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WILLING TO ACT, FAILING TO IMPACT: PSYCHOLOGICAL AND SOCIAL DRIVERS OF VOLUNTARY CLIMATE ACTION

Willing to Act, Failing to Impact: Psychological and Social Drivers of Voluntary Climate Action*

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Abstract

Despite widespread concern about climate change, voluntary mitigation efforts often fail to maximize impact. In two online experiments ($n = 1,500$), we elicit willingness to mitigate (WTM) by allowing subjects to delete actual CO_2 allowances and examine how they allocate the WTM between their own and another's footprint. While 75% contribute a nonzero WTM, allocations are often inefficient, and many avoid freely available footprint information, suggesting limited efficiency concerns. Self-reported motives show that only half prioritize impact, while others cite fairness, personal responsibility, or intuition. Moreover, both WTM and efficiency are malleable by impact-unrelated nudges: a video emphasizing personal responsibility increases both, whereas social image based on the own footprint raises WTM but reduces efficiency. Our results suggest that voluntary climate action is shaped as much by psychological and social factors as by concern for impact.

Keywords: climate change; pro-environmental behavior; climate action; willingness to mitigate; impact; efficiency; consequentialism; warm glow; fairness; online experiment

JEL codes: C90, D01, D61, D62, D64, D83, D91, H41, Q51, Q54

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1 Introduction

Climate change poses a critical threat to natural systems and human societies (IPCC, 2022). Despite growing scientific evidence and widespread awareness (the Paris Agreement 2015; Andre et al., 2024a), meaningful action remains insufficient (Emissions Gap Report 2024). Identifying the barriers to effective action is therefore essential.

Individual efforts, while not the ultimate solution, play a crucial role both as foundational steps toward broader change and complements to systemic solutions.[1] Individual actions often involve immediate personal costs, yet yield uncertain and often distant benefits. This tension raises a central question: what motivates individuals to act at all? Do people act out of genuine concern for impact, or are their contributions shaped by other psychological and social factors? Understanding this question is crucial, because preferences over who benefits from climate action have important implications for the overall efficiency of mitigation efforts. For instance, individuals often favor local offsets, visible actions such as tree planting, or domestic emission reductions—even when international options may achieve greater carbon savings per dollar spent.

We investigate whether willingness to pay for carbon mitigation (henceforth, willingness to mitigate or WTM) is truly driven by concern for impact and test the robustness of this motive. First, we introduce two nudges that may weaken its influence exogenously. Second, we introduce an information treatment that provides an endogenous excuse to disregard it.

In two online experiments ($n = 1,500$), we first ask subjects how much of an additional \$50 endowment they are willing to spend to delete actual CO_2 emissions allowances. Next, they allocate this WTM between their own carbon footprint (which they learn up front using a carbon calculator) and that of another randomly assigned subject. Crucially, we explain to them in advance that each dollar reduces 2% of the footprint it is assigned to, making the efficiency of options salient. Thus, a subject motivated purely by impact should allocate their entire WTM to the larger footprint.

This design separates the expression of willingness to mitigate (WTM) from the evaluation of impact efficiency (allocation). The allocation task mirrors a common real-world dilemma (Jakob et al., 2017): whether to improve one's own footprint (e.g., by paying a premium for green electricity at home) or to direct the same funds to more cost-effective mitigation efforts abroad (e.g., supporting NGOs that provide clean cookstoves in less developed regions). By removing the practical barriers of searching for and evaluating distant options, our design isolates the core trade-off between personal accountability and cost-effectiveness.

[1] Global carbon pricing is largely considered the main solution to climate change (Cramton et al., 2017; `https://clcouncil.org/economists-statement/`). Dechezleprêtre et al. (2024) document positive but imperfect correlation of 0.6 between support for climate policies and willingness to change behaviors. However, despite being associated, support for public policies and willingness to take private action are driven by different concerns and moved by different treatments.

In the first experiment, we introduce a treatment featuring a video appeal to personal responsibility. The second experiment follows a 2×2 design: one treatment arm invokes social disapproval by having a third-party evaluator judge the subject's final footprint after abatement, while the other arm hides information about the other subject's footprint, which can be easily revealed via a clickable link. In the latter experiment, we also collect open-ended responses regarding subjects' motivations after both the spending and allocation decisions.

We document several baseline patterns. First, subjects exhibit considerable generosity, though with substantial heterogeneity.[2] Around 75% of subjects have a nonzero WTM, with an average contribution of \$24, or 48% of their endowment. A cluster of contributions around this average suggests that many subjects think in relative rather than absolute terms; indeed, 25% explicitly state a motive that aligns with a "fair ratio" principle.

A strikingly similar pattern emerges in Andre et al. (2024b), where subjects also sacrifice *half* of their (much larger) endowment—on average, \$225 out of \$450. Yet the average *desired* mitigation impacts differ by an order of magnitude: participants in our study are willing to mitigate only around $0.6tCO_2$, while those in Andre et al. (2024b) aim for $8tCO_2$. This pattern suggests that people may struggle to assign economic value to the scope of impact (Kahneman and Knetsch, 1992) and derive utility from the mere act of contributing (Andreoni, 1990). To determine a specific contribution, they may resort to a form of mental accounting (Bailey et al., 2023; Harrison, 2007; Clark, 2002; Thaler and Johnson, 1990) and fairness considerations (Bolton and Ockenfels, 2000; Fehr and Schmidt, 1999). Admittedly, people find it more natural to think in relative terms rather than to assign absolute economic value to impact (Enke, 2024). Therefore, to investigate whether they respond to impact comparisons, we now turn to allocation decisions.

Second, voluntary contributions are generally not allocated efficiently. The average efficiency index in the control groups is only 67% in Experiment 1 and 60% in Experiment 2.[3] Self-reported justifications shed light on this inefficiency: while 47% of subjects report motives consistent with concern for total impact, 35% provide rationales that diverge from efficiency considerations. These include prioritizing a "fair ratio" between their own and the other's footprint, equalizing footprints, feeling responsible only for their own footprint, acting on intuition, or lacking understanding of the impact differences.[4]

[2] The generosity aligns with extensive prior evidence from experiments (Engel, 2011) and real-world charitable giving—individuals in the US donated \$374.40 billion in 2023 (`https://givingusa.org/`).

[3] Our measure of efficiency is introduced in (1) and discussed in Appendix A.2. It measures the achieved share of the mitigation potential; 1 corresponds to full efficiency, 0 to intentional anti-efficiency, and 0.5 to the average of any non-consequentialist rule.

[4] In a study conducted independently of ours, Kaufmann et al. (2024) report a roughly similar distribution of motives: 50% of subjects exhibit consequentialist concerns, while 19% display deontological or warm-glow motives (as reflected by their non-incentivized valuations of effective versus ineffective externality reductions). While their paper differs in focus and methods, this parallel is noteworthy.

Third, we describe the observed pattern of non-consequentialist behavior as reflecting what we term "self-centered fairness." On the one hand, in the other-footprint-higher group, subjects allocate, on average, as much as 47% of their WTM to their own footprint, indicating a self-centered bias. On the other hand, in the other-footprint-lower group, they do not allocate their entire WTM to their own footprint but only 68% on average—an apparent sign of fairness-driven restraint.[5] Self-reported justifications support the presence of both motives: 11% explicitly state a focus on their own footprint, while 14% mention a fairness-related rationale. This behavioral pattern is reminiscent of similar asymmetries documented in climate policy, such as self-serving bias in fairness judgments (Kriss et al., 2011). More broadly, it is consistent with behavioral attenuation due to cognitive noise (Enke et al., 2025) and the self-serving use of such confusion (Exley and Kessler, 2024; Saccardo and Serra-Garcia, 2023).

Our main finding is that both voluntary contributions and their efficiency are malleable and can be influenced in different directions. Specifically, our nudge featuring a video emphasizing individual responsibility increases both WTM and efficiency, whereas our nudge inducing social-image concerns raises WTM but reduces efficiency. The latter effect suggests that concern for impact can be crowded out by other considerations. For instance, if individuals operate within a moral budget, engaging in conspicuous virtue-signaling actions—such as commuting by bike—may satisfy their perceived moral obligations, leaving less goodwill for other, potentially more impactful, actions. This is reminiscent of how green nudges can crowd out support for more effective yet less popular policies, such as a carbon tax, as shown by Hagmann et al. (2019, 2023).

Since information is a prerequisite for efficient decisions, we study how people acquire it. On aggregate, subjects exhibit partial responsiveness to footprint information in line with the efficiency motive: in the control group in Experiment 2 (similarly in Experiment 1), the share allocated to oneself is 21pp higher when the other subject's footprint is lower rather than higher. Examining information acquisition more directly, we document widespread information avoidance: in the hidden-information treatment, information acquisition rate is only 60%. Moreover, how information acquisition varies with prior beliefs does not align with any of our initial hypotheses—neither rational inattention (Maćkowiak et al., 2023) nor motivated learning as a justification for self-centered allocation (Rabin, 2019). We find only suggestive evidence for a theory of image concerns, where people seek information to potentially improve their prior self-image and avoid it to preserve a positive prior self-image.

Our results can be related to several studies conducted independently of ours. In a field experiment on carbon offsets, Rodemeier (2025) finds that people are largely insensitive to the scope of mitigated CO_2 in a between-subject comparison, i.e., the willingness to buy an offset with a given price does not differ between groups with different amounts of compensated CO_2. This echoes the suggestive evidence from our first baseline pattern and its comparison to Andre et al. (2024b)—the difficulty in assigning absolute economic value to the scope of impact. However, Rodemeier

[5]The numbers are for the control in Experiment 2. The same pattern arises in Experiment 1.

(2025) also finds that the willingness to buy an offset becomes partially responsive to impact in a within-subject comparison, aligning with the partial responsiveness to footprint information in our allocation decisions—namely, the higher share allocated to oneself when the other subject's footprint is lower rather than higher. Finally, his finding that fairness plays an important role for WTM resonates with our third baseline pattern—the prevalence of "fair" interior allocations. We advance this line of work by documenting pervasive insensitivity to impact even within-subject, as reflected in low efficiency in allocation decisions, information avoidance, and self-reported motives.

Similarly, Heeb et al. (2023) highlight the role of warm glow and the difficulties in valuing absolute impact in sustainable investments. In a framed field experiment, investors exhibit a substantial willingness to pay for sustainable investments, driven primarily by positive emotions. Notably, investors' willingness to pay is insensitive to impact in a between-subject comparison but becomes weakly sensitive in a within-subject comparison. Like us, they also document pervasive insensitivity to impact even within-subject. We deepen these insights by examining information use, self-reported justifications, and the roles of personal responsibility and social concerns.

Additionally, Pace et al. (2025) and Imai et al. (2022) document a highly concave WTM: subjects are willing to pay substantially more for the first units of emissions reduction, but their willingness declines for subsequent units (without flattening entirely). The high spending yet limited efficiency observed in our experiments align with this pattern, suggesting that while people are willing to engage, they are failing to scale their contributions in proportion to impact.

Our paper also contributes to the broader literature on the demand for climate protection. While many studies in this field rely on hypothetical valuations (Andre et al., 2024a; Nemet and Johnson, 2010), several adopt a similar approach to ours—allowing subjects to delete actual CO_2 allowances from the EU ETS (Diederich and Goeschl, 2014; Löschel et al., 2013). These studies hold the impact fixed and elicit willingness to pay. Rodemeier (2025), Pace et al. (2025), Heeb et al. (2023), and Imai et al. (2022) take this further by varying the impact, bringing their approach closer to ours. We extend this line of research by effectively asking subjects to determine their desired impact directly. This parallels the method in Andre et al. (2024b), enabling the suggestive conclusions discussed above. Kölle et al. (2024) use effectively a similar elicitation method but with increasing marginal abatement costs, unlike our linear cost schedule. Our main contribution to this line of research is that we dissociate engagement (spending decision) and impact efficiency (allocation decision).

Finally, our paper integrates and extends insights dispersed across the extensive literature on charitable giving, applying them to the domain of pro-environmental behavior. For instance, Lilley and Slonim (2014) and Null (2011) document substantial inefficiencies in charitable giving, largely driven by warm-glow motivations. Additionally, Metzger and Günther (2019) and Null (2011) find limited demand for impact-related information. Similarly, Karlan and Wood (2017) report that providing impact information has no aggregate effect, though they highlight notable heterogeneity in responses. Social pressure has also been identified as an important driver of donations (DellaVigna et al., 2012). Finally, Karlan and List (2007) suggest that a form of fairness may increase charitable contributions—match offers boost giving, yet more impactful match ratios do not necessarily lead to higher contributions than less impactful ones.

At a broader level, our paper contributes to the literature on promoting climate action (Vlasceanu et al., 2024; Bergquist et al., 2023; Nisa et al., 2019). However, rather than merely assessing the effects of interventions on voluntary pro-environmental actions, we leverage these interventions as tools to gain deeper insights into the drivers of such behavior. Moreover, while green nudges are typically used to boost engagement, we investigate their largely unexamined effect on impact efficiency.

To summarize, we contribute mainly by separating impact efficiency from engagement, revealing a widespread within-subject neglect of impact in voluntary climate action. Moreover, we show that nudges can both enhance and undermine impact efficiency while increasing contributions. Ultimately, our findings call for a thoughtful design of institutions that channel goodwill toward its most effective use, rather than relying on voluntary climate action as an organic solution to climate change.

The paper is organized as follows. Section 2 outlines the conceptual background and presents the resulting hypotheses. Sections 3 details the experimental design. Section 4 discusses the results. Section 5 concludes.

2 Conceptual Background and Hypotheses

In this section, we formulate our hypotheses and provide their conceptual underpinnings. We start with the basic hypotheses about the extent of voluntary actions, but focus then on our main point of interest—their impact efficiency.

2.1 Willingness to Mitigate

Our measure of climate action is the incentive-compatible willingness to pay for real carbon footprint reduction (henceforth, Willingness To Mitigate or WTM). Namely, we ask each subject how much of an extra $50 endowment they want to use to delete actual CO_2 emission allowances from the EU ETS, thus reducing the total allowable emissions in the EU. The baseline hypothesis is about the existence of a non-trivial climate action.

Hypothesis 1. No voluntary climate action (WTM = 0).

Expected result. Standard theory would predict that everybody takes $50 for themselves. However, rich prior evidence suggests that many people are willing to take costly pro-environmental actions (e.g., Andre et al., 2024b; Berger et al., 2022), so we expect a sizeable proportion of people with non-zero WTM. Observing average WTM significantly greater than zero is sufficient to refute this hypothesis.

Next, we examine whether WTM responds to nudges—a natural first step given prior evidence that climate action reacts to nudges (e.g., Andre et al., 2024b; Berger et al., 2022). However, their effect on impact efficiency remains unknown—this is our central question, which we address in the next section. Here, we simply verify that WTM itself reacts to our two nudges: (i) an appeal to individual responsibility in climate action and (ii) the prospect of social disapproval of one's final footprint (after potential abatement).

Hypothesis 2. The appeal to individual responsibility has no effect on the WTM.

Expected result. The appeal to individual responsibility in climate action increases the WTM.

Hypothesis 3. The prospect of social disapproval has no effect on the WTM.

Expected result. The prospect of social disapproval increases the WTM.

2.2 Efficiency

Our main focus is to scrutinize the efficiency of the WTM. For that, we allow each subject to distribute their WTM to reduce their own footprint f_o or/and the footprint of another random subject f_a. Formally, the allocation choice can be captured by share $s \in [0, 1]$ of the WTM they allocate to the reduction of own footprint. Importantly, in the mechanism we use and explain to the subjects, each dollar reduces 2% of the carbon footprint it is allocated to. Hence, a rational consequentialist concerned about the reduction of emissions should allocate the whole WTM to the higher footprint to maximize the impact[6,7]

$$s \cdot \text{WTM} \cdot 0.02 \cdot f_o + (1 - s) \cdot \text{WTM} \cdot 0.02 \cdot f_a.$$

Our measure of efficiency of an allocation decision is[8]

$$e := \frac{sf_o + (1 - s)f_a - \min\{f_o, f_a\}}{\max\{f_o, f_a\} - \min\{f_o, f_a\}}. \tag{1}$$

[6]Let us clarify our use of the term "consequentialism" in this context. Observing WTM > 0 may be seen as a moral action, revealing that the person thinks the sacrifice achieves some common good. The subsequent allocation s then materializes a specific outcome (which the person revealed to perceive as achieving a common good) in a specific way. Achieving the largest outcome can then be called consequentialism as it puts a prime on the consequences of the actions as compared to other conceivable rigid principles, like responsibility for own footprint.

[7]In Appendix A.3, we comment on the possibility that people have diminishing sensitivity to the overall impact of the allocation decision. It does not change substantially any of the hypotheses in the main text. In particular, a rational consequentialist with diminishing sensitivity should still allocate the whole WTM to the higher footprint.

[8]In Appendix A.2, we discuss why we prefer this measure to the alternative measure

$$\frac{sf_o + (1 - s)f_a}{\max\{f_o, f_a\}}.$$

Our design intentionally places subjects in a frame where moral accountability ("clean up your own mess") competes with consequentialist reasoning ("maximize global impact"). This mirrors tensions in climate ethics and policy, where fairness-based approaches (e.g., historical responsibility) sometimes conflict with purely impact-based strategies (e.g., least-cost abatement). By making this trade-off explicit, our task enables us to study how individuals navigate this core ethical and strategic tension.

Hypothesis 4. Full efficiency ($e = 1$).

Expected result. Rational consequentialism dictates that everybody achieves full efficiency by choosing $s = \mathbb{1}(f_o \geq f_a)$.[9] Observing average efficiency significantly less than one is sufficient to refute the strict interpretation of this hypothesis, leading to the conclusion that some people violate either rationality (due to confusion or inattention) or consequentialism. We expect this to be the case due to the tendency to focus on own footprint (as explained below).

A necessary (but not sufficient) condition for full efficiency is paying attention to whether $f_o \geq f_a$. In other words, without acquiring this information, individuals cannot systematically achieve full efficiency. This leads us to test a weaker version of the rational consequentialism hypothesis—whether people at least improve efficiency in the direction of this information. As discussed above, we expect individuals to respond imperfectly. Next, we consider the opposite extreme: Do they acquire the information at all?

Hypothesis 5. People do not pay attention to whether $f_o \geq f_a$.

Expected result. We expect that the average share of WTM allocated to own footprint (s) is significantly higher in the decisions where own footprint is larger ($f_o \geq f_a$) than in the decisions where own footprint is smaller ($f_o < f_a$); the null is that the shares are equal. Observing this expected pattern is sufficient to refute the hypothesis. It reveals that (some) people (sometimes) pay attention to the event, and that they react to it in the direction of higher efficiency.

We expect that the main obstacle to efficiency is excessive focus on own footprint, e.g., due to the feeling of individual responsibility (Jakob et al., 2017) or social image. Our nudges evoke exactly these two frames. Specifically, we test whether they lead to more self-centered behavior and, consequently, reduce efficiency by crowding out impact concerns and reducing sensitivity to f_a. Hence, together with Hypotheses 2 and 3, we aim to show that higher efficiency is not a necessary condition for higher WTM—we can induce higher WTM but with lower efficiency. This is in line with the finding of Lilley and Slonim (2014) in a different context: a warm-glow framing increases overall charitable contributions but decreases their efficiency.

Hypothesis 6. The appeal to individual responsibility has no effect on s.

[9] Cases $f_o = f_a$ are negligible; we combine them with cases $f_o > f_a$ as we believe it is natural to focus on own footprint under indifference (see below).

Expected result. The appeal to individual responsibility increases the average share of WTM allocated to own footprint (relative to the control group).

Hypothesis 7. The prospect of social disapproval has no effect on s.

Expected result. The prospect of social disapproval (of one's own final footprint after abatement) increases the average share of WTM allocated to own footprint (relative to the control group).

Hypothesis 8. The appeal to individual responsibility has no effect on efficiency.

Expected result. The appeal to individual responsibility decreases the average efficiency (relative to the control group).

Hypothesis 9. The prospect of social disapproval has no effect on efficiency.

Expected result. The prospect of social disapproval (of one's own final footprint after abatement) decreases the average efficiency (relative to the control group).

2.3 Information Acquisition

In Hypothesis 5, we test indirectly whether people acquire some efficiency-relevant information. Next, we investigate information acquisition more directly to probe the motivations behind the voluntary climate action.

We design an information treatment where another footprint f_a is initially hidden and subjects have to actively click on a link to reveal it (own footprint f_o is always known—subjects have to calculate it using an online calculator and they are explicitly reminded of it when making each decision).[10] Rational consequentialists without other conflicting motives should always acquire information to make fully informed decisions.

Hypothesis 10. People always acquire information in the hidden information treatment.

Expected result. We expect a sizeable proportion of deliberately uninformed decisions. Observing information acquisition rate significantly less than one is sufficient to refute this hypothesis.

One explanation for information avoidance is rational inattention (Maćkowiak et al., 2023). Individuals may forgo acquiring instrumental information when effort-based costs ("laziness") or intrinsic aversion to information ("willful ignorance") outweigh the expected benefits.

[10] Although, under uncertainty about f_a, rational consequentialists choose a bang-bang allocation $s = \mathbb{1}(f_o \geq \mathbb{E}[f_a])$, we show in Appendix A.3 that diminishing sensitivity generates a hedging motive, which can lead to interior allocations $s \in (0, 1)$. Nevertheless, we argue that the resulting predictions about information acquisition—our main focus in this treatment—are not substantively affected.

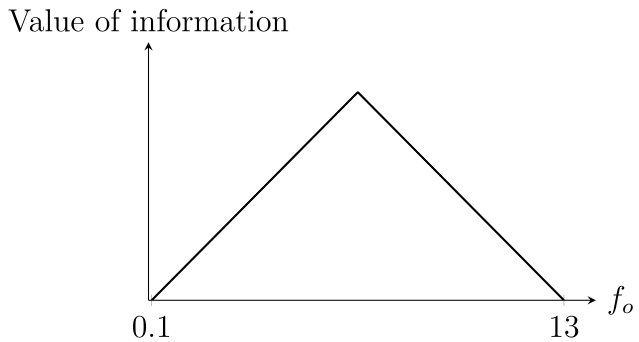
Hypothesis 11. The tendency to click on the link revealing another footprint f_a is independent of the value of information implied by the subjects' prior beliefs[11]

$$f_o\frac{1}{2} + \mathbb{E}\left[f_a|f_o < f_a\right]\frac{1}{2} - \max\left\{f_o, \mathbb{E}\left[f_a|f_o \geq f_a\right]\frac{1}{2} + \mathbb{E}\left[f_a|f_o < f_a\right]\frac{1}{2}\right\}. \quad (2)$$

Expected result. Although the alternative hypothesis is that the tendency to click on the link is increasing in the value of information, we expect to be unable to reject the null. We do not expect the effort-based costs or intrinsic aversion to information play a major role in our setup because we make the revelation of information about f_a as accessible as possible—just a click on a link.

The value of information (2) depends on the beliefs about f_a and own footprint f_o. In Figure 1, we illustrate the value of information for beliefs given by the uniform distribution on interval $[0.1, 13]$. This illustrates that the value of information is the highest in the regions with the highest uncertainty about how own footprint compares to others' footprints. In other words, if one expects to have the lowest or highest footprint, she does not expect to learn much from revealing f_a.

Figure 1: Illustration of the Value of Information for Uniform Beliefs on $[0.1, 13]$



At the other extreme, people may avoid information completely because of belief-based utility. In Appendix A.4, we consider an agent who wishes to believe that her own footprint is relatively low, and learns strategically to protect or improve her beliefs. Whether the agent wants to learn does not depend on prior beliefs, but

[11]The formula reflects the expected difference in abatement under perfect information and under no information under our "50-50 matching" procedure (which is described in Appendix A.1 and in the Experimental Design section). The expectation operator in the formula is the mathematical expectation, but we elicit the corresponding conditional expectations (in an incentivized manner) to construct subjects' implied value of information. As a robustness check, we also test the version of the hypothesis accounting for the possibility that subjects do not internalize our 50-50 matching procedure. The value of information under independent matching is

$$f_oF(f_o) + \mathbb{E}\left[f_a|f_o < f_a\right](1 - F(f_o)) - \max\{f_o, \mathbb{E}\left[f_a\right]\},$$

so we additionally elicit the believed share of people with lower footprints $F(f_o)$ (F is the CDF) and the simple expectation $\mathbb{E}\left[f_a\right]$.

Although we do not elicit the perceived cost of clicking on the link, as long as it does not depend on f_o and beliefs, we can still predict that people with beliefs implying a larger value of information are more likely to click on the link.

only on the curvature of the function that maps the beliefs to utility. In particular, if this function is concave, the agent is information averse.[12]

Hypothesis 12. People always avoid information in the hidden information treatment.

Expected result. We do not expect the simple concave belief-based utility to be the prevalent motive. Observing information acquisition rate significantly above zero is sufficient to refute this hypothesis.

Our primary hypothesis for information avoidance is that people seek to justify a self-centered allocation—a form of motivated learning. This behavior resembles self-serving exploitation of cognitive flexibility (Saccardo and Serra-Garcia, 2023), avoidance of moral constraints (Rabin, 2019), or moral wiggle room (Dana et al., 2007). Especially in the interaction with the social disapproval treatment, where the social-image concern is most pronounced, people might want to justify the allocation to own footprint f_o. If they believe their footprint is larger, they might avoid acquiring information about f_a to preserve an excuse for compensating their own footprint. Conversely, if they believe their footprint is smaller, they might seek information about f_a hoping to learn that their desired case, $f_o \geq f_a$, is true.

Hypothesis 13. Denote $G_{o>a}$ the group of people with prior beliefs[13]

$$f_o \geq \mathbb{E}\left[f_a | f_a \leq f_o\right] \frac{1}{2} + \mathbb{E}\left[f_a | f_a > f_o\right] \frac{1}{2}$$

and $G_{o<a}$ the group of people with prior beliefs

$$f_o < \mathbb{E}\left[f_a | f_a \leq f_o\right] \frac{1}{2} + \mathbb{E}\left[f_a | f_a > f_o\right] \frac{1}{2}.$$

The information acquisition rates in $G_{o>a}$ and $G_{o<a}$ are the same.

Expected result. We expect that the information acquisition rate in $G_{o>a}$ is lower than in $G_{o<a}$. Moreover, we expect the difference in information acquisition rates between $G_{o<a}$ and $G_{o>a}$ to be smaller in the treatment without social disapproval than in the treatment including social disapproval.

[12] This non-instrumental belief-based motive can be seen as a microfoundation for the cost of information in the rational inattention trade-off. However, note that such cost depends on prior beliefs. Hence, such a version of rational inattention can produce different patterns of information acquisition. For example, with exponentially distributed footprints, only people with low values of f_o find it optimal to acquire information; in contrast, with a fixed cost of information, only people with high values of f_o do so.

[13] The right-hand sides reflect the expected f_a under our "50-50 matching" procedure (described in Appendix A.1 and in the Experimental Design section). The expectation operator in the formulae is the mathematical expectation, but we elicit the corresponding conditional expectations (in an incentivized manner) to construct subjects' implied beliefs under our 50-50 matching procedure. As a robustness check, we also elicit the simple expectation to test the version of the hypothesis accounting for the possibility that subjects do not internalized our 50-50 procedure. In that version, the right-hand sides of the inequalities are replaced by $\mathbb{E}\left[f_a\right]$.

