The Marginal Impact of Emission Reductions: Estimates, Beliefs and Behavior*

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Abstract

An important driver of climate change inaction is the belief that individuals cannot have any tangible impact on climate change through their own actions. Currently available statistics are not suited to systematically assess or challenge this belief. In this paper, I derive the marginal impact of emission reductions – the effect of reducing emissions by 1 tonne of CO_2 (tCO_2) – on physical climate change outcomes, document important misperceptions, show how they affect behavior, and derive policy implications. Using climate models, I find that the impact of reducing emissions by 1 tCO_2 is thousands of liters less glacier ice melting, several additional hours of aggregate life expectancy, and multiple m^2 less vegetation undergoing ecosystem change. Subjects underestimate these figures by orders of magnitude. Moreover, their mental model is inconsistent with climate models. First, they misperceive climate change as a threshold public goods game. Second, they incorrectly assume that the marginal impact increases when others also reduce their emissions (strategic complementarity). Providing subjects with the climate scientific findings causally increases perceived self-efficacy, intentions to reduce own emissions, and real donations to reduce global emissions. The misperceptions and treatment effect are consistent with a mental model of threshold thinking, which predicts positive overall emission reductions of information provision in equilibrium. Providing information about the marginal impact is a cost-effective demand-side mitigation strategy. The information can also serve as a catalyst for other climate policies by reframing their benefits and challenging arguments against unilateral action that are based on threshold thinking.

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1 Introduction

Climate change is one of the biggest problems the world faces today (Steffen et al. 2015; Guterres 2018). Yet, there is a large gap between global emission targets – implying a budget of 2 tonnes of CO_2 (tCO_2) per person per year (IPCC 2021) – and actual emissions – 18 tCO_2 per household per year in the US (Crippa et al. 2023).[1] One driver of climate change inaction is low perceived self-efficacy – the widespread belief that one person cannot have a meaningful impact on climate change (Heath and Gifford 2006; Kothe et al. 2023). Emission reductions are costly and, thus, most people will not do them if they perceive the benefits to be zero.

Despite the importance of this low perceived self-efficacy, no suitable statistics are readily available to assess or challenge it. Climate scientists typically report projections for different levels of global warming—for example, a glacier ice loss of 29 teratonnes (Tt) under 1.8 °C of warming compared with 58 Tt under 3.7 °C (IPCC 2021). However, this resolution is too coarse to gauge individual impacts.[2] Similarly, the social cost of carbon – the net present monetary value of all societal damages due to increasing emissions by 1 tCO_2 (Newbold et al. 2013) – was created for policy-making and cannot generally be used to determine an individually optimal decision. It is difficult to understand for laypeople (Stango and Zinman 2009),[3] may not include all the outcomes the individual cares about (Tol 2011; Stern 2016; Auffhammer 2018),[4] and relies on normative assumptions – including damage valuations and discount rates (Weitzman 2001; Stern 2007; Nordhaus 2007) – that might not match those of the individual.

To address this issue, I propose and estimate a new measure to guide individual decision-making, document important misperceptions, show how they affect behavior, and derive policy implications. I define the marginal impact of emission reductions as the expected damage avoided in a physical climate change outcome due to decreasing overall emissions by 1 tCO_2 today. This measure can be derived for any climate change

[1] The budget also includes other greenhouse gases, converted into CO_2-equivalent (CO_2e) amounts. Throughout this paper, I use CO_2 as a shorthand for CO_2e. A global carbon budget of 50 tCO_2 per person gives a 66% probability of staying below 1.5 °C of global warming (IPCC 2021, sec. 5.5.2). Assuming we achieve carbon neutrality by 2050, that leaves each person with about 2 tCO_2 per year. The per household estimate is for 2022 and does not include the emissions of imports. As in most Western countries, the US consumption-based footprint per capita would be higher (Friedlingstein et al. 2022; Ivanova et al. 2020).

[2] There are some exceptions. Marzeion et al. (2018) and Notz and Stroeve (2016) present estimated effects of emitting 1 tCO_2. However, no unifying framework or systematic body of evidence exists. These papers use very different methods for calculating the effect, which I discuss in Section 3.

