all 12 questions on one page, and the order of the products was randomized across participants (Figure 2A). In the rest of the experiment, the same order was used every time participants answered additional questions about these products. To help participants keep track of their guesses and the rankings of the products, we presented an interactive box summarizing their (current) answers at the bottom of the page, including the ranking of the products by estimated impact. We incentivized a correct point estimate with a \$5.36 (£4) bonus. We considered an estimate correct if it was within a 5% interval from the scientific estimate. This incentive scheme truthfully elicits the mode of the subjective probability distribution about the scientific estimate (Schlag, Tremewan and van der Weele, 2015).[4]

In order to understand the participants' confidence in their answers, we then elicited the subjective probability distribution about the size of CO_2 emissions. For each product, we presented five "bins" around the point estimate participant reported in the first part and asked the participant to allocate 20 balls into these five bins. We told par-

[4]We did not incentivize the questions about the CO_2 emissions and the social cost of driving one mile by a car as we realized that answers to these questions can be straightforwardly obtained on Google.

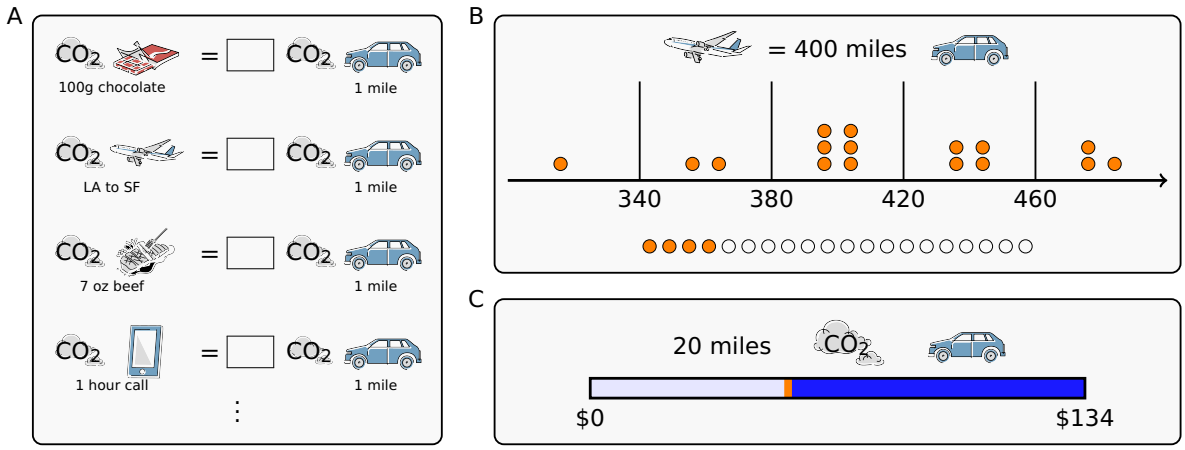

Figure 2: Illustration of the belief and WTM elicitation interface. (A) Point-belief elicitation task. (B) Bins-and-balls belief elicitation task. (C) WTM elicitation task. *Notes*: Panel B shows an example in which a participant stated 400 in the previous point belief elicitation task and is now asked to allocate 20 balls into five bins, centered around this number. See Online Appendix A.1 for screenshots of the interface.

ticipants that each bin represents an interval that might contain the scientific estimate and that they should allocate the balls to represent their level of confidence that the estimate is in fact in that bin. Figure 2B provides an illustration. We incentivized the elicitation by randomly selecting one of the bins, and scoring the answer according to a randomized quadratic scoring rule. This mechanism encourages participants to truthfully reveal their belief that the scientific estimate falls in a particular bin (Schlag and van der Weele, 2013). To keep things simple and avoid information overload, we did not provide participants with the exact details of the scoring rule, which were available with a mouse click, but told them that they would maximize their expected earnings by answering truthfully, an approach suggested by Danz, Vesterlund and Wilson (2022).

Willingness to mitigate

After the belief tasks, we elicited the participants' willingness to pay for mitigating CO_2 emissions of different sizes. We call this measure *willingness to mitigate (WTM)*. To introduce real consequences in the elicitation task, we offered participants trade-offs between monetary payments and carbon offset certificates. More precisely, we used donations to Carbonfund.org (`https://carbonfund.org/`), a charity that finances various projects to offset CO_2 emissions and offsets one ton of CO_2 for every $10 donated.

To cover the amounts of the emissions generated by all the consumer products we asked in the survey, we elicited the WTM for eight levels of CO_2 emissions, corresponding to emissions generated by driving 1, 5, 20, 50, 100, 200, 450, and 700 miles by car. Participants expressed their WTM to offset these amounts of CO_2 using a slider between $0 and $134 (£100), see Figure 2C.[5] The interface was designed to help participants

[5]Participants could also express their WTMs either in GBP (between £0 and £100), the official

make consistent choices and avoid anchoring. To this end, the sliders for each emission quantity were all displayed on the same screen, and the bottom of the page featured a graphical summary of reported WTMs by emission quantity (see Online Appendix A.1).

We incentivized the WTM with a Becker–DeGroot–Marschak (BDM) mechanism, which means that reporting the true WTM is in the best interest of the participant.[6] To make sure our donations were credible to participants, we emphasized that our ethics committee does not allow misleading instructions, and promised to send them the carbon offset receipts from the experiment. The method above provides data that are censored at $134. To mitigate this problem, we added a second, unincentivized set of questions. For every emission level for which a participant reported a WTM of $134, we asked the participant to indicate for which amount of money he or she would have agreed to allow the emissions. The participant could either type in a number or check a box to signal that no monetary compensation would have been enough.

At the end of the session, we asked a series of questions about demographic background, consumption habits (about the 12 products), and attitudes toward climate change. See Online Appendix A.1 for the complete list of questions.

Implementation

We recruited 1,430 participants on Prolific (`https://www.prolific.co/`) between the 3rd and 6th December 2020, and 1,022 of those completed the whole survey.[7] We restricted participation to US residents and we aimed to collect a sample representative for age, gender, and ethnicity.[8] Our sample is on average 42.7 years old (SD = 15.4) and 48.3% of the participants identified themselves as male. Table A.2 in the Online Appendix shows the demographic characteristics of the sample.

To make the instructions as accessible as possible, we used slides that displayed the instructions step by step with explanatory images complementing the written text. Besides, we divided the instructions into 5 blocks. After each block, we asked participants to answer several comprehension questions. We did not allow subjects to continue with

currency of Prolific, or in USD (between $0 and $134).

[6] We randomly selected one number from a discrete set of values between 0 and 100. If the number was bigger than what the participant reported, we paid the participant a bonus equal to the randomly selected number. If, instead, the number was smaller than the participant's report, we donated to Carbonfund.org as much money as needed to compensate for the CO_2 emissions stated in the question.

[7] We ran extra sessions on 21st and 22nd December 2020 to recover some participants' demographic data. These data were not originally saved due to a failure in the survey code. We managed to retrieve the data of 67 of the 69 participants for which the failure was verified. Only the demographic questions were asked in these extra sessions.

[8] We noticed that participants in the oldest age bracket (above 58 years old) particularly struggled with the comprehension questions about the WTM resulting in many dropouts on the page where those questions were asked. As subjects in this demographic category were hard to recruit, we opted to give them a second chance to complete the experiment. On 7th December 2020, we invited them to re-start the experiment from the WTM instructions and we gave them the solutions to two of the 7 related comprehension questions. Of the 41 subjects that were allowed to restart the experiment, 22 completed it.

the experiment until they answered all the questions of each block correctly. In total, participants had to answer 21 comprehension questions.

At the end of the experiment and for every participant, we randomly selected one question from the entire study. Depending on the participant's answer to that question and luck, we paid them a bonus. This incentive mechanism elicits truthful answers in experiments with multiple tasks (Azrieli, Chambers and Healy, 2018).[9] Participants received \$10.05 for completing the study plus a variable bonus depending on their answers (mean = \$2.67, SD = 4.31).[10] The median survey completion time was 55 minutes.

3.1 Results

Beliefs. Participants estimated CO_2 emissions from 12 common consumer products and activities in terms of miles of driving by car. Table 2 shows summary statistics of reported (point) beliefs and Figure 3A plots them against scientific estimates of CO_2 emissions.[11,12] Median beliefs lie below the identity line for all but one (microwave) products, indicating that participants underestimated the size of CO_2 emissions. This is in line with findings in Camilleri et al. (2019), despite differences in the sets of products, elicitation methods, and the reference items (lightbulb vs. car).

The fraction of participants who underestimated the size of emissions varies from 41% (microwave) to 92% (gas heating), with this fraction increasing in the true size of the emissions. Flying is a notable exception to this trend: it is a highly polluting activity but its emissions are underestimated only by 59% of participants. This could be due to the ample coverage of emissions from flying from media outlets, or because subjects simply took as an estimate the driving distance between San Francisco and Los Angeles ($\approx$ 350 miles), which is close to the right answer.

Even though participants misperceived the size of CO_2 emissions from each product, they had a good understanding of which products emit more CO_2. As Figure 3B shows, the "true" ranking of emission sizes based on scientific estimates and the ranking "revealed" by each participant's estimate are positively correlated.[13]

[9] The probability with which a question was selected for payment was not uniform but depended on the part of the experiment that the question came from. In the instructions, we informed participants of the probability that the question was drawn from each of the different tasks of the experiment.

[10] Participants received the completion reward and the bonus only if they completed the second part of the experiment. This second part of the experiment took place two weeks after the first. Participants that completed both parts of the experiment received a total completion reward of £10 and an average bonus of £2.20. Following the participants' decisions in the experiment, we donated \$88 to Carbonfund.org, offsetting 8.8 tons of CO_2 emissions.

[11] We focus on median beliefs since there are several extreme outliers.

[12] Figure A.5 in the Online Appendix shows empirical CDFs of reported CO_2 emission sizes for each product.

[13] We also calculated Spearman's rank-order correlation between the actual ranking of CO_2 emissions and "revealed" ranking of emissions for each participant. About 95% of the participants exhibited a positive correlation, and 45.6% of the participants exhibited a statistically significant positive correlation (two-sided, $p < 0.05$). The average correlation coefficient is $\rho = 0.559$.

Table 2: Summary statistics of elicited (point) beliefs about CO_2 emissions from 12 consumer products and activities.

			Belief			
Product	Emissions	Unit	Q1	Median	Q3	Under-est.
Beer	1.46	miles	0.50	1.20	6.00	0.516
Phone call	1.55	miles	0.40	1.00	5.00	0.549
Microwave	1.76	miles	0.80	2.15	10.00	0.406
Milk	2.60	miles	0.50	2.00	8.00	0.570
Shower	3.90	miles	0.50	1.50	5.00	0.689
Egg	4.81	miles	0.50	1.50	6.00	0.697
Poultry	6.78	miles	0.60	2.50	10.00	0.676
Chocolate	16.03	miles	0.40	1.20	8.00	0.831
Coffee	44.41	miles	0.50	2.00	10.00	0.885
Beef	68.39	miles	1.00	5.00	20.00	0.858
Flight	304.60	miles	10.00	150.00	600.00	0.586
Gas heating	606.68	miles	3.00	20.00	100.00	0.919
Car (drive 1 mile)	291.00	grams	5.03	85.00	403.00	0.677

Notes: The last column "Under-est." shows the fraction of participants who underestimated the size of emissions.

All the qualitative results of this section replicate if we express participants' beliefs in terms of grams of CO_2 using their beliefs about the CO_2 emissions linked with driving one mile by car. Figure A.6 in the Online Appendix shows that, since participants underestimate the grams of CO_2 emitted when driving, the underestimation is more severe if we express the beliefs in grams.

Taken together, the belief elicitation tasks in the climate survey suggest that consumers significantly underestimate the size of CO_2 emissions associated with common consumer products and activities, but they have more accurate perceptions about the ordinal ranking of CO_2 emissions.

Willingness to mitigate. We now turn to participants' willingness to mitigate CO_2 emissions. Note that we elicited WTM for eight levels of CO_2 emissions, that correspond to emissions generated by driving 1, 5, 20, 50, 100, 200, 450, and 700 miles by car. On average, participants have positive and sizable WTM for all levels of CO_2 emissions, and they exhibit a concave pattern (Figure 3C, dark line). Moving from emissions equivalent to driving 5 miles to 20 miles, a four-fold growth, increases the WTM by \$6.3 on average, while moving from 5 to 200 miles, a jump 10 times as large as the previous one, pushes the average WTM by only \$20.8. The marginal willingness to pay for mitigation decreases as the emission size increases, confirming findings in Pace and van der Weele (2020). This pattern is not due to top-censoring at \$134— the concave

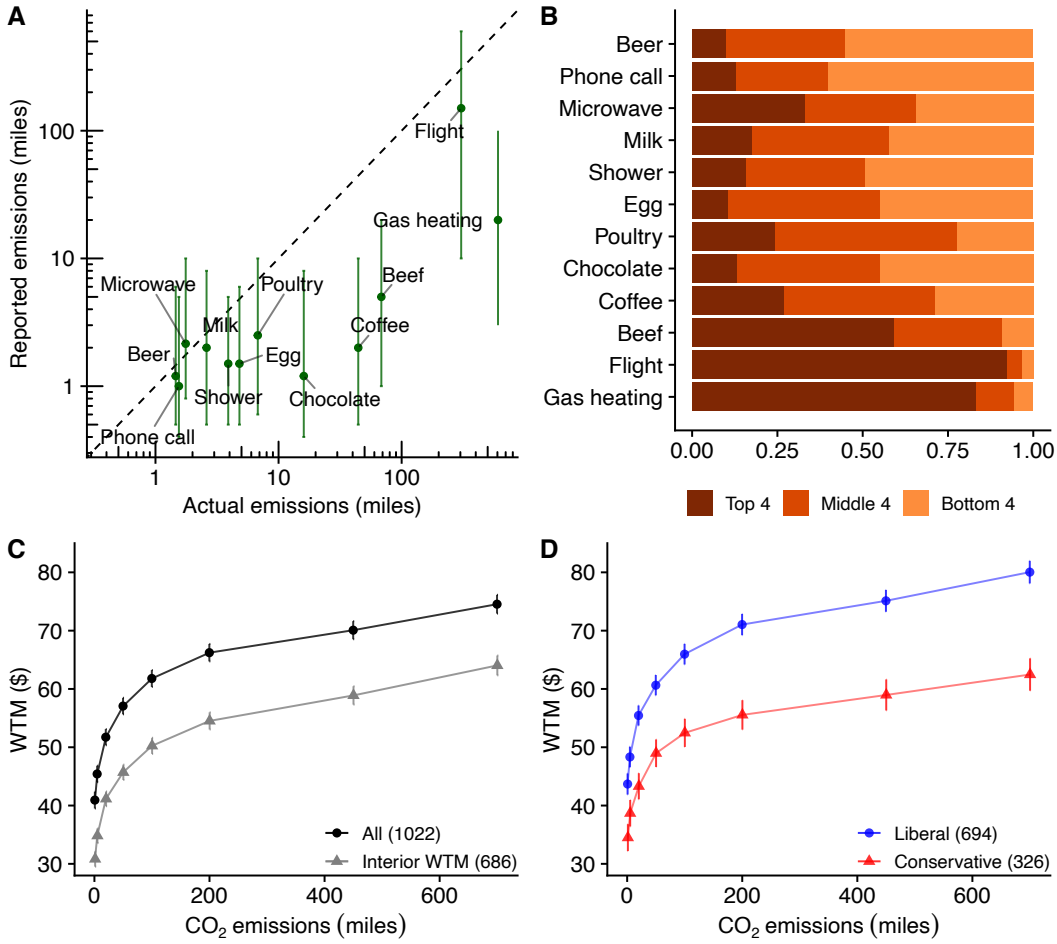

Figure 3: Beliefs and willingness to mitigate. (A) Summary statistics of reported CO_2 emissions (median and IQR). Axes are on a logarithmic scale. (B) Ranking of reported emission sizes. Products are sorted by the true emission size from low to high. (C) Concave WTM (mean and SEM). (D) WTM and political view (mean and SEM). *Notes*: In panels C and D, numbers in parentheses indicate the number of observations. In panel D, "somewhat liberal" and "somewhat conservative" are grouped into liberal and conservative, respectively.

pattern is preserved even when we focus on 686 participants whose WTMs are all strictly between \$0 and \$134 (Figure 3C, light gray line). See Tables A.4 and A.5 in the Online Appendix for summary statistics of WTMs and the number of "corner" observations for each level of emissions.

As in elicited beliefs, we observe strong correlations between WTM and some of the demographic characteristics. Participants who identified themselves as liberal on the political spectrum have uniformly higher WTM than conservative participants (Figure 3D). Female participants have higher WTM than male participants, and participants in the age ranges of 18-37 and 58 and older have higher WTM than those between 38 and 57 years of age (Figures A.7 and A.8 in the Online Appendix).

Figure 3C shows a smooth and concave WTM curve at the aggregate level, but it masks substantial heterogeneity across participants. There are 52 participants who "do not care" about CO_2 emissions and request \$0 for all eight levels of emissions, and

there are 77 participants who are "deontological" and request \$134 all the time. We can classify the shape of the WTM curve. We observe that 31% of individual-level WTM curves are concave, and 28% of WTM curves are non-monotonic. Less than 10 are convex. There are only 44 cases of decreasing WTM curve, an irrational pattern of WTM that is not captured by small mistakes. See Online Appendix A.2 for details.

In the next section, we describe how to combine these measures for the prediction of information provision.