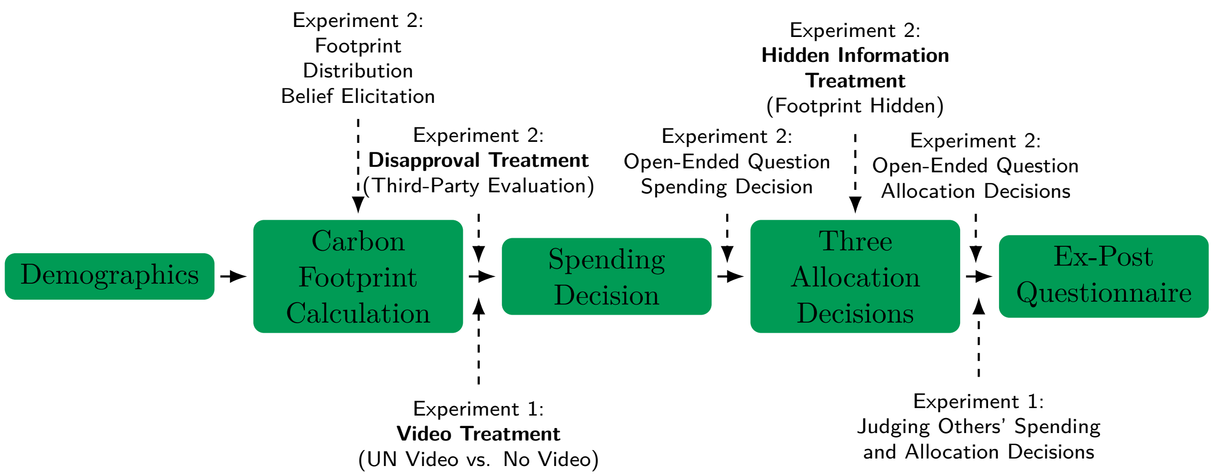
To summarize our conceptual framework, we expect a non-trivial WTM but question whether it is primarily driven by a concern for impact efficiency. While we anticipate some evidence of this motive, we examine its fragility. First, we employ two nudges that may crowd out this motive exogenously by shifting attention to one's own footprint. Second, we design a treatment in which the self-centered focus can manifest itself endogenously through information avoidance.

3 Experimental Design

We report two online experiments on the Prolific platform, both utilizing a similar experimental framework with distinct treatments and subject samples. Experiment 1 employs a single treatment design, while Experiment 2 follows a 2x2 design, introducing two treatment dimensions. Section 3.1 outlines the experimental procedure and task overview shared across both studies. Section 3.2 outlines the specific treatments administered. Section 3.3 describes the implementation process, subject recruitment, and data collection methods. Details on the instructions of both experiments are provided in Appendix E.

3.1 Experimental Procedure and Task Overview

Figure 2: Stepwise Experimental Flow



Both Experiment 1 and Experiment 2 follow a similar structure, detailed in this section. A step-by-step overview of the experimental flow is presented in Figure 2. The **first part** of each experiment collects **demographic information** from subjects, including age, gender, income, education, and political ideology. Subjects are then instructed to use an online **footprint calculator**[14] to estimate their personal annual CO_2 footprint, reported in metric tons of CO_2 per year. Subjects are required to submit their calculated footprint as part of the study. In Experiment 2, we further elicit subjects' prior beliefs regarding the distribution of CO_2 footprints

[14]Link to online footprint calculator: https://footprint.conservation.org/en-us/

among the study sample. Specifically, subjects provide four incentivized guesses (with bonus payments based on accuracy): (i) the average CO_2 footprint per year of all other subjects in the study, (ii) the percentage of subjects with a lower yearly CO_2 footprint than their own, (iii) the average CO_2 footprint per year of the subgroup of subjects with lower footprints than their own, and (iv) the average CO_2 footprint per year of the subgroup of subjects with higher footprints than their own.

In the **second part** of the experiment, subjects engage in four decision-making stages: one spending decision followed by three allocation decisions. All decisions are incentivized with the possibility of earning bonus payments and contributing to environmental protection by reducing actual CO_2 emissions through the purchase of CO_2 emission allowances. We provide subjects with a detailed explanation of the potential environmental impact and the mechanics of the allowance system.[15]

In the **spending decision**, subjects decide how to allocate \$50 between purchasing CO_2 emission allowances from the market—thus reducing the total allowable emissions—and keeping the remainder for themselves. In the **allocation decisions**, subjects decide how to distribute the amount they chose to spend on allowances between reducing their own carbon footprint and reducing that of another subject. Each dollar spent results in a 2% reduction in the monthly carbon footprint it is applied to, meaning it is always more efficient to reduce larger footprints. Before these decisions, subjects are given control questions to ensure they understand the instructions and the associated footprint reductions.

For each of the three allocation rounds, subjects are shown their own carbon footprint alongside the footprint of a randomly selected subject from the study, with both footprints displayed simultaneously. They then split the amount they decided to spend between their own footprint and the other subject's footprint, ensuring that the total allocation equals the amount they designated for emissions reduction. The position of the two footprints on the display is randomized, as is the order in which the input fields for their allocations appear. Both footprints and input fields are displayed simultaneously, with only their relative positioning randomized. Across the three rounds, subjects see footprints from three different randomly selected subjects.

In Experiment 1, subjects are randomly assigned with a 50-50 chance to either the "higher" or "lower" group, and they remain in their assigned category across all three allocation decision rounds. In the "lower" group, subjects see the footprints of other subjects who consistently have lower carbon footprints than their own in each of the three rounds. Conversely, in the "higher" group, subjects are paired with other subjects who have higher carbon footprints than their own across all rounds. Despite the fixed comparison group, subjects are still paired with three different others across the rounds.

In Experiment 2, the design of allocation decisions differs such that *in each* allocation round, subjects are presented with the footprint of another subject, which has

[15]Link to compensation provider: https://www.compensators.org/en/compensate-2/

an equal (50-50) chance of being either higher or lower than their own.[16] Subjects are informed about this randomization mechanism. Thus, subjects might see different comparisons across the three rounds, with no fixed group assignment as in Experiment 1. We choose this different 50-50 design in Experiment 2 for several reasons. First, we aim to examine information acquisition across all three rounds. To do this effectively, the assignment into higher versus lower groups needs to be independent across the decisions, ensuring that subjects are motivated to acquire new information each time. Second, this design allows us to explore whether subjects follow specific behavioral rules and whether they apply these rules consistently across rounds.

In Experiment 2, after the spending decision, subjects respond to an **open-ended question** probing the motivation behind their choice. Following the three allocation decisions, they are similarly asked to provide open-ended responses explaining the rationale behind their allocation decisions.

In the **final part** of the experiment, subjects complete an **ex-post questionnaire** that explores their self-image, social image, views on climate change, and perceptions of individual responsibility in mitigating climate damage. Before the ex-post questionnaire in Experiment 1, subjects also **evaluate the spending and allocation choices** of three randomly selected peers, assigning "disapproval points" from 0 (full approval) to 10 (full disapproval).

3.2 Treatments

Experiment 1 Video Treatment. Subjects in Experiment 1 are randomly assigned to one of two groups: the "video" treatment group or the control group ("no video"). After completing the demographic questions and calculating their own carbon footprint, but before receiving instructions for the decision-making stage (part 2), subjects in the "video" group are shown a brief video from the United Nations.[17] The video frames climate change and damage mitigation as an individual responsibility. During this video, all keyboard and mouse actions are disabled to ensure subjects cannot skip or bypass the content. Following the video, subjects proceed to the instructions for part 2, which includes the spending and allocation decisions,

[16] In both experiments, for the lowest- and highest-footprint subjects so far—as participants dynamically enter the task—we use carbon footprint values from a previous study in specific cases where no more extreme (lower or higher) values are yet available in the current sample. This situation arises when a participant is to be matched with another individual with a higher (or lower) carbon footprint, but the participant themselves currently has the highest (or lowest) footprint observed so far. In such cases, the intended comparison cannot be fulfilled using current data alone. To address this, we draw on data from a previous, comparable study with a broader range of footprint values, ensuring that participants are exposed to realistic and meaningfully extreme reference points. This procedure is transparently communicated to participants. Moreover, the earlier study provides a reliable basis for this substitution, as it used the same measurement instruments and sampling criteria, allowing for consistent integration of data across studies. Importantly, this situation occurs only rarely.

[17] Youtube video "Show the world what climate action looks like | #MyClimateAction | United Nations" available at: https://www.youtube.com/watch?v=S1-BwAkFwak

and then complete the four decision stages. The control group, labeled "no video," bypasses the video entirely and directly proceeds to part 2, where they receive the same instructions and go through the same decision-making stages.

Experiment 2 Disapproval Treatment. In Experiment 2, subjects are randomly assigned to a "disapproval" treatment or a control group. After instructions on the spending and allocation tasks (but before making decisions), treated subjects are told that their carbon footprint will later be shown to third-party evaluators who did not participate in the study. These evaluators see the subject's adjusted monthly CO_2 footprint—according to their allocation decision in one randomly chosen round—and assign disapproval points (0–10) based solely on that final value. Subjects are informed that fully spending the $50 on their own footprint reduces it to $0tCO_2$. Evaluators do not see initial footprints or other contextual information. Each footprint is evaluated by one randomly assigned evaluator; each evaluator evaluates 20 randomly selected subjects. Subjects are later shown their average disapproval score via their Prolific accounts. Additionally, they are asked a comprehension question confirming they understand how the disapproval score is determined.

Experiment 2 Hidden Information Treatment. Subjects in Experiment 2 are randomly assigned to either the "hidden information" treatment group or the "full information" control group. In the hidden information group, subjects are required to actively click a link in each of the three allocation rounds separately in order to reveal the other subject's carbon footprint. By contrast, those in the full information control group automatically see the other subject's carbon footprint without needing to take any additional action.

3.3 Implementation

Experiment 1 was conducted in October 2023 using the Prolific platform, with a sample of 500 US subjects who had an approval rate between 80 and 100 percent on Prolific.[18] The experiment lasted up to 30 minutes, and subjects were compensated with $7.45 for completing the study. At the conclusion of the experiment, we randomly selected three out of every 100 eligible subjects through a lottery to have one of their spending and allocation decisions implemented. For these selected subjects, we provided a bonus payment through Prolific equal to the amount they chose to keep from the $50. Additionally, we purchased CO_2 emission certificates to reduce emissions by the amount of CO_2 implied by one of their allocation rounds.

Experiment 2 was conducted in March 2024 using the Prolific platform, with a sample of 1,000 US subjects who had an approval rate between 80 and 100 percent on Prolific. The experiment lasted approximately 20 minutes, and subjects were compensated with $5.07 upon completion. There were two channels for bonus pay-

[18] As pre-registered, participants who complete the entire study are included in the main sample until the target sample sizes are reached—500 participants for Experiment 1 and 1,000 for Experiment 2. Participants who do not complete the full study are excluded from the final sample.

ments in this experiment: the first was linked to subjects' spending decisions, and the second to their performance in the belief elicitation task in part 1.

For the spending and allocation decisions, one subject out of every 100 was randomly selected through a lottery. The selected subjects received a bonus payment through Prolific equal to the amount they decided to keep from the initial \$50 endowment. Hence, the maximum bonus earned through this channel is \$50. Additionally, emission certificates were purchased based on the CO_2 offset implied by one of their allocation rounds.

The second channel of bonus payments was linked to subjects' guesses regarding the CO_2 footprint distribution in part 1. One out of every 100 subjects was randomly selected to receive a bonus of up to \$10. For the selected subjects, one of the four belief questions was randomly chosen, and the accuracy of their guess determined the bonus payment. Specifically, we used a quadratic scoring rule: the closer the subject's guess was to the true value, the higher their reward. If the guess was exactly correct, the subject received the full \$10 bonus. If the guess deviated from the truth, we calculated the squared difference between the guess and the actual value, subtracted this squared difference from \$10, and payed the remaining amount as a bonus (the minimum bonus is \$0, i.e., we did not penalize people for bad guesses).

In addition to the main Experiment 2, we conducted a short follow-up study involving a new set of 100 subjects who acted as third-party evaluators allocating disapproval points to the subjects in the "disapproval" treatment. This follow-up study lasted approximately 3 minutes, and subjects were paid \$0.65 for their time.

4 Results

The reported analyses were pre-registered as part of the study's design. Any deviations from the pre-registered analysis plan are explicitly noted in the respective sections.

4.1 Sample Characteristics

Table 1: Sample Characteristics

Demographics	Video Treatment		Disapproval Treatment		Hidden Information Treatment	
	Video	No Video	Disapproval	No Disapproval	Hidden Information	Full Information
Age 18-40	64.5	64.3	64.2	64.1	66.1	62
Age 41-60	32.5	31.1	30.3	29.7	27.7	32.3
Age > 60	3	4.7	5.5	6.2	6.1	5.7
Female	41.5	44.3	47.3	49.6	47.7	49.5
Male	57	53.2	50.2	49.5	51.3	48.3
Diverse	1.1	2.6	2.4	0.9	1	2.2
Net Monthly Income Less Than 3000	45.7	51.1	52.7	49.3	48.5	53.1
Net Monthly Income Between 3000−6000	38.1	32.8	34.7	35.4	37.8	32.3
Net Monthly Income Higher Than 6000	16.2	16.2	12.6	15.3	13.7	14.5
Less Than High School	1.1	0.4	2	0.4	0.8	1.4
High School Diploma	31.3	37.4	32.3	31	32.7	30.5
Bachelor's Degree Or Equivalent	43	43	43.4	48.2	46.3	45.7
Master's Degree Or Equivalent	20.8	16.6	17.3	15.1	15.6	16.6
Doctorate Or Professional Degree	3.8	2.6	5.1	5.3	4.6	5.9
Very Liberal	23.8	30.2	25.9	25.7	24.6	27.1
Somewhat Liberal	33.2	33.6	33.2	32.5	33.7	31.9
Moderate	23.4	18.7	24.3	20.1	22.8	21.2
Somewhat Conservative	12.1	14	11.5	16.8	13.7	15.2
Very Conservative	7.5	3.4	5.1	4.9	5.3	4.6
All	265	235	452	548	505	495

Notes: The table presents summary statistics for demographic variables across treatment and control groups. The last row ("All") displays the total number of subjects in each group, while all other values are reported as percentages. For each treatment/control group, percentages represent the distribution within each demographic category. Chi-squared tests for categorical variables show no significant differences in group allocation across age, gender, income, education, and political orientation (all $p > 0.05$). These findings confirm that the treatment and control groups are well balanced.

Table 1 summarizes the demographic characteristics of the subjects across treatment groups. The random assignment resulted in balanced treatment groups, with no significant differences in demographic variables across conditions. This ensures that any observed differences in outcomes can be attributed to the treatment effects rather than pre-existing differences in the sample.

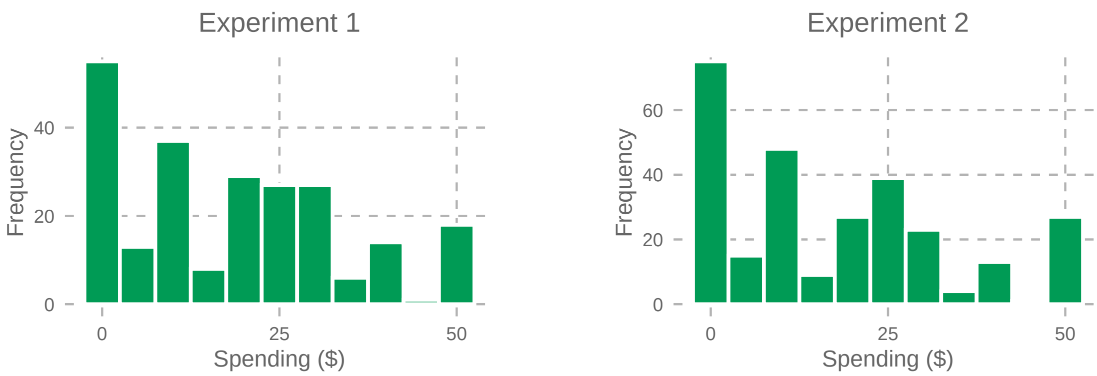
4.2 Willingness to Mitigate

Subjects receive an initial endowment of \$50, which they can spend on CO_2 emission allowances or keep for themselves. We begin by examining baseline spending behavior in the control groups of both experiments, before turning to treatment effects.

4.2.1 Exploratory Analyses

Figure 3 presents **histograms** of spending decisions for the control groups in both Experiment 1 and Experiment 2. We observe a sizeable portion of subjects with non-zero spending, rejecting Hypothesis 1 (as expected). Subjects in the control groups spend on average \$18, equivalent to 36% of their endowment. This spending behavior is consistent across both experiments. In Experiment 1, control group subjects allocate an average of \$18.46, or 36.92% of their endowment, while in Experiment 2, the mean spending is \$17.63, corresponding to 35.26% of the endowment. Notably, a substantial portion of subjects (approximately 25%) choose not to spend at all. Focusing on the subgroup with non-zero spending, the average spending is \$23.95, i.e., 47.90% of their endowment. This pattern holds steady across both experiments: subjects with non-zero spending spend an average of \$23.96 (47.92% of their endowment) in Experiment 1, and \$23.94 (47.88% of their endowment) in Experiment 2. The clusters around \$25 in the histograms reinforce this result, suggesting that many participants are indeed willing to forgo roughly half of their endowment to reduce CO_2 emissions by purchasing allowances.

Figure 3: Histograms of Spending Decisions



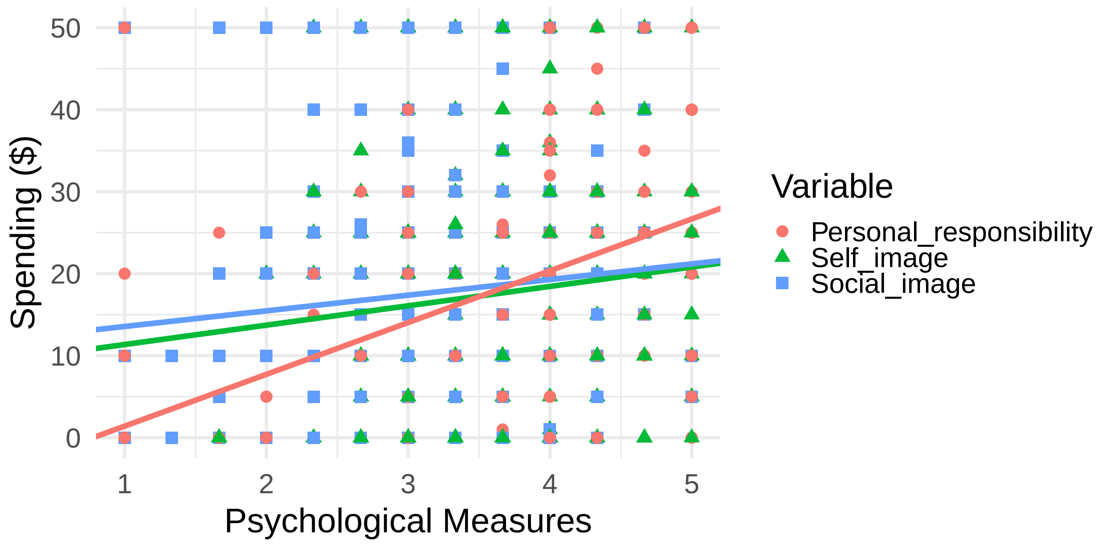
Notes: The maximum spending amount is \$50. The histograms use bins of 5-unit intervals (e.g., 0, 5, 10, etc.) to show the frequencies of spending amounts. The left panel represents spending frequencies for Experiment 1, with 235 subjects in the control group, while the right panel represents Experiment 2, with 281 subjects in the control group. Both diagrams focus exclusively on the control groups to establish baseline spending patterns.

To assess whether individuals are genuinely motivated by environmental concerns, we analyze **open-ended responses** from Experiment 2. Full details are in Appendix B; here, we report the two most common themes. First, 26% of subjects cite the intrinsic importance of the environment and a personal duty to contribute. Second, 25% refer to a "fair ratio" for spending—suggesting they aim for a perceived compromise, often around half their endowment. This supports the view that individuals think in relative terms when deciding how much to give.

To provide insight into the **psychological drivers** of voluntary spending decisions, Figure 4 depicts correlations between subjects' spending and self-assessed attitudes from the ex-post questionnaire, including self-image concerns, social-image concerns, and beliefs about individual responsibility for climate mitigation (each rated on a scale from 1-low to 5-high). In the control group of Experiment 2, social-image concerns show only a weak correlation with spending—likely due to limited observability, as actions were visible only to the experimenter. Self-image concerns correlate more strongly, but the clearest predictor is belief in personal responsibility: subjects who view climate mitigation as an individual obligation spend significantly more.

These patterns suggest that voluntary climate action is shaped not only by environmental concern but also by perceived responsibility, identity, and social influences.

Figure 4: Identity-Based Motivations for Spending



Notes: The ex-post questionnaire elicited self-image concerns (depicted in green on the x-axis), social-image concerns (depicted in blue), and beliefs in personal responsibility for climate damage mitigation (depicted in red). All variables are measured on a scale from 1 (low) to 5 (high). The y-axis shows spending on CO_2 reduction in dollars, out of a maximum of \$50. Linear regression lines are fitted to illustrate the relationship between these identity-based motivations and spending. The slopes of the fitted lines indicate that self-image concerns (slope = 2.36, p = 0.11), social-image concerns (slope = 1.91, p = 0.14), and personal responsibility beliefs (slope = 6.32, $p < 0.001$) are positively associated with spending. The data for this plot are drawn exclusively from the control group in Experiment 2.

4.2.2 Treatment Effects

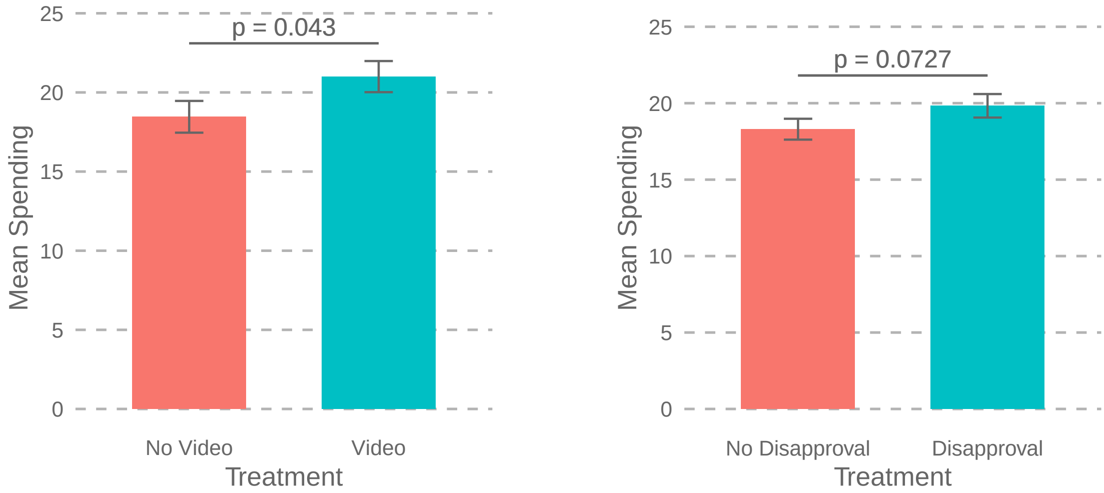
If spending is driven solely by a trade-off between personal welfare and intrinsic concern for environmental impact, it should be unaffected by our exogenous interventions targeting individual responsibility and social-image concerns. However, we find evidence to the contrary (Figure 5). In Experiment 1, subjects exposed to a video emphasizing personal responsibility increase their WTM. Mean spending rises by 13.76%, from \$18.46 to \$21.00 (one-sided Mann-Whitney U test, p = 0.043). This allows us to reject the null hypothesis of no effect in favor of the expected alternative (Hypothesis 2.

The video treatment also strengthens subjects' stated belief in individual responsibility: on a scale from 1 (strongly disagree) to 5 (strongly agree), the treatment group reports an average of 3.80, compared to 3.74 in the control group (one-sided Mann-Whitney U test, p = 0.10).

Similarly, in Experiment 2, a nudge based on social disapproval increases mean spending by 8.36%, from \$18.30 to \$19.83 (one-sided Mann-Whitney U test, p =

0.073). This provides marginally significant evidence against the null hypothesis of no effect in favor of the directional alternative specified in Hypothesis 3.

Figure 5: Responsiveness of Willingness to Mitigate

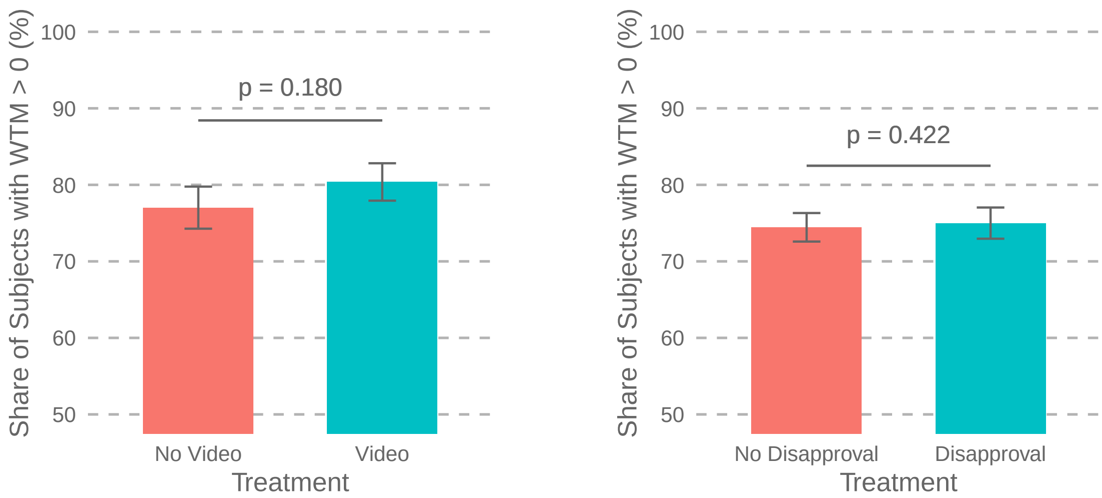


Notes: The figure displays mean spending out of $50 for the treatment and control groups, represented as bar plots with standard errors. The left panel presents data from Experiment 1, where the treatment group (blue) viewed an UN video emphasizing personal responsibility for climate mitigation, and the control group (red) did not. The right panel shows data from Experiment 2, where the treatment group (blue) received disapproval points, and the control group (red) did not. One-sided Mann-Whitney U tests indicate a significant difference in mean spending in Experiment 1 ($p = 0.043$, significant at the 5% level) and a marginally significant difference in Experiment 2 ($p = 0.073$, significant at the 10% level).

