Supplementary Material for Manuscript:
"People Misestimate the Carbon Footprint of Behaviors, Firms, and Industries"

1. Additional Survey Details

All surveys were designed in (and hosted by) Qualtrics. Studies 1 through 4 were collected on Prolific, using stratified convenience samples that are representative of the United States regarding the demographics of age, sex, and ethnicity.

1.1 Study 1

In this study, we relied on the six behaviors detailed by Heller and colleagues in their 2021 paper: *Six behaviors policymakers should promote to mitigate climate change*. We first provided respondents with details regarding each of the behaviors they would next be asked to evaluate. Each description listed the behavior of interest, specified the proportion of the population that would hypothetically adopt said behavior under the proposed scenario, and provided any additional details or descriptions necessary for fully comprehending the behavior. For example, we explained that "frequent fliers" are defined as "the 13% of Americans who take 5 or more round-trip flights per year." The dependent variable was measured using a Qualtrics rank order question: Respondents were asked to rank (via drag-and-drop) each of the actions they had read about in order of most effective at reducing carbon emissions (at the top) to least effective (at the bottom). We then measured respondents' confidence in their ranking accuracy and general topic knowledge. Next, we used seven-point Likert scales to measure additional attributes that we believed may be substituted in respondents' judgments. We then collected a broad set of demographic information, including the Six Americas Super Short Survey (SASSY) from Chryst et al. (2018). We conclude by providing respondents with a link to the Heller et al. report.

1.2 Study 2

We began by providing respondents with relevant information and terminology regarding climate change and emissions. Respondents then had three attempts to complete a simple quiz which confirmed their comprehension of this information. We next collected the industry-level dependent measure, using a Qualtrics rank order question. Respondents were asked to rank (via drag-and-drop) each of the industries under study in order of most carbon emissions (at the top) to least (at the bottom). Participants were then randomized (using Qualtrics' randomization function) into two conditions: The absolute (non-normalized) condition and the normalized (revenue normalized) condition. In both conditions, respondents were asked to rank seven sets of firms using a Qualtrics rank order question. For each of the seven industry groups, respondents were asked to rank (via drag-and-drop) each of the firms under study in order of most carbon emissions (at the top) to least (at the bottom). Table 1.2 lists each of the firms and industries included in the study. In the absolute condition, respondents were asked simply to rank the firms in the manner described above. We suspected that respondents may apply a firm size heuristic, judging larger firms to be larger emitters. In general, this is true—larger firms do emit more. While this does have important implications at the policy and investment levels, it is less relevant for understanding the marginal emissions impact of consumption. In the revenue normalized condition, respondents were asked to rank the firms in order of emissions that result from a fixed dollar amount spent at each. Respondents in this condition should be less sensitive to firm size, and a firm size heuristic should not prove as useful. For example, in the hotel industry, respondents were told to imagine that they "plan to spend $300 on a hotel this weekend…" They are then asked to rank the hotels in order of the emissions created to accommodate their stay. We next measured additional attributes that we believed may be substituted in respondents' judgments, measured respondents' confidence in their ranking accuracy and general topic knowledge, and measured a broad set of demographic information. In selecting stimuli, we chose firms and industries for which both sources of objective data (Bloomberg and the CDP) were in general agreement and we sought firms that were likely to be familiar to most respondents. Within each industry group, we sought firm sets that spanned a wide range of emissions, in order to simplify consumers' ranking task (and thereby air on the side of conservative estimates of consumer inaccuracy).

1.3 Study 3

In this study, we sought to indirectly replicate the findings of Studies 1 and 2. Much of the survey design mimics that of Studies 1 and 2, with a few critical departures. First, we restrict this study (and all future studies) to only the normalized question format. Second, we sought to rule out an alternative explanation for respondents' general inaccuracy: That respondents were simply not sufficiently motivated. In this study, we define two conditions. In the control condition, respondents were compensated only for completion of the survey. In the incentive compatible condition, respondents had the opportunity to receive greater compensation, commensurate with their accuracy on the tasks. Respondents in the incentive condition were instructed that:

"**Additional compensation will be awarded based on your performance on these questions.**

We will take the average of your performance on the 7 company questions, and then average this result with your performance on the actions question.