4 Modeling the Impact of Information

In this section, we outline a simple formal framework to combine beliefs about the impact and willingness to mitigate and produce a prediction about the resulting consumer decision. The key assumption is that consumers suffer a cost from the expected emissions produced by their actions and that they make utility-maximizing decisions about the quantities of emissions. Our approach is inspired by findings that subjects make rationalizable trade-offs about payoffs for themselves and others that allow for the construction of a utility function (Andreoni and Miller, 2002; Fisman, Kariv and Markovits, 2007).

Consider a consumer who gets material utility v from purchasing a good or activity. We assume that the good (or activity) is sold at a market price of p and is associated with a quantity of CO_2 emissions $c \geq 0$. The consumer's utility from consuming the product is:

$$U = v - p - w(c),$$

where $w : \mathbb{R}_+ \to \mathbb{R}_+$ captures the psychological cost from CO_2 emissions. We assume w is strictly increasing and $w(0) = 0$.

In writing the preferences in this way, we are making two assumptions. First, for simplicity, we assume that the consumer's overall utility is additively separable in v and in the psychological cost of emitting CO_2. Second, we assume that the psychological cost only depends on the emissions associated with the current purchase and not on the emissions linked to previous consumption of the same or other products. This last assumption finds support in our willingness to mitigate data. For us to observe the concavity of the function w, it must be the case that the consumers consider the emissions they can offset in the experiment separately from all the emissions they have generated so far. Without this "narrow bracketing" of emissions, participants with a concave WTM would report a flat WTM curve in the survey.[14]

[14]Narrow bracketing has also been documented in choices over monetary outcomes (Rabin and Weizsäcker, 2009; Ellis and Freeman, 2020) and in work choices (Fallucchi and Kaufmann, 2021). The concavity of the WTM function also implies that narrow bracketing is essential for an information campaign to have any effect on behavior. Given the beliefs and consumption levels of the average US consumer, broad bracketing implies that they will be on a flat part of w.

We assume that the consumer may not have precise knowledge about emission sizes c, but has some beliefs about them. Let F denote her belief about c. With this subjective belief and following standard expected utility, the consumer's preferences can be expressed as

$$U = v - p - E_F[w(c)].$$

Two key ingredients in this framework are the function w capturing psychological cost and the subjective belief about CO_2 emissions F. The climate survey we discussed above is designed to measure these two quantities as precisely as possible. Remember that we used "miles driving a car" as the common unit of emission size in the belief and WTM elicitation tasks in the survey.

The WTMs stated by each participant provide information about w. Requesting a bonus of y_m to allow emitting CO_2 corresponding to emissions generated by driving m miles by a car, c_m, reveals

$$y_m = w(c_m),$$

assuming a linear utility for money. Using eight pairs of observed (c_m, y_m) and extrapolating (see Online Appendix A.3), we can recover w for each participant. Hereafter we will refer to w as the WTM function.

Similarly, we use the second part of the belief elicitation, the bins-and-balls task, to recover subjective belief *distribution* F_k for each product k. See Online Appendix A.3 for details.

Quantifying the effect of information

Given a WTM function w and a subjective belief distribution F about CO_2 emissions associated with a good or activity, we can calculate the *expected WTM*,

$$\overline{W}(w, F) = E_F[w(c)] = \int w(c)\mathrm{d}F(c).$$

This quantity captures the extra amount of money a consumer is willing to pay in order to consume an imaginary, "carbon-neutral," version of the good or activity, taking into account the lack of knowledge about the actual size of CO_2 emissions.

We model an *information policy* as a device that shifts consumer i's belief about CO_2 emissions associated with good k from F_{ik} to F_k^*, a degenerate distribution at the "true" size of CO_2 emissions.[15] The difference in expected WTM before and after information

[15]Note that we impose an assumption that the consumer trusts the information and fully updates her belief, but the framework can easily accommodate the possibility that the updated belief is not exactly F_k^*, reflecting the idea that the consumer has some doubt in the information or has difficulty in giving up her original belief.

for each consumer i and product k is given by

$$\Delta_{ik} = \overline{W}(w_i, F_k^*) - \overline{W}(w_i, F_{ik}).$$

If $\Delta_{ik} > 0$, information raises the psychological cost from consuming a unit of good k for consumer i through a change in her beliefs. If this increase is large enough, information may result in a change in consumer i's buying behavior.

Finally, we define the effect of information provision on the consumption of good k, Δ_k, as the sample average of Δ_{ik} with respect to a reference group of agents G:

$$\Delta_k = \frac{1}{|G|} \sum_{i \in G} \left(\overline{W}(w_i, F_k^*) - \overline{W}(w_i, F_{ik}) \right).$$

Again, if $\Delta_k > 0$ and demand is downward sloping, then information is predicted to result in a decrease in buying behavior in target group G.

Several features of our structural model bear mentioning. First, the effect of an information campaign Δ_k has a simple interpretation: providing accurate information on the CO_2 emissions of product k increases the average subjective cost of consuming product k by Δ_k dollars. Therefore, Δ_k can be thought of as the equivalent of a price increase. As with a price increase, the ultimate effect of information on consumption choices will be mediated by a product's elasticity of demand, something we will address in the next section.

Second, because our model combines beliefs and willingness to mitigate CO_2 emissions that were both expressed as miles-driven-in-a-car equivalents, the unit of denomination of CO_2 emissions drops out of our prediction. This allows us to use an intuitive and common way of denominating CO_2 emissions while assuring that any systematic misperceptions about the climate impact of driving do not affect our predictions.

Prediction

We now calculate our measure of the effect of information provision using the data from the survey. Taking the entire sample of 1,022 participants as the reference group G, we obtain Δ_k for each product k as shown in Figure 4.

We observe a substantial variation in the effect of information provision. We expect a positive effect for five products (gas heating, beef, coffee, flight, chocolate), no effect for three products (shower, poultry, egg), and a negative effect for four products (phone call, milk, beer, microwave). Note that we expect a larger effect of information for products with larger CO_2 emissions: the ordering in Figure 4 is almost the mirror image of the ordering in Table 1. This is because the fraction of participants who underestimates the size of emissions is larger for these products, and our measure favors these participants as long as their WTM function responds to the size of emission (i.e.,

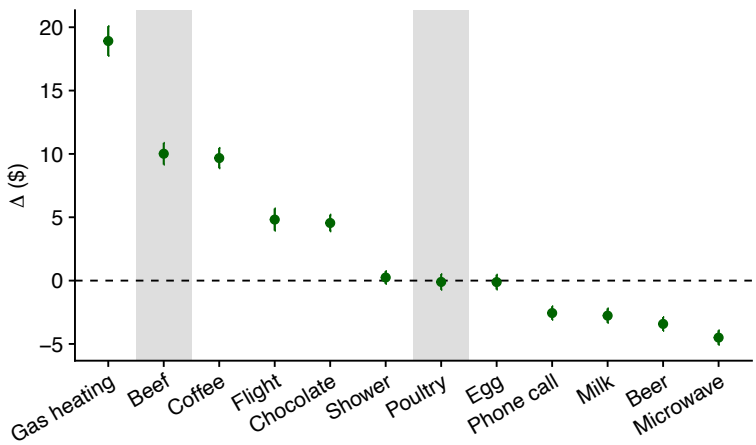

Figure 4: Predicted effect of information provision Δ_k for each product. *Notes*: The reference group G is the entire sample of survey participants ($N = 1,022$). Bars indicate SEM.

w is not constant on the relevant range). These predictions have received some support in the empirical literature. For instance, the negative effect for electrical appliances has been documented in several empirical papers (Rodemeier and Löschel, 2020; d'Adda, Gao and Tavoni, 2022). In a labeling intervention in an online Swedish supermarket, Bilén (2022) observes an effect for beef, but not poultry.

Taking different subgroups of participants as the reference group G, we can also quantify Δ_k depending on the target population. Figure 5 conducts such an exercise, focusing on two meat products, beef and poultry, that will be the subject of the experiment in the next section. While panel A shows the aggregate effect, panels B-G disaggregate the predictions across several subgroups. These panels illustrate the advantages of integrating preferences and beliefs over simpler approaches, like simply targeting populations with a high willingness to pay. For instance, the model predicts a larger effect for males than females (panel C), and for participants who have conservative political views than those with liberal views (panel D), despite the fact that in both cases, the former group has a lower WTM (see Figure A.7 in the Online Appendix). The reason is that these groups also have larger underestimations of climate impact, which more than offsets their lower WTM, resulting in a higher predicted impact of information.

Moreover, we can assess the robustness of our model's prediction for beef consumption. The predicted effect of an information campaign may be interpreted as a "subjective price increase" of the product under investigation. Just like with a conventional change in prices, a price increase will have little effect on demand if it is primarily experienced by individuals whose demand is inelastic or by individuals who do not consume the product, to begin with. Thus, one might ask whether the effect differs between groups that might have different elasticities of demand, based on self-reported consumption patterns in the survey.

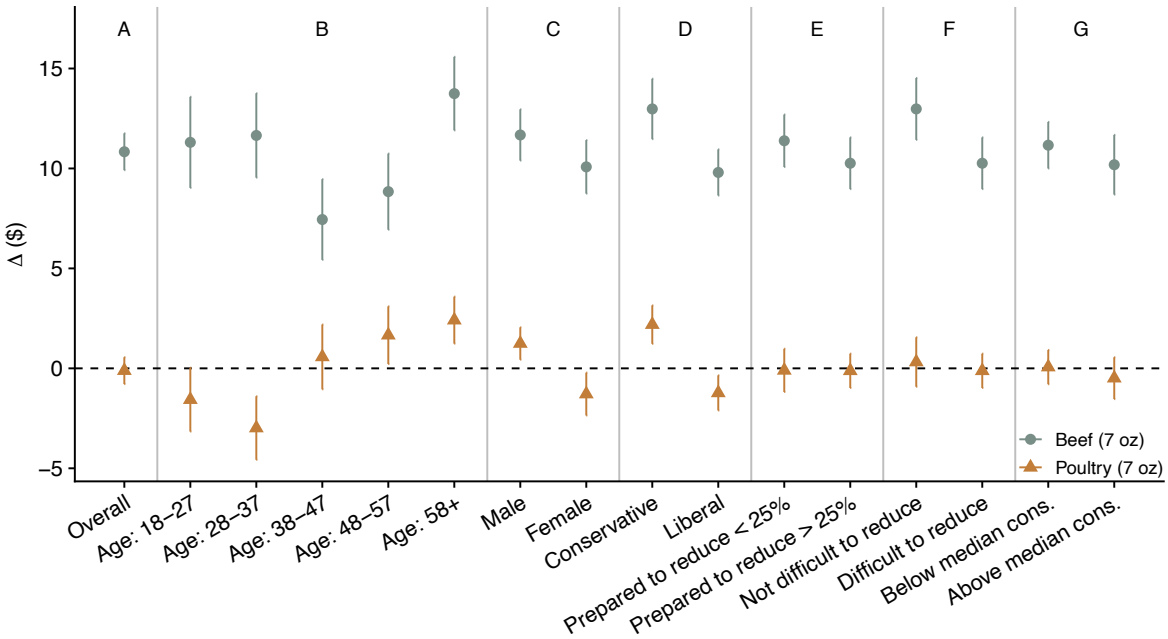

Figure 5: Predicted effect of information provision for each demographic group. *Notes*: (D) "Somewhat liberal" and "somewhat conservative" are grouped into liberal and conservative, respectively. (E) "Are you prepared to reduce your future consumption of beef/poultry in light of its CO_2 emission footprint?" (F) "How difficult would it be to reduce your current consumption of beef/poultry by half?" (G) "How many times do you eat beef/poultry per week?" Bars indicate SEM.

Such an exercise is shown in panels E-G of Figure Figure 5. The predicted effect of an information campaign is higher for those who are more prepared to reduce future meat consumption in light of its CO_2 emissions (panel E), those who find it "not difficult" to reduce beef consumption and hence should have more elastic demand (panel F), and those who consume beef below the median frequency (panel G). However, in each case, the effects of these splits are relatively small, illustrating that our predictions about interventions for beef are robust to prevailing demand levels and elasticities.[16]

5 Meat Experiment

We now turn to test the predictions we derive from our calibrated structural model in Section 4. To this end, we compare the effect of information between beef and poultry meat. There are three main reasons for choosing these two products. First,

[16]The prediction is based on the consumption of 7 oz of beef and poultry, the size of meat products participants reported their beliefs about CO_2 emissions. Figure A.10 in the Online Appendix shows the prediction about 5 lb (80 oz) of beef and poultry, the size of meat products offered to participants in the Meat Experiment, by "scaling up" their belief distributions by the factor of 80/7, which shifts Δ_k upward for both products. The overall prediction is different in absolute terms (e.g., the bottom panel of Figure A.10 shows a positive overall effect of information even for poultry), but qualitatively the results do not change: the model still predicts larger effects of information for beef.

meat products are an important application, as meat (and especially beef) consumption makes a meaningful contribution to climate change and is one of the main sources of emissions that are under the direct control of consumers.[17] Second, these two products are comparable in many respects as they fall into the same food category and may be considered substitutes for certain purposes. Third, despite their similarity, these two products have very different predicted effects of information provision, as we show in Figure 4. While the predicted effect of information on beef consumption is among the very highest on our product list, it is approximately zero for poultry. This is mainly because beef production is about 10 times more carbon-intensive than poultry production, an effect that is not incorporated into the expectations of consumers, and hence subject to correction through information provision.[18]

Thus, the main hypothesis that we test in our experiment is that information provision about carbon impact will have a bigger impact on consumer valuations of beef products than on valuations of chicken products.

Design

In this experiment, we offered participants an opportunity to purchase a bundle of high-quality meat products, either 10 beef sirloin steaks or 10 skinless chicken breasts. We kept the features of bundles as close as possible: they were sold on a premium online butcher Porter Road (`https://porterroad.com/`); they weighed about 5 lb ($\approx$ 2.3 kg); they cost \$100 (at the time of designing the experiment in 2021); they were pasture-raised in the US without hormones and antibiotics. We provided these descriptions in the relevant part of the instructions.

Across treatments, we varied between subjects whether the participants received information on the CO_2 emissions associated with beef and poultry meat (Info treatment) or not (NoInfo treatment). In keeping with our climate survey, we provided the information in terms of the number of miles by car one needs to drive to emit as much as 1 lb of the meat. We pinned down participants' beliefs about the car CO_2 emissions by including a scientific estimate of these emissions (in ounces) in the instructions. In this way, we made sure that our information treatment could only impact the beliefs about the meat. The information about car emissions was available in all treatments.

As an additional manipulation, we varied whether the participants were first offered the beef bundle (BeefFirst treatment) or the poultry bundle (PoultryFirst treatment). For these two products, subjects remained in the same information treatment. We test our main hypothesis about the differential impact of information for the two products

[17] Alexandre Koberle, Grantham Institute for Climate Change, Imperial College London, writes that "Next to flying less, it is probably right to say that, as individuals, reducing beef consumption is the most significant contribution directly under our control" (Vetter, 2020).

[18] This difference results mainly because beef involves the release of large amounts of methane, a greenhouse gas with about 30 times the warming equivalent of CO_2, and because beef requires large amounts of feed which spurs deforestation (Poore and Nemecek, 2018).

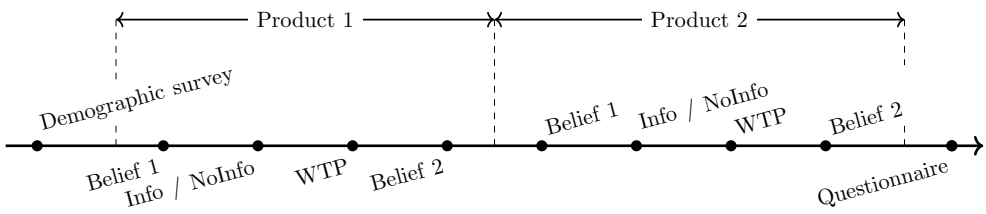

Figure 6: Timeline of the meat experiment.

using the first product offered in the experiment. The second part allows us to evaluate spill-over effects, whereby information about beef affects beliefs and WTP for poultry or vice versa.

The timeline of the experiment is illustrated in Figure 6. The experiment has two parts, one per each of the products we offer. The two parts followed the same structure. Each part of the experiment started with a description of the bundle the participants could purchase as well as its retail value ($100). We then asked the participants to guess the average CO_2 emissions associated with the production and distribution of 1 lb of the type of meat that they were offered. As in the climate survey, participants expressed their guesses in terms of CO_2 emitted by driving one mile by car.[19]

To help participants to get a sense of the magnitudes of emissions, just before they could express their guesses, we informed them of how the CO_2 emissions from driving one mile by car compared with the emissions generated by the production and distribution of 12 fl oz of beer and by taking a plane from Los Angeles to San Francisco. We provided this baseline information to all participants to keep the salience of emissions and possible norms around low-carbon consumption constant across treatments. To incentivize belief elicitation, we used the same sources of scientific estimates as in the climate survey and we rewarded accurate guesses (those within $\pm 5\%$ of the scientific estimate) with a $0.5 bonus.

Next, we had our treatment manipulation. The participants in the Info treatments were informed about the average emissions associated with the meat product they could purchase. To make sure that the participants paid attention to the information, we asked them to identify the true size of the emissions among three possible options. The participants in the NoInfo treatments, instead, saw three random numbers and answered a similar question.[20]

We then elicited participants' WTP using a two-stage multiple price list (MPL) with forced single switching.[21] On the first list, participants saw 11 choices between two

[19]We did not elicit belief distributions to fit the survey in the time constraint of 15-20 minutes.