To capture the extensive and intensive margins of malleability, we analyze treatment effects along two dimensions: (1) the decision to spend at all—capturing the extensive margin (Figure 6)—and (2) among those who do spend, differences in the amount spent—capturing the intensive margin (Figure 7).[19] The results suggest that treatment effects operate primarily along the intensive margin: they increase the amount contributed by already engaged subjects rather than inducing contributions from previously unwilling ones. In the video treatment, 213 out of 265 subjects have a WTM > 0 (80.38%) compared to 181 out of 235 (77.02%) in the control group. Therefore, the video treatment has a small non-significant effect along the extensive margin. In the disapproval treatment, 339 out of 452 subjects (75%) have a WTM > 0 compared to 408 out of 548 (74.45%) in the control group, which indicates a negligible effect along the extensive margin. In contrast, the effects along the intensive margin are more pronounced (Experiment 1, one-sided Mann-Whitney U test $p = 0.063$; Experiment 2, one-sided Mann-Whitney U test $p = 0.022$).

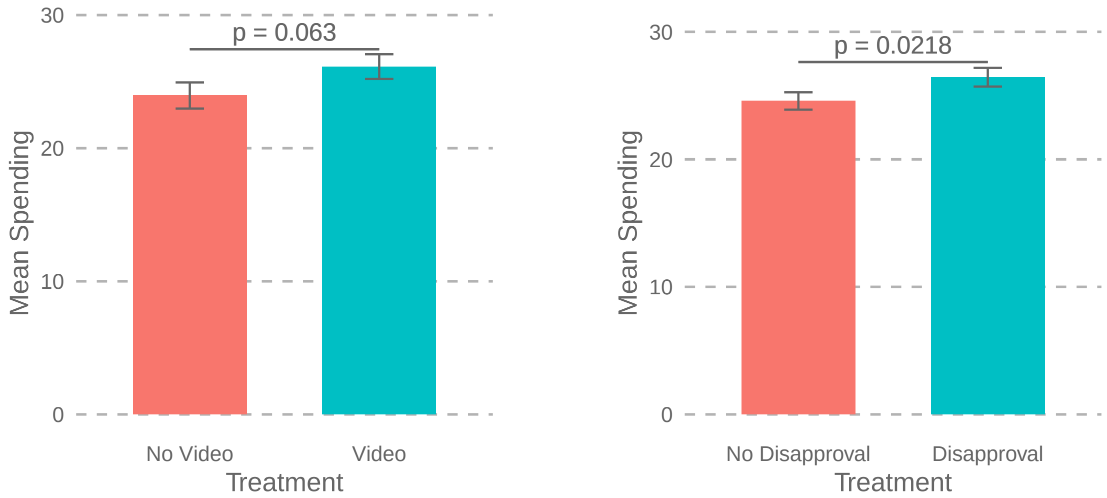
[19]This analysis goes slightly beyond the pre-registration plan but remains within the scope of evaluating treatment effects on spending decisions.

Figure 6: Responsiveness of Willingness to Mitigate—Extensive Margin



Notes: The figure displays the percentage share of subjects choosing non-zero spending. The left panel presents data from Experiment 1, where the treatment group (blue) viewed an UN video emphasizing personal responsibility for climate mitigation, and the control group (red) did not. The right panel shows data from Experiment 2, where the treatment group (blue) received disapproval points, and the control group (red) did not. One-sided Mann-Whitney U tests reveal no statistically significant differences in the share of subjects with non-zero spending between treatment groups in either Experiment 1 ($p = 0.18$) or Experiment 2 ($p = 0.42$).

Figure 7: Responsiveness of Willingness to Mitigate—Intensive Margin



Notes: The figure displays mean spending out of \$50 for the treatment and control groups, restricted to the subjects who spend a non-zero amount (represented as bar plots with standard errors). The left panel presents data from Experiment 1, where the treatment group (blue) viewed an UN video emphasizing personal responsibility for climate mitigation, and the control group (red) did not. The right panel shows data from Experiment 2, where the treatment group (blue) received disapproval points, and the control group (red) did not. One-sided Mann-Whitney U tests indicate a marginally significant difference in mean spending in Experiment 1 ($p = 0.06$, significant at the 10% level) and a significant effect in Experiment 2 ($p = 0.022$, significant at the 5% level).

Taken together, our findings suggest that environmental impact is not the sole motivation for voluntary climate action. Personal accountability and social considerations—such as fairness and image concerns—also appear to play some role.

4.3 Inefficiency of Voluntary Climate Action

We now turn to our main interest—the analysis of impact efficiency in the use of subjects' own WTM. In the allocation task, subjects are asked to split their WTM (expressed in the previous step) between reducing their own footprint and that of another randomly selected participant, knowing that each dollar reduces 2% of the allocated footprint. This setup parallels a common policy dilemma: whether to invest in improving one's own relatively clean environment (e.g., replacing a local bus with an electric model) or to fund more cost-effective mitigation elsewhere (e.g., providing clean cookstoves in regions with higher emissions per dollar). Both options reduce emissions but differ in personal proximity, symbolic accountability, and cost-effectiveness.

By design, allocating the entire WTM to the larger footprint yields the highest possible emission reduction. To quantify deviations from this benchmark, we use the efficiency measure defined in equation (1):

$$e = \frac{sf_o + (1-s)f_a - \min\{f_o, f_a\}}{\max\{f_o, f_a\} - \min\{f_o, f_a\}}. \tag{3}$$

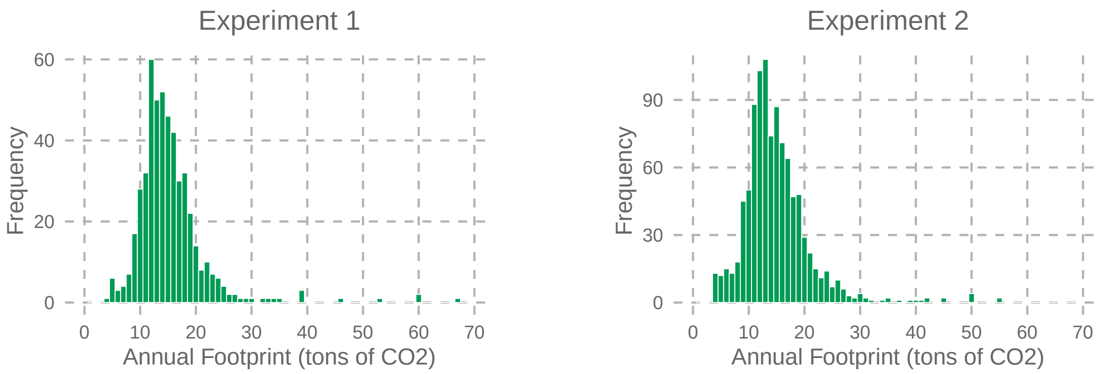
An efficiency score of $e = 1$ indicates full efficiency, corresponding to allocating the full WTM to the larger footprint. A score of $e = 0$ reflects fully anti-efficient behavior, achieving the minimal possible emission reduction. The benchmark score $e = 0.5$ represents behavior that is unresponsive to footprint differences (e.g., random allocation).[20,21]

We begin by describing the sample details and examining baseline behavior in the control groups, before turning to the analysis of treatment effects.

4.3.1 Sample Characteristics

The annual CO_2 **footprint distributions** in Experiment 1 and Experiment 2 are similar (Figure 8) and broadly align with typical U.S. per capita emissions. According to Statista (2023),[22] average U.S. emissions per capita were 13.8 tons of CO_2 in 2023. In Experiment 1, the sample mean is 15.39 tons, with a range from 4.23 to 67.00 tons. In Experiment 2, the mean is slightly lower at 15.02 tons, ranging from 3.96 to 69.96 tons.

Figure 8: Distributions of Footprints



Notes: The figure depicts the frequency distributions of annual carbon footprints in tons of CO_2. The bandwidth is 1 ton of CO_2. The left panel shows the distribution of footprints calculated by subjects using the carbon footprint calculator at the beginning of Experiment 1, while the right panel shows the distribution for Experiment 2. In Experiment 1, the sample mean is 15.39 tons per year, with a range from 4.23 to 67.00 tons. In Experiment 2, the sample mean is slightly lower at 15.02 tons per year, with a range from 3.96 to 69.96 tons.

Given our goal of understanding the nature of *voluntary* climate action, we focus in this and the next section **exclusively on subjects with a strictly positive**

[20]We discuss the properties of this efficiency measure and compare it to an alternative in Appendix A.2. Treatment effects based on the alternative measure are reported in Appendix D.4 and show similar results.

[21]Our main efficiency measure is undefined when $f_o = f_a$. Although the design ensures $f_o \neq f_a$, rounding both values to two decimal places occasionally results in apparent equality. These 27 cases (out of 3423 observations) are excluded from efficiency-related analyses.

[22]https://www.statista.com/statistics/1049662/fossil-us-carbon-dioxide-emissions-per-person/

willingness to mitigate (WTM > 0). This restriction is not only required by design, but also conceptually justified: analyzing voluntary mitigation naturally centers on individuals who are at least marginally willing to act. Still, this choice raises a potential concern for interpreting treatment effects. Since the video and disapproval treatments were administered before the spending decision, they could influence who expresses WTM > 0, thereby altering the composition of the analyzed sample. In that case, observed effects might reflect a shift in who participates rather than a change in behavior among comparable individuals.

We find no evidence for this concern. First, as shown in Figures 6 and 7, the treatments appear to operate primarily along the *intensive* margin, affecting how much already-willing individuals spend rather than whether they choose to participate at all. This suggests that behavioral malleability arises within the existing pool of willing individuals. Second, Table 2 shows that baseline characteristics of subjects with WTM > 0 are well-balanced across treatment and control groups, alleviating concerns about differential selection. Taken together, these findings support interpreting the treatment effects as changes in behavior rather than shifts in sample composition.

Table 2: Sample Characteristics of the Willing Subjects (WTM > 0)

Demographics	**Video Treatment**		**Disapproval Treatment**		**Hidden Information Treatment**	
	Video	No Video	Disapproval	No Disapproval	Hidden Info	Full Info
Age 18-40	63.8	64.1	61.9	64.2	63.2	63.2
Age 41-60	32.9	30.9	31.6	29.2	29.5	31
Age > 60	3.3	5	6.5	6.6	7.3	5.8
Female	45.1	46.4	52.2	51.5	51.3	52.4
Male	53.1	51.4	45.7	47.5	47.4	46
Diverse	1.4	2.2	2.1	1	1.3	1.7
Net Monthly Income Less Than $3000	44.6	48.6	51	44.6	44.8	50.4
Net Monthly Income Between $3000-$6000	38.5	36.5	35.4	38.7	39.9	34.3
Net Monthly Income Higher Than $6000	16.9	14.9	13.6	16.7	15.3	15.2
Less Than High School	1.4	0	1.2	0.2	0.5	0.8
High School Diploma	31	39.8	32.7	27.2	29.8	29.6
Bachelor's Degree Or Equivalent	43.7	41.4	41.3	50.2	46.6	45.7
Master's Degree Or Equivalent	21.1	17.1	19.5	16.4	18.1	17.5
Doctorate Or Professional Degree	2.8	1.7	5.3	5.9	4.9	6.4
Very Liberal	24.4	28.2	25.4	24.3	23.1	26.6
Somewhat Liberal	36.2	33.7	33.9	36.3	35.5	34.9
Moderate	23.9	20.4	24.5	17.6	22	19.4
Somewhat Conservative	9.9	14.4	11.8	17.6	14.8	15.2
Very Conservative	5.6	3.3	4.4	4.2	4.7	3.9
All	213	181	339	408	386	361

Notes: The table presents summary statistics for demographic variables across treatment and control groups only for the WTM > 0 sample. The last row ("All") displays the total number of subjects in each group, while all other values are reported as percentages. For each treatment/control group, percentages represent the distribution within each demographic category. Chi-square tests for categorical variables show no significant differences in group allocation across age, gender, income, education, and political orientation (all $p > 0.05$). These findings confirm that the treatment and control groups are well balanced even in this restricted sample.

We also address a common concern in online samples: **potential misunderstanding of the experimental task**. To test comprehension, we included control questions after the instructions that required subjects to compute the impact of a hypothetical decision. Subjects were given up to seven attempts to answer correctly, allowing them to refine their understanding and better internalize the task. If unsuccessful after seven attempts, they were shown the correct solution and allowed to proceed. The results are unimpressive: 127 out of 500 subjects in Experiment 1 and 311 out of 1,000 in Experiment 2 did not pass within seven tries, raising the possibility that roughly one-third of participants may not have fully internalized the logic of the allocation task.

However, we believe this concern is less severe than it might initially appear, for several reasons. First, the control questions involved numerical calculations, and it is likely that some subjects struggled with arithmetic rather than with conceptual understanding. Second, the key idea of comparing two corner allocations—allocating all funds to oneself versus another—is transparent, intuitive, and does not require precise computation. Third, the regression of disapproval points on efficiency in Experiment 1 suggests that efficiency is generally understood and valued.[23] Fourth, open-ended responses reinforce this interpretation, with roughly 50% of participants citing impact-related motives. Finally, in Appendix D.1, we report a robustness check excluding subjects who failed the control questions; the results remain similar.

4.3.2 Exploratory Analyses

Our findings indicate that subjects do not allocate their voluntary contributions particularly efficiently. In the control groups, **average efficiency** is 66.85% in Experiment 1 and 59.67% in Experiment 2—both substantially below full efficiency. Accordingly, and in line with expectations, we reject the full-efficiency hypothesis (Hypothesis 4).

Self-reported motives behind allocation decisions in our second study offer further insights. Details on how we analyze these responses are provided in Appendix C. In the control group, 52% of subjects explicitly state that their goal is to maximize impact. This group exhibits a higher average efficiency of 64.10%, compared to the overall control group average of 59.67%. However, even among these subjects, efficiency remains well below full potential.

Moreover, the responses indicate that other considerations shape allocation decisions. For instance, 8% of control group participants describe their reasoning in terms of fairness. In total, 27% of responses in the control group refer to motives unrelated to environmental impact, including fairness, a desire to equalize footprints, a sense of responsibility for one's own emissions, or intuition.

These findings suggest that while maximizing impact is a common and influential motive, it often coexists with other (cognitive or motivational) drivers. Even among those explicitly aiming to maximize impact, such considerations can diminish efficiency, reflecting a more nuanced and multifaceted decision-making process than a fully rational impact-maximizing model would predict.

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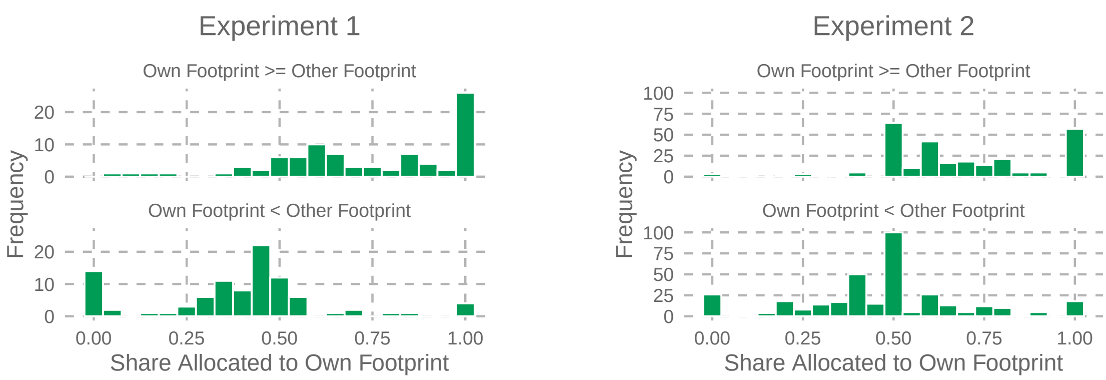
[23]We report this regression in Appendix D.5. Note that these are disapproval points allocated *by participants* to their peers in the same experiment, not to be confused with the disapproval treatment in Experiment 2. Subjects consistently assign more disapproval points to low spending and inefficient allocations, a pattern that holds independently of the video treatment.

One barrier to efficiency that our design explicitly targets is the potential tendency for individuals to prioritize self-centered actions over those that maximize environmental impact. A focus on self-image or social image may lead subjects to reduce their *own* footprint, even when doing so is less effective from an environmental standpoint. Indeed, in the control groups, subjects tend to split their contributions roughly evenly between reducing their own and another person's carbon footprint, with a slight preference for their own. On average, 55.52% of contributions in Experiment 1 and 56.22% in Experiment 2 are directed toward mitigating the subject's own emissions.

As shown in the **histograms** (Figure 9), subjects generally allocate more resources to the footprint that yields greater environmental impact. However, the distribution of allocations varies systematically depending on which footprint is larger. When the subject's own footprint exceeds the other's, the distribution is heavily skewed toward own mitigation, indicating that subjects tend to pursue efficiency when it aligns with self-serving action. In contrast, when the other's footprint is larger, the distribution is only slightly skewed toward the other's footprint and is concentrated around an equal split. This pattern suggests a modest preference for environmental impact but also highlights a persistent self-centered bias: even when maximizing efficiency requires prioritizing the other's footprint, many subjects opt for more balanced allocations, thereby limiting the environmental gains that could have been achieved.

Additionally, the frequent use of interior allocations—often centered around an equal split, regardless of which footprint is larger—may reflect a fairness motive or heuristic, echoing the patterns in the self-reported reasoning discussed above. This behavior may ultimately stem from attenuated optimization due to cognitive noise (Enke et al., 2025).

Figure 9: Histograms of Allocation Decisions

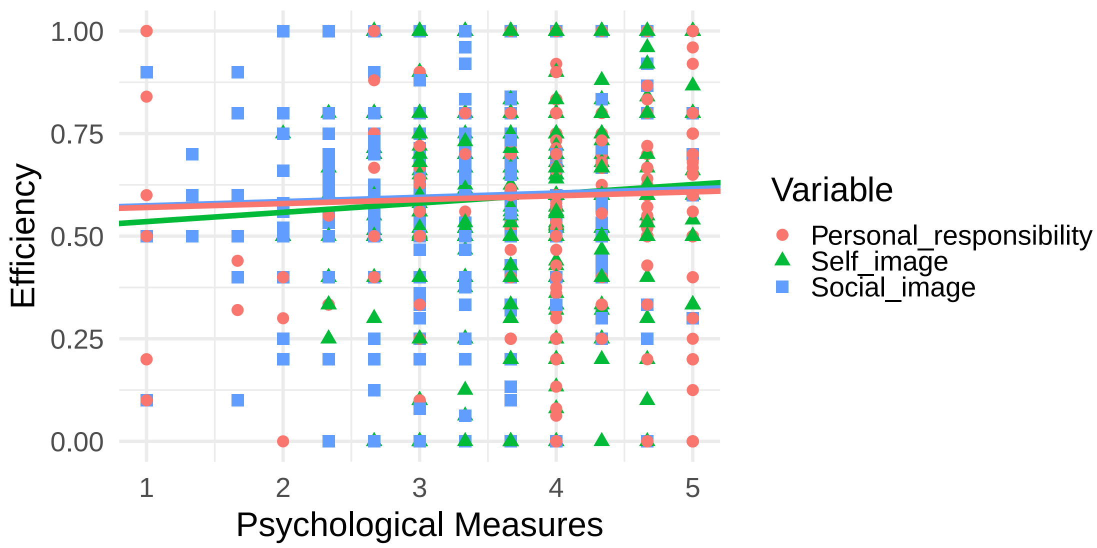


Notes: The histograms use bins of 0.05 intervals to show the frequencies of shares spent on the own footprint. The left panel represents allocation frequencies for Experiment 1, with 181 observations in the control group with WTM > 0, while the right panel represents Experiment 2, with 621 observations in the control group with WTM > 0. Both diagrams focus exclusively on the control groups to establish baseline allocation patterns. Mean shares are 0.39 (other higher) and 0.74 (own higher) for Experiment 1 and 0.47 (other higher) and 0.68 (own higher) for Experiment 2.

Psychological measures from the ex-post questionnaire also correlate (albeit not significantly) with efficiency (Figure 10). Specifically, higher self-image concerns and a stronger belief in personal responsibility are associated with greater efficiency in the control group of Experiment 2. Our first nudge—the video treatment—appeals directly to these dimensions, potentially reinforcing them. This raises the question of whether such identity-related attitudes, and the associated efficiency, can be shifted by the nudge.

We also find that efficiency increases with stronger social-image concerns. In the control group, subjects are observed only by the experimenter. In contrast, the second nudge—the disapproval treatment—alters the evaluative frame: subjects are now assessed by other participants based on the size of their individually abated footprint, rather than on efficiency. This raises the question of whether subjects reduce efficiency in response to the altered framing and heightened social pressure.

Figure 10: Identity-Based Motivations for Efficiency



Notes: The ex-post questionnaire elicited self-image concerns (depicted in green on the x-axis), social-image concerns (depicted in blue), and beliefs in personal responsibility for climate damage mitigation (depicted in red). All variables are measured on a scale from 1 (low) to 5 (high). The y-axis shows the efficiency of subjects' allocation decisions (1 is full efficiency, 0 is full anti-efficiency). Linear regression lines are fitted to illustrate the relationship between these identity-based motivations and efficiency. The slopes of the fitted lines indicate that self-image concerns (slope = 0.023, p = 0.13), social-image concerns (slope = 0.010, p = 0.44) and personal responsibility beliefs (slope = 0.009, p = 0.42) are positively associated with efficiency. Results are not significant. The data for this plot are drawn exclusively from the control group in Experiment 2.

4.3.3 Treatment Effects

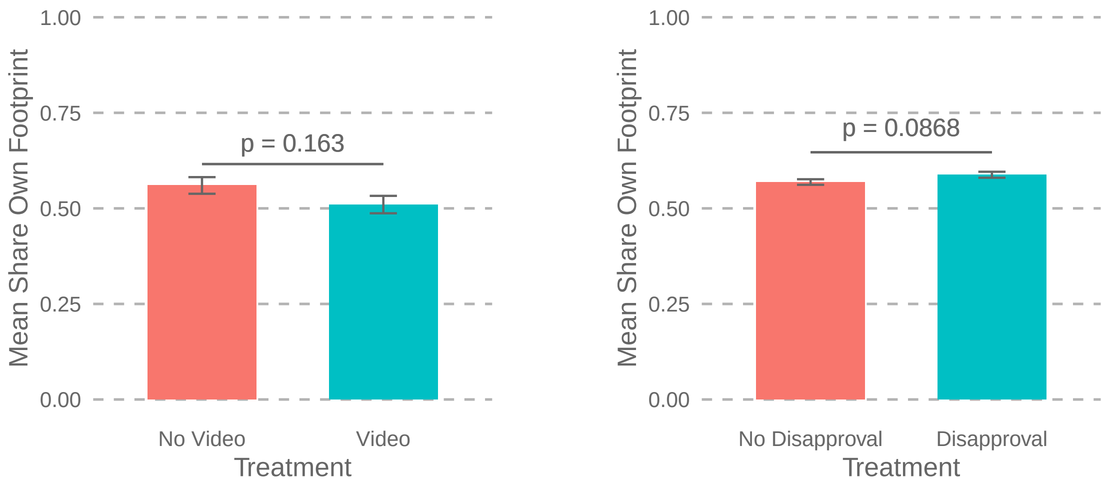
We examine the effects of our two nudges—appeal to personal responsibility and social disapproval—to test whether efficiency is malleable in response to appeals to emotion, self-image, and social perception. This allows us to investigate whether allocation decisions are solely driven by environmental intent, or if such nudges can shift attention further away from environmental impact as the primary motivator. Full-sample results are presented in Figures 11 and 12, while results restricted to decisions in which the other footprint is higher—where we expect the most pronounced effects—are shown in Figures 13 and 14.[24]

The personal responsibility (video) treatment in Experiment 1 decreases the mean share of contributions allocated to subjects' own footprint from 56% to 51% (two-sided exploratory Mann-Whitney U test, p = 0.16). Not only can we not reject Hypothesis 6 (pre-registered one-sided test in the predicted direction has p = 0.92), but the effect also goes in the opposite direction from what we expected (and pre-registered). Furthermore, the video treatment significantly increases mean efficiency from 67% to 74% (two-sided exploratory Mann-Whitney U test, p = 0.005), leading us to reject Hypothesis 8—again in the opposite direction of our prediction (pre-registered one-sided test in the predicted direction has p = 0.997). Thus, our expectation that the appeal to personal responsibility would lead subjects to prioritize their own footprint proves incorrect: instead, the treatment appears to activate an intrinsic motivation to contribute more effectively to the collective goal.

Conversely, the social disapproval treatment in Experiment 2 increases the mean share of contributions allocated to subjects' own footprint from 56.9% to 58.8%. This provides marginally significant evidence against the null hypothesis of no effect in favor of the directional alternative specified in Hypothesis7 (one-sided Mann-Whitney U test, p = 0.087). Moreover, the disapproval treatment significantly decreases mean efficiency from 59.12% to 57.32% (one-sided Mann-Whitney U test, p = 0.021), leading us to reject Hypothesis 9, as predicted. This suggests that social-image concerns may reduce the effectiveness of individual environmental action by increasing the tendency to prioritize self-presentation over environmental impact.

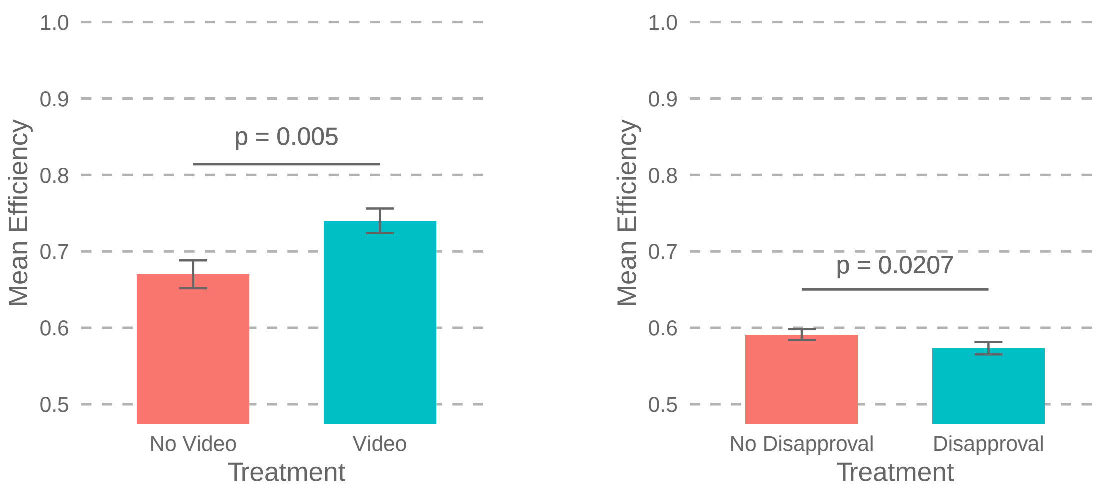
[24] In the main analyses, we use data from all three allocation decisions. To rule out learning or fatigue effects, we re-run the analyses using only first-round data in Appendix D.3—reducing the sample to one-third. As expected with a smaller sample, some estimates become less precisely estimated, though the general patterns remain similar.