[3] Stango and Zinman (2009) shows that people exhibit exponential growth bias (in the context of household finance). That is, they linearize exponential functions when assessing them intuitively. Discounting leads to an exponential decay in the weight put on future damages in the social cost of carbon. Thus, the calculations are likely to be difficult to understand for laypeople.

[4] For example, many non-market outcomes are typically excluded, due to difficulties in eliciting non-use valuations (Kahneman and Knetsch 1992; Arrow et al. 1993; Diamond and Hausman 1994).

outcome and time horizon. In this paper, I focus on selected end-of-century outcomes that are simple, tangible and quantifiable – such as the amount of glacier ice melting by 2100. To put the emission amount into perspective, 1 tCO_2 is roughly emitted by driving 10 miles a day for 1 year (with an average diesel car), eating 5 servings of meat per week for 1 year (beef, pork or lamb), or taking 1 long-distance return flight (Jones and Kammen 2011; Ivanova et al. 2020).[5]

Using climate models, I find that the marginal impact is tangible, continuous and mostly exhibits strategic substitutability. I flexibly estimate damage functions, linking climate change outcomes to emissions, and quantify the marginal impact using Monte Carlo simulations. Given current government targets, the estimated marginal impact of reducing emissions by 1 tCO_2 today is: 4 kiloliters less glacier ice melting, 6 hours more aggregate life expectancy, and 5 square meters less vegetation undergoing ecosystem change. The marginal impact – an expected value – is continuous as a function of overall emission reductions, due to large epistemic uncertainty about discontinuities, including tipping points.[6] Moreover, even if tipping points were known exactly, the marginal impact would be strictly positive. As a result, I argue that climate change is a continuous or "monotonous" public goods game.[7] Finally, emission reductions are strategic substitutes in terms of their physical benefits for most outcomes, in that the marginal impact is decreasing in overall emission reductions.[8]

I run two experiments to elicit beliefs about the marginal impact and test the effect of the information on attitudes, intentions and behavior. I develop an "augmented staircase" method to elicit a point estimate belief and vignettes to understand participants' mental model – that is, their beliefs about the structure of the climate change mitigation game. Participants are incentivized to give an answer that matches the climate-scientific results. To get conservative estimates for the point estimate, I anchor partic-

[5]These are average emissions, based on a literature review. The amount of emissions saved by avoiding these actions may be different in general equilibrium (Kaufmann et al. 2024; Trammell 2023). I focus on the effect of emission reductions on outcomes, abstracting from how these emission reductions are achieved.

[6]The argument that large uncertainty around tipping points leads to a continuous expected damage function was also made by Cai and Lontzek (2019).

[7]A threshold public goods game is usually defined as a game where the benefit of contributions to a public good are constant before and zero after a threshold (e.g., Milinski et al. 2008). This leads to both discontinuity and non-monotonicity. However, for the climate change outcomes considered here, even if discontinuities such as tipping points were known exactly, the marginal impact would not be zero. To capture this dynamic, I introduce the concept of a "monotonous" public good game, where the return to contributions may have discontinuities, but is strictly monotone (see Section 3.2).

[8] The result follows directly from the convexity of the damage function, as it is generally assumed in environmental economics (Hassler and Krusell 2018). Strategic substitutability in terms of utility – as defined in Cooper and John (1988) – follows if the cross-derivative of utility from emission reductions has the same sign as that of the physical effect, see Section 8. The assumption may not hold – for example, if there are complementarities in the cost structure or due to carbon leakage.

ipants with the correct value. I employ a between-subject design to test the effect of correcting beliefs. I measure attitudes and intentions three days after the information treatment in an obfuscated follow-up survey to rule out experimenter demand effects. In a second experiment, I investigate the effect of the information on a real donation to reduce global emissions.

I find overwhelming evidence that subjects' beliefs and mental model are inconsistent with the climate scientific results. First, the median participant underestimates the marginal impact by 2 orders of magnitude. Second, most participants think climate change is a threshold public goods game. Specifically, 77% of subjects overestimate certainty about thresholds by at least one order of magnitude and 56% falsely believe the marginal impact is zero after crossing those thresholds. Finally, most participants falsely believe that emission reductions exhibit strategic complementarity. In particular, 67% of subjects think their impact is strictly larger if everyone else also reduces their emissions.