[20]In both treatments, participants were allowed to proceed regardless of their answers. However, participants who answered incorrectly received an alert warning them of the mistake and repeating the correct answer.

[21]We used an MPL instead of the slider interface from the climate survey since we elicited only two valuations in this experiment while we elicited eight in the survey. The small number of valuations

options: the left option is the meat bundle and the right option is the monetary bonus ranging from \$0 to \$100 in \$10 increment. In the remainder, we refer to this bonus as the "price", although it was not framed as such in the experiment. The second list "zoomed in" around the switching point and asked another nine questions. With this procedure, we measured WTP in the precision of \$1.[22] The instructions encouraged the participants to think about their own valuation of the meat bundle and to use this valuation to make the decisions.

After completing the MPL task, we asked participants to guess one more time the size of the emissions associated with the meat product they had the opportunity to purchase. This second guess was not incentivized.

The second part of the experiment followed the same structure as the first one, but it asked participants about their beliefs and WTP for the other meat bundle—the poultry bundle if the first part was about beef, and the beef bundle if the first part was about poultry. Thus, in the Info treatments, participants saw the information about the CO_2 emissions associated with the new meat bundle together with all the information previously provided. In the NoInfo treatment, instead, participants saw four randomly generated numbers.

At the end of the experiment, we asked the participants about their meat consumption patterns, attitudes toward climate change, and trust in the experimenters. We also asked for their contact information (both home address and email) to deliver the meat product or the monetary bonus, if any.

Implementation

We recruited participants on the platform Lucid between 31st March 2022 and 15th April 2022.[23] We focused on participants who consume meat and excluded those who lived outside contiguous US states due to shipment requirements by Porter Road.[24] 2,081 participants satisfied the pre-registered inclusion criteria: 1,047 were assigned to the NoInfo treatment and 1,034 were assigned to the Info treatment.[25] Participants

makes an elicitation strategy that requires simpler instructions (MPL) preferable to a strategy that requires more complicated instructions but allows the participants to input their decisions more quickly.

[22]We used a BDM procedure to make this two-stage MPL incentive compatible. We randomly selected a price (an integer) between 1 and 100 to determine whether the participant receives the monetary reward or the meat bundle. Each price has the same chance of being extracted *independently* of the participant's choice in the first multiple price list. If the randomly selected price was not the one the participant had seen, we inferred his or her choice for this price from the choices for the other price levels. This strategy was feasible because we forced a single switching and hence we enforced consistency in choices.

[23]Lucid was acquired by Cint (`https://www.cint.com`) in January 2022, but still operated under the old name at the time of our experiment.

[24]To enhance data quality, we included five attention checks and three comprehension questions about the instructions. Participants were excluded if they failed any of the attention checks or if they needed more than five attempts to answer the comprehension questions correctly.

[25]Number of participants in each treatment is: 520 in the BeefFirst, Info treatment, 528 in the BeefFirst, NoInfo treatment, 514 in the PoultryFirst, Info treatment, 519 in the PoultryFirst, NoInfo

are representative along gender and age. Table B.1 in the Online Appendix shows that demographic characteristics are balanced across treatments. Our sample is on average 46.8 years old (SD = 17.1) and 48.4% of the participants identified themselves as male. The median survey completion time was 17 minutes.

We implemented one of the two MPL decisions for one in every 20 participants and delivered the meat bundle (beef or poultry, depending on the selected MPL) or the monetary bonus, based on the participant's choice for the randomly selected price level. Finally, one (lucky) participant received a $500 completion reward. All bonus amounts were paid using Amazon gift cards. We preregistered our hypotheses and sample sizes on Aspredicted.org, the preregistration is available in the Online Appendix B.2.

5.1 Results

Following our preregistration, we focus on the belief and WTP data from the first part of the experiment for a clean analysis of the treatment effect.This means that belief and WTP data about the beef bundle come from BeefFirst treatments ($N = 1,048$) and the data about the poultry bundle come from PoultryFirst treatments ($N = 1,033$).

As in the climate survey discussed in Section 3, participants exhibited a significant underestimation of the size of CO_2 emissions from beef and poultry. Figure 7 shows that the magnitude and the prevalence of underestimation are more significant in the experiment as compared to the survey—median beliefs are much lower in the experiment (even though the quantity of meat products presented to the participants was more than twice as large as the quantity used in the survey) and the fraction of participants who underestimated the emission size was 92.7% for beef and 89.4% for poultry, respectively. Like in our survey, we see a large difference in the size of underestimation between the two products: the absolute level of underestimation for the median subject is 153 miles for beef and 14.4 miles for poultry, respectively.

Participants were initially equally uninformed about CO_2 emissions across treatments. The distributions of prior beliefs (asked before WTP) show no differences between Info and NoInfo treatments for both meat products (Figure 8AB). Providing information successfully shifted the beliefs of many participants in the treated groups, as evident in jumps in the distributions of posterior beliefs (asked after WTP), illustrated in Figure 8CD. In particular, 64.8% (337/520) of participants moved their beliefs to the correct value for beef, and 51.0% (262/514) did so for poultry.[26]

Remember that our model in Section 4 predicts that information has a positive impact in the direction of reducing the demand for beef but has no impact on the valuation of poultry. In the experiment, these predictions are translated into a *decrease* in average WTP for the beef bundle and no effect for the poultry bundle. These pre-

treatment.

[26]If we allow a margin of ±10%, the number increases to 68.3% (351/514) for poultry.

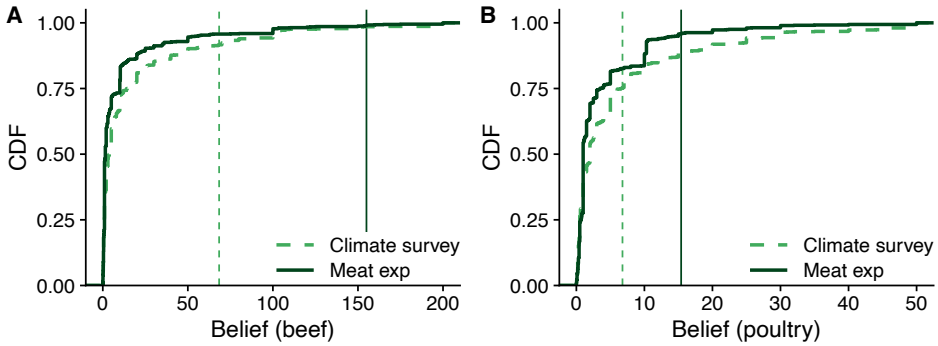

Figure 7: Empirical CDFs of beliefs about CO_2 emissions from two samples. (A) Beef. (B) Poultry. *Notes*: The size of meat products for belief elicitation was 7 oz in the climate survey and 1 lb (= 16 oz) in the meat experiment. For the data from the meat experiment, we focus on belief data from the first elicitation in the first part of the experiment. Vertical dashed lines correspond to the "true" size of CO_2 emissions (A: 155 miles for the meat experiment and 68.39 miles for the climate survey; B: 15.4 miles for the meat experiment and 6.78 miles for the climate survey).

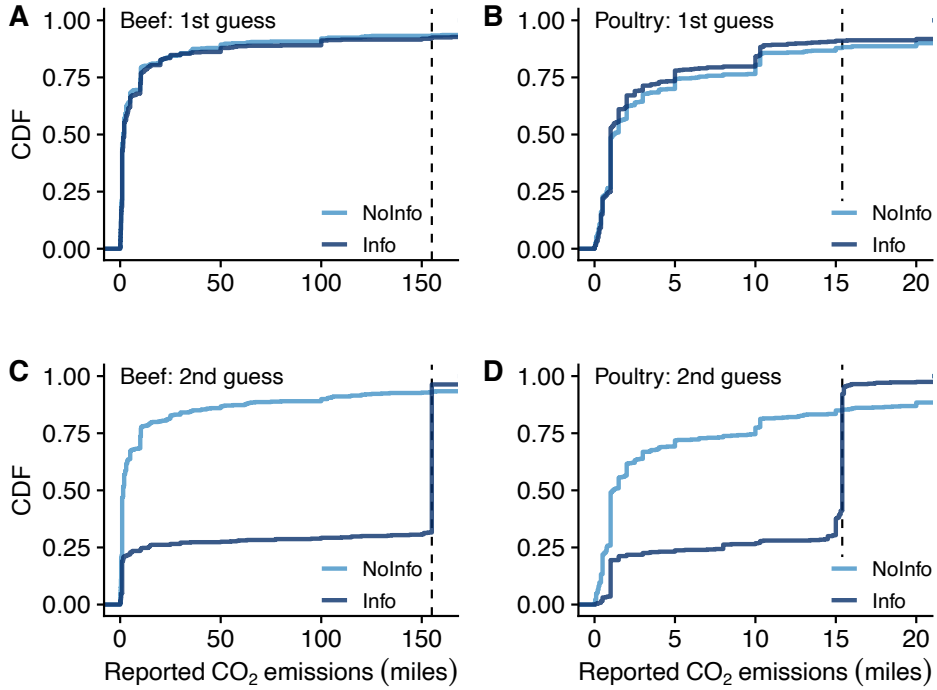

Figure 8: Beliefs about CO_2 emissions from two meat products. *Notes*: We focus on the data from the first part of the experiment (panels AC: BeefFirst treatments; panels BD: PoultryFirst treatments). Vertical lines correspond to the "true" size of CO_2 emissions (15.4 miles for poultry and 155 miles for beef).

dictions are not supported in the data. Figure 9A shows the WTP for meat products by treatment. If anything, there is a small *upward* movement in the valuation of the beef package after information provision. Average WTPs are not significantly different between treatments for both products (beef: $t(1046) = -1.200$, $p = 0.230$; poultry: $t(1031) = 0.938$, $p = 0.349$). Panels B and C of Figure 9 give a more complete overview

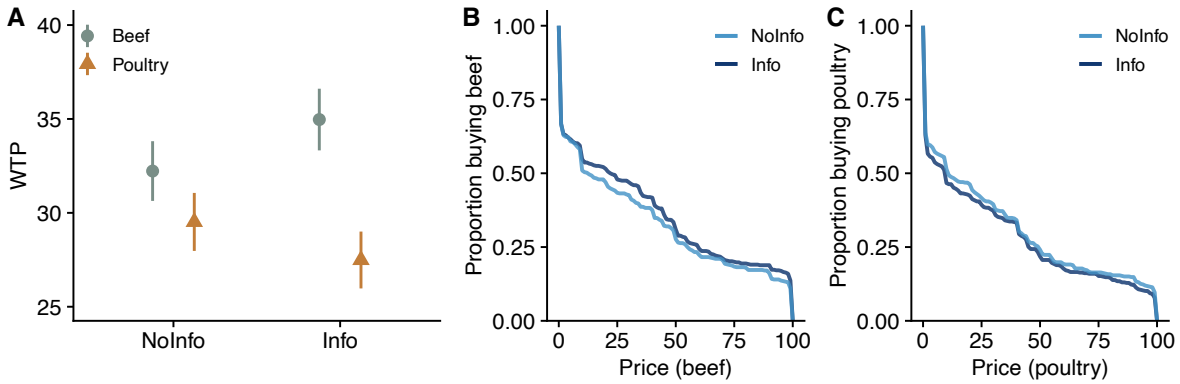

Figure 9: (A) Average willingness to pay for the first meat product. (BC) The proportion of participants buying the meat product at each price. *Notes*: We focus on the data from the first part of the experiment. In panel A, Bars indicate SEM. Figure B.4 in the Online Appendix shows the CDFs of WTPs.

of demand and show the proportion of buyers for each price, confirming that there is no discernible difference between the treatments.

Table 3, column (1) shows the effect of information on beef valuation in a regression analysis. This "null" finding is robust to the inclusion of several control variables in the regression (Table B.2 and Figure B.6 in the Online Appendix). Several of those covariates have sensible signs: we find a higher WTP for beef for those subjects who report above-average beef consumption, or who report that it is difficult to reduce beef consumption. We also find a lower WTP for both beef and poultry amongst women and younger individuals. Finally, in Online Appendix Figure B.6 we also conduct an analysis of the treatment effect by subgroup. For all subgroups, we cannot reject the null hypothesis that the information effect for beef is zero.

5.2 Interpretation of the Null Effect

We now turn to investigate possible reasons for the observed null effect of information about CO_2 emissions on the demand for meat. We focus on beef, where we predicted that information should affect willingness to pay negatively and decisively.

Were participants' beliefs insensitive to the information treatment? In both the Info and the NoInfo treatments, we measure beliefs twice (Figure 6). In the Info treatment, the second belief, or posterior, is measured after information about beef consumption is provided. Participant's posterior is affected by the information treatment and exhibits, on average, less optimism about CO_2 emissions (see Figure 8CD). This shows that participants' beliefs were changed by the information they saw. However, these belief changes do not translate into differences in WTP. Column (2) of Table 3 shows regression results of WTP on a dummy for the Info treatment, including only participants in the latter treatment who responded to information by updating

their beliefs upward. While the coefficient on the Info treatment declines relative to the full sample (column (1)), the null effect remains.

Did participants become more pessimistic about other meat products? It is possible that information about beef made participants more pessimistic about other meat products. This would limit the options for (low carbon) substitution, rendering demand for beef inelastic in information. We can address this point in several ways. The first is to directly control for this spillover in beliefs. In the BeefFirst treatment, we measure participants' beliefs about the CO_2 emissions associated with poultry after the participants received information about and stated their willingness to pay for beef. We find that participants do indeed become much more pessimistic about poultry after receiving information about beef. About 63% of the participants in the BeefFirst, Info treatment (317/505) overestimated the size of CO_2 emissions from poultry (reported numbers above 15.4 miles) and 48 subjects reported 155 miles, which is exactly the size of CO_2 emissions from beef they learned about in the first part of the experiment (see Figure B.5 in the Online Appendix). However, this updating about a substitute product does not appear to be an important mediator of the information effect on beef demand: the null effect persists after controlling for the beliefs associated with poultry consumption (Table 3, column (3)).

In addition, We can look at the case where beef is the second product participants can buy. Here, by the time participants state their willingness to pay for beef in the Info treatment, they have received information on both poultry and beef. This group is therefore aware of a climate-friendly substitute. However, we find no treatment effect in the second product either (Table 3, column (8)).

We can also test for this confound using participants' stated intentions about future consumption in the post-experimental questionnaire. At the end of the experiment, we asked participants "Do you intend to reduce your beef/poultry consumption in light of its CO_2 emissions?" and they answered on a Likert scale from 1 to 5. In the Info treatment, participants will have received information about both beef and poultry by the time they answer this question, and hence know about poultry being a low-carbon substitute for beef. Yet, a chi-squared test of independence shows no differences in response distribution between Info and NoInfo treatments for intention to reduce beef (Figure 10; $\chi^2(4) = 0.964$, $p = 0.915$).

Preaching to the choir: Is there a mismatch between who is optimistic about the CO_2 emissions associated with meat consumption and who cares about mitigating CO_2 emissions? One reason that information may have little impact on CO_2 emissions is that prior optimism about CO_2 emissions is concentrated among individuals who have little willingness to mitigate. The info treatment would then correct the beliefs of only those who have no interest in mitigation. Our structural

Table 3: Interpretation of the null effect of information on WTP for beef.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Info	2.743	0.528	2.914	1.673	5.277		4.835	−0.860
	(2.285)	(2.448)	(2.400)	(2.847)	(3.284)		(3.191)	(2.292)
Belief (poultry)			−0.011					
			(0.012)					
Difficulty (beef)						3.074***		
						(1.004)		
Constant	32.225***	32.225***	33.018***	32.912***	34.574***	25.580***	35.062***	33.080***
	(1.590)	(1.590)	(1.660)	(1.984)	(2.263)	(2.942)	(2.162)	(1.616)
First product	Beef	Beef	Beef	Beef	Beef	Beef	Beef	Poultry
Observations	1,048	901	1,032	672	529	991	579	1,013
R^2	0.001	0.0001	0.002	0.001	0.005	0.010	0.004	0.0001

Notes: The dependent variable is WTP for beef. Samples are as follows. (1) All participants in the BeefFirst treatments. (2) Participants in the NoInfo treatment, and those in the Info treatment who responded to information by updating their beliefs upward. (3) Participants who completed both parts of the experiment. One subject who reported an extremely large belief ($\approx 1.46 \times 10^9$) about CO_2 emissions from poultry is excluded. (4) Participants in the BeefFirst treatments who self-proclaimed to care about the environment (based on the response to the question "How severe do you consider the problem of climate change?"). (5) Participants in the BeefFirst treatments who self-reported consuming beef at least three times per week. (6) Participants in the BeefFirst treatments who self-reported consuming beef. (7) Participants in the BeefFirst treatments who expressed trust in us actually sending meat. (8) All participants in the PoultryFirst treatments. Robust standard errors are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

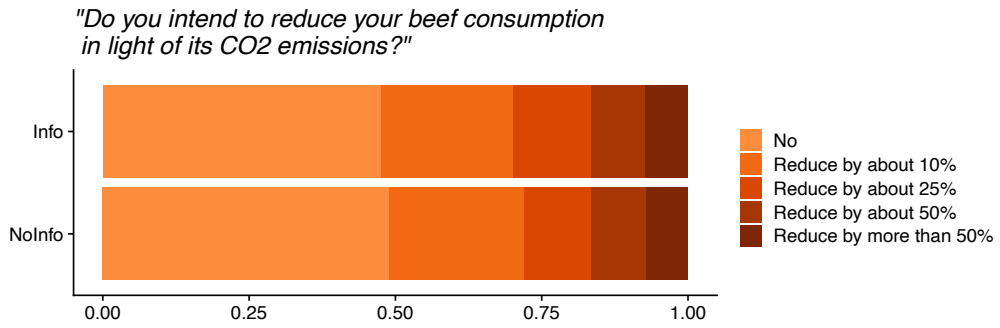

Figure 10: Distribution of responses to a survey question: "Do you intend to reduce your beef consumption in light of its CO_2 emissions?" *Notes*: We focus on 1,013 participants in the BeefFirst treatments. Participants responded on a 5-point Likert scale. (1: "No." 2: "Yes, I am prepared to reduce my current consumption by about 10%." ... 5: "Yes, I am prepared to reduce my current consumption by more than 50%.")

model was explicitly designed to make predictions that take this mismatch into account, so our initial predictions, based on the representative survey, are not subject to this concern.