Figure 11: Responsiveness of Share-Own (Full Sample)



Notes: The figure displays the mean share of total spending spent on the own footprint in the allocation decision for the treatment and control groups, represented as bar plots with standard errors. The left panel presents data for all decisions (of subjects with WTM > 0) from Experiment 1, where the treatment group (blue) viewed a UN video emphasizing personal responsibility for climate mitigation, and the control group (red) did not. The right panel shows data for all decisions (of subjects with WTM > 0) from Experiment 2, where the treatment group (blue) received disapproval points, and the control group (red) did not. Mann-Whitney U tests indicate non-significant difference in mean share spent on the own footprint in Experiment 1 (exploratory two-sided test, p = 0.163) and marginally significant difference in Experiment 2 (one-sided test, p = 0.087).

Figure 12: Responsiveness of Efficiency (Full Sample)



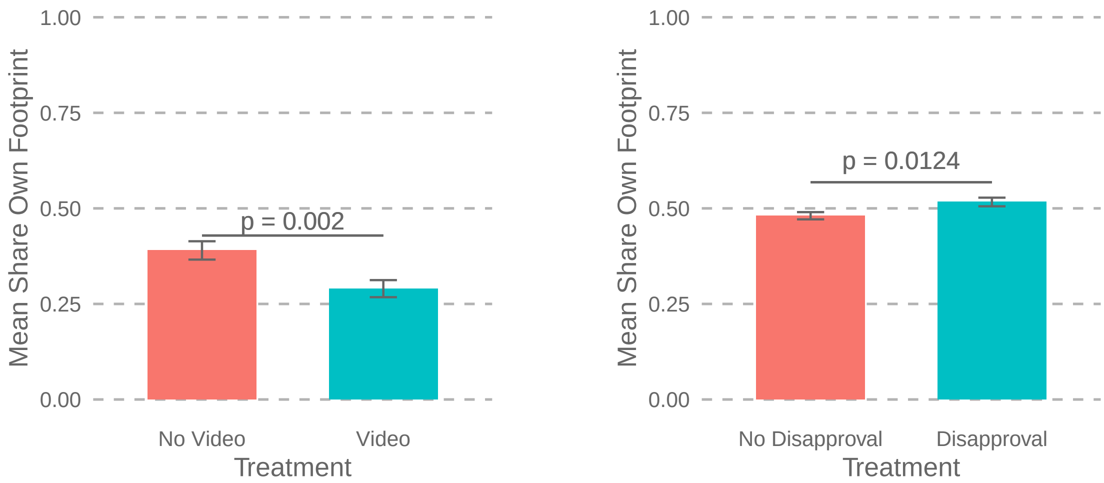
Notes: The figure displays the mean efficiency of the allocation decision for the treatment and control groups, represented as bar plots with standard errors. The left panel presents data for all decisions (of subjects with WTM > 0) from Experiment 1, where the treatment group (blue) viewed a UN video emphasizing personal responsibility for climate mitigation, and the control group (red) did not. The left panel shows data for all decisions (of subjects with WTM > 0) from Experiment 2, where the treatment group (blue) received disapproval points, and the control group (red) did not. Mann-Whitney U tests indicate significant differences in efficiency in Experiment 1 (exploratory two-sided test, p = 0.005, significant at the 1% level) and Experiment 2 (one-sided test, p = 0.021, significant at the 5% level).

These results suggest that behavioral nudges can influence allocation decisions and resulting efficiency. Notably, we also find that willingness and efficiency can be affected independently: while the video treatment increases both WTM and efficiency, the disapproval treatment increases WTM but decreases efficiency. This decoupling is an unexpected finding because we had pre-registered the opposite prediction for the video treatment—anticipating a decrease in efficiency. The findings thus support the view that willingness and efficiency are not psychologically tightly coupled.

As noted in the exploratory analyses of the control groups, one barrier to efficiency is the tendency to focus primarily on reducing one's own footprint (Jakob et al., 2017). To better understand when and how strongly individuals respond to nudges, we stratify the sample based on whether the other footprint is higher or lower than the own footprint.

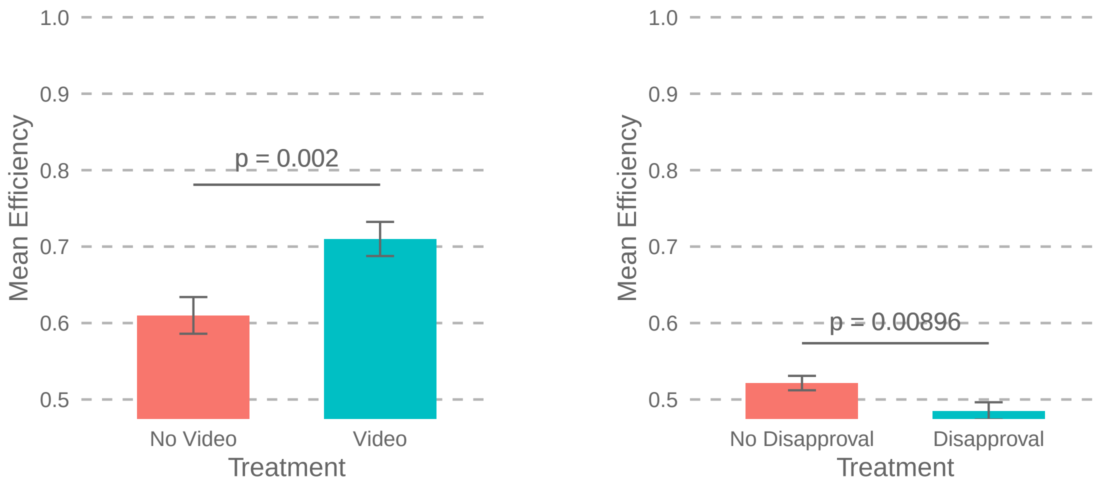
In decisions where the other footprint is higher, the effects of the nudges are more pronounced than in the full sample. In this subgroup, we observe significant differences between treatment and control groups in both the share allocated to the own footprint and overall efficiency (see Figures 13 and 14). The direction of the effects is consistent with the full sample: the video treatment leads to a reduced share allocated to the own footprint and higher efficiency, while the disapproval treatment increases the share allocated to the own footprint and results in lower efficiency.

Figure 13: Responsiveness of Share-Own (Other-Footprint-Higher Sample)



Notes: The figure displays the mean share of total spending spent on the own footprint in the allocation decision for the treatment and control groups, represented as bar plots with standard errors. The left panel presents data for all decisions where subjects (with WTM > 0) see another footprint that is higher than their own (other-footprint-higher sample) from Experiment 1, where the treatment group (blue) viewed a UN video emphasizing personal responsibility for climate mitigation, and the control group (red) did not. The right panel shows data for all decisions where subjects (with WTM > 0) see another footprint that is higher than their own (other-footprint-higher sample) from Experiment 2, where the treatment group (blue) received disapproval points, and the control group (red) did not. Mann-Whitney U tests indicate statistically significant differences in the mean share spent on the own footprint in Experiment 1 ($p = 0.002$, significant at the 1% level) and Experiment 2 ($p = 0.012$, significant at the 5% level). As for the full sample, for Experiment 1 the reported p-value is from a two-sided exploratory test because the effect goes in the opposite direction of our pre-registered prediction, whereas for Experiment 2 the one-sided test in the pre-registered direction is used.

Figure 14: Responsiveness of Efficiency (Other-Footprint-Higher Sample)



Notes: The figure displays the mean efficiency of the allocation decision for the treatment and control groups, represented as bar plots with standard errors. The left panel presents data for all decisions where subjects (with WTM > 0) see another footprint that is higher than their own (other-footprint-higher sample) from Experiment 1, where the treatment group (blue) viewed a UN video emphasizing personal responsibility for climate mitigation, and the control group (red) did not. The right panel shows data for all decisions where subjects (with WTM > 0) see another footprint that is higher than their own (other-footprint-higher sample) from Experiment 2, where the treatment group (blue) received disapproval points, and the control group (red) did not. Mann-Whitney U tests indicate statistically significant differences in efficiency in Experiment 1 ($p = 0.002$, significant at the 1% level) and Experiment 2 ($p = 0.009$, significant at the 1% level). As for the full sample, for Experiment 1 the reported p-value is from a two-sided exploratory test because the effect goes in the opposite direction of our pre-registered prediction, whereas for Experiment 2 the one-sided test in the pre-registered direction is used.

In contrast, in the subgroup where the own footprint is higher than the other's, responses to the nudges are much weaker and not statistically significant (see Appendix D.2).[25] This suggests that subjects in this group may already be allocating a share to their own footprint that they find personally acceptable, and that this allocation is relatively resistant to external manipulations. The findings point to considerations beyond environmental impact in shaping allocation decisions. Even when investing more in their own footprint would lead to greater efficiency, subjects appear to adhere to a certain threshold—possibly informed by norms of fairness.

[25]Even though the effects in the other-footprint-lower group are weak and not significant, we briefly describe the qualitative patterns: Participants allocate slightly more to their own footprint under the video treatment and slightly less under the disapproval treatment—the opposite pattern compared to the other-footprint-higher group. This again leads to higher efficiency in the video treatment and lower efficiency in the disapproval treatment, mirroring the direction of effects in the other-footprint-higher group.

4.4 Information Avoidance in Allocation Decisions

In the second treatment strand of Experiment 2—the hidden-information treatment—we further investigate whether subjects' behavior changes when they lack the full information required to achieve maximum efficiency. In this condition, information about the other subject's footprint is initially concealed, making it optional for participants to actively seek out the details necessary for an informed decision. The cost of acquiring this information is minimal: it requires only a single click to reveal the relevant data. If subjects were purely driven by efficiency, we would expect them to access the hidden information and display no significant differences in behavior compared to the control group.[26]

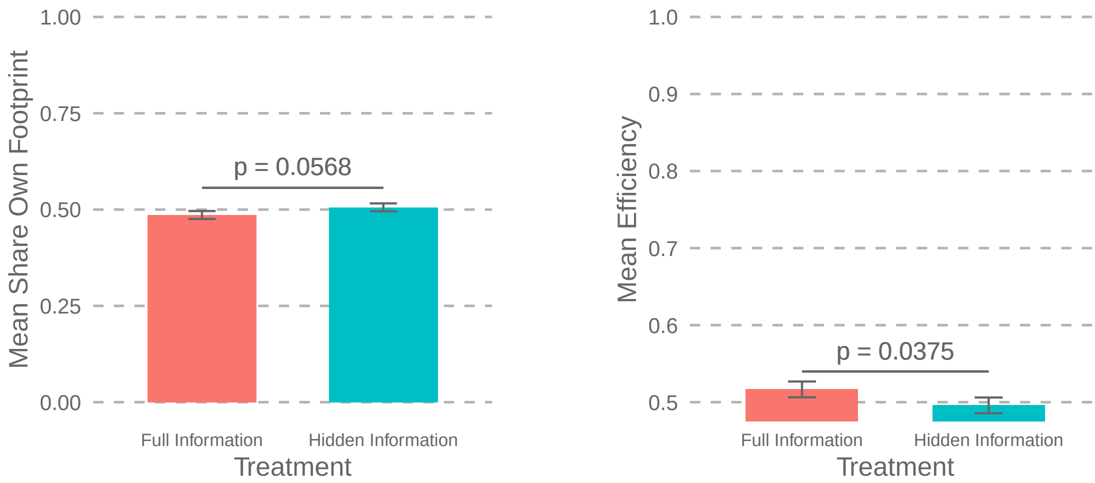
However, our findings indicate otherwise. The **information acquisition rate** in the hidden-information treatment is only 59.93%, falling well short of full uptake and thereby rejecting Hypothesis 10, as expected.[27] Subjects in this treatment allocate a larger share of their contributions to reducing their own footprint, and overall efficiency is lower compared to the control group. These effects are most pronounced when the other subject's footprint is larger: the share allocated to one's own footprint is 2 percentage points higher (one-sided Mann-Whitney U test, $p = 0.057$), and the efficiency index is 2 percentage points lower ($p = 0.038$) in the hidden-information treatment relative to the full-information control group (Figure 15).[28]

[26]As discussed in the previous section, we also restrict the analysis in this section to subjects with WTM > 0.

[27]At the same time, the acquisition rate is well above zero, rejecting Hypothesis 12, which is also consistent with our expectations.

[28]The pattern holds for the full sample as well: subjects in the treatment allocate more to their own footprint ($p = 0.267$), and overall efficiency is lower ($p = 0.028$).

Figure 15: Effect of Information Treatment on Share-Own and Efficiency (Other-Footprint-Higher Sample)



Notes: The figure shows the mean share spent on one's own footprint (left) and the mean efficiency of allocation decisions (right) for the hidden-information treatment (other footprint visible only after clicking a link; blue bars) and full-information control groups (both footprints visible before allocation; red bars) in Experiment 2. The sample consists of all decisions where subjects (with WTM > 0) see another footprint that is higher than their own (other-footprint-higher sample). Standard errors are displayed. One-sided Mann-Whitney U tests show a marginally significant difference in mean share ($p = 0.057$, significant at the 10% level) and a significant difference in efficiency ($p = 0.038$, significant at the 5% level).

The aggregate data suggest a degree of **responsiveness to information** about others' carbon footprints, though this responsiveness is not uniform across subjects. In the full-information group, we observe a significant 18 percentage-point gap in the share allocated to the subject's own footprint, depending on whether the other footprint is higher or lower, thus rejecting Hypothesis 5, as expected. This indicates that, when provided with complete information, subjects tend to adjust their allocations in line with the goal of higher efficiency. Moreover, individuals who actively acquire information in the hidden-information treatment exhibit behavior comparable to those in the full-information group, both in terms of allocation patterns and efficiency outcomes. Accordingly, the efficiency loss in the hidden-information treatment is driven by those who choose not to acquire information, reinforcing the importance of information access for optimizing decisions. Still, responsiveness remains incomplete: not all subjects adjust their behavior fully in light of the available information. Especially when the other footprint is larger, subjects in the full-information group still allocate as much as 49% to their own footprint, and those in the hidden-information treatment who acquire information allocate 46% to their own footprint.

For subjects who explicitly state that their goal is to maximize impact, the rate of information acquisition is substantially higher than average, reaching 83.73%. This suggests a stronger inclination toward making informed decisions among those who prioritize environmental impact. However, even within this group, behavioral patterns indicate that the responsiveness to efficiency trade-offs is not absolute. When the other footprint is higher, those who prioritize environmental impact and who acquire information in the hidden-information treatment still allocate on average 40% of their spending to their own footprint. These findings suggest that while subjects recognize the efficiency trade-offs associated with footprint allocation, their responses remain partial. The tendency to continue directing a significant portion of spending toward their own footprint, despite understanding the higher efficiency of targeting the larger footprint, implies that other factors may moderate their decision-making. We observe a directional, yet incomplete, adjustment in allocation behavior.

We test two hypothesized mechanisms underlying (non-)acquisition of information. To do so, we focus exclusively on subjects who consistently either acquire or do not acquire information across all three allocation rounds. We exclude extreme outliers in footprint belief distributions (e.g., subjects reporting expected annual footprints exceeding 100 tons of CO_2) as well as subjects with zero WTM.

The first mechanism, **motivated learning** (Hypothesis 13), posits that subjects' decisions to acquire information are influenced by their prior beliefs about their own footprint relative to others'. Specifically, subjects who expect their own footprint to be larger may avoid acquiring information to preserve justification for prioritizing their own footprint, whereas those who expect their footprint to be smaller might seek information in the hope of learning the opposite. Our findings do not support Hypothesis 13.[29] In fact, we observe a weak (not statistically significant) trend in the opposite direction, as confirmed by linear and logistic regressions in Table 8 in Appendix D.6. The probability of information acquisition is 65% among subjects who expect their own footprint is larger than the footprint of others, compared to 60% among those who expect their footprint is smaller.

Motivated by this (albeit non-significant) pattern, we provide in Appendix A.5 an ex-post theoretical account based on S-shaped belief-based utility with the subject's own footprint as a reference point.[30] Specifically, the agent derives utility from believing that her own footprint is relatively low. She holds prior beliefs about the distribution of others' footprints and decides whether to reveal the footprint of another participant, which would update her beliefs. The model captures the intuition that, if the agent expects her own footprint to be relatively high, she may seek information in the hope of learning that she is not that bad. Conversely, if she expects her footprint to be relatively low, she may avoid information in order to preserve a favorable self-image.

The second mechanism we examine is **rational inattention** (Hypothesis 11), which posits that subjects' decisions to acquire information depend on the expected benefit of that information. Our findings do not support Hypothesis 11. If anything, we

[29]The hypothesis is not supported even when restricting to the interaction with the disapproval treatment.

[30]This is an ex-post theory that was not pre-registered.

observe a weak (not statistically significant) trend in the opposite direction, as confirmed by linear and logistic regressions in Table 9 in Appendix D.6. Hence, subjects generally do not appear to acquire information even in a boundedly rational manner.

4.5 Revealed Behavioral Rules

We further describe the behavioral rules applied by subjects in Experiment 2, focusing on the control group and individuals who spend non-zero amounts (WTM > 0). This allows us to distinguish whether subjects consistently adhere to a fixed rule independent of the provided footprint information across all three decisions, or whether they adjust their behavior dynamically in response to the information received in each round.[31]

A large share of subjects (29.96%) display non-consequentialist behavior. Among them, 5.80% consistently allocate their entire budget to their own footprint across all rounds, and 10.63% consistently allocate more to their own footprint without allocating the full amount. Another 8.21% follow a consistent 50-50 split in each round. Only a small proportion (0.97%) consistently allocate their full budget to another footprint across all rounds, with 4.35% consistently allocating more to another footprint but not the full amount.

In contrast, 28.02% of subjects exhibit consequentialist behavior, meaning they respond to the provided footprint information. Fully efficient behavior—allocating all resources to the highest footprint—is observed in 5.80% of subjects, while 20.29% exhibit directionally efficient behavior, allocating more to the higher footprint but without full efficiency. Fully anti-efficient behavior, where subjects allocate their entire budget to the lowest footprint, is observed in 1.45% of subjects, with 0.48% displaying directionally anti-efficient behavior.

5 Conclusion

Our findings show that while most individuals are willing to contribute to carbon mitigation, their contributions are not tightly coupled with impact efficiency. Although many express a desire for impact, behavior is often guided by feelings of personal responsibility and fairness norms—likely used as heuristics to cope with cognitive limitations—resulting in inefficient, self-centered compromise allocations. Many participants also avoid easily accessible information that could improve their decisions. The prevalence of non-consequentialist behavior is further underscored by the fact that both the level and efficiency of contributions are malleable through interventions unrelated to impact: our appeal to personal responsibility enhances both, whereas the social-image nudge increases contributions but reduces efficiency. These interventions primarily shift the behavior of the already willing, rather than converting the unwilling.

[31] This is an additional suggestive result which was not pre-registered.

The uncovered nature of voluntary willingness to mitigate has several practical consequences. On the positive side, it suggests that minor systemic inefficiencies may not entirely deter people's willingness to contribute. On the negative side, it means we cannot easily infer intrinsic concern for environmental outcomes, nor can we count on individuals to pursue the most impactful actions on their own. Coupled with the risk of moral licensing, this calls for careful design of institutions that complement and channel goodwill toward its most effective use.

References

Andre, P., Boneva, T., Chopra, F., and Falk, A. (2024a). Globally representative evidence on the actual and perceived support for climate action. *Nature Climate Change*, 14(3):253–259.

Andre, P., Boneva, T., Chopra, F., and Falk, A. (2024b). Misperceived social norms and willingness to act against climate change. *Review of Economics and Statistics*, pages 1–46.

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving. *Economic Journal*, 100(401):464–477.

Bailey, N. T., Ramalingam, A., and Stoddard, B. V. (2023). Experimental (re-)analysis of the house-money effect in a public goods game. *Journal of the Economic Science Association*, 9(1):1–14.

Berger, S., Kilchenmann, A., Lenz, O., Ockenfels, A., Schlöder, F., and Wyss, A. M. (2022). Large but diminishing effects of climate action nudges under rising costs. *Nature Human Behaviour*, 6(10):1381–1385.

Bergquist, M., Thiel, M., Goldberg, M. H., and Van Der Linden, S. (2023). Field interventions for climate change mitigation behaviors: A second-order meta-analysis. *Proceedings of the National Academy of Sciences*, 120(13):e2214851120.

Bolton, G. E. and Ockenfels, A. (2000). ERC: A theory of equity, reciprocity, and competition. *American Economic Review*, 91(1):166–193.

Chancel, L. (2022). Global carbon inequality over 1990–2019. *Nature Sustainability*, 5(11):931–938.

Clark, J. (2002). House money effects in public good experiments. *Experimental Economics*, 5:223–231.

Cramton, P., MacKay, D. J., Ockenfels, A., and Stoft, S. (2017). *Global carbon pricing: the path to climate cooperation*. The MIT Press.

Dana, J., Weber, R. A., and Kuang, J. X. (2007). Exploiting moral wiggle room: experiments demonstrating an illusory preference for fairness. *Economic Theory*, 33:67–80.

Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Chico, A. S., and Stantcheva, S. (2024). Fighting climate change: International attitudes toward climate policies. *American Economic Review*.

DellaVigna, S., List, J. A., and Malmendier, U. (2012). Testing for altruism and social pressure in charitable giving. *Quarterly Journal of Economics*, 127(1):1–56.

Diederich, J. and Goeschl, T. (2014). Willingness to pay for voluntary climate action and its determinants: Field-experimental evidence. *Environmental and Resource Economics*, 57:405–429.

Engel, C. (2011). Dictator games: A meta study. *Experimental Economics*, 14:583–610.

Enke, B. (2024). The cognitive turn in behavioral economics. Manuscript.

Enke, B., Graeber, T., Oprea, R., and Yang, J. (2025). Behavioral attenuation. NBER Working Paper.

Exley, C. L. and Kessler, J. B. (2024). Motivated errors. *American Economic Review*, 114(4):961–987.

Fehr, E. and Schmidt, K. M. (1999). A theory of fairness, competition, and cooperation. *Quarterly Journal of Economics*, 114(3):817–868.

Hagmann, D., Ho, E. H., and Loewenstein, G. (2019). Nudging out support for a carbon tax. *Nature Climate Change*, 9(6):484–489.

Hagmann, D., Liao, Y.-t., Chater, N., and Loewenstein, G. (2023). Costly distractions: Focusing on individual behavior undermines support for systemic reforms. SSRN Working Paper 4426034.

Harrison, G. W. (2007). House money effects in public good experiments: Comment. *Experimental Economics*, 10:429–437.

Heeb, F., Kölbel, J. F., Paetzold, F., and Zeisberger, S. (2023). Do investors care about impact? *The Review of Financial Studies*, 36(5):1737–1787.

Imai, T., Pace, D. D., Schwardmann, P., and van der Weele, J. J. (2022). Correcting consumer misperceptions about CO2 emissions. CESifo Working Paper CESifoWorking Paper No. 10138.

IPCC (2022). *Climate Change 2022: Impacts, Adaptation, and Vulnerability.* Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press.

Jakob, M., Kübler, D., Steckel, J. C., and van Veldhuizen, R. (2017). Clean up your own mess: An experimental study of moral responsibility and efficiency. *Journal of Public Economics*, 155:138–146.

Kahneman, D. and Knetsch, J. L. (1992). Valuing public goods: the purchase of moral satisfaction. *Journal of Environmental Economics and Management*, 22(1):57–70.

Karlan, D. and List, J. A. (2007). Does price matter in charitable giving? Evidence from a large-scale natural field experiment. *American Economic Review*, 97(5):1774–1793.

Karlan, D. and Wood, D. H. (2017). The effect of effectiveness: Donor response to aid effectiveness in a direct mail fundraising experiment. *Journal of Behavioral and Experimental Economics*, 66:1–8.

Kaufmann, M., Andre, P., and Kőszegi, B. (2024). Understanding markets with socially responsible consumers. *Quarterly Journal of Economics*, page qjae009.

Kölle, F., Kübler, D., and Ockenfels, A. (2024). Impartial policymakers prefer to impose carbon pricing to capping, especially when combined with offsets. *Ecological Economics*, 226:108348.

Kriss, P. H., Loewenstein, G., Wang, X., and Weber, R. A. (2011). Behind the veil of ignorance: Self-serving bias in climate change negotiations. *Judgment and Decision Making*, 6(7):602–615.

Lilley, A. and Slonim, R. (2014). The price of warm glow. *Journal of Public Economics*, 114:58–74.

Löschel, A., Sturm, B., and Vogt, C. (2013). The demand for climate protection—Empirical evidence from Germany. *Economics Letters*, 118(3):415–418.

Maćkowiak, B., Matějka, F., and Wiederholt, M. (2023). Rational inattention: A review. *Journal of Economic Literature*, 61(1):226–273.

Mayring, P. (2022). Qualitative Inhaltsanalyse: Grundlagen und Techniken (13. Neuausgabe). Julius Beltz GmbH & Co. KG.

Metzger, L. and Günther, I. (2019). Making an impact? The relevance of information on aid effectiveness for charitable giving. A laboratory experiment. *Journal of Development Economics*, 136:18–33.

Nemet, G. F. and Johnson, E. (2010). Willingness to pay for climate policy: A review of estimates. La Follette School Working Paper.

Nisa, C. F., Bélanger, J. J., Schumpe, B. M., and Faller, D. G. (2019). Meta-analysis of randomised controlled trials testing behavioural interventions to promote household action on climate change. *Nature Communications*, 10(1):4545.

Null, C. (2011). Warm glow, information, and inefficient charitable giving. *Journal of Public Economics*, 95(5-6):455–465.

Pace, D. D., Imai, T., Schwardmann, P., and van der Weele, J. J. (2025). Uncertainty about carbon impact and the willingness to avoid CO2 emissions. *Ecological Economics*, 227:108401.

Rabin, M. (2019). Moral preferences, moral constraints, and self-serving biases. Manuscript.

Rodemeier, M. (2025). Willingness to pay for carbon mitigation: Field evidence from the market for carbon offsets. Manuscript.

Saccardo, S. and Serra-Garcia, M. (2023). Enabling or limiting cognitive flexibility? evidence of demand for moral commitment. *American Economic Review*, 113(2):396–429.

Thaler, R. H. and Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science*, 36(6):643–660.

Vlasceanu, M., Doell, K. C., Bak-Coleman, J. B., Todorova, B., Berkebile-Weinberg, M. M., Grayson, S. J., Patel, Y., Goldwert, D., Pei, Y., Chakroff, A., et al. (2024). Addressing climate change with behavioral science: A global intervention tournament in 63 countries. *Science Advances*, 10(6):eadj5778.

Appendix

A Theoretical Appendix

A.1 50-50 Matching

We remind that the footprints f_o, f_a in our experiments are not sampled iid, but using the "50-50 matching:" first, f_o is sampled from a distribution of footprints F, then f_a is sampled conditional on f_o—with probability 0.5 from F conditional on $f_a < f_o$, with probability 0.5 from F conditional on $f_a > f_o$ (we assume that the probability of $f_a = f_o$ is zero). Hence, when writing the expectation operator over f_o and f_a, we actually mean the following modified operator

$$\hat{\mathbb{E}}\left[\cdot\right] = \mathbb{E}\left[\mathbb{E}\left[\cdot|f_a < f_o\right]\frac{1}{2} + \mathbb{E}\left[\cdot|f_a > f_o\right]\frac{1}{2}\right], \tag{4}$$

where the outer expectation is over f_o and the inner expectations are over f_a. This operator is also linear.