Providing participants with the climate scientific results has a large positive impact on attitudes, intentions and behavior. Three days after the intervention, the information treatment increases perceived self-efficacy and intentions to reduce emissions by 0.29 and 0.11 standard deviations, respectively. I confirm the obfuscation of the follow-up study by asking participants about what they thought the purpose of the study was (Allcott and Taubinsky 2015; Bursztyn et al. 2020). Only 0.3% of participants mention the first survey. In the second experiment, information provision increases donations to reduce global carbon emissions by £14 (21% or 0.26 standard deviations). Surprisingly, neither the average misperception nor the treatment effect vary between environmentalists and non-environmentalists, despite large differences in baseline intentions to reduce emissions. I show that environmentalists are more likely to agree with moral arguments that are independent of direct impacts (Kant 1797; Glover and Scott-Taggart 1975; Hooker 2002), suggesting that the information gives both groups an additional reason to reduce emissions.

I build a simple model of climate change beliefs that is consistent with the above findings and makes predictions about the effects of providing everyone with the climate scientific results. The two main assumptions of the model are that people engage in "threshold thinking" and that they have uncertainty about the overall level of end-of-century emissions. To the extent that expected emissions are above the threshold, reductions by others will increase the perceived probability of being pivotal and thus the expected marginal impact (strategic complementarity). Moreover, being far from the target, the probability of being pivotal and, hence, the expected marginal impact is infinitesimal (Downs 1957; Falk et al. 2020). The model predicts that informing sub-

jects about the marginal impact leads to higher emission reductions. I show that under mild assumptions, that are consistent with the experimental results, this effect dominates free-riding concerns (due to the change in the perceived strategic complementarity) in strategic equilibrium, leading to overall emission reductions if everyone was provided with the information.

The findings inform policy by providing a cost-effective new mitigation strategy and a catalyst for other policies. I assess the cost-effectiveness of a public information campaign about the marginal impact, assuming that the effect on per capita emissions is 10% (5%) of the treatment effect on donations for the UK (US) population and lasts one year. Using estimates from the literature of the social cost of carbon (EPA 2023), per capita emissions (Friedlingstein et al. 2022) and the costs of an information campaign (Khavjou et al. 2018), I find that the campaign has a Marginal Value of Public Funds (MVPF) – the ratio of aggregate net welfare benefits to costs (Hendren and Sprung-Keyser 2020) – of 8.8 in the UK and 12.8 in the US, substantially higher than those of many important existing climate policies, including US electric vehicle, solar and wind subsidies (Hahn et al. 2024).

However, while the effect on individual behavior is substantial, there remains a need for systemic change (Chater and Loewenstein 2023). The marginal impact can increase policy support, first, by reframing benefits in terms of tangible climate change outcomes. For example, using estimates from Bistline et al. (2023), I find that the impact of the Inflation Reduction Act from 2022 to 2024 was: 1.0 trillion liters less glacier ice melting, 200,000 years more aggregate life expectancy, and 14 million acres less vegetation undergoing ecosystem change. Second, the same mental model of climate change as a threshold public good that limits private mitigation, is also frequently used as an argument against climate policies. Updating the mental model may therefore increase both individual mitigation and support for policies. In this sense, individual emission reductions can be a complement to, as well as a catalyst for, other climate policies.

This study relates to several strands of the literature. A large literature in environmental economics estimates damages from climate change. Traditionally, these studies have focused on aggregate economic damages (Nordhaus 1977; Greenstone et al. 2013; Burke et al. 2015). More recent studies have estimated damages for other impacts, including sector-specific output (Carleton and Hsiang 2016), mortality (Carleton et al. 2022) and ecosystem services (Taylor and Druckenmiller 2022). These damage estimates are aggregated into the social cost of carbon to derive optimal policies, including by the US government (EPA 2023). The social cost of carbon, however, is not well suited to derive optimal individual decisions, including because of missing outcomes

and heterogeneity in moral preferences (Tol 2011; Stern 2016; Auffhammer 2018). I contribute to this literature by proposing and estimating a measure of the impact of marginal emission reductions suited for individual decision-making. This literature also finds that the damage function for GDP is continuous, even with climate tipping points due to large uncertainties (Cai and Lontzek 2019; Dietz et al. 2021), and convex (Hassler and Krusell 2018). I extend these findings, by showing that the damage function is continuous, monotone and weakly convex for a large class of climate change outcomes.[9]