To see whether these concerns could matter in the second dataset, we can restrict our analysis to those participants who self-proclaim to care about the environment. The null effect persists in this restricted sample (Table 3, column (4)).

Is there a mismatch between who is optimistic about the CO_2 emissions associated with meat consumption and who consumes a lot of meat? If only near-vegetarians are optimistic about the CO_2 emissions associated with meat consumption, then providing this information will do little to curb the demand for meat. Of course, this state of affairs is ex-ante implausible, but, for the sake of completeness, we can provide an explicit test for this hypothesis by restricting our dataset to participants who consume meat at least three times per week (i.e., above-median frequency). The null effect persists in this restricted sample (Table 3, column (5)).

Do participants suffer from an intention-action gap? An intention-action gap would manifest itself as a stated intention to reduce meat consumption in the future, but a failure to do so in the present. The underlying reason could be a preference for immediate gratification or a self-control problem. Yet, as we reported above, and as Figure 10 shows, intentions to reduce beef consumption are not much affected by the information treatment. Thus, the null effect of information does not stem from a failure to implement virtuous plans, but from a failure to make such plans, to begin with.

Does the information cause participants to decrease their consumption of lower-quality meat outside of the experiment? A key challenge of our experimental setup is to sell participants a product that they find appealing. To this end,

we used high-quality meat. But this may invite the concern that participants respond to information by demanding less, but better, meat. If this were the case, then the information treatment may decrease average meat consumption, but not the willingness to pay for the meat we sell to participants. Again, the fact that information does not impact participants' stated intention to consume beef rules out this conjecture.

Do participants react to information not by demanding less beef, but by offsetting the CO_2 emissions of their consumption outside of the experiment? We deem this hypothesis unlikely. It requires individuals to care about mitigating CO_2, to take into account and feel the pain of their meat consumption emitting CO_2, but to be completely inelastic in their meat consumption. Empirically the price elasticity of demand for beef steaks in the US is between -0.42 and -0.52, making beef demand far from inelastic (Dong, Davis and Stewart, 2015). So if learning about the CO_2 emissions increases the subjective cost of buying meat, it seems unlikely that participants do not use the rather elastic margin of adjustment that is a decrease in the WTP for meat, and instead adjust only buy purchasing offsets outside of the experiment.

Does our willingness to pay measure suffer from noise, misinterpretation, or lack of trust? A possible reason for a null effect of the information treatment may be that our measure of demand is very noisy. If our WTP measure is a very poor proxy for actual demand, then it would follow that this measure does not necessarily change with new information, even if this information would have had an impact on participants' actual demand for meat. To shed some light on this possible reason for a null effect, we ask whether our willingness to pay measure is correlated with other measures of preferences for meat. This would not be the case if WTP was very noisily measured. We find that WTP for beef is significantly correlated with participants' self-reported difficulty in reducing beef consumption if they had to (Table 3, column (6)).

A related worry may be that despite our elaborate efforts to be credible, (some) participants did not believe us that we would actually send them the meat they purchased with positive probability. Then, what they answered in the willingness to pay elicitation may not reflect their sincere demand for beef. To test this hypothesis we ask whether there was a treatment effect among those who expressed a lot of trust in us actually sending meat in the post-experimental survey.[27] The null effect persists in this restricted sample (Table 3, column (7)).

A final, somewhat related, concern is that the participants misunderstood our WTP question and thought they had to indicate the (socially) fair price for the beef shipment. This misunderstanding could generate a null result if some participants in the Info treatment thought that the fair price should be higher due to the high emissions.

[27]Participants responded to the question "Do you trust that the researchers will indeed ship meat products as described in the instructions?" on a 5-point Likert scale (1: not at all; 5: completely).

Several considerations assure that this misunderstanding is unlikely. First, the word "price" did not appear in the experiment: subjects made a sequence of binary buying decisions from which we infer a WTP. Second, we advised the participants to use their valuation of the meat to make their decisions. Third, the instructions did not contain any reference to CO_2 offsets or to other environmental actions associated with the product (and indeed there was no such offset), so there is no reason to pay more out of fairness concerns. Finally, if the information made participants think that the fair price is higher, we should find that information reduces the intention to consume beef. However, as we discussed above, we do not find evidence for this treatment effect.

Was the null effect a fluke? Even relatively well-powered studies may sometimes result in erroneous null effects. Three results speak against this hypothesis. First, we can ask whether there is any correlational evidence that beliefs about CO_2 are predictive of the willingness to pay for meat. While any such evidence is subject to the usual caveats and endogeneity concerns, a strong negative correlation between beliefs about CO_2 emissions and WTP in the NoInfo treatment should give us pause in interpreting the null effect of the info treatment. We find that prior beliefs in the NoInfo treatment do not correlate with meat consumption.

Second, we can use the comparison of the Info and NoInfo treatments when beef was offered in the second part as a replication experiment. Of course, because these data stem from Part 2 of the experiment, the treatment comparison is less tightly controlled, with information about poultry possibly also bearing on participants' willingness to pay for beef. At the same time, it is hard to construct an explanation of how this additional information would lead to a null effect. We find that experiment 2 also features null effects of the information treatment.

Third, the lower bound of the 95% confidence interval for the effect of information on the willingness to pay for beef is $-\$1.74$. Hence, even if the information has an effect that we are not powered to detect, this effect is likely less than 2% of the market price of the meat.

Finally, and as we have already seen, the information does not affect participants' stated intention to reduce meat consumption.

What, then, causes the null effect? Having ruled out several possible explanations for the observed null effect, we are led to conclude that people's decision to eat meat appears not to be subject to concerns about associated CO_2 emissions. That is, even though we see that people are willing to invest in emission reduction when this willingness is elicited directly, their desire to curb emissions in meat consumption appears to be drowned out by the many other considerations that go into their consumption decision. If this is the reason behind the null effect, then we should be no more optimistic about finding an effect of information in still "wilder" settings. After

all, we made sure that our information actually moved beliefs and we can be confident the climate impact of various consumption activities was a salient feature of the decision making environment.

6 Conclusion

We have used incentivized survey techniques to elicit both beliefs about the carbon impact of consumer products and the valuation of this impact. We find that most consumers underestimate the impact, but heterogeneity is large. While they are willing to pay to offset carbon emissions, this willingness is highly concave and varies by subgroups. We use these inputs in a simple structural model to predict the impact of information. In an experimental test, we find little support for our predictions: despite a large correction in their beliefs about beef meat, subjects are largely unresponsive in their valuations of beef products.

Our results show that correcting consumer beliefs does not necessarily lead to lower demand for carbon-intense consumer products, even in settings where misperceptions are large, and consumers indicate that they are interested in offsetting emissions. This suggests that the climate impact of behavior is not a strong motivating force for most consumers in our experiment. Our findings are not inconsistent with those of other experiments discussed in Section 2, which find that any effects of carbon labels are typically small and short-lived. Because our design keeps the salience of climate change constant across conditions, we show that pure shifts in beliefs do little to change consumption behavior. This suggests that results in these other experiments are driven at least in part by increasing the salience of the climate change phenomenon, or by highlighting the emerging social norms around low-carbon consumption.

Our results also speak to the implications that can and cannot be drawn from some existing evidence. Evidence of widespread misperception of the climate impact of different consumption behaviors has sometimes been used to argue that information campaigns can lead to meaningful change. We show that this is not necessarily the case. Similarly, other papers have investigated attitudes toward climate change by using donation decisions, willingness to mitigate and survey responses. The results from these papers may be important in their own right, but our results temper confidence that these measures translate directly into everyday behavior like food consumption.

In fact, the picture that emerges from our and other studies is that the immediate return on information provision policies does not justify their current popularity among policy makers. It suggests that relying on the good intentions of informed individuals will not by itself deliver the important changes that we need in our carbon consumption, and that we may need to rely on more systemic approaches (Chater and Loewenstein, 2022). Of course, our results leave open the possibility that other types of information

provision, in a different context or evaluated using a different metric will be more effective in changing behavior. Having more informed citizens may also have other beneficial effects through long-run reflective processes, for instance by increasing political support for a carbon or meat tax. Future research should help elucidate such mechanisms.

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Online Appendix

Correcting Consumer Misperceptions about CO_2 Emissions

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Contents

A Climate Survey

A.1 Design Details

A.1.1 Consumer Products and Activities

Table A.1: Comments on the calculation of CO_2 emissions.

Product	Comment
Beer	It takes into account all the emissions starting with the production and ending with the distribution of the products to the consumer.
Phone call	It takes into account the CO_2 emissions generated to operate the phone and the communication network.
Microwave	It takes into account only the emissions generated by the power plants that produce the energy used by the microwave.
Milk	It takes into account all the emissions starting with the production and ending with the distribution of the products to the consumer.
Egg	It takes into account all the emissions starting with the production and ending with the distribution of the products to the consumer.
Poultry meat	It takes into account all the emissions starting with the production and ending with the distribution of the products to the consumer.
Shower	It takes into account the emissions generated by warming up the water and all the emissions connected to the water delivery and cleaning.
Chocolate	It takes into account all the emissions starting with the production and ending with the distribution of the products to the consumer.
Coffee	It takes into account all the emissions starting with the production and ending with the distribution of the products to the consumer.
Beef	It takes into account all the emissions starting with the production and ending with the distribution of the products to the consumer.
Flight	It takes into account only the emissions generated by burning the plane fuel.
Gas heating	It is the average of the estimates of 10 different carbon footprint calculators.

A.1.2 Elicitation Interface

We explain the interface and several measures we took to ensure the highest possible data quality in the survey.

Point estimates of the emission sizes. When asking about the CO_2 emissions generated by driving, we allowed the participants to express their guesses either in ounces or grams so they could use the more familiar unit of measure (Figure A.1).

For all the other products, we elicited the point estimates on a single interface that allowed the participants to easily go back and modify their previous answers. The order of the products on the interface was randomized at the individual level.

The 12 questions were graphically displayed (Figure A.2). The product in each question was represented by clip art, below which the name of the product and its size appeared. The participants could see which emissions were taken into account by the scientific estimate, by hovering the mouse cursor on an info icon ❶ shown above each question. The list of products, their amount, and the emissions to be considered were all described in the instructions as well.

The participants' answers were summarized in an interactive box displayed at the bottom of the page. The box appeared as soon as a participant filled in the first question on the screen and it stayed visible until the moment the participant confirmed his/her answers. The "Confirm" button appeared inside the summary box to draw the participant's attention to the box itself.

The summary box showed a participant's guesses graphically on a line. Crucially, we designed the line to avoid any anchoring effects. No number appeared on it if the participant had not entered any guesses. Moreover, the scale of the line adjusted dynamically depending on the highest guess.

Belief distribution. The elicitation interface showed the name and the quantity of the product and reminded the participants of their point estimates. The participants could see which emissions were taken into account by the scientific estimate, by hovering the mouse cursor on an info icon ❶.

The interface displayed five bins for each question (Figure A.3). The participant's point estimate for the product, call it m, was taken as the midpoint of the central bin. The central bin covers numbers from $0.95m$ to $1.05m$. The two bins on both sides of the central bin cover numbers from $0.85m$ to $0.95m$ and from $1.05m$ to $1.15m$. Finally, the farthest two bins cover numbers below $0.85m$ and above $1.15m$, respectively.

The interface showed a box containing the 20 balls the participants had to allocate among the bins. The participants could move the balls to a bin by (i) moving a slider below the bin, (ii) directly typing the number of balls they wanted to move in a text field below the bin, or (iii) clicking on the arrows next to the text field. The participants could move all the balls back to the box by pressing the button "Reset".

Willingness to mitigate. The participants indicated their WTMs using sliders (Figure A.4). In each of the eight questions, the current value of the slider was indicated both in £ and in $. The participants could also directly type their WTM in the text fields below the slider.

The interface was designed to (i) not anchor participants' answers and (ii) help participants make consistent choices. To achieve the first objective, the sliders had no default value and the participants had to click on the slider for a cursor to appear. Moreover, all the sliders were presented on the same page and they all ranged from £0 to £100. To achieve the second objective, we designed the interface in the following way.

(i) We showed the sliders in increasing order of emission sizes and they were aligned vertically.

(ii) We made sure that more than one slider was visible on the page simultaneously so that participants could see their answers to the other questions.

(iii) We displayed a summary box at the bottom of the page, which showed the participant's answers on a line ranging from £0 to £100. If two or more responses were identical or close to each other, the label position was vertically adjusted to avoid overlapping.

(iv) We placed the "Submit" button inside the summary box to draw the participants' attention to the summary. The button appeared only after the participant entered his/her WTM for all eight emission levels.

Additional measures. At the beginning of the experiment, we explicitly asked the participants not to use external help while taking the survey. We implemented a "Google trap" to check whether the participants complied with this request. The trap consists of three questions about climate-related facts that are hard to know by heart but that are easily googlable. We rewarded each correct answer with an additional £0.20 bonus.

Only 47 participants answered all three questions with values close to the ones that could be found on Google or Wikipedia at the time (call them Google answers for brevity); another 132 and 214 participants reported two or one answer(s) close to the Google answers, respectively. Finally, 629 participants reported responses that were always far from the Google answers. We conclude that Googling was not widespread during the survey. We verified that excluding the 179 subjects who reported two or more answers close to the Google answers does not change our qualitative results.

As a final quality check, at the end of the survey, we asked the participants whether we should use their answers in the analysis or we should discard their data because they were not attentive during the survey, Only 21 participants out of 1,022 indicated we should not use at least some of their answers. Excluding these participants does not change our results.

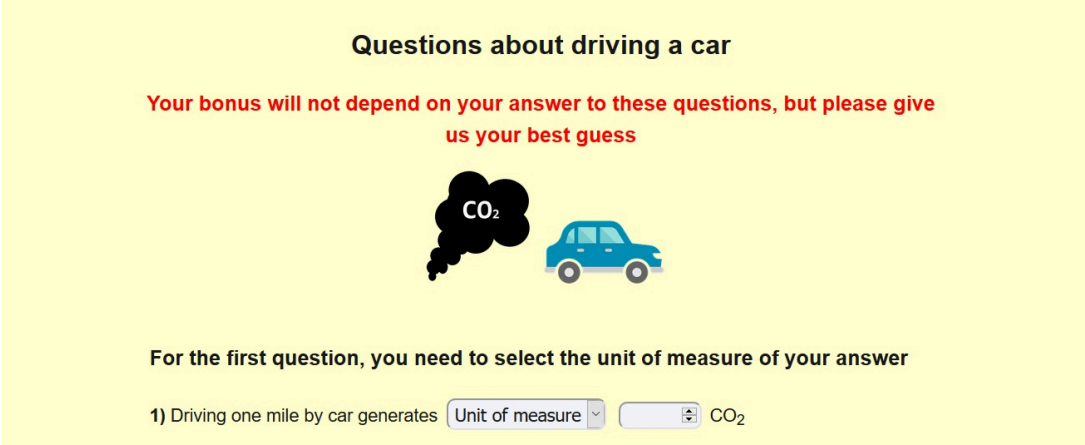


Figure A.1: Beliefs about CO_2 emissions from driving one mile by car.

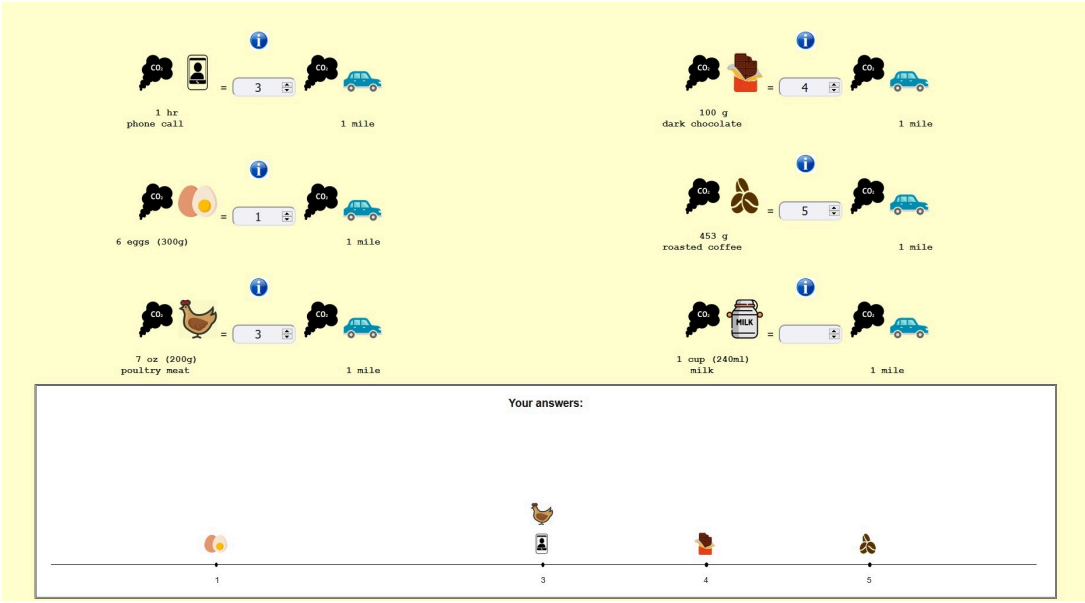


Figure A.2: Beliefs about CO_2 emissions from consumer products and activities.