- The top 20% of respondents will receive an additional $2.00 in compensation.
- Respondents in the top 40% (but not top 20%) will receive an additional $1.50.
- Respondents in the top 60% (but not top 40%) will receive an additional $1.00.
- Respondents in the top 80% (but not top 60%) will receive an additional $0.50.
- Respondents in the bottom 20% will not receive additional compensation."

Using custom code in Qualtrics, we were able to conclude the survey by providing each respondent with feedback about their accuracy and the resulting additional compensation awarded. The final key difference is that we replaced the six behaviors from Heller et al. with a novel set of behaviors calculated using publicly available data from the United States Environmental Protection Agency (EPA).

1.4 Study 4

As with Study 3, Study 4 was an incentive-compatible replication at the industry level. The design of Study 4 closely mimics that of Study 2 (omitting the firm-level questions) with the critical departure being incentive-compatibility. As this survey was shorter than that used in Study 3, the incentive amounts differed (yet the structure remained the same). Respondents in the incentive condition were instructed that:

"**Additional compensation will be awarded based on your performance on this question.**

- The top 20% of respondents will receive an additional $1.50 in compensation.
- Respondents in the top 40% (but not top 20%) will receive an additional $1.15.
- Respondents in the top 60% (but not top 40%) will receive an additional $0.75.
- Respondents in the top 80% (but not top 60%) will receive an additional $0.40.
- Respondents in the bottom 20% will not receive additional compensation."

1.5 Study 5

In Study 5, we sought to extend the behavior-level studies to broader and distinct populations. In Study 5a, we surveyed two samples of carbon experts. The first sample was from employees at Rare, an international conservation organization that uses insights from behavioral science to inspire change. The survey was distributed internally through a contact. The second sample was from past presenters at the Behavior Energy and Climate Change (BECC) conference, a large industry and academic focused conference concerned primarily with reducing carbon emissions. The survey was distributed by email and LinkedIn message to all individuals (for whom contact information was available) listed in association with a recent presentation at BECC focused on carbon emissions. Given the nature of these samples, the survey was a highly abridged version of that used in Study 3. Following a brief introduction, respondents were asked the key rank order question for behaviors only. Respondents were then asked a few demographic questions and were provided with feedback regarding their performance before exiting the survey. In Study 5b, we surveyed social media respondents through the social media networks of the authors. Links to the surveys (which follow the abridged format described for Study 5a) were provided on via Instagram, LinkedIn, Facebook, and Twitter posts. In Study 5c, we surveyed readers of two distinct newsletters. Again, following the abridged survey format, links to the survey were distributed through the Columbia Business School magazine (both online and in print) and through the weekly newsletter of an anonymous climate change resource platform that offers a wide array of curated climate change content. In Study 5d, we surveyed attendees of a large climate change finance conference in live time, using a link (QR code) to the abridged survey presented on a slide within a presentation.

Table 1.2 Firms.

Industry	Firm	CO_2 (CDP)	CO_2 (Bloomberg)
Apparel	Levi Strauss & Co.	8967	8777
	NIKE Inc.	47398	47520
	Hanesbrands Inc.	69689	60429
	Fossil Inc.	3514	7798
Non-Alcoholic Beverages	PepsiCo Inc.	3552706	4071887
	The Coca-Cola Company	793460	776099
	Keurig Dr Pepper	289755	319409
	Monster Beverage Corporation	4203.63	4663
Fast Food Restaurants	McDonald’s Corporation	97398	138417
	Yum! Brands Inc.	38907	29187
	Chipotle Mexican Grill	118296	103833
	The Wendy’s Company	14214	14241
Hotels	Hilton Worldwide Inc.	329570	283066
	Marriott International Inc.	972725	734238
	Hyatt Hotels	220251	158222
	Wyndham Hotels & Resorts	54613	48413
Personal & Household Products	Clorox Company	75164	82415
	Colgate Palmolive Company	191143	205908
	Estee Lauder Companies Inc.	27225	24490
	Procter & Gamble Company	2217501	2386522
Passenger Airlines	Delta Air Lines	17549100	20026522
	Jetblue Airways Corporation	4063538	6296074
	Southwest Airlines Co.	12591984	13389820
	United Airlines Holdings	15485363	24197956
Telecommunications	AT&T Inc.	1044751	974458
	Verizon Communications Inc.	336831	339993
	T Mobile USA Inc.	53180	53205

Note. All CO_2 figures are in metric tons.