This paper also relates literatures in behavioral economics on mental models and beliefs about climate change. Several papers have documented systematic errors in people's mental models (Enke 2020; Andre et al. 2022; Chinoy et al. 2023).[10] I contribute to this literature, by documenting fundamental misperceptions about the structure of climate change mitigation that are consistent with a mental model of climate change as a threshold public goods game. Existing studies on climate change beliefs have documented misperceptions about the causal chain (Hornsey et al. 2016), effectiveness of climate policy (Dechezleprêtre et al. 2025), willingness of others to reduce emissions (Andre et al. 2024), co-benefits (Allcott and Knittel 2019) and carbon footprints (Camilleri et al. 2019; Imai et al. 2022). By contrast, this paper is the first to document misperceptions about the impact of emission reductions on climate change outcomes. This belief is crucial, since most people care about those outcomes – rather than emissions *per se* (Stern and Dietz 1994; de Groot and Steg 2010). Methodologically, this paper adds to a growing literature in economics that use survey experiments (Stantcheva 2023), and information provision experiments with obfuscated follow-ups (Haaland et al. 2023).[11] The finding that environmentalists and non-environmentalists differ in their moral reasoning about climate change mitigation adds to the growing literature on eliciting moral preferences in economics (Bénabou et al. 2022; Hart et al. 2022).

Finally, I contribute to a large literature on climate change policies. Economists

[9] These findings are contrary to the assumptions made in some experimental work that models climate change as a threshold public goods game (Milinski et al. 2008; Tavoni et al. 2011; Feige et al. 2014; Dannenberg et al. 2015).

[10] When forming beliefs over issues covered in news reports, many people only use the information that is right in front of them (Enke 2020). Similarly, when constructing expectations about macroeconomic variables, many people selectively recall specific mechanisms, leading to large dispersion in beliefs (Andre et al. 2022). Another mental model is "zero-sum thinking" – the belief that gains for one individual or group tend to come at the cost of others – which is strongly associated with preferences for government redistribution and more restrictive immigration policies (Chinoy et al. 2023).

[11] Other information provision experiments have informed participants about the energy efficiency of light bulbs (Allcott and Taubinsky 2015), recession forecasts (Roth and Wohlfart 2020), labor market impacts of immigration (Haaland and Roth 2020), racial discrimination (Haaland and Roth 2021), tax policy (Stantcheva 2021), and immigrant shares and origins (Alesina et al. 2023).

have evaluated the net benefits of a large number of government policies, including carbon taxes (Metcalf and Stock 2023), cap-and-trade (Colmer et al. 2024), renewable energy subsidies (Shrimali et al. 2015; Pless and van Benthem 2019), electric vehicle subsidies (Muehlegger and Rapson 2022), regulation (Anderson and Sallee 2011) and nudges (Allcott 2011; Fowlie et al. 2018). These policies typically have MVPFs below 6 (Hahn et al. 2024).[12] I provide a new "demand-side" policy (IPCC 2022b), based on correcting peoples' mental model about climate change, with an estimated MVPF of 9-13. Moreover, I argue that the marginal impact estimates can be used to increase public support for policies, which are often a bottleneck for the adoption of first- and second-best climate policies (Douenne and Fabre 2022; Dechezleprêtre et al. 2025). A related literature finds that individual actions can crowd out public support (Maniates 2001; Chater and Loewenstein 2023). Instead, I argue that because threshold thinking undermines both individual mitigation and policy support, updating peoples' mental model is likely to crowd-in policy support.

The remainder of this paper is structured as follows. Section 2 formally defines the marginal impact of emission reductions and discusses various aspects of the definition. Section 3 derives the properties of the marginal impact from climate models. Section 4 presents the design and results of the belief elicitation. Section 5 covers the obfuscated follow-up survey and the effect of correcting misperceptions on attitudes and intentions. Section 6 covers the second information provision experiment and the effect on donations to reduce emissions. Section 7 analyzes heterogeneity in both the misperceptions and treatment effect. Section 8 proposes a behavioral framework that is consistent with the findings. Section 9 explains policy implications. Section 10 concludes.