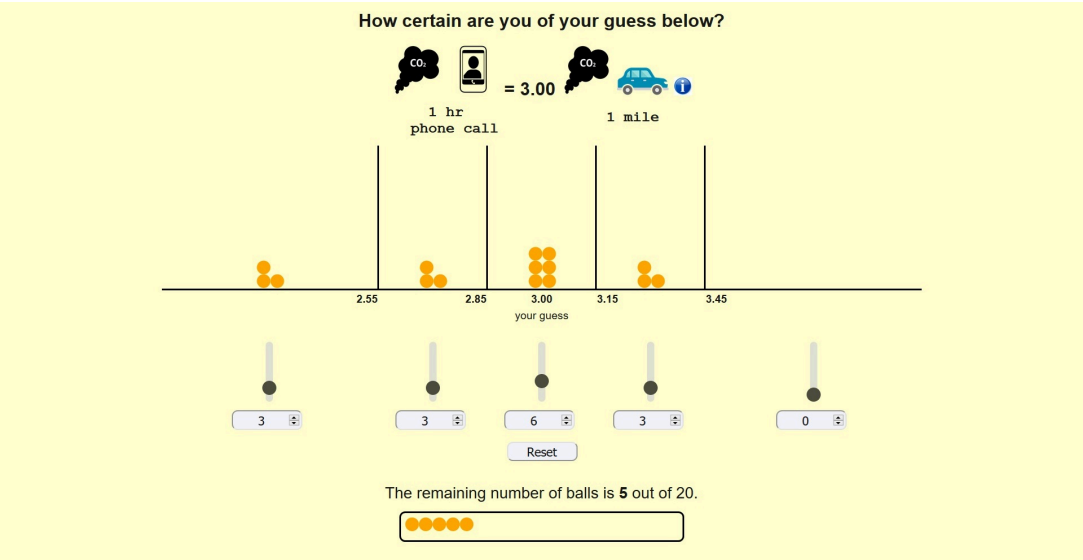


Figure A.3: Belief distribution.

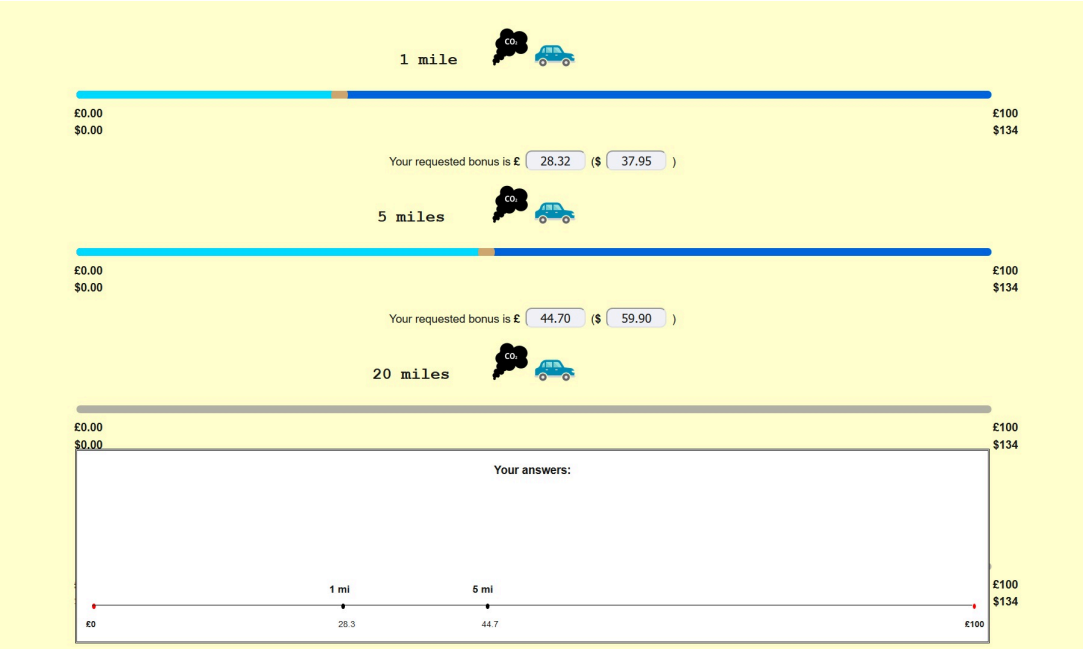


Figure A.4: Willingness to mitigate.

A.1.3 Survey Questions

Questions asked in Part 1

Page 1/2: Climate change

1. How much higher was the average global temperature in 2017 compared to the average in the pre-industrial era (1870-1900)? [ ] [°C / °F].

2. Compare the consequence of a 1.5°C and a 2°C increase in global temperature. How many more million people will be exposed to extreme heatwaves at least once every 5 years with an increase of 2°C? [ ] million.

3. Compare the consequence of a 1.5°C and a 2°C increase in global temperature. How many more million people will be exposed to the impacts of sea-level rise globally in 2100 with an increase of 2°C? [ ] million.

Page 2/2: Driving a car

1. Driving one mile by car generates [g / oz] of [ ] CO_2.

2. The social cost of carbon takes into account all future cost to humans of a given amount of CO_2 emissions today. The scientific estimate for the social cost of driving one mile by car is $ [ ].

3. Some people think scientists either over- or underestimate the social cost of carbon. Please give us your best guess of the social cost of driving one mile by car. I think that the social cost is $ [ ].

Survey questions at the end of Day 1

Page 1/5: Demographic information

1. Age

2. Gender
   Male; Female; Other

3. Ethnicity
   White; Black; Asian; Mixed; Other

4. In which state do you live?

5. What are the first 5 digits of your ZIP code?

6. Generally speaking, where do you place yourself on the Liberal-Conservative political spectrum?
   Liberal; Somewhat Liberal; Somewhat Conservative; Conservative

7. Generally speaking, how do you consider yourself?
   A Republican; A Republican-leaning Independent; Independent; A Democrat-leaning Independent; A Democrat

8. What is the highest level of school you have completed or the highest degree you have received?
   Less than high school degree; High school degree; Some University but no degree; Bachelor's degree; Postgraduate degree

9. How much total combined money did all members of your household earn last year?
   Below $5,000; $5,000 to $15,000; $15,000 to $30,000; $30,000 to $45,000; $45,000 to $60,000; $60,000 to $75,000; $75,000 to $90,000; $90,000 to $105,000; $105,000 to $120,000; $120,000 to $135,000; $135,000 to $150,000; $150,000 and up

10. Which device are you using to complete this session?
    Phone; Tablet; Laptop or Desktop

11. Do you trust that the researchers will indeed buy CO_2 offsets as described in the instructions?
    1 - Not at all; 2; 3; 4; 5 - Completely

12. Did you encounter any problem with the way the pages of the experiment were displayed? If so please indicate the model of your device, the browser you are using, and the problem you encountered.

13. Was there anything in the instructions that was unclear or do you have any other feedback?

Page 2/5: Current consumption, intention to reduce future consumption, and difficulty in reducing consumption (for all 12 products)

1. How many hours do you spend making phone calls from a cell phone per week?

2. Do you intend to reduce your call consumption in light of its CO_2 emissions?
   No.; Yes, I am prepared to reduce the time I spend on the phone by about 10%.; Yes, I am prepared to reduce the time I spend on the phone by about 25%.; Yes, I am prepared to reduce the time I spend on the phone by about 50%.; Yes, I am prepared to reduce the time I spend on the phone by more than 50%.

3. How difficult would it be to reduce the time you spend on the phone by half?
   Not applicable, I am not consuming this product.; Very easy.; Easy.; Neither easy nor difficult; Difficult.; Very difficult.

Notes: Similar questions were asked for all 12 products.

Page 3/5: Climate change knowledge

"Climate change, which includes global warming, is widely seen as a significant issue today. We are often asked to make changes in our lives that will lessen climate change. However, there may be reasons leading us to choose not to make changes."

1. How well-informed do you consider yourself on the issue of climate change?
   1 - Not informed; 2; 3; 4; 5 - Completely informed;

2. To what extent do you believe human activity is contributing to climate change?
   1 - Not at all; 2; 3; 4; 5 - A lot

3. How severe do you consider the problem of climate change?
   1 - Not a problem; 2; 3; 4; 5 - A huge problem

4. How soon should climate change be dealt with?
   1 - Never; 2; 3; 4; 5 - Immediately

5. Have you changed your actions, at least partly, due to consideration of climate change?
   No; Yes

6. If you answer Yes to the last question. How much has climate change been a factor in changing your actions?
   1 - A minor factor; 2; 3; 4; 5 - A major factor

7. How influential have the following factors been in shaping your own decisions about actions that might affect climate change?
   1 - Not influential; 2; 3; 4; 5 - Very influential

   (a) The monetary cost of changing my actions.
   (b) The availability of options for change.
   (c) The inconvenience of options for change.
   (d) Fitting changes in with family and others.
   (e) Lack of knowledge about possible changes I can make.
   (f) Uncertainty about the best option to contribute to reducing climate change.
   (g) Uncertainty as to whether climate change is a significant problem.
   (h) Select option 4 in this question. [Attention check]
   (i) The feeling that my actions will not affect the outcome of climate change.
   (j) Feeling that other individuals will not change their actions even if I do.
   (k) Other countries or people not taking equivalent action currently.

(l) Feeling that government policies, like carbon taxes, should be used to fix climate change, not individual action.

Page 4/5: Covid-19

1. Have you or someone in your close family suffered severe physical symptoms due to a Covid-19 infection?
   No; Yes

2. How worried are you that you or someone in you close family will get infected with Covid-19?
   1 - Not worried; 2; 3; 4; 5 - Very worried

3. Have you incurred personal economic losses due to Covid-19?
   No; Yes

4. How worried are you about the future economic impact that Covid-19 will have on your personality?
   1 - Not worried; 2; 3; 4; 5 - Very worried

5. How much do you think unemployment in your country increased due to Covid-19?

6. How long do you think the economic depression/recession in your country induced by Covid-19 will last?

Page 5/5: Self-reported data quality
"For the success of this study, it is essential that we analyze only those responses that have been dully answered. Therefore, we would like to know if you answered the questions attentively and in an honest way. Your answers here will not compromise your approval and bonus. Should we use your answers for the following parts of the experiment?"

1. Questions about the size of CO_2 emissions (Parts 1, 2, and 3)
   Yes, I paid attention to this part of the study and you should use my answers.; No, I didn't pay much attention to this part of the study and you should not use my answers.

2. Questions about getting a bonus vs emitting CO_2 (Part 4)
   Yes, I paid attention to this part of the study and you should use my answers.; No, I didn't pay much attention to this part of the study and you should not use my answers.

3. Final questionnaire
   Yes, I paid attention to this part of the study and you should use my answers.; No, I didn't pay much attention to this part of the study and you should not use my answers.

A.2 Additional Results

A.2.1 Demographic Characteristics

Table A.2: Demographic characteristics.

Age		
18-27	204	0.200
28-37	235	0.230
38-47	177	0.173
48-57	166	0.162
58+	240	0.235
Gender		
Female	516	0.505
Male	494	0.483
Other	12	0.012
Ethnicity		
Asian	68	0.067
Black	135	0.132
Mixed	29	0.028
White	765	0.749
Other	25	0.024
Party affiliation		
Republican	152	0.149
Republican leaning independent	67	0.066
Independent	205	0.201
Democratic leaning independent	144	0.141
Democratic	452	0.443
Political orientation		
Conservative	101	0.099
Somewhat conservative	225	0.221
Somewhat liberal	318	0.312
Liberal	376	0.369

Education		
Less than high school	8	0.008
High school degree	109	0.107
Some University but no degree	286	0.280
Bachelor Degree	370	0.363
Postgradute degree	247	0.242
Household income		
- $5,000	26	0.025
$5,000 - $15,000	67	0.066
$15,000 - $30,000	129	0.126
$30,000 - $45,000	130	0.127
$45,000 - $60,000	137	0.134
$60,000 - $75,000	114	0.112
$75,000 - $90,000	90	0.088
$90,000 - $105,000	80	0.078
$105,000 - $120,000	88	0.086
$120,000 - $135,000	30	0.029
$135,000 - $150,000	37	0.036
$150,000 -	92	0.090

Notes: 1,022 participants completed Session 1.

A.2.2 Beliefs about CO_2 Emissions

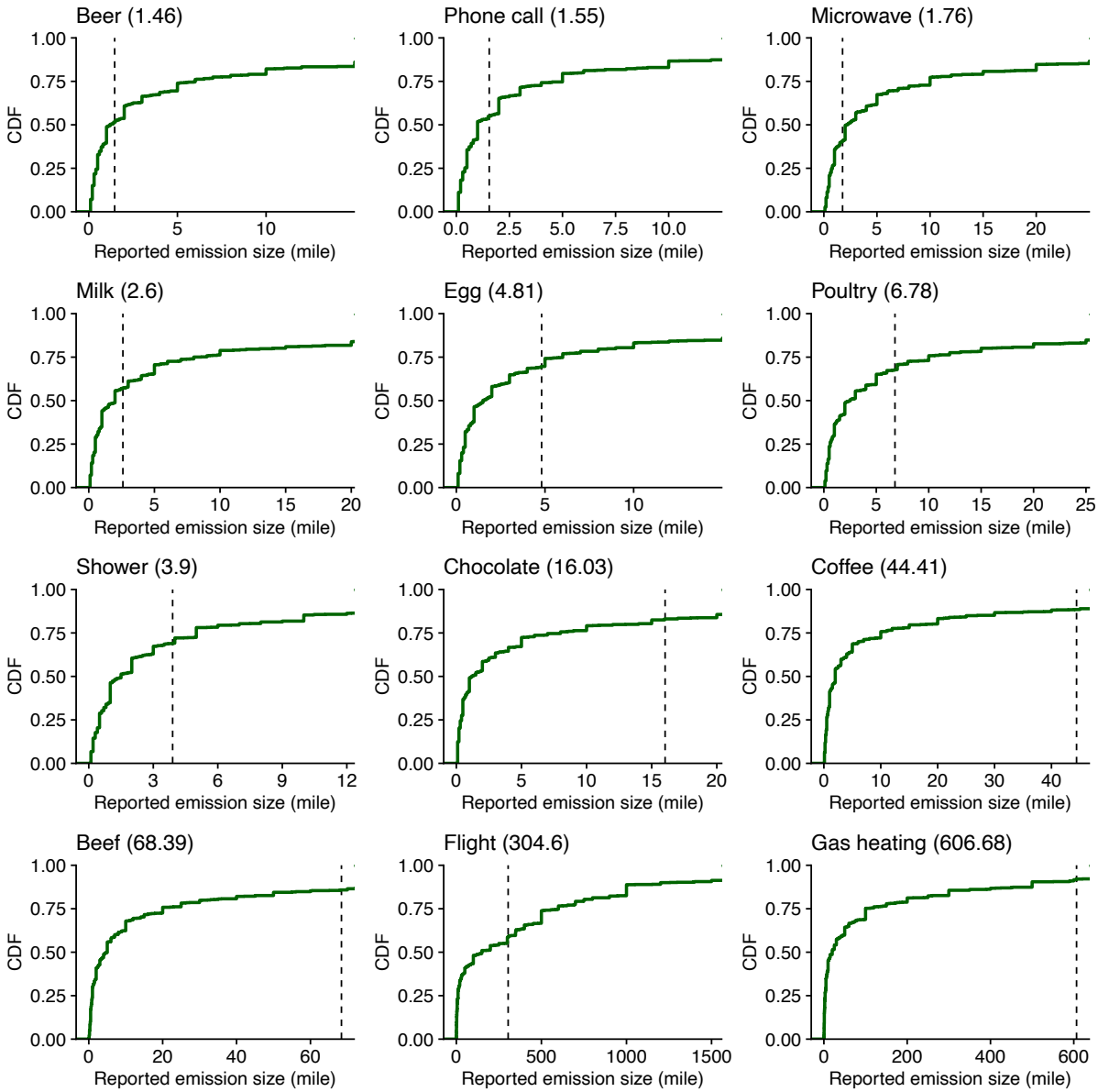


Figure A.5: Empirical CDFs of beliefs about CO_2 emissions. *Notes*: Vertical dashed lines indicate "true" emission sizes (numbers in parentheses). The x-axis is cut at the larger of the true emission size and the bound $Q3 + 1.5 \times IQR$.

Table A.3: Summary statistics of elicited (point) beliefs about CO_2 emissions (in kilograms) from 12 consumer products and activities. Cf. Table 2.