A.2 Efficiency Measure

We derive some properties of our chosen efficiency measure (1)

$$\frac{sf_o + (1-s)f_a - \min\{f_o, f_a\}}{\max\{f_o, f_a\} - \min\{f_o, f_a\}},$$

which can be also rewritten as

$$s\mathbb{1}(f_o > f_a) + (1-s)\mathbb{1}(f_o < f_a).$$

Then, we contrast it to a (perhaps) more natural but technically less appealing efficiency measure

$$\frac{sf_o + (1-s)f_a}{\max\{f_o, f_a\}}. \tag{5}$$

First, our chosen measure (1) achieves the value of 1 for the fully efficient allocation ($s = \mathbb{1}(f_o > f_a)$) and, more importantly, it achieves the value of 0 for the anti-efficient allocation ($s = \mathbb{1}(f_o < f_a)$).

Second, all non-consequentialist rules (whose s is independent of f_o, f_a) achieve the average efficiency of 0.5. For iid matching,

$$\begin{aligned}
&\mathbb{E}\left[\frac{sf_o + (1-s)f_a - \min\{f_o, f_a\}}{\max\{f_o, f_a\} - \min\{f_o, f_a\}}\right] \\
&= \mathbb{E}\left[s\mathbb{1}(f_o > f_a) + (1-s)\mathbb{1}(f_o < f_a)\right] \\
&= \mathbb{E}\left[s\right]\mathbb{E}\left[\mathbb{1}(f_o > f_a)\right] + (1-\mathbb{E}\left[s\right])\mathbb{E}\left[\mathbb{1}(f_o < f_a)\right] \\
&= \frac{1}{2},
\end{aligned}$$

where the second equality follows from the independence of s on f_o, f_a and the third one follows from f_o, f_a being iid, i.e., $\mathbb{E}\left[\mathbb{1}(f_o < f_a)\right] = \Pr(f_o < f_a) = \frac{1}{2}$ (assuming $\Pr(f_o = f_a) = 0$). Similarly, for the 50-50 matching

$$\begin{aligned}
&\hat{\mathbb{E}}\left[\frac{sf_o + (1-s)f_a - \min\{f_o, f_a\}}{\max\{f_o, f_a\} - \min\{f_o, f_a\}}\right] \\
&= \hat{\mathbb{E}}\left[s\mathbb{1}(f_o > f_a) + (1-s)\mathbb{1}(f_o < f_a)\right] \\
&= \mathbb{E}\left[s\right]\hat{\mathbb{E}}\left[\mathbb{1}(f_o > f_a)\right] + (1 - \mathbb{E}\left[s\right])\hat{\mathbb{E}}\left[\mathbb{1}(f_o < f_a)\right] \\
&= \frac{1}{2},
\end{aligned}$$

where the second equality follows from the independence of s on f_o, f_a and the third one follows from the 50-50 matching.

Hence, irrespective of the distribution of footprints and the sampling procedure, our chosen efficiency measure covers meaningfully the whole interval $[0, 1]$ with an intuitive benchmark of 0.5 attributable to non-consequentialist rules.

In contrast, the average of the alternative efficiency measure (5) is generally well above 0 and it depends on the behavior, the distribution of footprints, and the matching mechanisms. Indeed, as we can see in Table 3, the average alternative efficiency measure varies widely across behavioral rules, distributions of footprints, and matching mechanisms. It is also quite high—even for the intentionally inefficient rule, this efficiency measure is around 0.4-0.6 for realistic distributions of footprints. Consequently, it is very concentrated at higher values: although the noisy efficient rule achieves unambiguously higher efficiency than the non-consequentialist rules, it does so by a lower amount than one might intuitively expect (by 0.15-0.25 efficiency units). Finally, the non-consequentialist rules are equivalent under the independent matching, but differ under the 50-50 matching.

Table 3: Average Efficiency (5) for Various Behavioral Rules, Footprint Distributions, and Matching Mechanisms (based on simulations)

	Uniform	Exponential	Pareto	Empirical	Uni50	Exp50
Own	0.75	0.69	0.82	0.73	0.82	0.74
Another	0.75	0.69	0.82	0.73	0.76	0.72
Fair	0.75	0.69	0.82	0.73	0.79	0.73
Random	0.75	0.69	0.82	0.73	0.79	0.73
Anti-efficient	0.50	0.38	0.63	0.46	0.58	0.46
Noisy-efficient	0.95	0.94	0.96	0.95	0.96	0.95

Notes: Each number is the average over efficiencies (5) based on 10 000 own and another simulated footprints. Behavioral rules: "own" always allocates the whole WTM to own footprint, "another" always allocates to another footprint, "fair" splits the WTM 50-50 between own and another footprint, "random" chooses a completely random (uniform) allocation, "anti-efficient" always allocates to the lower footprint, "noisy-efficient" allocates to the higher footprint but with probability 0.1 makes an error and allocates to the lower footprint. Distributions: the empirical distribution is based on the second column in Fig. 2c in Chancel (2022) (global 2019 emissions in tCO_2 per person), the uniform is on interval $[0.1, 13]$ (the bounds are chosen to match the thresholds for the bottom 20% and top 10% of footprints; the mean is then roughly equal to the global mean of 6 tCO_2 per person), exponential with mean 6, Pareto with scale 1 and shape 1.7 (the scale is set ad hoc (roughly equal to the threshold for the top 80% of footprints), the shape is chosen to reflect approximately the top tail; the mean is not defined for such parameters, we just simulate until the simulated average is close to the global average of 6, namely between 5 and 7). Own and another footprints are drawn independently from the corresponding distribution for the first four columns. In Uni50, own footprint is drawn from the same uniform distribution as above, but another footprint is drawn conditionally on own footprint with probability 0.5 from above own footprint and with probability 0.5 from below using corresponding conditional uniform distributions. Similarly for Exp50.

The two efficiency measures are complementary, offering different perspectives on the results. Our main measure (1) captures how much of the mitigation potential was realized, and thus more directly reflects deviations from rational consequentialism. However, it can obscure the assessment of practical significance. In contrast, the alternative measure (5) highlights that some inefficiencies may have limited real-world impact—particularly when the footprint distribution exhibits low variance. Still, this measure can downplay the extent of the inefficiencies present.

It is also worth noticing that the two efficiency measures do not always lead to the same ordering of triples (f_o, f_a, s). For example, consider two triples $(f_o, f_a, s) = (5, 6, 1)$ and $(f'_o, f'_a, s') = (5, 10, 0.4)$. While our main efficiency measure (1) considers the latter more efficient $(5, 6, 1) \prec_1 (5, 10, 0.4)$, the alternative efficiency measure (5) considers the former more efficient $(5, 6, 1) \succ_2 (5, 10, 0.4)$.

A.3 Diminishing Sensitivity to the Overall Impact

In this section, we outline the implications of diminishing sensitivity to the overall impact of the allocation decision, i.e., the implications of the assumption that people maximize

$$\mathbb{E}\left[u(0.02 \cdot \text{WTM} \cdot (sf_o + (1-s)f_a))\right]$$

with a C^2 function $u : (0, \infty) \to \mathbb{R}$ such that $u' > 0$ and $u'' < 0$, instead of a linear u assumed in the main text. This can capture decreasing marginal utility from the impact, or higher cognitive limitations in discerning larger amounts than smaller amounts.

With diminishing sensitivity, hedging motive arises, which may (but does not have to) lead to an interior optimal share $s^* \in (0, 1)$ under uncertainty about f_a. Under perfect information about f_a, nothing changes compared to the main text, so diminishing sensitivity cannot explain chosen interior shares in the full-information groups.

Regarding motivated learning, there are two opposing forces. On one hand, if the agent is confident that $f_o \geq f_a$, she might be tempted to learn f_a to justify full allocation to own footprint $s = 1 \geq s^*$; if the agent is not confident that $f_o \geq f_a$, she might want to avoid learning f_a to justify at least some allocation to own footprint $s^* \geq 0$. This may potentially reverse the predictions of the original motivated learning hypothesis. On the other hand, the confidence about $f_o \geq f_a$ is already reflected in the optimal s^*, and the agent might be averse to risking a sufficiently high safe allocation to own footprint s^* or willing to risk a sufficiently low safe allocation to own footprint s^*. This is the attenuated version of the original motivated-learning hypothesis. Which effect dominates depends on the interplay of the distribution of f_a and function u. Let us provide some insight.

Let us capture the selfish motive for increasing own footprint by an increasing function $v(s), s \in [0, 1]$. This explicit formulation of the motivated learning is similar to the model of a morally constrained agent of Rabin (2019): the agent is choosing between no information and learning f_a perfectly to maximize the selfish desire $v(s)$ while being constrained by the moral obligation of maximizing her perception of the impact given her information. In other words, given information, she is bound by the impact maximization motive; nevertheless, she may choose the most desirable information to satisfy her selfish motive $v(s)$. Not learning anything leads to $v(s^*)$, while learning f_a leads to the expected selfish satisfaction $F(f_o)v(1) + (1 - F(f_o))v(0)$ (F is the CDF of f_a). If v is concave (which is a reasonable assumption given that we are developing the idea of diminishing sensitivity here), then by the Jensen inequality,

$$F(f_o)v(1) + (1 - F(f_o))v(0) \leq v(F(f_o)).$$

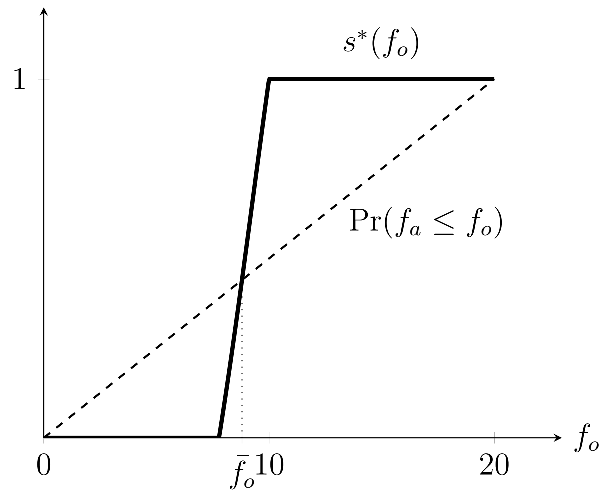
Then, by v being increasing, a sufficient condition for the preference of no learning for a general concave function v is

$$F(f_o) \leq s^*.$$

If v is linear, this condition is also necessary. Naturally, s^* also depends on f_o, and is in fact increasing in f_o and equals 0 or 1 for the extreme values of f_o. Hence, one might expect a crossing point $\bar{f}_o$ below which the agent prefers learning f_a and above which she prefers to stay uninformed. This situation is illustrated in the example in

Figure 16 when $u(x) = x(50-x)$, $f_a \sim U[0, 20]$, and WTM $= 50$.[32] Importantly, the pattern of information acquisition in this example (assuming linear v) coincides with the original motivated-learning hypothesis (with an enlarged area of own footprints f_o for which no learning is chosen: $[\bar{f}_o, 20] \supseteq [10, 20]$).

Figure 16: Optimal s^* when $u(x) = x(50 - x)$, $f_a \sim U[0, 20]$, and WTM $= 50$



We assumed above independent matching for simplicity, but a similar picture arises under the 50-50 matching. There are two differences. First, in the impact maximization program and related conditions, we replace the simple expectation $\mathbb{E}[\cdot]$ by the modified expectation $\hat{\mathbb{E}}[\cdot]$ defined in (4). Second, the sufficient (and under linearity of v also necessary) condition for no learning is

$$s^* \geq \frac{1}{2}.$$

This aligns even more intuitively with the spirit of the original motivated-learning hypothesis. Finally, the example from Figure 16 leads to a very similar function $s^*(f_o)$ under the 50-50 matching, just with a larger region of values of f_o leading to interior s^* (roughly $f_o \in [6, 10]$); the no-learning region is also slightly larger.

Regarding rational inattention, diminishing sensitivity changes only the expression for the value of information. The value of information under the independent matching becomes

$$u(f_o)F(f_o) + \mathbb{E}\left[u(f_a) | f_o < f_a\right](1 - F(f_o)) - \mathbb{E}\left[u(s^* f_o + (1 - s^*) f_a)\right],$$

[32] The optimal share under $u(x) = x - \eta x^2$, where η is small enough to push the peak of u beyond the support of f_a, is

$$s^* = \max\left\{0, \min\left\{1, \frac{f_o - \mathbb{E}[f_a] - 2\eta(0.02\text{WTM})\mathbb{E}[(f_o - f_a)f_a]}{2\eta(0.02\text{WTM})\mathbb{E}[(f_o - f_a)^2]}\right\}\right\}.$$

where s^* maximizes $\mathbb{E}\left[u(sf_o + (1-s)f_a)\right]$. The value of information under the 50-50 matching becomes

$$\frac{1}{2}\Big(u(f_o) + \mathbb{E}\left[u(f_a)|f_o < f_a\right] \\ - \mathbb{E}\left[u(s^* f_o + (1-s^*)f_a)|f_o \geq f_a\right] - \mathbb{E}\left[u(s^* f_o + (1-s^*)f_a)|f_o < f_a\right]\Big),$$

where s^* maximizes $\mathbb{E}\left[u(sf_o + (1-s)f_a)|f_o \geq f_a\right] + \mathbb{E}\left[u(sf_o + (1-s)f_a)|f_o < f_a\right]$. The problem with this quantification of the value of information is that we would need to know function u. Given that the relevant content of the value of information comes from the beliefs and not the utility function, this modification adds little practical usefulness compared to the complications it entails. Indeed, it is still true that the value of information is the highest when the uncertainty about how own footprint compares to others' footprints is the highest (the pattern illustrated in Figure 1). We can thus take our original quantification of the value of information as a proxy if u is non-linear.

A.4 Belief-Based Utility

In this section, we discuss the predictions about information acquisition when the agent derives utility from holding particular beliefs. This model is different from our motivated-learning model where the agent wants to hold particular beliefs to justify a self-serving allocation of WTM. In the belief-based model, she wants to hold particular beliefs intrinsically and does not care about the allocation of WTM.

Imagine the agent derives utility from believing that she has relatively low footprint. Let us distinguish two cases:

- case R, in which rank matters: she derives utility from believing $f_o < f_a$ is more likely;
- case M, in which magnitude matters: she derives utility from expecting larger deviation $\mathbb{E}\left[f_a\right] - f_o$.

In contrast to our previous theories, we assume now that the agent does not know the distribution F of f_a and has to learn it. What she ultimately cares about is one characteristic of F: in case R, $\theta := 1 - F(f_o)$; in case M, $\mu := \mathbb{E}_F\left[f_a\right]$. She has a prior about the relevant characteristic (for example, a beta distribution about θ and an exponential distribution about μ) and uses the Bayes rule to update the prior using observations of f_a to form a posterior. Denote the beliefs about θ G_θ and the beliefs about μ G_μ. The utility is then[33]

- $U(G_\theta) = u(\mathbb{E}_{G_\theta}\left[\theta\right])$ in case R,
- $U(G_\mu) = u(\mathbb{E}_{G_\mu}\left[\mu\right] - f_o)$ in case M,

where u is an increasing function—we slightly abuse the notation by using the same function in both cases.

[33]In general, the agent might care about the shape of her beliefs G, but we assume for simplicity that she cares only about the first moment $\mathbb{E}_G\left[\cdot\right]$.

Abusing the notation a bit more, denote G^0 the prior and G^1 the posterior after observing one f_a. The beliefs have to be consistent, i.e., the agent should expect to observe such f_a (leading to updated beliefs G^1) that are consistent with initial beliefs G^0. In other words, the martingale condition is satisfied

$$\mathbb{E}_{G^0}\left[\mathbb{E}_{G^1}\left[\cdot\right]\right] = \mathbb{E}_{G^0}\left[\cdot\right],$$

where $\cdot$ stands for either θ or $\mu - f_o$. Hence, by the Jensen inequality,

- if u is convex, $\mathbb{E}_{G^0}\left[u(\mathbb{E}_{G^1}\left[\cdot\right])\right] \geq u(\mathbb{E}_{G^0}\left[\cdot\right])$, so the agent wants to learn;
- if u is concave, $\mathbb{E}_{G^0}\left[u(\mathbb{E}_{G^1}\left[\cdot\right])\right] \leq u(\mathbb{E}_{G^0}\left[\cdot\right])$, so the agent does not want to learn;
- if u linear, $\mathbb{E}_{G^0}\left[u(\mathbb{E}_{G^1}\left[\cdot\right])\right] = u(\mathbb{E}_{G^0}\left[\cdot\right])$, so the agent is indifferent between learning and no learning.

In any case, the desire to learn is independent of the prior. Therefore, we cannot distinguish the pattern of information acquisition from intrinsic preferences for/against information.

With the 50-50 matching, the agent learns nothing about the rank, so she is indifferent between learning and no learning in case R. In case M, she learns at least about the magnitude, specifically about the conditional expectations $\mu_l := \mathbb{E}_F\left[f_a | f_a \leq f_o\right]$ and $\mu_h := \mathbb{E}_F\left[f_a | f_a > f_o\right]$; she just does not improve her information about $\theta = 1 - F(f_o)$ on how to combine them to compute $\mu = \mathbb{E}_F\left[f_a\right] = (1-\theta)\mu_l + \theta\mu_h$.[34] Hence, we assume the agent starts with priors G_l^0, G_h^0, G_θ^0 about μ_l, μ_h, θ, updates only G_l^0 or G_h^0 to G_l^1 and G_h^1 depending on the data, and finally combines distributions G_l^1, G_h^1, G_θ^0 (treating them as independent) to compute the distribution G_μ^1 of μ. By independence

$$\mathbb{E}_{G_\mu^1}\left[\mu\right] = (1 - \mathbb{E}_{G_\theta^0}\left[\theta\right])\mathbb{E}_{G_{\mu_l}^1}\left[\mu_l\right] + \mathbb{E}_{G_\theta^0}\left[\theta\right]\mathbb{E}_{G_{\mu_h}^1}\left[\mu_h\right].$$

Denoting by G^0 the joint distribution of independent elements μ_l, μ_h, and θ, if u is convex, then

$$\mathbb{E}_{G^0}\left[u(\mathbb{E}_{G_\mu^1}\left[\mu\right])\right] \geq u(\mathbb{E}_{G^0}\left[\mathbb{E}_{G_\mu^1}\left[\mu\right]\right]).$$

Applying the martingale property to μ_l and μ_h, we obtain

$$\mathbb{E}_{G^0}\left[u(\mathbb{E}_{G_\mu^1}\left[\mu\right])\right] \geq u\left((1 - \mathbb{E}_{G_\theta^0}\left[\theta\right])\mathbb{E}_{G_{\mu_l}^0}\left[\mu_l\right] + \mathbb{E}_{G_\theta^0}\left[\theta\right]\mathbb{E}_{G_{\mu_h}^0}\left[\mu_h\right]\right) = u(\mathbb{E}_{G^0}\left[\mu\right]).$$

Hence, we obtain the same conclusion as with the independent matching (the cases with concave and linear u are analogous).

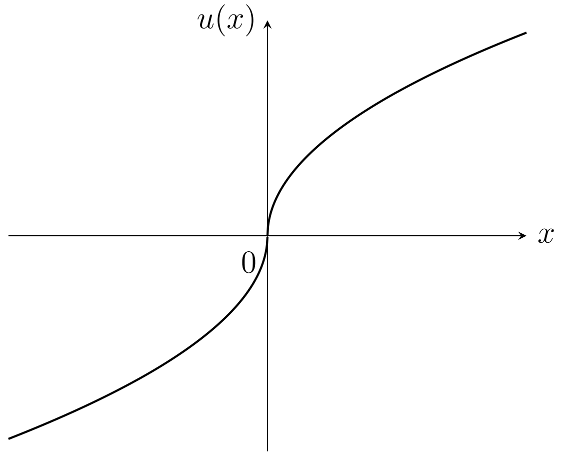
A.5 Ex-Post Theory of Information Acquisition

In this section, we provide an ex-post theory capturing the pattern of information acquisition in our data that runs contrary to the motivated-learning hypothesis.

[34] If the agent assumed smoothness of F and had many data, she might learn also $F(f_o)$ even with the 50-50 matching. However, she has few data in our setup, so we assume she stays completely agnostic about $F(f_o)$.

Namely, we observe that people who expect their footprint to be relatively high compared to others acquire more information (although this pattern is not strong). We realized we can explain this pattern by the following model only after seeing the results, hence, the "ex-post" theory.

Figure 17: Depiction of an S-shaped function u in the ex-post theory



The model builds on version M of the belief-based utility model from Appendix A.4, where the agent derives utility from expecting her footprint to be low compared to others

$$U(G_\mu) = u(\mathbb{E}_{G_\mu}[\mu] - f_o),$$

where u is increasing. In Appendix A.4, we considered that u can take shape of only one type—concave, convex, or linear—on the whole domain. However, inspired by the utility function from prospect theory, we can envisage an S-shaped function u with an inflection point at zero, as depicted in Figure 17. Function $u(x - f_o)$ will then capture the desire to learn *or* avoid information around the reference point of own footprint f_o. Intuitively, given the prior distribution G^0_μ about $\mu = \mathbb{E}[f_a]$, high f_o shifts function $u(x - f_o)$ such that most mass of G^0_μ falls under the convex region, while low f_o shifts function $u(x - f_o)$ such that most mass of G^0_μ falls under the concave region. The arguments from Appendix A.4 then suggest that high f_o should lead to information acquisition, while low f_o should lead to information avoidance. In other words, if the agent expects her footprint to be relatively high, she wants to give it a shot to learn that she actually is not that bad (risk seeking). On the other hand, if she expects her footprint to be relatively low, she wants to avoid information to maintain a positive self-image (risk aversion). We illustrate this with the following example.

We consider the distribution of footprints F to be exponential with rate λ (so $\mu = \mathbb{E}_F[f_a] = \frac{1}{\lambda}$). The agent learns λ and has a gamma prior with shape α and rate β. This prior is conjugate for the exponential likelihood, so the posterior after observing f_a will also be gamma—with shape $\alpha + 1$ and rate $\beta + f_a$. By a direct calculation, the posterior expectation of μ is equal to

$$\mathbb{E}_{G^1_\lambda}\left[\frac{1}{\lambda}\right] = \frac{\beta + f_a}{\alpha}.$$

We assume the agent has utility

$$U(G_\mu; f_o) = u(\mathbb{E}_{G_\mu}[\mu] - f_o) = \begin{cases} \sqrt{\mathbb{E}_{G_\mu}[\mu] - f_o} & \text{if } \mathbb{E}_{G_\mu}[\mu] \geq f_o, \\ -\sqrt{-(\mathbb{E}_{G_\mu}[\mu] - f_o)} & \text{if } \mathbb{E}_{G_\mu}[\mu] < f_o. \end{cases} \tag{6}$$

We use simulations to compute

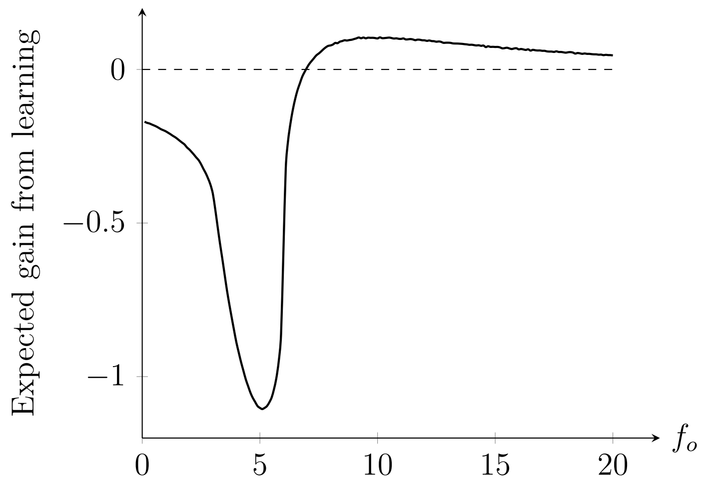
$$\int\int u\left(\frac{\beta + f_a}{\alpha} - f_o\right) g(f_a; \lambda) g^0(\lambda; \alpha, \beta)\, \mathrm{d}f_a\, \mathrm{d}\lambda,$$

where $g(f_a; \lambda)$ is the exponential PDF with rate λ and $g^0(\lambda; \alpha, \beta)$ is the gamma PDF with shape α and rate β. In the simulations, we choose $\alpha = 2$ and $\beta = 6$ so that the prior expected mean $\mathbb{E}_{G^0_\mu}[\mu] = \frac{\beta}{\alpha - 1}$ is 6, which is the global 2019 mean (in tCO_2 per person) from Chancel (2022), and the prior uncertainty is large. In Figure 18, we depict the expected gain from learning

$$\mathbb{E}_{G^0_\mu}\left[u(\mathbb{E}_{G^1_\mu}[\mu] - f_o)\right] - u(\mathbb{E}_{G^0_\mu}[\mu] - f_o).$$

As advertised, agents with higher footprints (roughly above 7 in this example) want to acquire information, while agents with lower footprints do not.

Figure 18: Expected gain from learning with utility (6) and Gamma(2, 6) prior



B Open-Ended Question Analysis Spending Decision

A coding scheme was developed through inductive analysis (Mayring, 2022, p. 84-89), yielding a 10-code framework with an additional "no code applies" option. Since subjects often cited multiple motivations, multiple codes could be assigned to each response. Each coder assessed the applicability of each code for every subject statement individually.

Alongside the primary coder, two additional research assistants were trained and subsequently applied the coding framework. Each received a written coding manual and an Excel file structured to allow coding decisions on each statement-code pair.

Final coding for each statement-code combination was determined by a majority rule, assigning codes endorsed by at least two of the three coders. Frequencies for each code were calculated as the proportion of statements to which that code was applied. Due to the possibility of multiple codes per statement, cumulative percentages exceed 100%.[35]

Coding Manual "Spending Decision"

The subjects were given $50 and could split it between keeping it for themselves or contributing to reducing carbon emissions. They were asked to state their motivation for their choice in an open-ended textbox.

The following coding scheme was created, providing actual examples from the study: **It is your task to assign codes to each statement that you are given. You can apply more than one code to each statement. Each statement needs at least one code (if none applies, choose Code 0).**

Nr.	Code Title	Code Definition	Examples
0	No code applies	Motivations that are empty, non-understandable or that do not fit into any other code.	