2 Definition

2.1 Baseline Definition

Let $y_t(\mathbf{x}_t)$ be the realization of climate change outcome y, given a sequence of annual net anthropogenic greenhouse gas emissions $\mathbf{x}_t = (x_{1901}, ..., x_t)$ since preindustrial times until year t.[13] Throughout this study I focus on end-of-century outcomes, denoted $y(\mathbf{x}) \equiv y_{2100}(\mathbf{x}_{2100})$ for convenience. Example outcomes include glacier ice melting (in liters) by 2100 and the area of vegetation undergoing ecosystem change (in m²),

[12] This is the MVPF for the category averages. Individual policies sometimes have higher MVPFs (Hahn et al. 2024). It excludes development assistance, which is not typically considered a climate policy. Development assistance can have an exceptionally high MVPF, such as 37-323 for providing efficient cooking stoves (Berkouwer and Dean 2022).

[13] The preindustrial period is usually defined as the period 1850-1900, although other reference periods are used in some studies.

see Section 3.1. Following the IPCC, emissions are measured in metric tonnes and also include other greenhouse gas emissions, converted into CO_2-equivalent amounts (CO_2e). The damage function for variable y is the change in that variable that is due to anthropogenic emissions $\mathbf{x}$:

$$d_y(\mathbf{x}) \equiv y(\mathbf{x}) - y(\mathbf{0}),$$

where $\mathbf{0}$ is a vector of zeros with the same length as $\mathbf{x}$.

The main quantity of interest is the marginal impact of emission reductions, defined as the damage avoided due to decreasing emissions today by 1 tCO_2. Formally,

$$m_y(\mathbf{x}) \equiv d_y(\mathbf{x}) - d_y(\tilde{\mathbf{x}}),$$

where $\tilde{\mathbf{x}} \equiv (x_{1901}, ..., x_{\tau-1}, x_\tau - 1, x_{\tau+1}, ..., x_{2100})$ and τ is the present year.

The two definitions can be simplified by assuming that cumulative emissions in 2100, $x \equiv \sum_{\tau=1901}^{2100} x_\tau$, are a sufficient statistic for $y(\mathbf{x})$. Then, the damage function and marginal impact become:

$$d_y(x) \equiv y(x) - y(0), \tag{1}$$

$$m_y(x) \equiv d_y(x) - d_y(x-1). \tag{2}$$

The next subsection motivates various aspects of Equation (2) and discusses possible alternatives. Section 2.3 introduces a baseline level of expected overall emissions and an alternative specification of the marginal impact in terms of overall emission reductions.

2.2 Discussion

Total emissions. Instead of calculating the marginal impact given total emissions until 2100, one could calculate the effect given current emissions. For example, Notz and Stroeve (2016) observe a linear relationship between cumulative emissions and Arctic September sea ice in both historic observations and simulations up to $x \approx 2$ $TtCO_2$. As a result, it was widely reported that the average carbon footprint "destroys 30 square meters of Arctic sea ice" (Carrington 2016). A reader may deduce from this that reducing one's carbon footprint would preserve some Arctic September sea ice. However, this is unlikely. Taking a conservative measure of expected emissions $x \approx 4$ $TtCO_2$ – by assuming governments fulfill their targets, leading to 2.4 °C of global warming (see Section 2.3) – all September Arctic sea ice will be lost this century (Notz and Stroeve

2016; IPCC 2021, sec. 4.3.2).[14] Thus, a small reduction in emissions cannot be expected to preserve any Arctic sea ice in the long-run. By contrast, the marginal effect given overall expected emissions can be interpreted as the long-term effect of reducing CO_2 emissions by a small amount, taking others' emissions as given.

Outcome year $t = 2100$. The above discussion makes it clear that t should be sufficiently large. In principle, one could look at the outcome in equilibrium ($t = \infty$). I instead focus on end-of-century outcomes for several reasons. First, an equilibrium may not exist for some outcomes such as mortality, which depends on the non-stationary variables population and GDP (Carleton et al. 2022). Second, there is more certainty about outcomes at $t = 2100$ (see Section 3.2). Third, estimates for $t = 2100$ are available for all considered outcomes. Forth, unlike equilibrium quantities, which are reached at different times for different outcomes, setting $t = 2100$ ensures comparability. Fifth, the end of this century is a time span that most people can relate to, since it is within the expected lifetime of people born today. Sixth, 2100 is a round number that participants are likely to correctly perceive and remember.