		Belief			
Product	Emissions	Q1	Median	Q3	Under-est.
Beer	0.425	0.007	0.100	0.851	0.67
Phone call	0.451	0.006	0.082	0.648	0.71
Microwave	0.512	0.011	0.191	1.494	0.62
Milk	0.757	0.009	0.112	1.232	0.69
Shower	1.135	0.007	0.100	0.800	0.79
Egg	1.400	0.007	0.121	1.000	0.78
Poultry	1.973	0.010	0.192	1.814	0.75
Chocolate	4.665	0.007	0.090	1.000	0.85
Coffee	12.923	0.009	0.142	1.417	0.90
Beef	19.901	0.020	0.271	2.835	0.87
Flight	88.639	0.300	5.670	98.129	0.75
Gas heating	176.544	0.060	1.000	15.444	0.93

Notes: The last column "Under-est." shows the fraction of participants who underestimated the size of emissions.

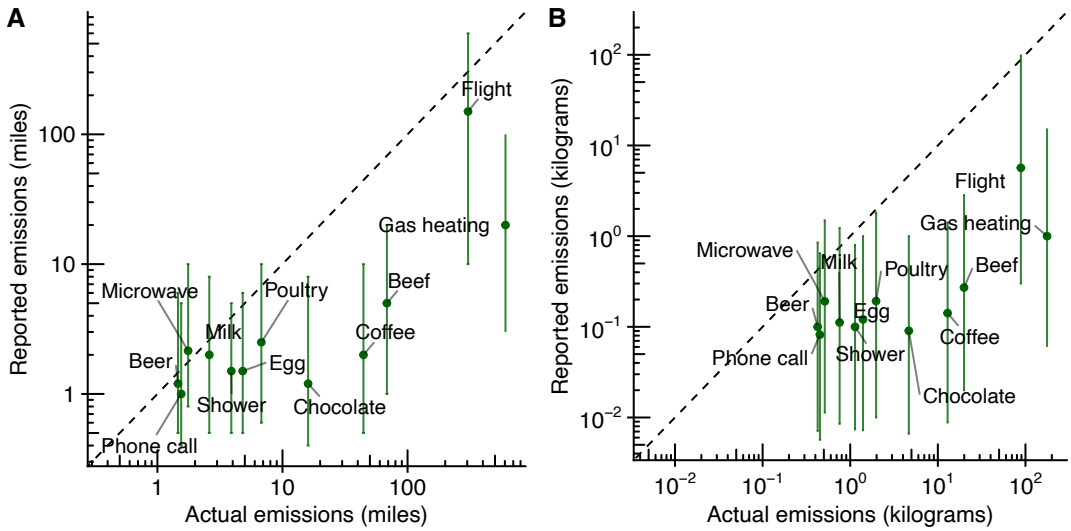


Figure A.6: Summary statistics of reported CO_2 emissions in (A) miles and (B) kilograms. *Notes*: Medians and IQRs are plotted on a logarithmic scale. The actual amount of CO_2 emissions from driving one mile by car is 291 grams. The participants' beliefs about CO_2 emissions from driving one mile by car were elicited in Part 1 of the study.

A.2.3 Willingness to Mitigate CO_2 Emissions

Summary statistics

Table A.4: Summary statistics of willingness to mitigate ($N = 1,022$).

Emission size	Mean	SD	SEM	Q1	Median	Q3	Interior	$0	$134
1	40.94	46.22	1.45	3.90	20.08	67.00	835	80	107
5	45.42	45.22	1.41	6.70	27.93	73.47	848	72	102
20	51.73	44.35	1.39	12.15	40.20	80.81	854	68	100
50	57.07	45.33	1.42	14.75	50.00	93.56	845	59	118
100	61.79	46.21	1.45	18.76	59.19	100.50	834	59	129
200	66.22	47.90	1.50	20.01	67.00	110.00	820	57	145
450	70.08	49.57	1.55	20.01	73.15	120.60	801	58	163
700	74.54	51.48	1.61	20.10	80.53	129.99	749	58	215

Notes: The last three columns show the number of interior WTMs and corner WTMs, respectively.

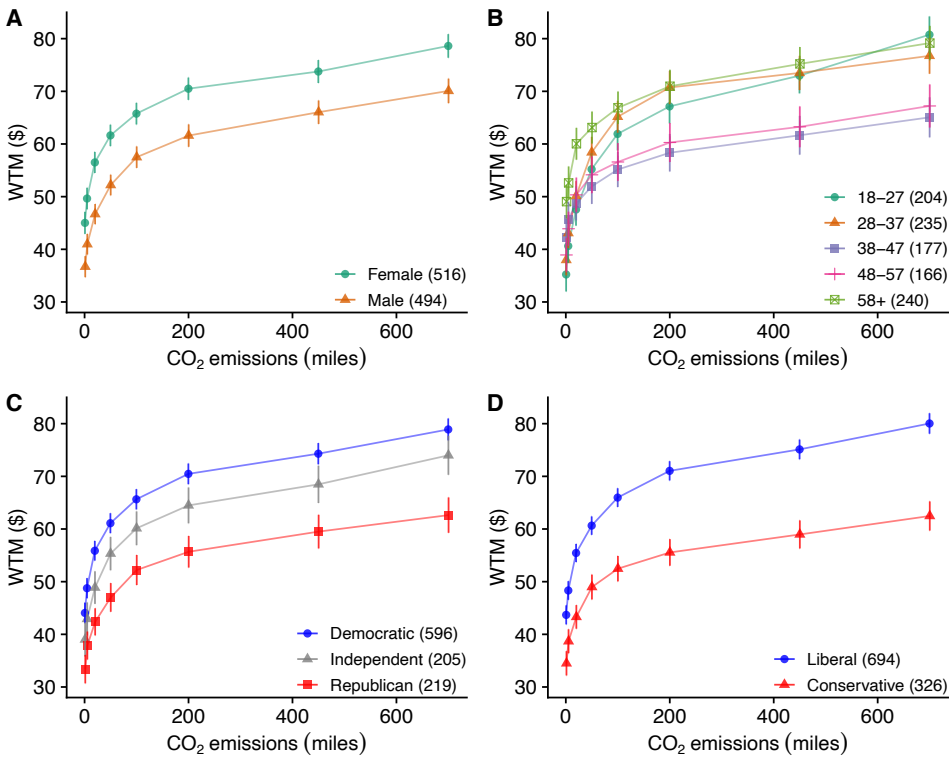


Figure A.7: Willingness to mitigate and demographic characteristics. *Notes*: Points represent the means and bars represent SEMs. In panel C, "Republican-leaning independent" and "Democratic-leaning independent" are grouped into Republican and Democratic, respectively. In panel D, "somewhat liberal" and "somewhat conservative" are grouped into liberal and conservative, respectively.

Table A.5: Summary statistics of willingness to mitigate. Participants whose WTMs are all strictly between 0 and 100 are included ($N = 686$). Cf. Table A.4.

Emission size	Mean	SD	SEM	Q1	Median	Q3
1	30.83	34.26	1.31	5.00	17.42	46.81
5	34.82	32.94	1.26	6.92	26.71	52.68
20	41.15	33.13	1.26	13.34	33.52	64.96
50	45.70	34.42	1.31	14.81	40.20	69.87
100	50.24	36.11	1.38	18.43	45.03	77.91
200	54.51	38.52	1.47	20.01	51.90	88.88
450	58.89	41.21	1.57	20.01	58.81	93.82
700	64.03	44.59	1.70	20.03	63.77	106.54

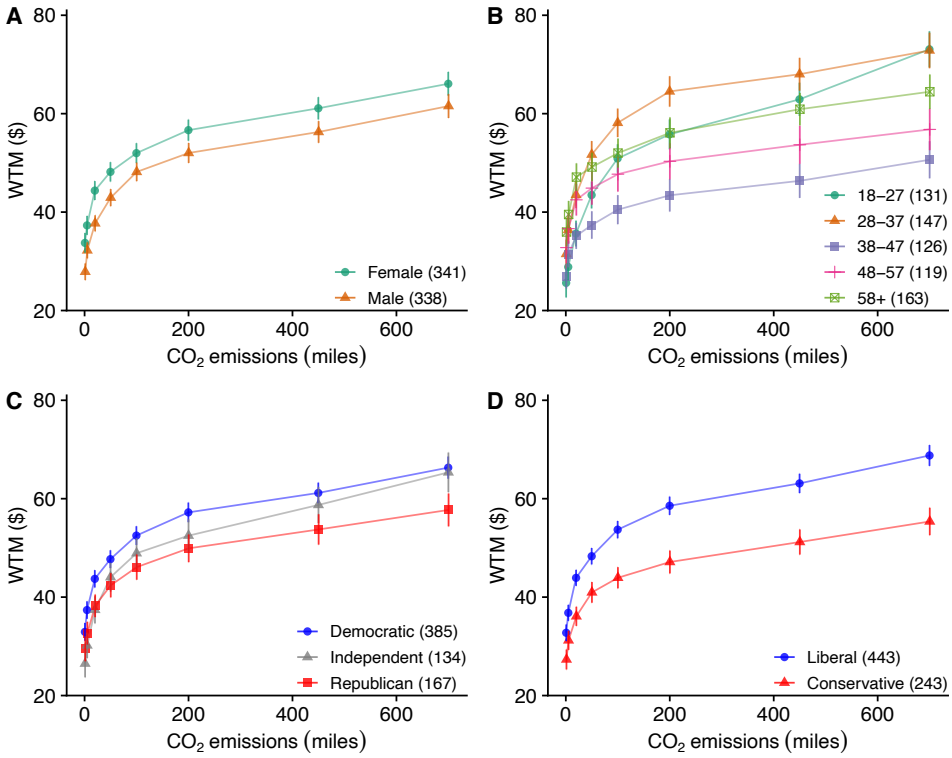


Figure A.8: Willingness to mitigate and demographic characteristics. *Notes*: Participants whose WTMs are all strictly between 0 and 100 are included ($N = 686$). Cf. Figure A.7. Points represent the means and bars represent SEMs. In panel C, "Republican-leaning independent" and "Democratic-leaning independent" are grouped into Republican and Democratic, respectively. In panel D, "somewhat liberal" and "somewhat conservative" are grouped into liberal and conservative, respectively.

Shape of the individual-level WTM curve

We elicited WTM for eight levels of CO_2 emissions, that correspond to emissions generated by driving 1, 5, 20, 50, 100, 200, 450, and 700 miles by car. We observe a concave WTM curve at the aggregate level (Figure 3). Here we classify the shape of the individual-level WTM curve. Let (e_i, w_i) denote the pair of emission size e_i and the reported WTM $w_i \in [0, 134]$, for each $i = 1, \ldots, 8$.

Step 1. For each participant, we construct a piecewise linear WTM curve by linear interpolation. The WTM curve has seven line segments. Let s_i be the slope of the ith line segment given by

$$s_i = \frac{w_{i+1} - w_i}{e_{i+1} - e_i}.$$

We apply the following rule sequentially to classify the shape of the WTM curve.[1] We say that a WTM curve is

- *constant* if $s_i = 0$ for all i;
- *almost constant* if $\max w_i - \min w_i \leq 1.34$ - that is deviation for a constant value are smaller than 1% of the range of possible answers ;
- *decreasing* if $s_i \leq 0$ for all i with at least one strict inequality;
- *concave* if $s_{i+1} \leq s_i$ for all i with at least one strict inequality;
- *convex* if $s_{i+1} \geq s_i$ for all i with at least one strict inequality;
- *increasing* if $s_i \geq 0$ for all i with at least one strict inequality;
- *non-monotonic* if it is none of the above.

There are 210 (almost) constant, 34 decreasing, 107 concave, 2 convex, and 293 increasing, WTM curves. The remaining 376 WTM curves are non-monotonic.

Step 2. Let us focus on 293 participants whose WTM curves are increasing but neither concave nor convex. There are 59 participants whose WTMs are top-censored at \$134. Let $\bar{w}$ denote the largest WTM. If $\bar{w} = 134$, let $\bar{e}$ be the smallest emission level e_i at which $w_i = 134$. If $\bar{w} < 134$, let $\bar{e} = e_8$. Now, we draw a chord connecting two points (e_1, w_1) and $(\bar{e}, \bar{w})$. We say that a WTM curve is *concave*† (*convex*†) if the points (e_i, w_i) for which $e_i \leq \bar{e}$ lie above (below) the chord. There are 212 concave† and 6 convex† WTM curves.

[1] This means that *concave* and *convex* WTM curves in this classification are non-decreasing, and *increasing* WTM curves are neither concave nor convex.

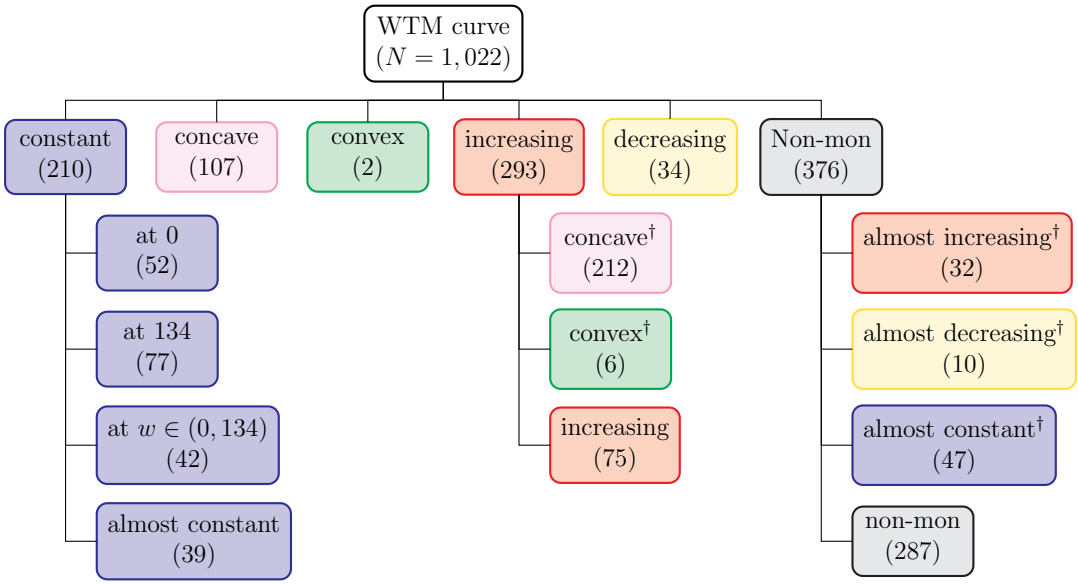


Figure A.9: Classification of individual-level WTM curves.

Step 3. Finally, we turn to the remaining 376 participants whose WTM curves are non-monotonic.

First, we say that a WTM curve is *almost constant*† if the difference between the largest WTM and the smallest WTM is less than \$4.02 (3% of the maximum possible range, \$134). This relaxation captures the shape of additional 47 WTM curves.

Second, we say that a WTM curve is *almost increasing*† (*almost decreasing*†) if the piecewise linear WTM curve has only one line segment with a negative (positive) slope, and the relative change of WTM on that segment is "not too large".[2] This relaxation captures the shape of additional 42 WTM curves.

Classification summary. Allowing some margin of error, we have the following (mutually exclusive) classification of individual-level WTM curves: 257 are constant, 319 are concave, 8 are convex, 107 are increasing, 44 are decreasing, and 287 are non-monotonic.

[2]Suppose the sign of the slopes change on the segment connecting (e_j, w_j) and (e_{j+1}, w_{j+1}). We require the absolute relative change to be less than 10%, i.e., $|(w_{j+1} - w_j)/w_j| \leq 0.1$.

A.3 Quantify the Effect of Information

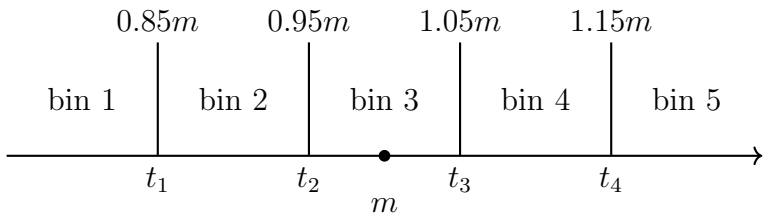
A.3.1 Recover Subjective Belief Distribution

The goal of the belief elicitation task is to elicit the participant's subjective belief distribution F about CO_2 emissions from each of the 12 products.

In the first part of the belief elicitation task, we elicited a point estimate for the modal value of the emissions. Let $m \in \mathbb{R}_+$ denote a participant's belief about how much CO_2 a given product emits relative to driving one mile by car. In the second part of the task, we elicited the subjective probability distribution about the size of the CO_2 emissions. We first constructed five bins around the reported modal belief m,

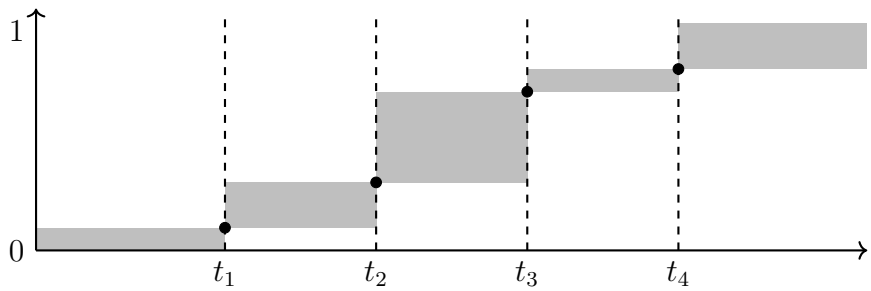
$$[0, t_1), [t_1, t_2), [t_2, t_3), [t_3, t_4), [t_4, \infty),$$

where each t_i is the threshold separating bins, given by $t_1 = 0.85m$, $t_2 = 0.95m$, $t_3 = 1.05m$, and $t_4 = 1.15m$, as illustrated below.