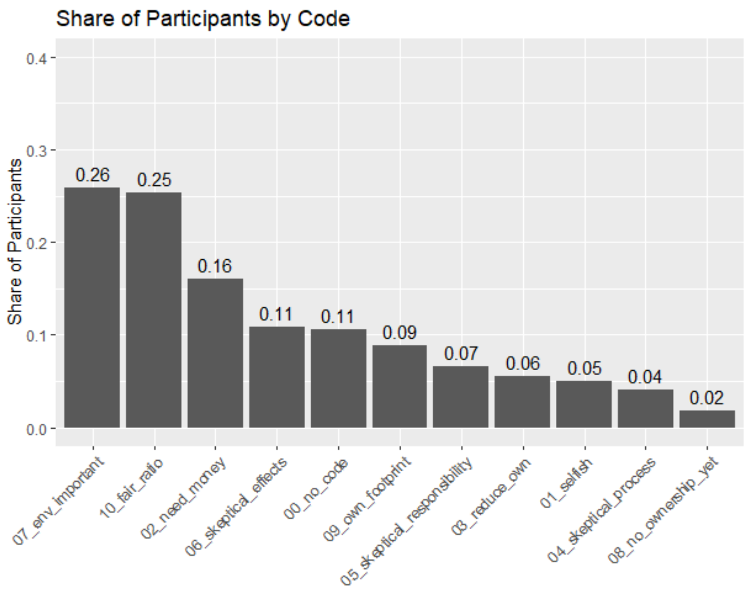
[35] We deviate from our initial plan to use Natural Language Processing for our open-ended question analysis in Appendix B and Appendix C. Human classifiers excel in interpreting nuanced, context-specific language, ensuring accuracy, especially in small datasets where training an NLP model would be inefficient. Additionally, humans can dynamically adapt classification criteria as patterns emerge, offering flexibility that NLP models lack without retraining.

Nr.	Code Title	Code Definition	Examples
1	Am selfish	Motivations that only say that they keep it without giving reasons that fit into other codes.	• "Mainly selfishness I guess." • "I always keep the money for anything and never give any away. I decided that years ago. There is never a moral dilemma that I have because of it as the decision has been made for many years."
2	Need the money	Motivations that include needing the money, being poor, or having obligations.	• "I could also really use it" • "I am one of the lowest income individuals in the United States."
3	Can better use money to reduce emissions on my own	Motivations that state that they keep (most of) the money because they could invest it better themselves for the environment.	• "I might as well keep some of the money and look at other things I can do to change my habits that have a larger impact on CO_2 emissions."
4	Am skeptical regarding process	Motivations that say they are skeptical that the money would be spent for the given purpose by the experimenters or that express skepticism of the process in other ways.	• "I don't really trust the process."
5	Am skeptical regarding own responsibility	Motivations that say that the respective person is not responsible or that others, e.g., the government, or corporations, should be held responsible.	• "I think business on a global scale can have more impact than the individual struggling to pay bills." • "I cannot solve the world's problems, only try to fight for myself."

Nr.	Code Title	Code Definition	Examples
6	Am skeptical regarding positive effects of contributing	Motivations that say that contributing has no, no large or even negative impacts.	• "I feel like it's a futile effort otherwise to try to offset. Careless people will just use more knowing its covered." • "I doubt if my effort is going to make a difference."
7	Think environment is important, everyone should do their part	Motivations that say that the environment is important or that everyone should contribute.	• "By using the money to reduce emissions, I am actively taking steps to combat climate change. I prioritize the well-being of the planet and future generations over personal gain." • "WE MUST ALL SUPPORT EMISSIONS CONTROL"
8	Have no ownership of money therefore contribute	Motivations that say that the money at stake is not the property of the subject and can therefore be spent on the environment.	• "Since this isn't actually my money at this point, I tend to lean toward trying to do good with it." • "I never had the money so it makes sense to contribute it to the greatest good."
9	Have high or low footprint myself (polluter pay principle)	Motivations that are based on the subject having a high or a low footprint.	• "I would feel like 10 would be more than enough for myself because I don't use planes or cars." • "I feel like my carbon print is high so I would give myself half in order to reduce it."

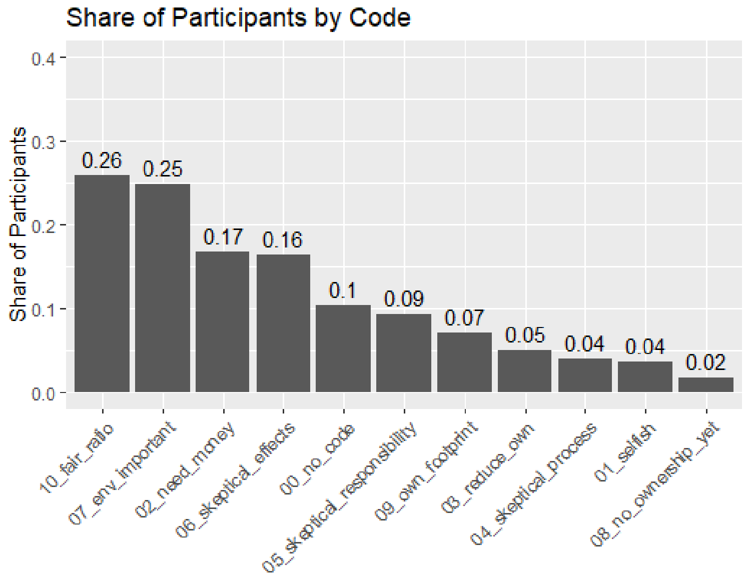
Nr.	Code Title	Code Definition	Examples
10	Think that a certain ratio is fair or a good compromise	Motivations that say that a certain ratio of keeping and contributing is fair or a good compromise, e.g., half-half.	• "I think that I can share equally." • "Keeping 40 dollars would have more benefit to me than spending it on CO_2 emission allowances, however I'm not completely oblivious to the harmful effects of emissions on the environment so I will spend a little bit on it."

Figure 19: Bar Plot Motivation Spending Decision (Full Sample)



Similarly for the control group only:

Figure 20: Bar Plot Motivation Spending Decision (Control Group)



C Open-Ended Question Analysis Allocation Decision

Initially, a coding scheme was formulated using a sample of 200 subjects and validated by an independent researcher. To ensure consistency and accuracy, a detailed coding manual was prepared, and coders received a brief training session. This included a trial round where 25 random statements were coded, allowing coders to ask clarifying questions. Following this trial, coding decisions were reviewed collectively, and adjustments were made to the coding scheme as necessary. Subsequently, three coders independently coded the complete set of 1,000 statements.

Coding Manual "Allocation Decision"

We conducted a study in which subjects had to make several decisions: First, they were given \$50 and distributed it freely between keeping it for themselves and spending it for reducing CO_2 emissions. Then, they were asked to distribute the amount they wanted to spend between the carbon footprint of another subject and themselves, causing a partial reduction of the footprint. The reduction was relative to the footprints, meaning that, e.g., \$25 invested caused a 50% reduction and consequently had a bigger environmental impact for a very large footprint than for a small one. After three rounds of decisions, we asked them why they distributed money towards reducing their own carbon footprint or towards that of another subject. Using an open-ended textbox, they were asked: Please tell us in a few sentences the motivation behind your "allocation choices."

The following coding scheme was created, providing actual examples from the study: **It is your task to assign codes to each statement that you are given. You can apply more than one code to each statement, please assign all that fit. Each statement needs at least one code (if none applies, choose code 0 or code 5). Please read the whole coding manual once before you begin! Please do not use ChatGPT or something similar. The template includes three columns that indicate the share that the subjects allocated to themselves (instead of to the other subject) to give you some context information.**

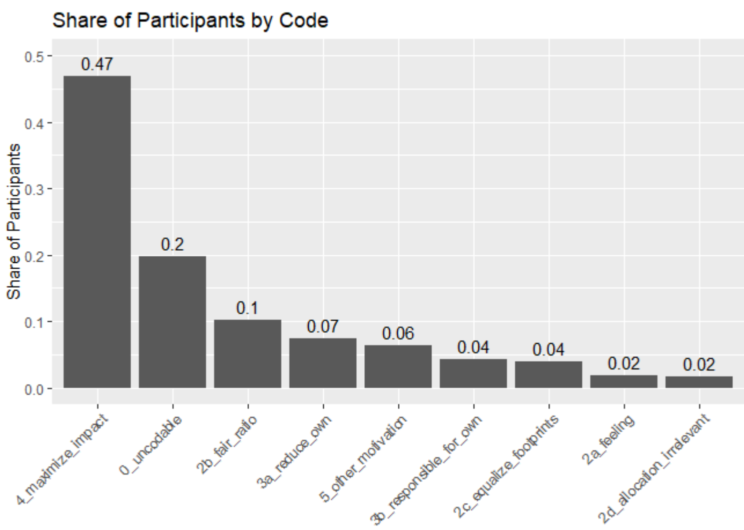
Category	Nr.	Code Title	Code Definition	Examples
-	0	UNCODEABLE / no motivation for allocation decision in the statement	Statements that are empty, not valid, or do not answer the question of motivation for the allocation decision. If this is coded, no other code can be applied. Differentiation from other codes: • If the statement appears to try to be understandable but lacks logical sense, code "OTHER MOTIVATION". • If the statement (seemingly) repeats the motivation for their spending decision, e.g., skepticism about effects, personal responsibility, or process, and keeping all money, code "NO MONEY TO ALLOCATE".	
-	1	NO MONEY TO ALLOCATE / skeptical	Statements that reflect having no money to allocate (due to an earlier spending decision) or repeat the motivation for spending, e.g., skepticism about effectiveness, personal responsibility, or process, leading to retaining all funds.	• I was left with no choice for allocation as I did not elect to buy out emissions. • I do not think carbon offsets really help the environment and they are misleading. • When the total needs to be zero, zero and zero are the only options.
"Irrational"	2a	Explicitly NO REASON / just a feeling	People who explicitly state that they had no reason or "just feel it". Differentiation from other codes: • If someone says they feel that splitting half or something similar is right, code "FAIR RATIO".	• I just feel this is the right investment for me. • I don't really have a motivation either way in any of the three rounds.

-	2b	Think that there is a certain FAIR RATIO or just split evenly	Statements suggesting that a specific ratio between footprints is fair or a good compromise (e.g., half-half), or statements about splitting evenly without further reason. Differentiation from other codes: • Code "MAXIMIZE IMPACT" if they split evenly because the footprints are similar.	• I feel splitting in half sounds about right. • I will invest the same amount regardless of the other subject's carbon footprints. • I think just evenly distributing it is the fair way to go about it.
-	2c	Invest to EQUALIZE FOOT-PRINTS	Statements explicitly indicating an intention to equalize footprints by making them more similar.	• Also allocating 3 to the other footprint will lower their footprint, bringing it closer to mine currently. • Reduce everyone's carbon footprint to an equal level, not just single individuals.
-	2d	ALLOCATION is IRRELE-VANT because impact is the same	Statements indicating that the allocation does not matter because the impact is identical regardless of who receives it.	• There was no real motive, CO_2 is CO_2 at the end of the day. • It really doesn't matter who gets the credit overall because the amount being reduced is the same. • Either way it would be the same net reduction.
"Egoistic"	3a	JUST want to REDUCE OWN footprint	Statements reflecting a preference for reducing one's own footprint. Differentiation from other codes: • If responsibility is mentioned, code "RESPONSIBLE FOR OWN".	• By investing more in my own footprint, I want to dramatically reduce my own emissions. • I don't want to donate money to offsetting anyone else's footprint, just my own.

-	3b	Am RESPONSIBLE FOR OWN footprint	Statements emphasizing personal responsibility for one's own emissions or that others are responsible for theirs.	• I allocate all the funds to my own footprint to maximize the impact within my control. • I feel more responsible for my own than others, so I feel the need to allocate more to my own CO_2 emissions.
"Maximize Impact"	4	Want to MAXIMIZE IMPACT	Statements about maximizing impact or minimizing emissions, often by investing in the larger footprint.	• Judging by the calculation, I have a much higher footprint than the other subject. • Tried to allocate the money proportionally to the current carbon footprint. • I believe it is best to spend where it will have the biggest impact.
-	5	OTHER MOTIVATION	Statements that are logically valid but do not fit other codes. Can be coded alongside other codes if the statement includes multiple motivations.	

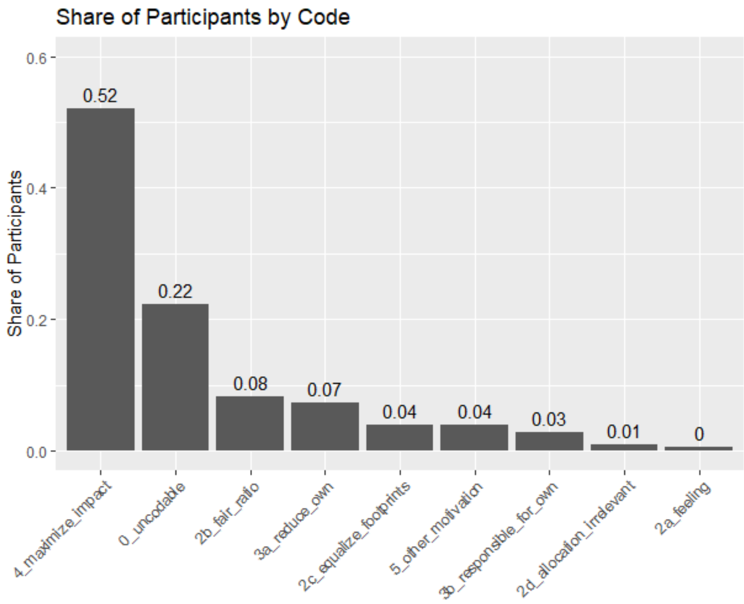
Results are reported for subjects who indicate a higher spending than zero.

Figure 21: Bar Plot Motivation Allocation Decision (Full Sample)



Results are reported for control group subjects who indicate a higher spending than zero.

Figure 22: Bar Plot Motivation Allocation Decision (Control Group)



D Additional Results

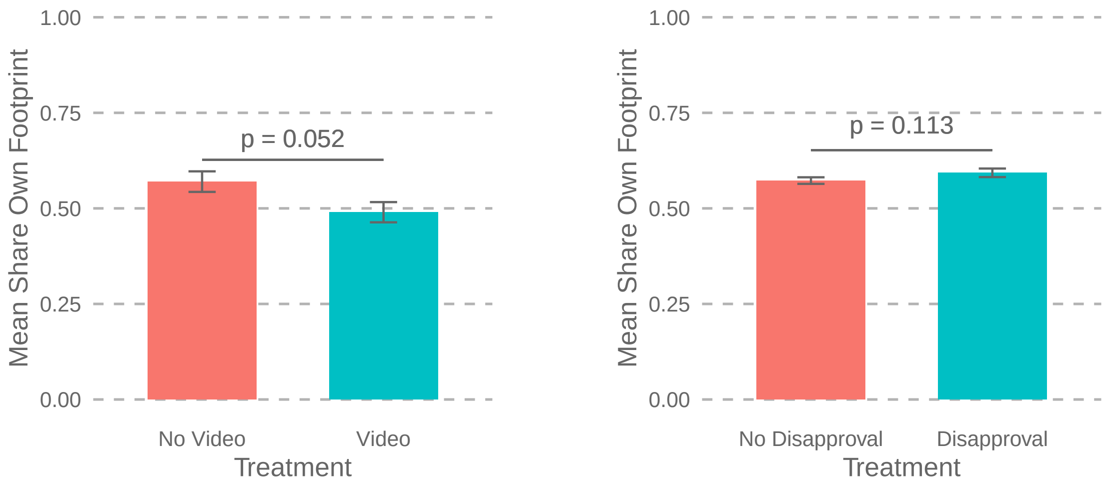
D.1 Robustness Check: Elimination of Subjects Failing the Understanding Quiz

This section demonstrates that our main results remain robust after excluding subjects who failed the quiz questions after the maximum number of attempts. All results reported below refer only to the subset of subjects who passed the quiz (373 subjects in Experiment 1, 689 subjects in Experiment 2).

Excluding those who failed, we observe a slightly higher efficiency in the control groups of both experiments, though average efficiency remains well below 1. In Experiment 1, mean efficiency is 68.97%, and in Experiment 2, it is 61.72%.

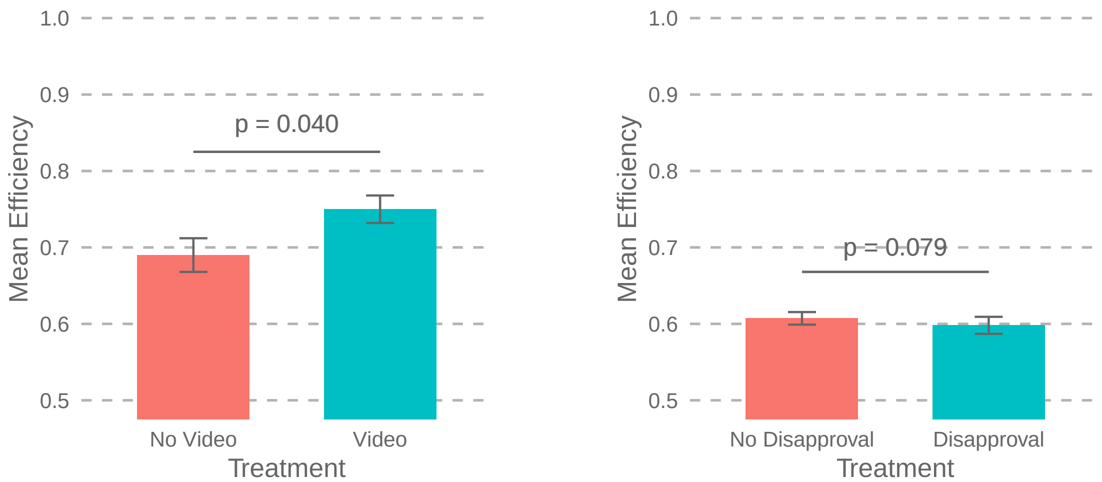
Analysis of the open-ended responses reveals that 54% of subjects explicitly stated their intention to maximize impact. Among this group, the mean efficiency is 65.82%, representing an improvement over the overall average of 61.72%. However, despite this increase, efficiency remains well below the optimal level, suggesting that even when subjects are motivated to maximize impact and likely understand how to do so, their behavior still falls short of full efficiency.

Figure 23: Responsiveness of Own-Share (Full Sample)



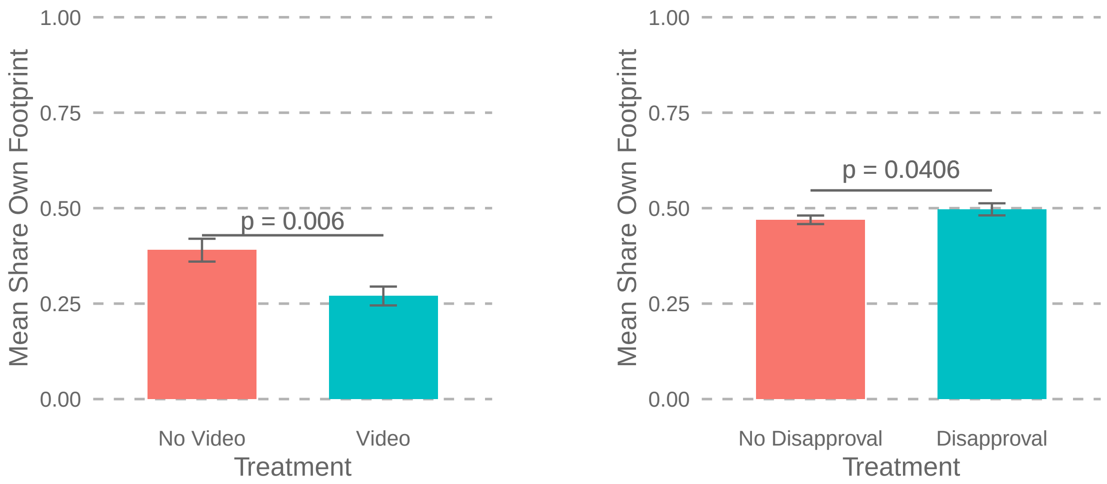
Notes: Standard errors are displayed. Tests: two-sided Mann-Whitney U (left) and one-sided Mann-Whitney U (right).

Figure 24: Responsiveness of Efficiency (Full Sample)



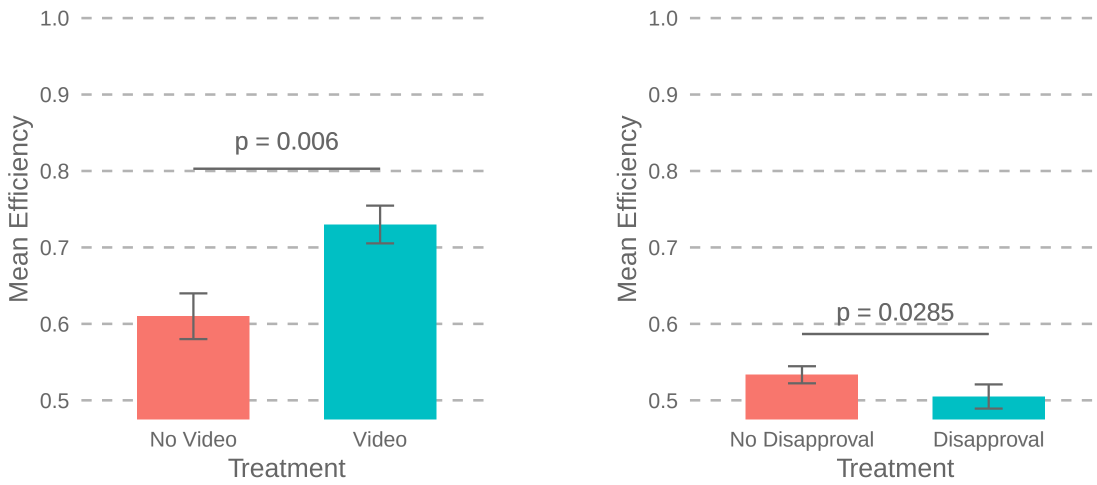
Notes: Standard errors are displayed. Tests: two-sided Mann-Whitney U (left) and one-sided Mann-Whitney U (right).

Figure 25: Responsiveness of Own-Share (Other-Footprint-Higher Sample)



Notes: Standard errors are displayed. Tests: two-sided Mann-Whitney U (left) and one-sided Mann-Whitney U (right).

Figure 26: Responsiveness of Efficiency (Other-Footprint-Higher Sample)



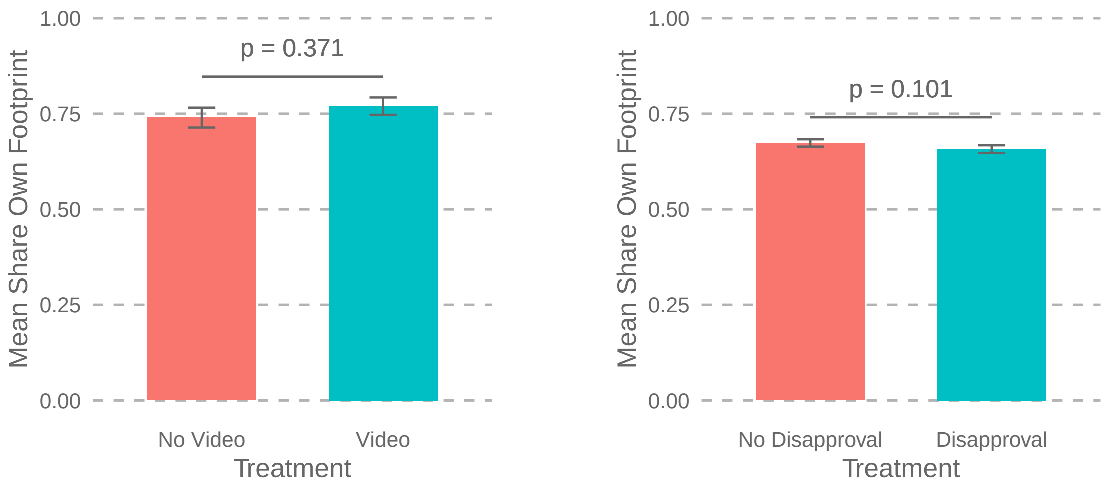
Notes: Standard errors are displayed. Tests: two-sided Mann-Whitney U (left) and one-sided Mann-Whitney U (right).

Figure 27: Effect of Information Treatment on Own-Share and Efficiency (Other-Footprint-Higher Sample)

Notes: Standard errors are displayed. Tests: one-sided Mann-Whitney U.

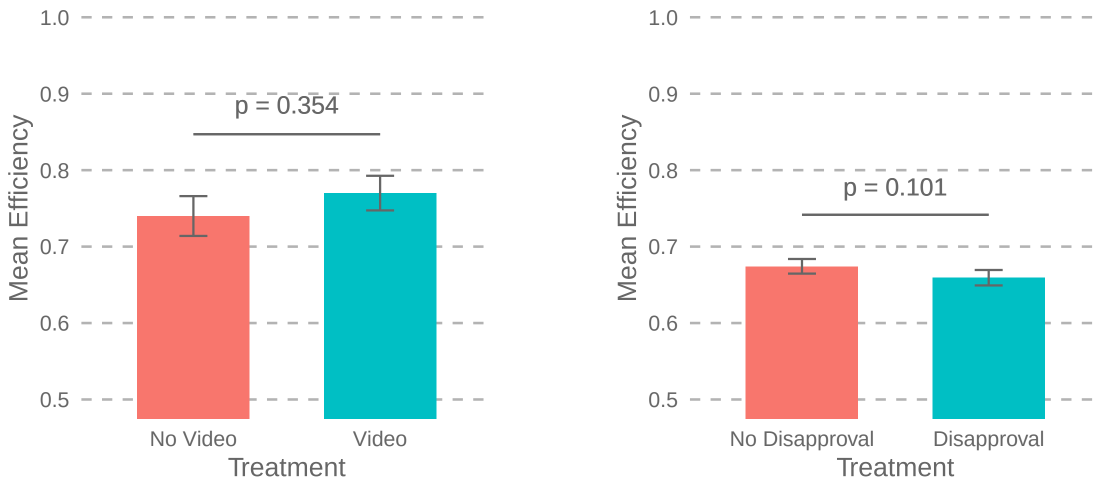
D.2 Other-Footprint-Lower Group

Figure 28: Responsiveness of Own-Share to Nudges (Other-Footprint-Lower Sample)



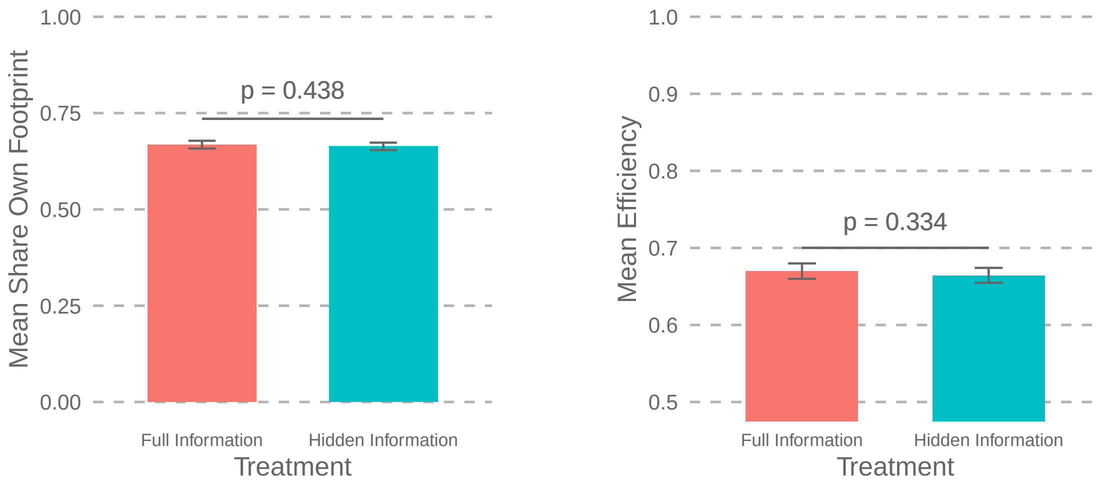
Notes: Standard errors are displayed. Two-sided Mann-Whitney U tests.