x as a sufficient statistic. The assumption that x is a sufficient statistic for $y(\mathbf{x})$ is in line with the fact that the emission scenarios (SSPs in CMIP6) used to estimate climate models are monotonic transformations of each other. One can interpolate these scenarios to determine an emission path $\mathbf{x}$ for a given x. However, this means that the 1 tCO_2 reduction in Equation (2) is implicitly assumed to follow this trajectory, if one interpolates results from these scenarios, as is done below. For climate change outcomes measured in 2100 that react instantaneously to temperature, this assumption is unproblematic. The reason is that the temperature difference induced by an emission reduction today will have reached near steady-state within about 10 years, well before the end of the century (Mattauch et al. 2020; IPCC 2021). For other outcomes, this assumption is likely to be conservative. This is because delayed damages are underestimated, see Appendix A.2.

Discrete change in x. The above definition of the marginal impact compares the damage at x and $x - 1$. I thus use the popular (a small amount) not the mathematical (an infinitesimal amount) meaning of marginal. Alternatively, one could use the derivative of $d_y(x)$ (Notz and Stroeve 2016; Marzeion et al. 2018). However, it is not clear *a priori* that this derivative is well-defined, as there may be discontinuities in $d_y(x)$. Another advantage of the "impact of a one ton reduction" definition is that is easier

[14] This result holds even if I assume that the Paris goal of 1.5 °C of warming is reached.

to communicate to laypeople. Finally, for all scenarios considered in this paper $x > 1$ $TtCO_2$ and, as shown in Section 3.3, changes in the slope of $d_y(x)$ require very large changes in x. Hence, the two approaches give nearly the same result and $m_y(x)$ can be thought of as the derivative of $d_y(x)$:

$$m_y(x) \approx \frac{\mathrm{d}d_y(x)}{\mathrm{d}x}.$$

2.3 Expected Emissions and Overall Reductions

In Equation (2) I define the marginal impact as a function of overall emissions. This is the form in which the underlying damage functions are typically presented in the climate scientific literature. However, two requirements merit a second formulation. First, for point estimates of $m_y(x)$ it is necessary to fix a level of expected overall emissions. Second, to assess the potential strategic complementarity between emission reductions it is useful to specific $m_y(x)$ as a function of overall emission reductions. To meet these demands, I let x^e be the expected level of overall emissions and x^r a hypothetical reduction *vis-à-vis* x^e.[15] Thus,

$$x \equiv x^e - x^r. \tag{3}$$

The empirical analysis below requires specifying x^e. IPCC (2022b) provides an estimate for the warming induced by government actions, based on Höhne et al. (2021) and updated in Climate Action Tracker (2021). According to this analysis, optimistic assumptions, government pledges, 2030 targets and current policies will most likely lead to 1.8 °C (68% CI: 1.5-2.4), 2.1 °C (1.7-2.6), 2.4 °C (1.9-3.0) and 2.7 °C (2.0-3.6) of warming, respectively.[16] Any of those estimates could reasonably be used for x^e. For the point estimate, I assume that government targets are implemented. Letting x_T be the overall emissions associated with T°C warming, we have

$$x^e \equiv x_{2.4}.$$

[15] Although I am mainly interested in values of x^r between 0 and x^e, x^r could also be negative (leading to more than expected emissions) or more than x^e (leading to overall negative emissions).

[16] Central estimates are the median. The older results in IPCC (2022b) and Höhne et al. (2021) have central estimates that are within 0.2 °C of those of Climate Action Tracker (2021). Point estimates remained unchanged in a June 2022 update (Climate Action Tracker 2022). A recent analysis by Meinshausen et al. (2022) similarly finds that if all conditional and unconditional pledges are implemented, global warming will most likely be 1.9-2.0 °C. UNEP (2021) estimates that optimistic assumptions and pledges would result in 2.2 °C and 2.7 °C of warming, respectively. The difference can be attributed to reporting the 66$^{\text{th}}$ percentile and a different modeling approach (Höhne et al. 2021). These estimates are all within the confidence interval provided in Climate Action Tracker (2021).