The participant then allocated 20 balls into these five bins. Let $p_i \in [0, 1]$ denote the probability assigned to the ith bin (i.e., 1/20 times the number of balls in the bin). The collection $(m, (p_1, \ldots, p_5))$ represents the response from the participant, from which we recover the subjective belief distribution F.

Let $q_i = \sum_{j=1}^{i} p_j$ be the cumulative probability for the emission size being below threshold t_i. Assuming that there is no measurement error, we have $F(y \leq t_i) = q_i$ for each $i = 1, \ldots, 4$. Given the observation $\{(t_1, q_1), \ldots, (t_4, q_4)\}$, we can bound the cumulative distribution function (CDF) of the subjective belief F by the gray shaded rectangles as illustrated below.



We fit a *cubic interpolating spline* following Breunig et al. (2021), which took the idea from Bellemare, Bissonnette and Kröger (2012). The detail will not be shown here, but this method interpolates observed quantile points by a smooth and monotonic curve. To

apply this procedure, we need some assumptions about the boundaries of the support of F. We take $t_0 = 0.75m$ and $t_5 = 1.25m$, where t_0, t_5 are such that $t_0 = \sup_t\{t \leq t_1 : F(y \leq t) = 0\}$ and $t_5 = \inf_t\{t \geq t_4 : F(y \leq t) = 1\}$.

A.3.2 Expected WTM

We elicited the participants' willingness to mitigate (WTM) for eight levels of CO_2 emissions, corresponding to the emissions generated by driving 1, 5, 20, 50, 100, 200, 450, and 700 miles by car. We recover the participant's WTM function w by linear interpolation.

Given a WTM function w and a subjective belief distribution F about CO_2 emissions associated with a given product, we can calculate the *expected WTM*,

$$\overline{W}(w, F) = E_F[w(c)] = \int w(c)\mathrm{d}F(c),$$

by numerically evaluating the integral with the Adaptive Gauss-Kronrod Quadrature.

A.3.3 Prediction for Beef and Poultry

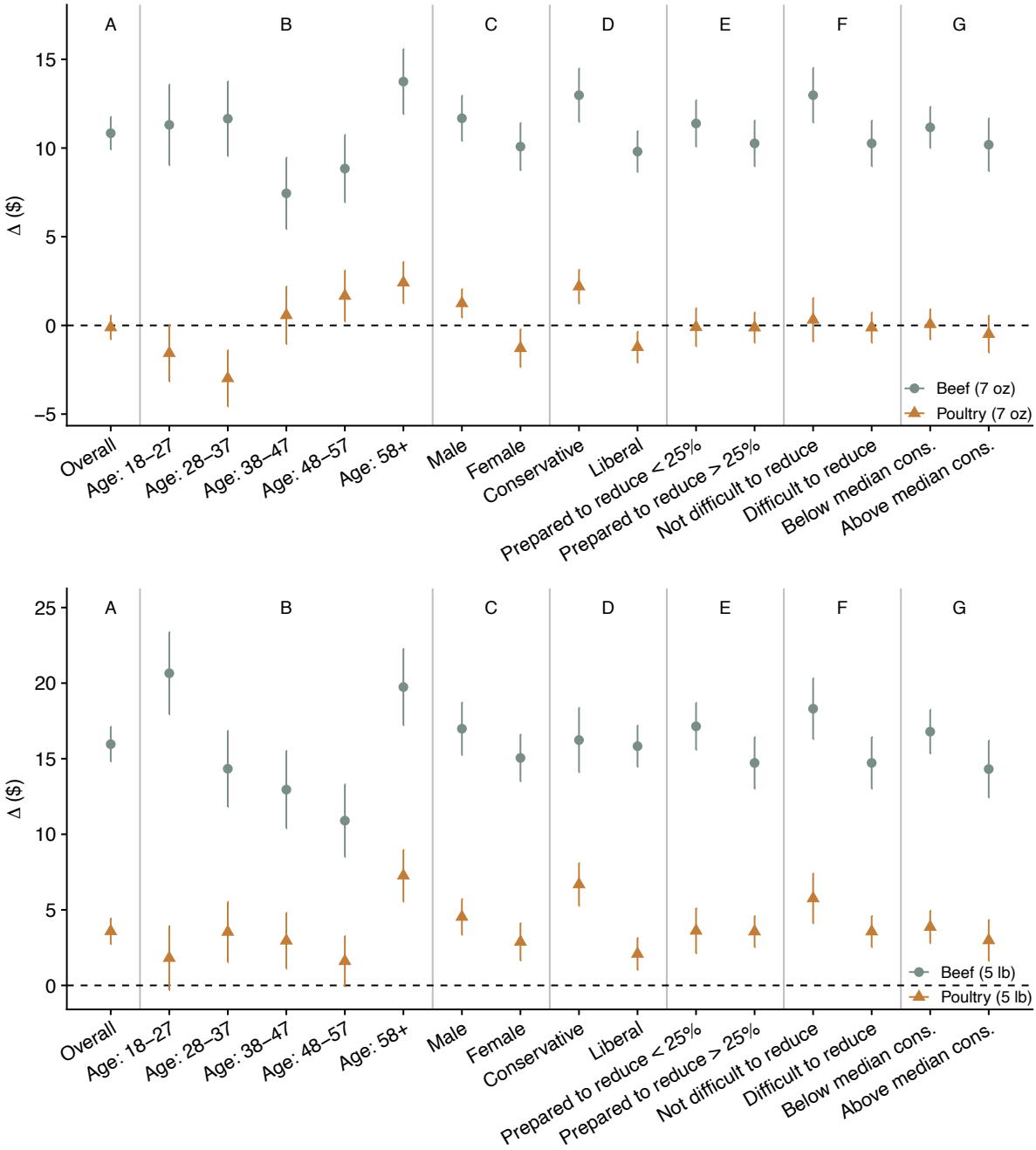


Figure A.10: Predicted effect of information provision for each demographic group. (Top) 7 oz of meat products as in the Climate Survey. (Bottom) 5 lb (80 oz) of meat products as in the Meat Experiment. *Notes*: (D) "Somewhat liberal" and "somewhat conservative" are grouped into liberal and conservative, respectively. (E) "Are you prepared to reduce your future consumption of beef/poultry in light of its CO_2 emission footprint?" (F) "How difficult would it be to reduce your current consumption of beef/poultry by half?" (G) "How many times do you eat beef/poultry per week?" Bars indicate SEM.

B Meat Experiment

B.1 Design Details

B.1.1 Information Screen

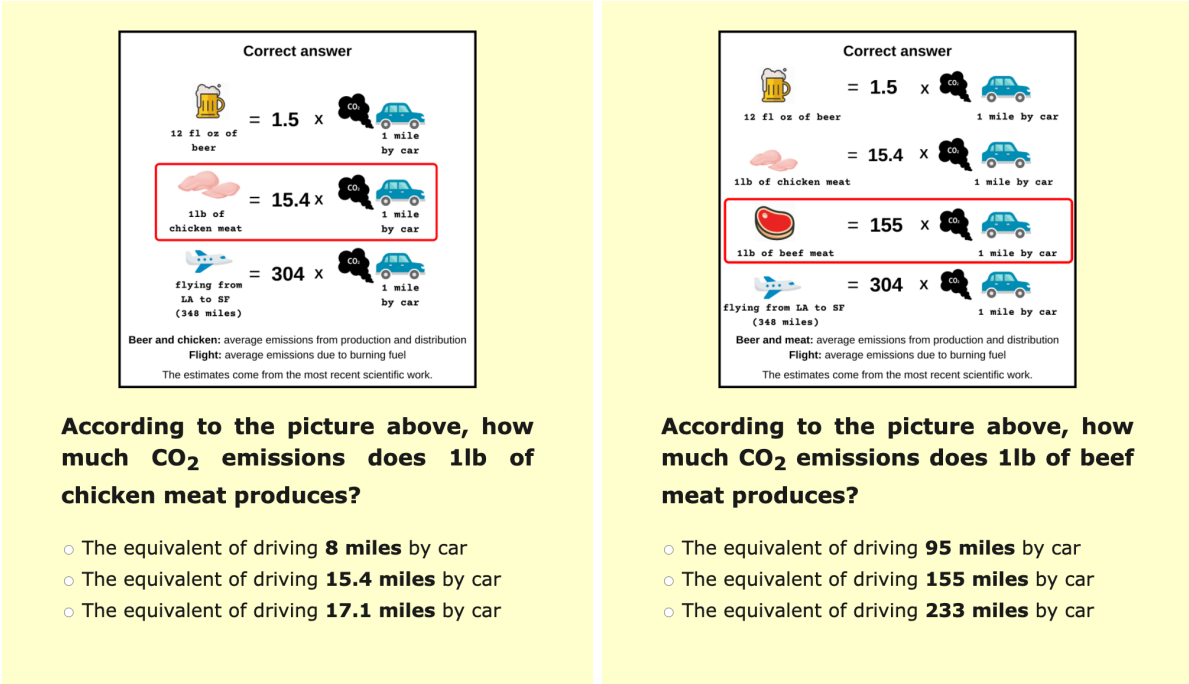


Figure B.1: Information screens in the Info treatment. (Left) The first product (poultry in this case). (Right) The second product (beef in this case).

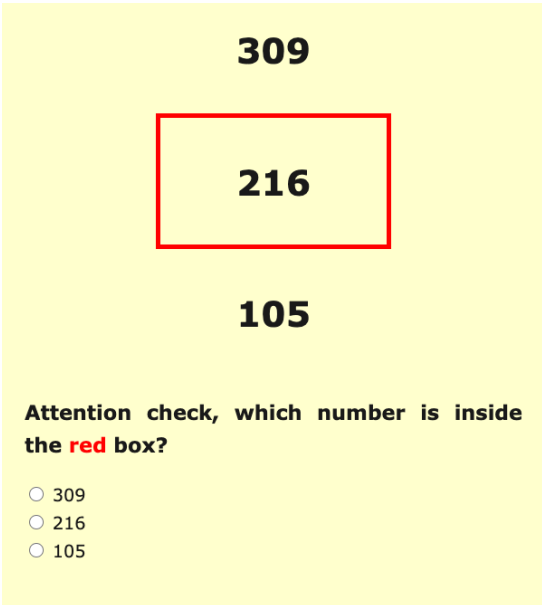


Figure B.2: Screen for the NoInfo treatments.

B.1.2 WTP Elicitation Interface

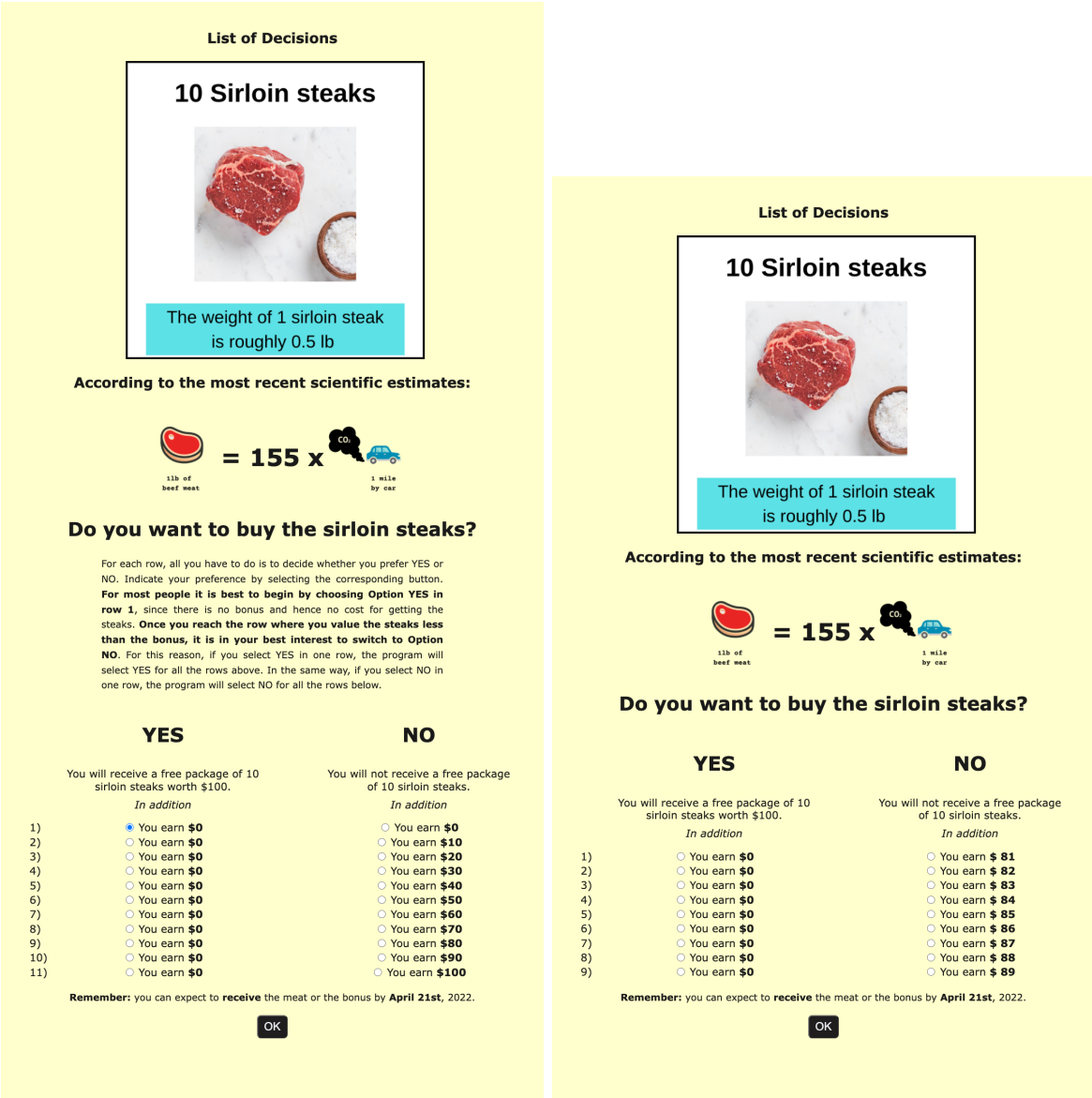


Figure B.3: Willingness to pay elicitation screen for the beef product in the Info treatments. (Left) On the first list, the monetary bonus in the right option ranged from $0 to $100 in $10 increment. (Right) The second list "zoomed in" around the switching point and asked another nine questions. *Notes*: In the NoInfo treatments, information about the true emission size is shown as **?**.

Initial screening questions

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1. What is your age?
2. What sex were you assigned at birth, such as on an original birth certificate?
   Male; Female
3. What is your ethnicity?
   White; Black; Asian; Mixed; Other
4. In which state do you live?
5. What are the first 5 digits of your ZIP code?

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1. Generally speaking, where do you place yourself on the Liberal-Conservative political spectrum?
   Liberal; Somewhat liberal; Somewhat conservative; Conservative
2. Generally speaking, how do you consider yourself?
   A Republican; A Republican-leaning Independent; A Democrat-leaning Independent; A Democrat
3. What is the highest level of school you have completed or the highest degree you have received?
   Less than high school degree; High school degree; Some University but no degree; Bachelor's degree; Postgraduate degree

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1. How many people live in your household (including yourself)?
2. What was the combined income of all the members of your household last year?
   Below $5,000; $5,000 to $15,000; $15,000 to $30,000; $30,000 to $45,000; $45,000 to $60,000; $60,000 to $75,000; $75,000 to $90,000; $90,000 to $105,000; $105,000 to $120,000; $120,000 to $135,000; $135,000 to $150,000; $150,000 and up
3. Do you eat meat?
   Yes; No

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1. Do you live with a partner?
   Yes; No

2. What is the gender of your partner?
   I don't have a partner; Male; Female; Other

3. What is the education level of your partner?
   I don't have a partner; Less than high school degree; High school degree; Some University but no degree; Bachelor's degree; Postgraduate degree

4. This is an attention check, please answer that you strongly agree.
   Strongly disagree; Disagree; Neither agree nor disagree; Strongly agree

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1. Which device are you using to complete this study?
   Phone; Tablet; Laptop or Desktop

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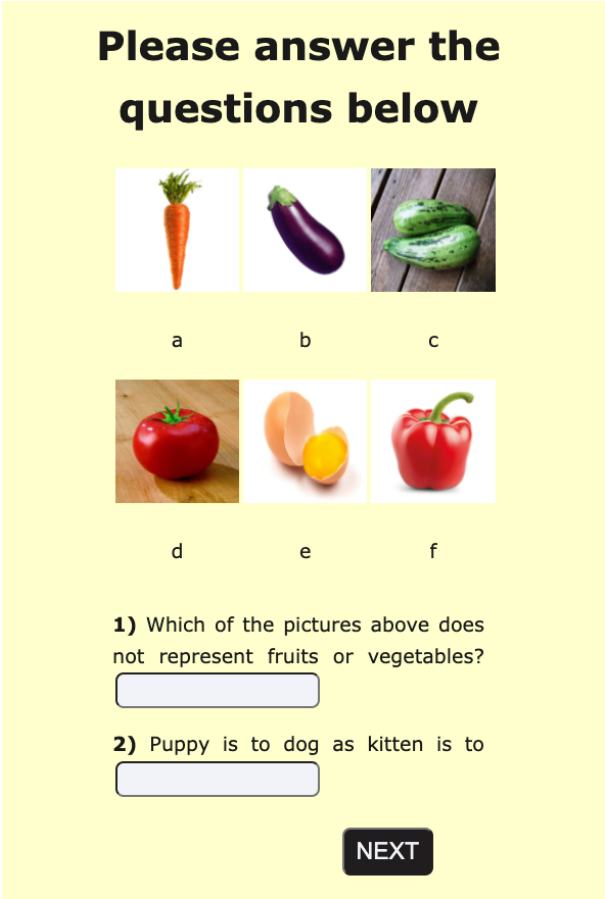

Post-experiment questionnaire

Notes: MEAT1 below is either beef or poultry, depending on the first product the participant saw, and MEAT2 is the other meat product.