Figure 29: Responsiveness of Efficiency to Nudges (Other-Footprint-Lower Sample)



Notes: Standard errors are displayed. Two-sided Mann-Whitney U tests.

Figure 30: Responsiveness of Own-Share and Efficiency to Hidden Information (Other-Footprint-Lower Sample)

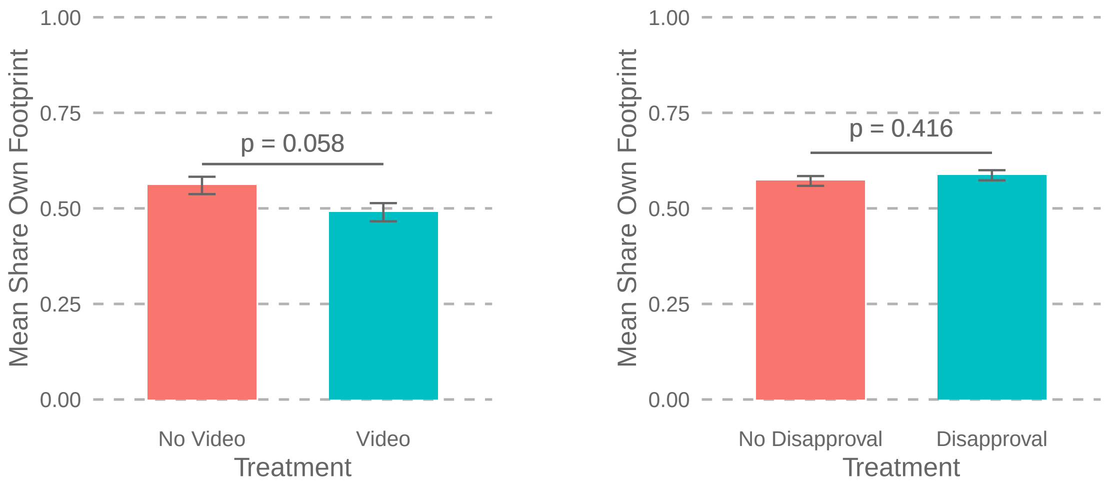


Notes: Standard errors are displayed. Two-sided Mann-Whitney U tests.

D.3 First Decision Round Only

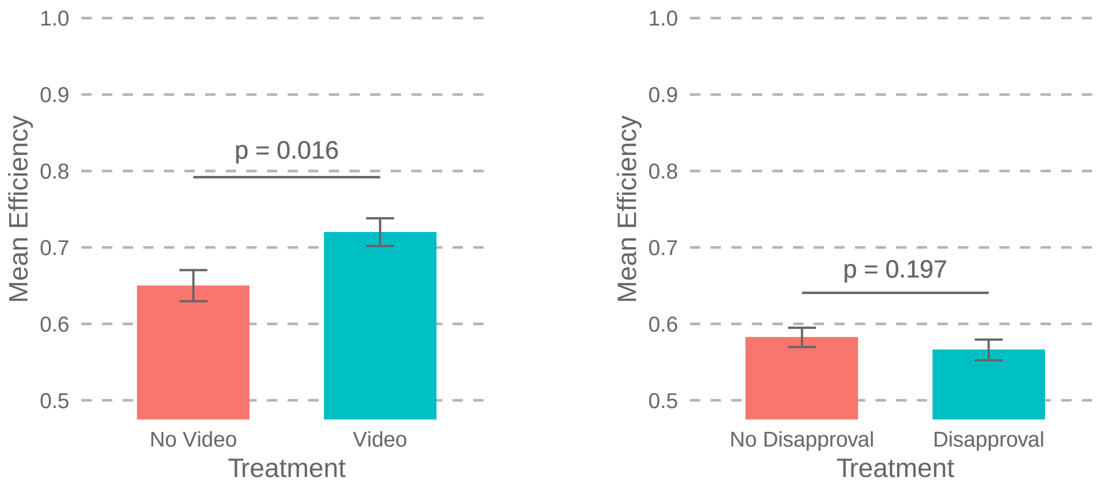
To ensure that our results are not driven by learning effects or fatigue over the three rounds, we conduct robustness checks using data from the first round only. We notice that the sample is reduced to one third.

Figure 31: Responsiveness of Own-Share (Full Sample)



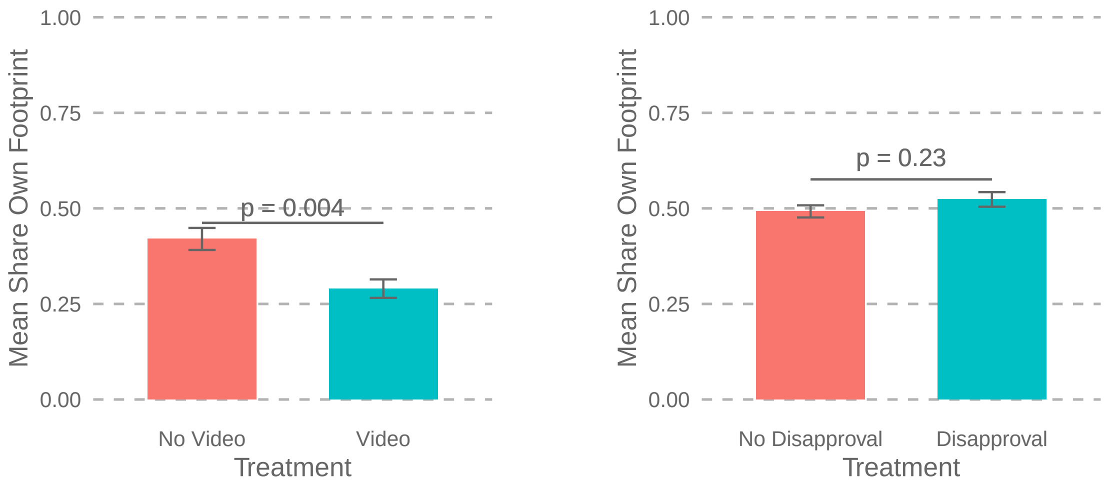
Notes: Standard errors are displayed. Tests: two-sided Mann-Whitney U (left) and one-sided Mann-Whitney U (right).

Figure 32: Responsiveness of Efficiency (Full Sample)



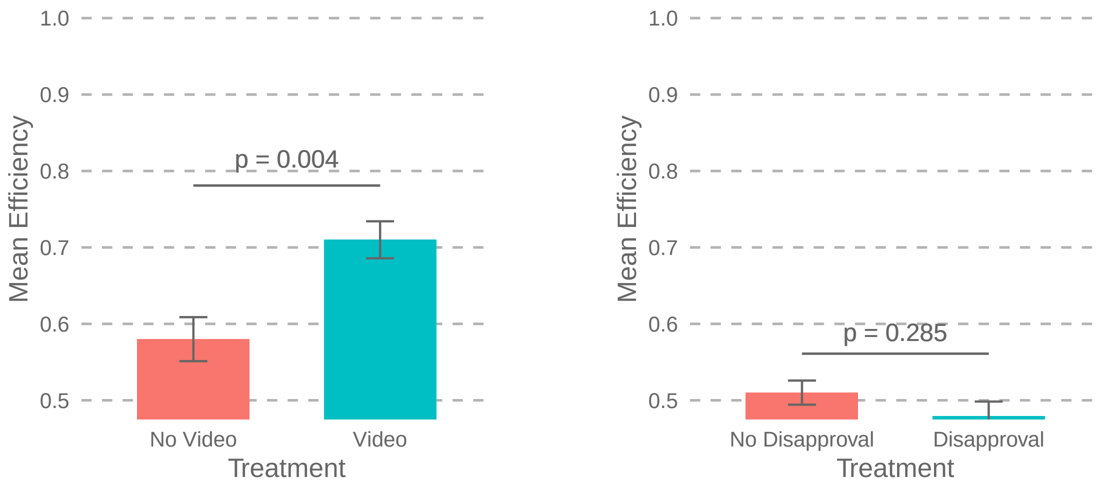
Notes: Standard errors are displayed. Tests: two-sided Mann-Whitney U (left) and one-sided Mann-Whitney U (right).

Figure 33: Responsiveness of Own-Share (Other-Footprint-Higher Sample)



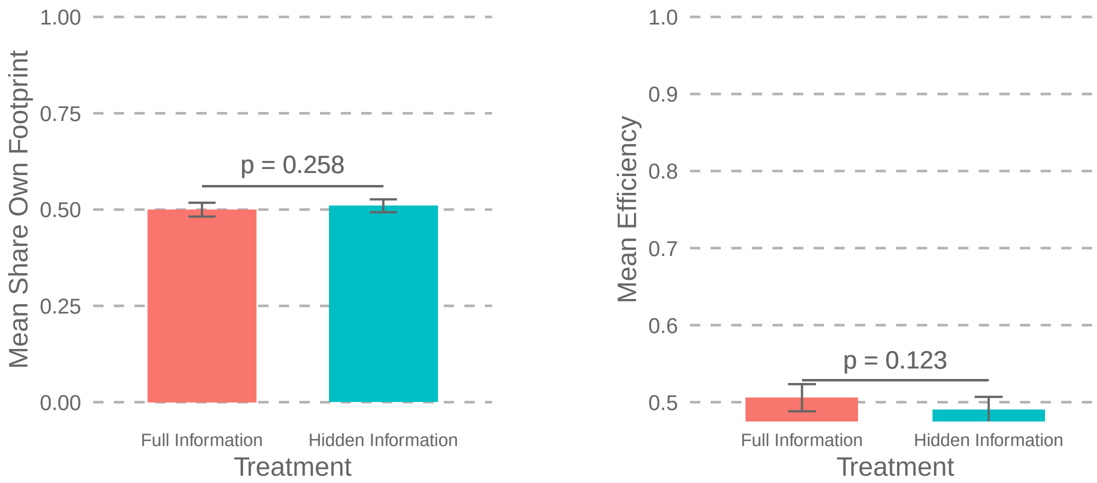
Notes: Standard errors are displayed. Tests: two-sided Mann-Whitney U (left) and one-sided Mann-Whitney U (right).

Figure 34: Responsiveness of Efficiency (Other-Footprint-Higher Sample)



Notes: Standard errors are displayed. Tests: two-sided Mann-Whitney U (left) and one-sided Mann-Whitney U (right).

Figure 35: Effect of Information Treatment on Own-Share and Efficiency (Other-Footprint-Higher Sample)



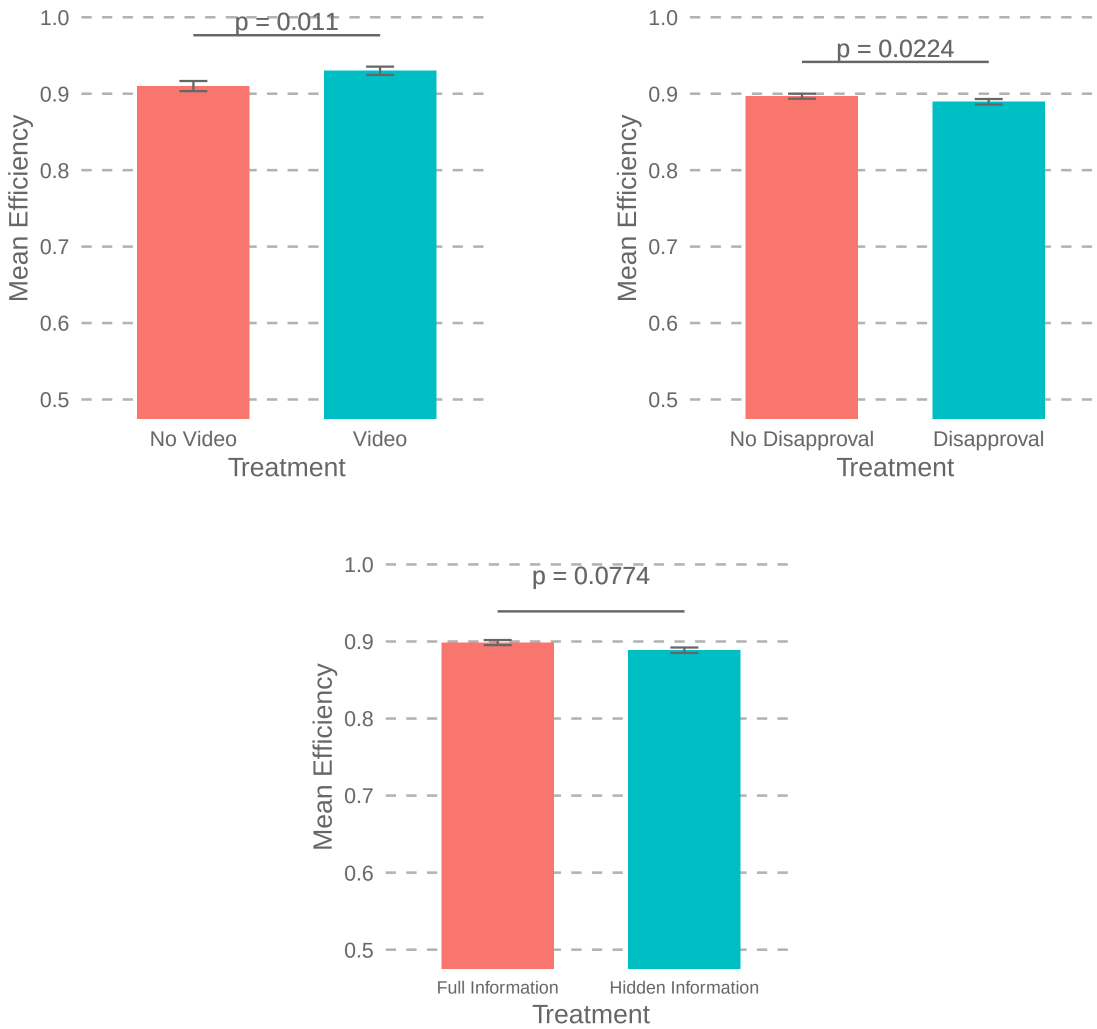
Notes: Standard errors are displayed. Tests: one-sided Mann-Whitney U.

D.4 Alternative Efficiency Measure

In this section we show that results also hold for the alternative efficiency measure

$$\frac{sf_o + (1-s)f_a}{\max\{f_o, f_a\}}.$$

Figure 36: Responsiveness of Efficiency to Nudges (Alternative Efficiency Measure)



Notes: Standard errors are displayed. Tests: two-sided Mann-Whitney U (top left) and one-sided Mann-Whitney U (top right and bottom).

D.5 Allocation of Disapproval Points in Experiment 1

Table 6: Dependence of Disapproval Points on Spending

	Dependent variable:	
	Disapproval Points	
	No Controls	With Controls
	(1)	(2)
Decision Maker Spending	-0.088***	-0.089***
	(0.005)	(0.006)
Disapproval Allocator Footprint		-0.009
		(0.014)
Decision Maker Footprint		0.017
		(0.015)
Decision Maker Video		0.111
		(0.174)
Disapproval Allocator Video		0.188
		(0.173)
Decision Maker Other Footprint		-0.014
		(0.009)
Constant	5.133***	5.134***
	(0.141)	(0.370)
Observations	1,470	1,418
R^2	0.151	0.157
Adjusted R^2	0.151	0.153
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 7: Dependence of Disapproval Points on Efficiency

	Dependent variable:	
	Disapproval Points	
	No Controls	With Controls
	(1)	(2)
Decision Maker Efficiency	-1.383***	-1.344***
	(0.357)	(0.363)
Decision Maker Other Footprint		-0.015
		(0.009)
Decision Maker USD (Your Footprint)		-0.027***
		(0.008)
Disapproval Allocator Footprint		0.027*
		(0.015)
Decision Maker Footprint		0.026
		(0.016)
Decision Maker Video		0.197
		(0.194)
Disapproval Allocator Video		-0.039
		(0.189)
Decision Maker USD (Other Footprint)		-0.025***
		(0.009)
Constant	3.966***	3.956***
	(0.268)	(0.464)
Observations	1,167	1,167
R^2	0.013	0.031
Adjusted R^2	0.012	0.024
Note:	*p<0.1; **p<0.05; ***p<0.01	

D.6 Information Acquisition Regressions

Table 8: Regression Models of Information Acquisition on Difference

	Dependent variable:	
	Information Acquisition	
	OLS Linear	Logistic
	(1)	(2)
Difference	0.002	0.009
	(0.002)	(0.010)
Constant	0.624***	0.505***
	(0.017)	(0.072)
Observations	912	912
R^2	0.001	
Adjusted R^2	-0.0001	
Log Likelihood		-605.884
Akaike Inf. Crit.		1,215.767

Notes: The table shows regression models with "Information Acquisition" as the dependent variable and "Difference" (own CO_2 footprint minus others' expected footprint, in tons per year) as the predictor. Positive values of "Difference" indicate a larger own footprint. A positive but non-significant trend suggests a slightly higher likelihood of information acquisition when one's footprint exceeds expected others'. *p<0.1; **p<0.05; ***p<0.01

Table 9: Regression Models of Information Acquisition on Information Benefit

	Dependent variable:	
	Information Acquisition	
	OLS Linear	Logistic
	(1)	(2)
Information Benefit	-0.001	-0.006
	(0.013)	(0.054)
Constant	0.620***	0.491***
	(0.024)	(0.102)
Observations	912	912
R^2	0.00001	
Adjusted R^2	-0.001	
Log Likelihood		-606.320
Akaike Inf. Crit.		1,216.641

Notes: The table shows regression models with "Information Acquisition" as the dependent variable and "Information Benefit" (2) as the predictor. We observe a slight negative trend which is not statistically significant. *p<0.1; **p<0.05; ***p<0.01

E Experimental Instructions

Experiment 1

Welcome

The setup of this experiment is different from experiments that you might be used to completing via Prolific.
To some degree, you will be involved in interaction with other participants of this study.
It is therefore important that you complete this experiment **without interruptions**.
Including the time for reading these instructions, the experiment will take up to **30 minutes** to complete.

During the experiment, please **do not close this window**.
If you do close your browser or leave the experiment, you will not be able to re-enter the experiment.

Your decisions may also have real impact on the environment.
In particular, you will have an option to reduce the emission of carbon dioxide into the atmosphere.
Carbon dioxide is a substance that plays a major role in climate change.
There is an agreement among scientists all over the world that the reduction of carbon emissions is a major way of mitigating climate change.

The experiment consists of **two stages**.
In the first stage, we ask you for some demographics and to calculate your carbon footprint based on a simple questionnaire, that is how many tons of CO2 per year are caused by your life activities.
After that, you will be asked to go through four decision tasks in the second stage.

You will receive 6 GBP (approx. 7.45 USD) in total for completing the experiment. 3 randomly drawn participants out of 102 might receive an additional payment.

You will receive a code to collect your payment via Prolific upon completion.

If you decide to quit earlier, you can withdraw from the experiment but do not receive a payment.

Please make your decisions within the time limit shown on your screen. If you fail to do so, you will be removed from the experiment and do not receive any payment.

Please provide your Prolific ID first:

button appears in 57 seconds

Remaining time: 03:19

Please indicate your age:

Please indicate your gender: Female | Male | Divers

Which of these categories describes your personal net income last month? Less than $3,000 | $3,000 – $6,000 | More than $6,000

What is the highest level of education you have completed?

Less than high school | High school diploma | Bachelor's degree or equivalent | Master's degree or equivalent | Doctorate or professional degree

How would you describe your political ideology?

Very liberal | Somewhat liberal | Moderate/centrist | Somewhat conservative | Very conservative

Continue

Remaining time: 03:17

Stage 1

Please calculate your carbon footprint based on a simple questionnaire (that is, how many tons of CO_2 per year are caused by your life activities) by clicking on "Carbon Footprint Calculator" below. The "Carbon Footprint Calculator" will open in a separate tab. Once you have conducted the calculation, you can come back to this experiment tab, and insert your CO_2 emissions here. Below you will be asked for your footprint in tons of CO_2 per year (2 decimal places).

Please provide your footprint in tons of CO_2 per year and NOT the offset in USD!

When you click on the Carbon Footprint Calculator below, please first select USA as region and English-US as language in the first step on the top right corner. Please further select "An Individual"! Then you can calculate your footprint.

The link directs you to a carbon footprint calculator on a separate page (tab):

Click here for Carbon Footprint Calculator

Please insert your footprint that you have just calculated in tons of CO_2 per year (NOT the offset in USD) into the input field (2 decimal places).

In which country are you located at the moment?

In which state are you located at the moment? (Optional)

button appears in 196 seconds

Remaining time: 09:58

Thank you for completing part 1 of the experiment. You can now proceed with part 2 of the experiment by pressing the "continue" button.

Continue

Remaining time: 00:56

Welcome to part 2 of the experiment!

In the next step you will see detailed instructions for this second part of the experiment. Please press "continue" to enter the instructions stage.

Continue

Remaining time: 00:51

For the treatment group “video”, we additionally have the following two screens:

Welcome to part 2 of the experiment!

In the next step you will be shown a short (approx. 2-minute) YouTube video. Please press "continue" to enter the video stage.

Continue

Remaining time: 00:54

Show the world what climate action looks like | #MyClimateAction | United Nations

Please watch the following youtube video completely and then press the "Continue" button to go on with the experiment.

After pressing play your keyboard and mouse is disabled for the webpage until the video is over.

(In case the video does not start automatically due to technical issues, please copy the link and open it in a separate tap to watch the video. Then, you can come back to this tap and continue with the experiment.)

Reference: https://www.youtube.com/watch?v=S1-BwAkFwak

button appears in 104 seconds

Remaining time: 04:56

Stage 2

We begin with **Stage 2**.

Now, you have a possibility to contribute to the environment by reducing **actual** CO_2 emissions in Europe. In particular, EU issues emission allowances to companies each year. Each allowance entitles the holder to emit one ton of CO_2. Thus, if one buys out CO_2 emission allowances from the market, the amount of allowable CO_2 emissions within Europe is reduced.

Now, you will be asked:

1. How much of **50 USD** would you spend to buy out CO_2 emission allowances from the market, thus reducing the amount of allowable emissions and how much of the 50 USD you would keep for yourself?

2. How would you allocate the amount you decided to spend to buy out CO_2 emission allowances between the following two options:

- **Option A**: For each USD invested into Option A, we will buy CO_2 emission allowances corresponding to **2%** of **another participant's** monthly carbon footprint, which will be disclosed to you. Thus, if you invest all money (50 USD) into this option, you will achieve CO_2 reduction by the whole amount of that participant's monthly carbon footprint.

- **Option B**: This option is equivalent to Option A, except that for each USD invested into Option B, we will buy CO_2 emission allowances corresponding to **2%** of **your** monthly carbon footprint. Thus, if you invest all money (50 USD) into this option, you will achieve CO_2 reduction by the whole amount of your monthly carbon footprint.

(Note that in rare cases the other participant might be from a previous study)

At the end of the experiment, we will implement one decision of 3 participants out of 102 participants of the experiment, randomly chosen by a lottery.

button appears in 82 seconds

Remaining time: 04:54

Stage 2

Please answer the following control questions testing your understanding of the previous instructions.

Remember the following meaning of Options A and B:

Option A:

For each USD invested into Option A, we will buy CO_2 emission allowances corresponding to **2%** of **another participant's** monthly carbon footprint, which will be disclosed to you. Thus, if you invest all money into this option, you will achieve CO_2 reduction by the whole amount of that participant's monthly carbon footprint.

Option B:

This option is equivalent to Option A, except that for each USD invested into Option B, we will buy CO_2 emission allowances corresponding to **2%** of **your** monthly carbon footprint. Thus, if you invest all money into this option, you will achieve CO_2 reduction by the whole amount of your monthly carbon footprint.

Control questions:

Assume your monthly carbon footprint corresponds to **1** ton of CO_2, and the carbon footprint of the other participant, which is disclosed to you, corresponds to **2** tons of CO_2.

Assume you decided to spend 20 USD to buy out CO_2 emission allowances from the market and to keep the remaining 30 USD to yourself. Then, you allocate 10 USD of your spending amount into Option A and 10 USD into Option B.

1) How large is the reduction of CO_2 emissions (in t) resulting from your allocation of 10 USD into Option B? (Recall: 2% of X is 0.02*X)

	t

2) How large is the reduction of CO_2 emissions (in t) resulting from your allocation of 10 USD into Option A? (Recall: 2% of X is 0.02*X)

	t

Continue

Remaining time: 09:58

Please indicate how much of **50 USD** you would spend to buy out CO2 emission allowances from the market, thus reducing the amount of allowable emissions and how much of the 50 USD you would keep for yourself.

I would spend:

I would keep:

Continue

Remaining time: 01:59

In the following, you will go through three decision rounds where you will decide how to allocate the amount you decided to spend to buy out CO_2 emission allowances from the market. The three rounds are independent of each other. Remember that the computer will randomly select three participants out of 102 whose decision in one of the three decision rounds (also randomly selected) will be implemented.

Stage 2

Round 1

The carbon footprint of the **other participant** calculated per year is: **12.23** tons of CO_2

Thus, the footprint of the **other participant** calculated per month is: **1.02** tons of CO_2

You have just indicated that **your** footprint calculated per year is: **9.88** tons of CO_2

Thus, **your** footprint calculated per month is: **0.82** tons of CO_2

Please decide how to allocate the **30** USD you decided to spend to buy out CO_2 emission allowances from the market between:

Option A (each allocated USD reduces the **other participant's** monthly CO_2 emissions by 2%)

Option B (each allocated USD reduces **your** monthly CO_2 emissions by 2%)

button appears in 32 seconds

Remaining time: 04:34

Stage 2

Round 2

The carbon footprint of the **other participant** calculated per year is: **18.85** tons of CO_2

Thus, the footprint of the **other participant** calculated per month is: **1.57** tons of CO_2

You have just indicated that **your** footprint calculated per year is: **9.88** tons of CO_2

Thus, **your** footprint calculated per month is: **0.82** tons of CO_2

Please decide how to allocate the **30** USD you decided to spend to buy out CO_2 emission allowances from the market between:

Option A (each allocated USD reduces the **other participant's** monthly CO_2 emissions by 2%)

Option B (each allocated USD reduces **your** monthly CO_2 emissions by 2%)

button appears in 15 seconds

Remaining time: 04:57

Stage 2

Round 3

The carbon footprint of the **other participant** calculated per year is: **22.19** tons of CO_2

Thus, the footprint of the **other participant** calculated per month is: **1.85** tons of CO_2

You have just indicated that **your** footprint calculated per year is: **9.88** tons of CO_2

Thus, **your** footprint calculated per month is: **0.82** tons of CO_2

Please decide how to allocate the **30** USD you decided to spend to buy out CO_2 emission allowances from the market between:

Option A (each allocated USD reduces the **other participant's** monthly CO_2 emissions by 2%)

Option B (each allocated USD reduces **your** monthly CO_2 emissions by 2%)

button appears in 15 seconds

Remaining time: 04:57

You went through all spending and allocation decisions. We now show the spending and allocation decisions of three randomly chosen other participants of this study to you. Please allocate "**disapproval points**" to those decisions where 0 points means that you fully approve of the decision of the other participant and 10 points means that you fully disapprove of the decision of the other participant.