Table 1.4 Industries.

Industry	CO_2 (Bloomberg)
Apparel	0.41714
Non-Alcoholic Beverages	5.08219
Fast Food Restaurants	2.66561
Hotels	2.23397
Personal & Household Products	5.39174
Passenger Airlines	120.04192
Telecommunications	1.63122

Note. All CO_2 figures are in thousands of metric tons. Figures represent sums of CO_2 across all firms classified by Bloomberg to be in the given industry.

Table 1.1 Consumer Actions used in Study 1 (Heller et al. 2021).

Action	Compliance	Details	Mitigated Emissions
Reduce Food Waste	10% of American Households	Reduce food waste by 20%	13 million
Purchase Green Energy	10% of Americans	Use entirely carbon-neutral energy	82 million
Reduce Air Travel	10% of American frequent fliers	Take one fewer round-trip flight	4 million
Purchase an Electric Vehicle	10% of Americans who intend to buy a car	Purchase an electric vehicle	65 million
Purchase Carbon Offsets	5% of Americans	Offset entire carbon footprint	276 million
Eat a Plant-Rich Diet	10% of Americans in the top 4 meat-consumption quintiles	Reduce consumption to level of next lowest quintile	25 million

Note. All emissions figures are in metric tons of CO_2.

Table 1.3 Behaviors used in Studies 4 and 5.

Behavior	CO_2e Mitigation
Reduce home electricity usage by 75%	1.8
Reduce waste (garbage) by 25%	0.1
Purchase carbon offsets equal to 50% of emissions	7.0
Reduce meat consumption by 50%	0.5
Live car-free	3.1
Take one less long-haul round-trip flight	0.9

Note. All emissions figures are in metric tons of CO_2e. All behaviors were framed in terms of the annual effect for an average American.

2. Additional Attribute Substitution Analyses

Within the main manuscript, we opted to report the results of the linear mixed models in order to aid in interpretability for the general audience, and because findings were robust to model specification. Here, we report the results of ordinal logistic models.

2.1 Study 1

```
Coefficients:
                      Estimate Std. Error z value   Pr(>|z|)
mitigation.rank        0.04228    0.02765   1.529     0.1263
as.numeric(Difficult) -0.02809    0.02791  -1.007     0.3141
as.numeric(network)    0.07507    0.03250   2.310     0.0209 *
as.numeric(recommend)  0.11828    0.02495   4.741 0.00000213 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

2.2 Study 2

```
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
obj_rank    -0.6297499  0.0195569 -32.201  < 2e-16 ***
familiarity  0.3902505  0.0224963  17.347  < 2e-16 ***
liking      -0.0426825  0.0144523  -2.953  0.00314 **
revenue     -0.0059201  0.0004658 -12.710  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

2.3 Study 3

2.3.1 Firms

```
Coefficients:
             Estimate Std. Error z value            Pr(>|z|)
CO2e        0.0374090  0.0022977  16.281 <0.0000000000000002 ***
familiarity 0.3555743  0.0157492  22.577 <0.0000000000000002 ***
revenue.b   0.0006506  0.0003267   1.991              0.0464 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

2.3.2 Behaviors

```
Coefficients:
                Estimate Std. Error z value          Pr(>|z|)    
mitigation.rank  0.13167    0.01763   7.470 0.0000000000000803 ***
network         -0.06923    0.02059  -3.362           0.000773 ***
recommend       -0.02567    0.01739  -1.476           0.139974    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

2.4 Study 4

```
Coefficients:
             Estimate Std. Error z value            Pr(>|z|)    
objCO2Rank   -0.30840    0.01597 -19.316 < 0.0000000000000002 ***
subjSize.rvs  0.35500    0.01765  20.108 < 0.0000000000000002 ***
familiarity   0.08325    0.02836   2.935             0.00334 ** 
liking       -0.19672    0.03225  -6.100        0.00000000106 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```