1. How many times do you eat MEAT1 per week?

2. Do you intend to reduce your MEAT1 consumption in light of its CO_2 emissions?
   No.; Yes, I am prepared to reduce my current consumption by about 10%.; Yes, I am prepared to reduce my current consumption by about 25%.; Yes, I am prepared to reduce my current consumption by about 50%.; Yes, I am prepared to reduce my current consumption by more than 50%.

3. How difficult would it be to reduce your current MEAT1 consumption by half?
   Not applicable. I don't consume this product.; Very easy.; Easy.; Neither easy nor difficult.; Difficult.; Very difficult.

4. If you wanted to avoid the CO_2 impact of MEAT1, how would you change your consumption patterns? Choose the answer that most applies.
   I would eat more lamb and pork.; I would eat more MEAT2.; I would eat more vegetarian dishes.; I would not reduce my consumption of poultry.; I would eat less MEAT1 without necessarily eating more of anything else.

5. Do you trust that the researchers will indeed ship meat products as promised in the instructions?
   1 - Not at all; 2; 3; 4; 5 - Completely

6. How severe do you consider the problem of climate change?
   1 - Not a problem; 2; 3; 4; 5 - A huge problem

B.2 Preregistration

ASPREDICTED

Wharton CREDIBILITY LAB
UNIVERSITY of PENNSYLVANIA

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Information provision about CO2 emissions and meat consumption. (#92070)

Created: 03/25/2022 03:41 AM (PT)

This is an anonymized copy (without author names) of the pre-registration. It was created by the author(s) to use during peer-review.
A non-anonymized version (containing author names) should be made available by the authors when the work it supports is made public.

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1) Have any data been collected for this study already?
No, no data have been collected for this study yet.

2) What's the main question being asked or hypothesis being tested in this study?
Correcting perceptions about CO2 emissions associated with meat products will affect demand for these products.
In particular, in previous work we have used data on a) misperceptions about CO2 emissions and b) willingness to pay to avoid CO2 emissions to predict the effect of providing information about the emissions. Following these predictions, we expect that providing information about CO2 emissions will have a larger negative effect on the demand for beef than on the demand for chicken.

3) Describe the key dependent variable(s) specifying how they will be measured.
The key dependent variable is the willingness to pay (WTP) for a package of meat products. Willingness to pay is measured by an incentive compatible multiple price list mechanism.

4) How many and which conditions will participants be assigned to?
The experiment has two parts. The first part contains our main design, which is a 2x2:
·The meat package consists of either beef products (sirloin steaks) or chicken products (chicken breasts).
·Participants either obtain a scientific estimate of the emissions associated with the package ("info" treatment) or not ("no info" treatment).
These four conditions are between-subjects.

In the second part of the experiment (again a 2x2), we will ask each subject for their WTP for the alternative meat product. In the information treatment, this implies that subjects now have knowledge about both beef and chicken products ("double info" treatment).

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
We will regress the WTP for both meat products in Part 1 of the experiment on a treatment dummy for information provision and meat type, and we will test the interaction of meat type and information provision. Our regression analysis will control for covariates like political orientation and household income.

6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
We will not exclude observations. However, we will conduct robustness checks where we exclude people who were not able to reproduce the information we gave them in the info treatments or that did not give us their address for sending the meat products.

7) How many observations will be collected or what will determine sample size? No need to justify decision, but be precise about exactly how the number will be determined.
We aim at collecting 2000 observations, 500 in each treatment cell. We consider an observation collected if a participant completed the first part of the experiment.

8) Anything else you would like to pre-register? (e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)
We conduct a questionnaire where we ask several personal characteristics. We will correlate these characteristics with WTP. We will study how people update beliefs about CO2 emissions in response to the information and will study whether prior and posterior beliefs affect purchases.
We will also conduct heterogeneity analyses by subgroups that have been shown to have a higher elasticity of meat consumption, or, per our previous survey, have shown particularly large predicted effects of information.
As robustness checks for the model specification, we will conduct Tobit regressions with censoring above. We will also look quantile regressions for 10 WTP quantiles, and focus on the interaction effects among the middle quantiles that are away from the extremes of the WTP distribution.
Finally, to understand the impact of information about substitutes, we will compare the results of the first part of the experiment (info vs. no info), with the results of the second part (double info vs. no info).

B.3 Additional Results

B.3.1 Willingness to Pay for the First Product

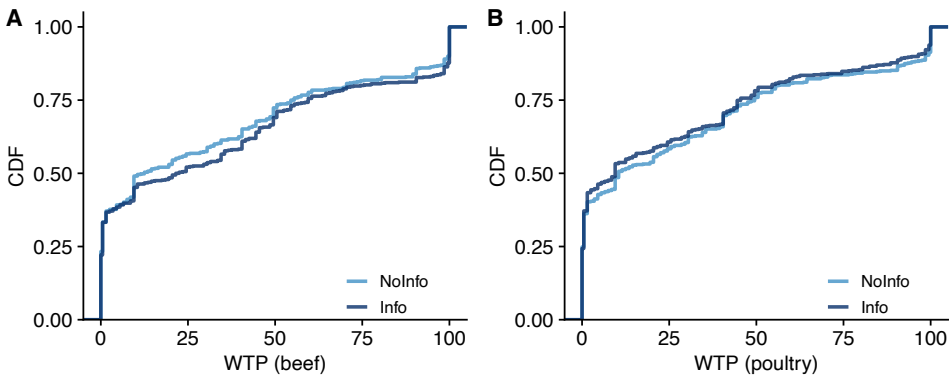

Figure B.4: Distribution of the willingness to pay for the first meat product.

B.3.2 Belief about the Second Product

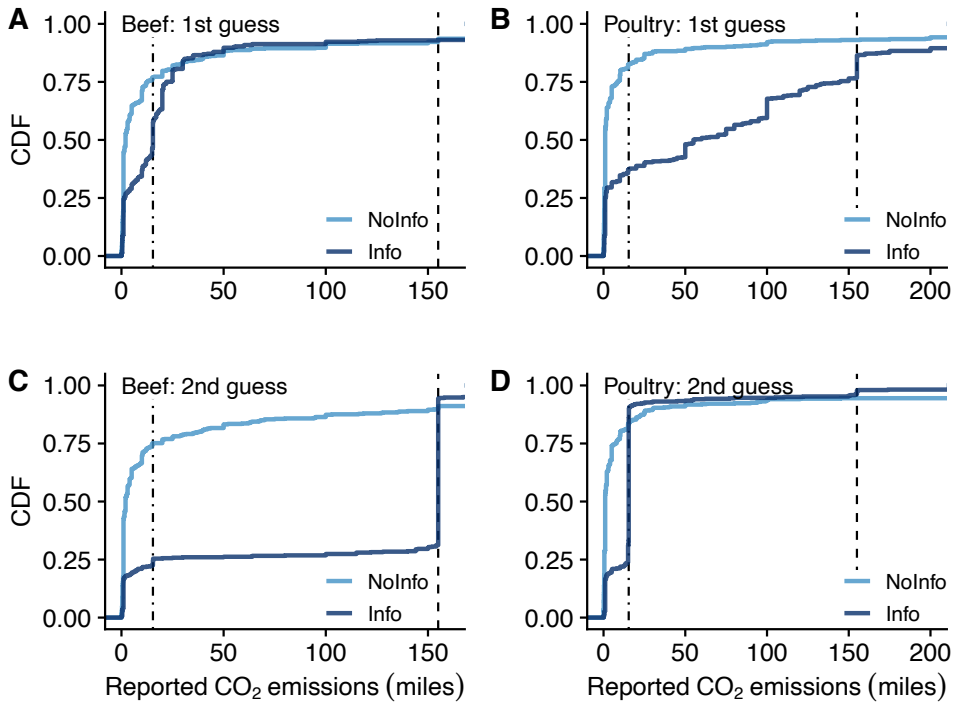

Figure B.5: Beliefs about CO_2 emissions from two meat products. *Notes*: We focus on the data from the second part of the experiment (panels AC: "poultry first" treatments; panels BD: "beef first" treatments). Vertical lines correspond to the "true" size of CO_2 emissions (dash-dotted: poultry, 15.4 miles; dashed: beef, 155 miles). Cf. Figure 8.

B.3.3 Demographic Characteristics

Table B.1: Demographic characteristics.

			BeefFirst		PoultryFirst	
	All		NoInfo	Info	NoInfo	Info
Age						
18-27	367	0.176	0.174	0.177	0.189	0.165
28-37	364	0.175	0.161	0.185	0.156	0.198
38-47	332	0.160	0.153	0.162	0.166	0.158
48-57	356	0.171	0.191	0.181	0.158	0.154
58+	662	0.318	0.320	0.296	0.331	0.325
Gender						
Male	1008	0.484	0.489	0.483	0.484	0.482
Female	1073	0.516	0.511	0.517	0.516	0.518
Ethnicity						
Asian	68	0.033	0.036	0.029	0.029	0.037
Black	265	0.127	0.146	0.117	0.106	0.140
Mixed	79	0.038	0.027	0.035	0.050	0.041
White	1605	0.771	0.769	0.785	0.778	0.753
Other	64	0.031	0.023	0.035	0.037	0.029
Party affiliation						
Republican	595	0.286	0.288	0.312	0.270	0.274
Republican leaning independent	169	0.081	0.072	0.073	0.094	0.086
Independent	404	0.194	0.188	0.165	0.202	0.222
Democratic leaning independent	160	0.077	0.078	0.096	0.073	0.060
Democratic	753	0.362	0.375	0.354	0.360	0.358
Political orientation						
Conservative	434	0.209	0.195	0.213	0.216	0.210
Somewhat conservative	662	0.318	0.320	0.338	0.289	0.325
Somewhat liberal	579	0.278	0.278	0.277	0.291	0.267
Liberal	406	0.195	0.206	0.171	0.204	0.198
Education						
Less than high school	48	0.023	0.023	0.029	0.019	0.021
High school degree	527	0.253	0.259	0.248	0.252	0.253
Some University but no degree	661	0.318	0.324	0.319	0.337	0.290
Bachelor Degree	546	0.262	0.267	0.275	0.225	0.282
Postgradute degree	299	0.144	0.127	0.129	0.166	0.154
Household income						
- $5,000	68	0.033	0.025	0.025	0.042	0.039
$5,000 - $15,000	130	0.062	0.062	0.044	0.067	0.076
$15,000 - $30,000	339	0.163	0.186	0.156	0.150	0.160
$30,000 - $45,000	313	0.150	0.129	0.163	0.158	0.152
$45,000 - $60,000	322	0.155	0.136	0.165	0.160	0.158
$60,000 - $75,000	220	0.106	0.098	0.112	0.106	0.107
$75,000 - $90,000	188	0.090	0.102	0.081	0.092	0.086
$90,000 - $105,000	109	0.052	0.055	0.050	0.054	0.051
$105,000 - $120,000	93	0.045	0.051	0.037	0.052	0.039
$120,000 - $135,000	67	0.032	0.049	0.033	0.025	0.021
$135,000 - $150,000	89	0.043	0.030	0.065	0.037	0.039
$150,000 -	143	0.069	0.076	0.069	0.056	0.074

Notes: 2,081 participants completed Part 1 of the study. The last four columns present the proportion of subjects in each treatment.

B.3.4 Treatment Effect

We estimate the following linear model,

$$WTP_i = \beta_0 + \beta_1 T_i + \gamma X_i + \varepsilon_i,$$

where $T_i = 1$ if participant i is assigned to the Info treatment, X_i is a vector of dummy variables capturing demographic characteristics of participant i, and ε_i is an error term.

Table B.2: Effect of information on the willingness to pay for meat products.

	WTP (beef)			WTP (poultry)		
	(1)	(2)	(3)	(4)	(5)	(6)
Info	2.743	2.907	2.622	−2.028	−1.944	−2.395
	(2.285)	(2.281)	(2.305)	(2.162)	(2.151)	(2.178)
Age		0.170**	0.216***		0.189***	0.229***
		(0.067)	(0.068)		(0.061)	(0.066)
Female		−5.400**	−5.287**		−3.712*	−3.892*
		(2.276)	(2.312)		(2.159)	(2.201)
Liberal		−0.753	−0.297		1.064	0.025
		(2.296)	(2.366)		(2.158)	(2.223)
Belief (beef)		−0.010	−0.007			
		(0.012)	(0.013)			
Above-median consumption (beef)			6.493***			
			(2.410)			
Intention to reduce (beef)			−0.412			
			(0.979)			
Difficult to reduce (beef)			2.140**			
			(1.038)			
Belief (poultry)					0.009	0.008
					(0.007)	(0.008)
Above-median consumption (poultry)						3.433
						(2.345)
Intention to reduce (poultry)						1.330
						(1.000)
Difficult to reduce (poultry)						−0.452
						(0.993)
Constant	32.225***	27.697***	16.869***	29.517***	21.795***	18.737***
	(1.590)	(4.007)	(5.263)	(1.544)	(3.586)	(5.310)
First product	Beef	Beef	Beef	Poultry	Poultry	Poultry
Observations	1,048	1,048	1,011	1,033	1,033	1,005
R^2	0.001	0.014	0.032	0.001	0.013	0.018

Notes: Robust standard errors are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Subgroup analysis. We estimate the following linear model for each demographic group,

$$WTP_i = \beta_0 + \beta_1 T_i + \varepsilon_i,$$

where $T_i = 1$ if participant i is assigned to the Info treatment and ε_i is an error term. Estimated coefficients and their 95% confidence intervals are plotted in Figure B.6 below.

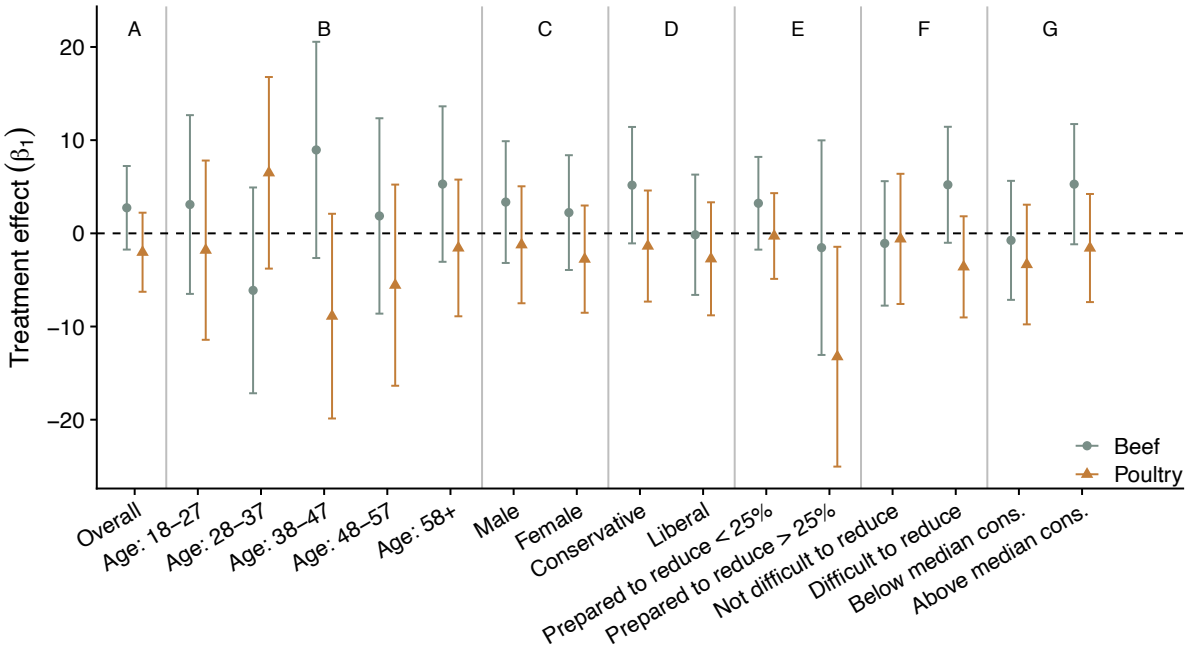

Figure B.6: Effect of information on WTP for meat products. *Notes*: Estimated coefficients and 95% confidence intervals are plotted. Cf. Figures 5 and A.10. (D) "Somewhat liberal" and "somewhat conservative" are grouped into liberal and conservative, respectively. (E) "Do you intend to reduce your consumption of beef/poultry in light of its CO_2 emissions?" (F) "How difficult would it be to reduce your current consumption of beef/poultry by half?" (G) "How many times do you eat beef/poultry per week?"

References

Bellemare, Charles, Luc Bissonnette, and Sabine Kröger. 2012. "Flexible Approximation of Subjective Expectations Using Probability Questions." *Journal of Business & Economic Statistics*, 30(1): 125–131.

Breunig, Christoph, Steffen Huck, Tobias Schmidt, and Georg Weizsäcker. 2021. "The Standard Portfolio Choice Problem in Germany." *Economic Journal*, 131(638): 2413–2446.