Participant 1 had the following information on his/her own and other participant's footprint:

Own footprint per year: **8.98**

Own footprint per month: **0.75**

Other footprint per year: **18.85**

Other footprint per month: **1.57**

Participant 1 made the following spending choice based on that information:

Spending (out of 50 USD) to buy out CO_2 emission allowances from the market: **5**

full approval full disapproval

0

Participant 1 made the following allocation choice based on that information:

Money available for spending based on previous spending decision: **5**

USD spending on reduction of own footprint: **4**

USD spending on reduction of other footprint: **1**

full approval full disapproval

0

Participant 2 had the following information on his/her own and other participant's footprint:

Own footprint per year: **22.19**

Own footprint per month: **1.85**

Other footprint per year: **63**

Other footprint per month: **5.25**

Participant 2 made the following spending choice based on that information:

Spending (out of 50 USD) to buy out CO_2 emission allowances from the market: **30**

full approval full disapproval

0

Participant 2 made the following allocation choice based on that information:

Money available for spending based on previous spending decision: **30**

USD spending on reduction of own footprint: **15**

USD spending on reduction of other footprint: **15**

full approval full disapproval

0

Participant 3 had the following information on his/her own and other participant's footprint:

Own footprint per year: **12.23**

Own footprint per month: **1.02**

Other footprint per year: **22.19**

Other footprint per month: **1.85**

Participant 3 made the following spending choice based on that information:

Spending (out of 50 USD) to buy out CO_2 emission allowances from the market: **10** full approval full disapproval

0

Participant 3 made the following allocation choice based on that information:

Money available for spending based on previous spending decision: **10**

USD spending on reduction of own footprint: **8**

USD spending on reduction of other footprint: **2**

full approval full disapproval

0

Continue

Remaining time: 04:57

Please answer the following questionnaire:

Which of the following best describes your views about climate change?

- Climate change is happening mostly because of natural changes in the atmosphere.
- Climate change is happening mostly because of human activity such as burning fossil fuels.
- Climate change is happening equally because of human activity and natural changes.
- Climate change is happening, but there is not enough evidence to determine its cause.
- Climate change is not happening.

How worried are you about climate change?

- Not at all worried
- Not very worried
- Somewhat worried
- Very worried
- Extremely worried

How much do you think climate change will harm you personally?

- None at all
- Only a little
- A moderate amount
- A great deal
- Don't know

Please indicate which emotions you have when thinking of climate change and your personal future. (Indicate one or more)

- Fear
- Joy
- Anger
- Happiness
- Surprise
- Sadness
- Remorse
- Despair
- No emotion at all

Please indicate how much you agree or disagree with the following statements:

It is my responsibility to take actions to mitigate climate change.

- Strongly agree
- Fairly agree
- Neutral
- Fairly disagree
- Strongly disagree

Personal behavior is important to respond to climate change.

- Strongly agree
- Fairly agree
- Neutral
- Fairly disagree

Strongly disagree

I am willing to make personal contribution to cope with climate change.

Strongly agree

Fairly agree

Neutral

Fairly disagree

Strongly disagree

Explanation: **Carbon pricing** is a market-based policy tool used to reduce greenhouse gas emissions by putting a price on carbon pollution. This can be done through a carbon tax or a cap-and-trade system, where companies must purchase permits for their emissions. The goal of carbon pricing is to create an economic incentive for companies to reduce their emissions and transition to cleaner energy sources.

Carbon pricing is a tool that should definitely not be implemented to address climate change.

Strongly agree

Fairly agree

Neutral

Fairly disagree

Strongly disagree

Do you have any final comments on this experiment? Please write it down here:

Continue

Remaining time: 04:59

Experiment 2

Welcome

The setup of this experiment is different from experiments that you might be used to completing via Prolific.
To some degree, you will be involved in interaction with other participants of this study.
It is therefore important that you complete this experiment **without interruptions**.
Including the time for reading these instructions, the experiment will approximately take **20 minutes** to complete.

During the experiment, please **do not close this window**.
If you do close your browser or leave the experiment, you will not be able to re-enter the experiment.

Your decisions may also have real impact on the environment.
In particular, you will have an option to reduce the emission of carbon dioxide into the atmosphere.
Carbon dioxide is a substance that plays a major role in climate change.
There is an agreement among scientists all over the world that the reduction of carbon emissions is a major way of mitigating climate change.

The experiment consists of **two stages**.
In the first stage, we ask you for some demographics and to calculate your carbon footprint based on a simple questionnaire, that is how many tons of CO2 per year are caused by your life activities.
After that, you will be asked to go through four decision tasks in the second stage.

You will receive 4 GBP (approx. 5.07 USD) in total for completing the experiment. At one stage, one randomly drawn participant out of approx. 100 might receive an additional payment (bonus) of up to 50 USD. At another stage, one randomly drawn participant out of approx. 100 might receive an additional payment (bonus) of up to 10 USD.

You will receive a code to collect your payment via Prolific upon completion.

If you decide to quit earlier, you can withdraw from the experiment but do not receive a payment.

Please make your decisions within the time limit shown on your screen. If you fail to do so, you will be removed from the experiment and do not receive any payment.

Please provide your Prolific ID first:

button appears in 24 seconds

Remaining time: 04:56

Please indicate your age:

Please indicate your gender: Female | Male | Divers

Which of these categories describes your personal net income last month? Less than $3,000 | $3,000 – $6,000 | More than $6,000

What is the highest level of education you have completed?

Less than high school | High school diploma | Bachelor's degree or equivalent | Master's degree or equivalent | Doctorate or professional degree

How would you describe your political ideology?

Very liberal | Somewhat liberal | Moderate/centrist | Somewhat conservative | Very conservative

Continue

Remaining time: 02:39

Stage 1

We begin with Stage 1.

Please calculate your carbon footprint based on a simple questionnaire (that is, how many tons of CO2 per year are caused by your life activities) by clicking on "Carbon Footprint Calculator" below. The "Carbon Footprint Calculator" will open in a separate tab. Once you have conducted the calculation, you can come back to this experiment tab, and insert your CO2 emissions here. Below you will be asked for your footprint in tons of CO2 per year (2 decimal places).

Please provide your footprint in tons of CO2 per year and NOT the offset in USD!

When you click on the Carbon Footprint Calculator below, please first select USA as region and English-US as language in the first step on the top right corner. Please further select "An Individual"! Then you can calculate your footprint.

The link directs you to a carbon footprint calculator on a separate page (tab):

Click here for Carbon Footprint Calculator

Please insert your footprint that you have just calculated in tons of CO2 per year (NOT the offset in USD) into the input field (2 decimal places).

In which country are you located at the moment?

In which state are you located at the moment? (Optional)

button appears in 117 seconds

Remaining time: 09:59

You have just indicated that your footprint calculated per year is: 12.34 tons of CO_2

Carbon Dioxide

(if you wish to learn more about Carbon Dioxide, you can click the link).

Below, you will make four guesses.

We will randomly draw one out of approx. 100 participants. For chosen participants, we randomly draw one of the 4 guessing questions below and pay a bonus according to the following rule:

The closer your guess is to the actual number (the truth), the more money you will win. The maximum amount you can win as a bonus at this stage is 10 USD.

If your guess is exactly right, you get the full 10 USD. If your guess is not exactly right, we calculate how far off you are from the correct number. We then square this difference (multiply it by itself). Next, we subtract this squared number from 10 USD. That is the amount you will win. Formula for reward: 10-(guess-truth)^2

For example, if the correct number is 11 and you guess 8, you are 3 numbers off. Squaring this, 3 times 3 is 9. We subtract 9 from 10, so you win 1 USD.

Remember, if the squared difference is 10 or more, you will not win any money, because the smallest amount you can win is 0 USD.

What do you think is the average footprint per year of all other participants in this study?

What do you think is the share of participants with a lower footprint per year than yours (in percent)?

Restricting only to the subgroup of participants with a lower footprint than yours, what do you think is the average footprint per year there?

Restricting only to the subgroup of participants with a higher footprint than yours, what do you think is the average footprint per year there?

Continue

Remaining time: 06:39

Instructions for part 2 for No-Disapproval Control Group:

Stage 2

We begin with Stage 2. Please read the instructions carefully as we will ask some control questions on them in the next step.

Now, you have a possibility to contribute to the environment by reducing **actual** CO2 emissions in Europe. In particular, EU issues emission allowances to companies each year. Each allowance entitles the holder to emit one ton of CO2. Thus, if one buys out CO2 emission allowances from the market, the amount of allowable CO2 emissions within Europe is reduced.

Now, you will be asked:

1. How much of **50 USD** would you spend to buy out CO2 emission allowances from the market, thus reducing the amount of allowable emissions and how much of the 50 USD you would keep for yourself?

2. You can use the money devoted to reducing emissions to reduce your footprint and/or the footprint of another participant. How would you allocate the amount you devoted to buy out CO2 emission allowances? For every USD you spend, you will achieve a reduction of 2% in the corresponding monthly carbon footprint that the money is invested in (reduction achieved = 0.02 * monthly footprint invested in * USD invested in that footprint).

At the end of the experiment, we will actually implement one spending and allocation decision of one participant out of approx. 100 participants of the experiment, randomly chosen by a lottery.

Continue

Remaining time: 05:26

Instructions for part 2 for Disapproval Treatment Group:

Stage 2

We begin with Stage 2. Please read the instructions carefully as we will ask some control questions on them in the next step.

Now, you have a possibility to contribute to the environment by reducing **actual** CO2 emissions in Europe. In particular, EU issues emission allowances to companies each year. Each allowance entitles the holder to emit one ton of CO2. Thus, if one buys out CO2 emission allowances from the market, the amount of allowable CO2 emissions within Europe is reduced.

Now, you will be asked:

1. How much of **50 USD** would you spend to buy out CO2 emission allowances from the market, thus reducing the amount of allowable emissions and how much of the 50 USD you would keep for yourself?

2. You can use the money devoted to reducing emissions to reduce your footprint and/or the footprint of another participant. How would you allocate the amount you devoted to buy out CO2 emission allowances? For every USD you spend, you will achieve a reduction of 2% in the corresponding monthly carbon footprint that the money is invested in (reduction achieved = 0.02 * monthly footprint invested in * USD invested in that footprint).

At the end of the experiment, we will actually implement one spending and allocation decision of one participant out of approx. 100 participants of the experiment, randomly chosen by a lottery.

Once the experiment is finished, we will conduct a follow-up session with individuals who were not part of the experiment. These third-party evaluators will review the monthly carbon footprints of the participants of this experiment.

Specifically, each evaluator will be given a list showing the adjusted carbon footprints of 20 randomly selected participants after their investment in CO2 reduction in one randomly selected decision round. So, your footprint they will see on the list will reflect your initial footprint as calculated at the start of the experiment, adjusted by the corresponding reduction achieved through your investment in reducing your carbon footprint in one randomly selected decision round.

Thus, if you invest all money (50 USD) into your monthly carbon footprint, you will achieve CO2 reduction by the whole amount of your monthly carbon footprint. The evaluator will see that you have an adjusted footprint of 0 tons.

The evaluators will only see your final, adjusted carbon footprint, not your initial one or any other details or instruction from this experiment. They will have a list of 20 participants' adjusted footprints, with each evaluator getting a randomly selected list. They will give disapproval points to each footprint: 0 points for full approval, up to 10 points for full disapproval. We will calculate the average disapproval score for your footprint and send it as a message to your Prolific account.

Quiz Stage for No-Disapproval Control Group:

Please answer the following control questions, testing your understanding of the previous instructions.

Remember: For every USD you spend, you will achieve a reduction of 2% in the monthly carbon footprint that the money is invested in.

Control questions:

Assume some monthly carbon footprint (Footprint 1) corresponds to **1** ton of CO_2, and another monthly carbon footprint (Footprint 2) corresponds to **2** tons of CO_2.

Assume you decided to spend 20 USD to buy out CO_2 emission allowances from the market and to keep the remaining 30 USD to yourself. Then imagine, you allocate 10 USD of your spending amount to Footprint 1 and 10 USD to Footprint 2.

1) How large is the reduction of CO_2 emissions (in t) resulting from your allocation of 10 USD to Footprint 1? (Recall: 2% of X is 0.02*X)

t

2) How large is the reduction of CO_2 emissions (in t) resulting from your allocation of 10 USD to Footprint 2? (Recall: 2% of X is 0.02*X)

t

Continue

Remaining time: 09:58

Quiz Stage for Disapproval Treatment Group:

Please answer the following control questions, testing your understanding of the previous instructions.

Remember: For every USD you spend, you will achieve a reduction of 2% in the monthly carbon footprint that the money is invested in.

Control questions:

Assume some monthly carbon footprint (Footprint 1) corresponds to **1** ton of CO_2, and another monthly carbon footprint (Footprint 2) corresponds to **2** tons of CO_2.

Assume you decided to spend 20 USD to buy out CO_2 emission allowances from the market and to keep the remaining 30 USD to yourself. Then imagine, you allocate 10 USD of your spending amount to Footprint 1 and 10 USD to Footprint 2.

1) How large is the reduction of CO_2 emissions (in t) resulting from your allocation of 10 USD to Footprint 1? (Recall: 2% of X is 0.02*X)

	t

2) How large is the reduction of CO_2 emissions (in t) resulting from your allocation of 10 USD to Footprint 2? (Recall: 2% of X is 0.02*X)

	t

3) Assume your monthly footprint is Footprint 1, and you decide as described above. How large is your monthly footprint that the evaluator will see and evaluate?

	t

Continue

Remaining time: 09:58

Thank you; you answered the control questions correctly.

In the following, you will make your spending and allocation decisions:

Please indicate how much of **50 USD** you would spend to buy out CO2 emission allowances from the market, thus reducing the amount of allowable emissions, and how much of the 50 USD you would keep for yourself.

I would spend:

I would keep:

Please tell us in a few sentences the motivation behind your "spending choice".

button appears in 23 seconds

Remaining time: 04:15

Three Allocation Decisions for Information Control Group:

In this experiment, you have calculated your carbon footprint.

In the following, you will decide in three decision rounds (where the other participant varies) how to allocate the amount you decided to spend to buy out CO2 emission allowances from the market among footprints (yours and the assigned other participant's). The other participant's footprint is higher than your footprint with 50% chance and lower/equal your footprint with 50% chance in each decision round.

Round 1

Please decide how to allocate the **40** USD you decided to spend to buy out CO2 emission allowances from the market between the two footprints:

You have just indicated that your footprint calculated per year is: **12.34** tons of CO2.

Thus, your footprint calculated per month is: **1.03** tons of CO2.

Another participant in this study has calculated their monthly carbon footprint to be **0.66** tons of CO2.

I invest _____ USD in the other footprint.

I invest _____ USD in my footprint.

Continue

Remaining time: 06:10

<u>Round 2</u>

Please decide how to allocate the **40** USD you decided to spend to buy out CO_2 emission allowances from the market between the two footprints:

You have just indicated that your footprint calculated per year is: **12.34** tons of CO_2.

Thus, your footprint calculated per month is: **1.03** tons of CO_2.

Another participant in this study has calculated their monthly carbon footprint to be **0.84** tons of CO_2.

I invest _____ USD in the other footprint.

I invest _____ USD in my footprint.

button appears in 25 seconds

Remaining time: 06:37

Round 3

Please decide how to allocate the **40** USD you decided to spend to buy out CO_2 emission allowances from the market between the two footprints:

You have just indicated that your footprint calculated per year is: **12.34** tons of CO_2.

Thus, your footprint calculated per month is: **1.03** tons of CO_2.

Another participant in this study has calculated their monthly carbon footprint to be **1.62** tons of CO_2.

I invest _____ USD in the other footprint.

I invest _____ USD in my footprint.

Please tell us in a few sentences the motivation behind your "allocation choices".

button appears in 27 seconds

Remaining time: 06:39

Three Allocation Decisions for No-Information Treatment Group:

In this experiment, you have calculated your carbon footprint.

In the following, you will decide in three decision rounds (where the other participant varies) how to allocate the amount you decided to spend to buy out CO2 emission allowances from the market among footprints (yours and the assigned other participant's). The other participant's footprint is higher than your footprint with 50% chance and lower/equal your footprint with 50% chance in each decision round.

Round 1

Please decide how to allocate the **5** USD you decided to spend to buy out CO2 emission allowances from the market between the two footprints:

You have just indicated that your footprint calculated per year is: **19.45** tons of CO2.

Thus, your footprint calculated per month is: **1.62** tons of CO2.

Another participant in this study has calculated their monthly carbon footprint (if you wish to learn more about the other's footprint, you can click the link).

I invest _____ USD in the other footprint.

I invest _____ USD in my footprint.

button appears in 24 seconds

Remaining time: 06:36

Round 2

Please decide how to allocate the **5** USD you decided to spend to buy out CO_2 emission allowances from the market between the two footprints:

You have just indicated that your footprint calculated per year is: **19.45** tons of CO_2.

Thus, your footprint calculated per month is: **1.62** tons of CO_2.

Another participant in this study has calculated their monthly carbon footprint (if you wish to learn more about the other's footprint, you can click the link).

I invest _____ USD in the other footprint.

I invest _____ USD in my footprint.

button appears in 26 seconds

Remaining time: 06:38

Round 3

Please decide how to allocate the **5** USD you decided to spend to buy out CO_2 emission allowances from the market between the two footprints:

You have just indicated that your footprint calculated per year is: **19.45** tons of CO_2.

Thus, your footprint calculated per month is: **1.62** tons of CO_2.

Another participant in this study has calculated their monthly carbon footprint (if you wish to learn more about the other's footprint, you can click the link).

I invest _____ USD in the other footprint.

I invest _____ USD in my footprint.

Please tell us in a few sentences the motivation behind your "allocation choices".

button appears in 27 seconds

Remaining time: 06:39

Please answer the following questionnaire:

How important is it for you to maintain a positive self-image when facing criticism?

Very Low Importance

Low Importance

Moderate Importance

High Importance

Very High Importance

To what extent do your personal expectations about yourself influence your day-to-day life?

Not at all

Slightly

Moderately

Highly

Completely

How important is meeting your own standards and expectations to your sense of self?

Very Low Importance

Low Importance

Moderate Importance

High Importance

Very High Importance

When you are part of a group (like in a meeting or social gathering), how much do you think about the way others perceive your contributions?

I rarely think about it

I occasionally think about it

I sometimes think about it

I often think about it

I always think about it

How do you feel when you are publicly praised or recognized? How much does this impact your mood or behavior in social settings?

It has no impact on me

It has a slight impact on me

It has a moderate impact on me

It has a significant impact on me

It has a great impact on me

In new or unfamiliar social environments, how much do you adjust your behavior to fit in?

I do not adjust my behavior

I slightly adjust my behavior

I moderately adjust my behavior

I significantly adjust my behavior

I completely adjust my behavior

Which of the following best describes your views about climate change?

Climate change is happening mostly because of natural changes in the atmosphere.

Climate change is happening mostly because of human activity such as burning fossil fuels.

Climate change is happening equally because of human activity and natural changes.

Climate change is happening, but there is not enough evidence to determine its cause.

Climate change is not happening.

How worried are you about climate change?

Not at all worried

Not very worried

Somewhat worried

Very worried

Extremely worried

How much do you think climate change will harm you personally?

Not at all

Only a little

A moderate amount

A great deal

Don't know

Please indicate which emotions you have when thinking of climate change and your personal future. (Indicate one or more)

Fear

Joy

Anger

Happiness

Surprise

Sadness

Remorse

Despair

No emotion at all

Please indicate how much you agree or disagree with the following statements:

It is my responsibility to take actions to mitigate climate change.

Strongly agree

Fairly agree

Neutral

Fairly disagree

Strongly disagree

Personal behavior is important to respond to climate change.

Strongly agree

Fairly agree

Neutral

Fairly disagree

Strongly disagree

I am willing to make personal contribution to cope with climate change.

Strongly agree

Fairly agree

Neutral

Fairly disagree

Strongly disagree

<u>Explanation</u>: **Carbon pricing** is a market-based policy tool used to reduce greenhouse gas emissions by putting a price on carbon pollution. This can be done through a carbon tax or a cap-and-trade system, where companies must purchase permits for their emissions. The goal of carbon pricing is to create an economic incentive for companies to reduce their emissions and transition to cleaner energy sources.

Carbon pricing is a tool that should definitely not be implemented to address climate change.

Strongly agree

Fairly agree

Neutral

Fairly disagree

Strongly disagree

Do you have any final comments on this experiment? Please write it down here:

Continue

Remaining time: 08:16

Your earnings

You will receive 4 GBP (approx. 5.07 USD) for completing the experiment.

The computer will also randomly select one participant out of approx. 100 for whom one of the guessing tasks will be considered with a maximum Bonus of 10 USD. If this is you, the bonus will be added to your final payment.

Further, the computer will also randomly select one participant out of approx. 100, whose decision on the split of 50 USD will be implemented. If this is you, the amount you decided to keep will be added to your final payment (maximum Bonus of 50 USD). Further, the respective emission allowances will be bought.

We will then send this additional payment to you separately as a Bonus payment at a later stage.

To receive your earnings, please enter this code into Prolific: CFT7BCY0.

You can also be automatically redirected to Prolific via:

https://app.prolific.com/submissions/complete?cc=CFT7BCY0

After you have done that, you can close this window.
We thank you for participating in our study.

Follow-Up Experiment Conducted with Third-Party Evaluators

Please provide your Prolific ID first.

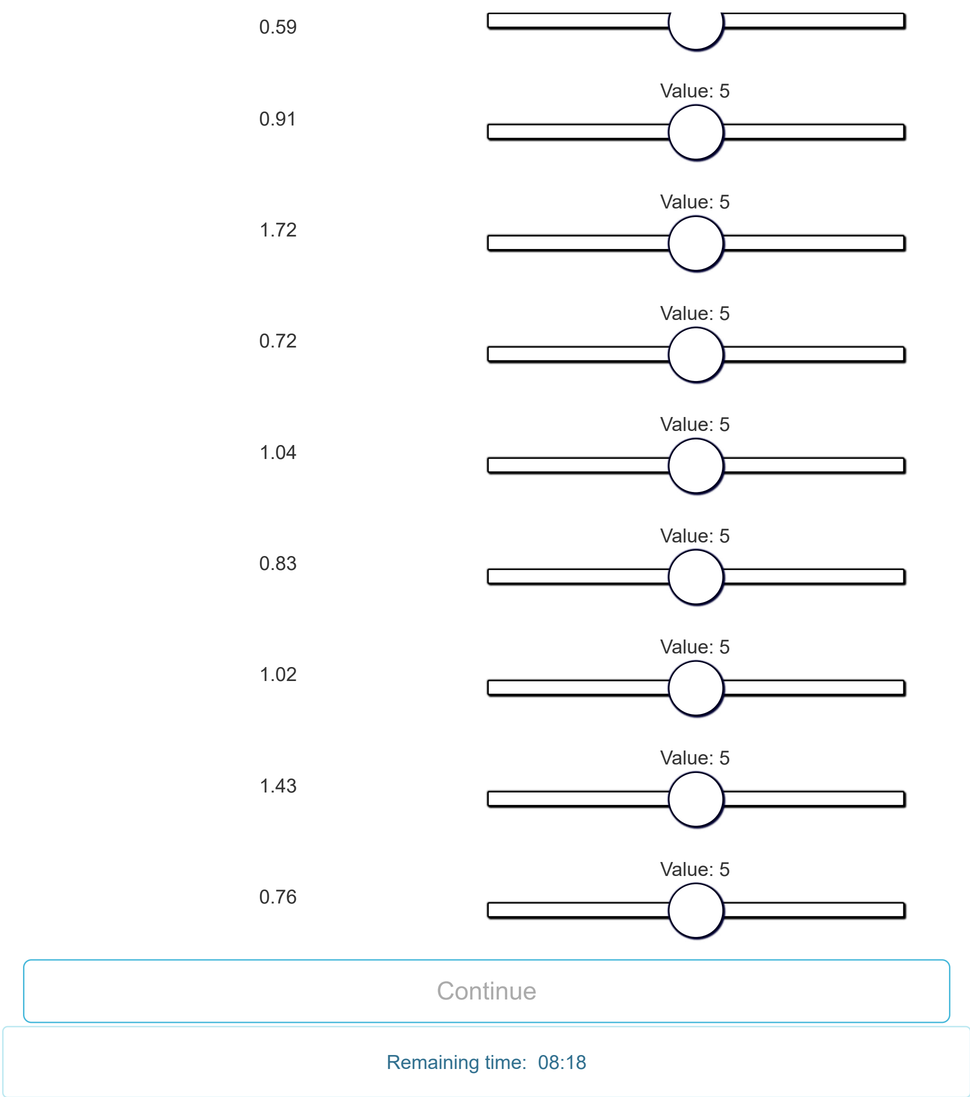
You are in the role of an evaluator:

As an evaluator, your task is to assess the carbon footprints of 20 participants from another study. These footprints, expressed in tons of CO2 (carbon dioxide) per month, reflect the participants' footprints after any potential investments in reducing their own carbon emissions. You will rate these footprints on a scale from **0 (full approval)** to **10 (full disapproval)**, based on the net carbon footprint presented to you. The average score from your evaluation, along with those from other evaluators, will be calculated for each participant and communicated to them individually, reflecting only their own footprint's assessment. You will remain anonymous.

Explanation:

The carbon footprint is the amount of carbon dioxide released into the atmosphere as a result of the activities of a particular individual. Carbon dioxide is a substance that plays a major role in climate change. There is an agreement among scientists all over the world that the reduction of carbon emissions is a major way of mitigating climate change.

Footprints:	Disapproval Point Allocation:
1.38	Value: 5
1.11	Value: 5
1.02	Value: 5
0.89	Value: 5
0.83	Value: 5
1.16	Value: 5
0.84	Value: 5
0.69	Value: 5
1.03	Value: 5
0	Value: 5
1.47	Value: 5
	Value: 5


0.59
Value: 5
0.91
Value: 5
1.72
Value: 5
0.72
Value: 5
1.04
Value: 5
0.83
Value: 5
1.02
Value: 5
1.43
Value: 5
0.76
Continue
Remaining time: 08:18

Your earnings

You will receive 0.50 GBP (approx. 0.63 USD) for completing the experiment.

To receive your earnings, please enter this code into Prolific: CFT7BCY0.

You can also be automatically redirected to Prolific via:

https://app.prolific.com/submissions/complete?cc=CFT7BCY0

After you have done that, you can close this window.

We thank you for participating in our study.