3 Estimates

In this section, I derive features of the marginal impact of emission reductions from climate scientific models. The section is structured as follows. Section 3.1 describes the methods and data used. Section 3.2 argues that the marginal impact $m_y(x)$ is continuous and strictly monotonic in x. It also discusses potential objections and the role of tipping points. Section 3.3 describes the shape of $m_y(x)$, showing that for most considered outcomes it is constant or decreasing in emission reductions. Section 3.4 provides point estimates for $m_y(x)$ for selected outcomes. Section 3.5 interprets the results.

3.1 Methods and Data

Thresholds and strategic interaction. To investigate the continuity and shape of $m_y(x)$, I review the existing literature. The continuity and monotonicity arguments are mainly based on IPCC reports and a recent review on tipping points (McKay et al. 2022). To assess the shape of the marginal impact as a function of overall emissions, I rely on the results from the IPCC for a representative set of physical outcomes that the IPCC classifies as important. Specifically, I select all outcomes relevant to the assessment of Representative Key Risks (RKRs) and Reasons for Concern (RFCs) according to IPCC (2021). I then search the report for assessments of the shape of the damage function. The exact point from which I retrieve the assessment is shown in Table B.1. The remainder of this section discusses how I estimate point estimates for the marginal impact.

Point estimate. I calculate the marginal impact based on ensemble studies through a novel framework and quantify uncertainty using a Monte Carlo simulation. I employ climate-impact model ensemble data used by the Intergovernmental Panel on Climate Change (IPCC) for glacier ice (Marzeion et al. 2020), life expectancy (Carleton et al. 2022) and vegetation change (Warszawski et al. 2013).[17] I estimate a damage function using polynomials up to order five. I fit a hierarchical model that estimates different parameters for each impact model in the ensemble. In a Monte Carlo simulation, I explicitly model differences in the marginal impact arising from different possible (1) impact models, (2) statistical models, (3) statistical model parameters and (4) temperature responses to emissions. The full methodology is explained in Appendix A.1.

I choose units for the point estimates that maximize the likelihood that the marginal

[17] These models are used in the IPCC's 6th assessment report (IPCC 2021; IPCC 2022a; IPCC 2022b; IPCC 2023). Where appropriate, newer findings from the literature are discussed, see Footnotes 16 and 21 and Sections 2.3 and 3.2.

impact is correctly perceived and remembered. This is the case for whole (Gigerenzer et al. 2000), small (Woodford 2020; Summerfield and Parpart 2022), and round (Nguyen et al. 2022) numbers. I follow the advice of Heath and Starr (2022) and pick familiar units, such that the numerical part of the point estimate meets these characteristics. Thus, I measure glacier ice in thousands of liters (kiloliters, kL), life expectancy loss in hours (h), and vegetation change in square meters (m^2).

3.2 Thresholds

Types of public goods games. To discuss the role of thresholds in climate change, it is helpful to distinguish different types of public goods. In theoretical and experimental economics, a threshold public goods game is typically defined as a settings in which subjects can make contributions to a public good, where the public good is provided only if total contributions reach a certain level. If that level is not reached the contributions are lost (e.g., Milinski et al. 2008). As a result, the impact of an individual's on public good provision is both discontinuous and non-monotonic: the impact is large if they are pivotal in reaching the threshold and zero otherwise.

In a continuous public goods game, on the other hand, every contribution by a participant increases the total payoff. For example, in a typical linear public goods game, participants can contribute any amount of their endowment, which then raises everyone's payoff. The increase in the total payoff is larger than the individual contribution, but the increase in an individual's own payoff is smaller than their contribution (e.g., Fischbacher et al. 2001). Here, the social return on an individual's contribution is both continuous and strictly monotonic. Note that both types of public goods give rise to free-riding concerns. However, in a threshold public goods game, participants may not contribute *even if* they were perfectly altruistic, if they do not expect to be pivotal.

Alas, the above classification into threshold and continuous public goods is non-exhaustive and insufficient to describe climate change. In particular, a public good can be non-continuous (have thresholds) but be strictly monotonic. That is, a contribution may lead to a discontinuous jump in total payoffs (if a threshold is reached), but always increase the amount of public good. I call this a monotonous public good. In the remainder of this subsection, I will argue that climate change mitigation is a continuous public good when considering expected outcomes, but would still be a monotonous public good even if we knew the relevant thresholds exactly.

Physical process. To assess the continuity and monotonicity of $d_y(x)$ it helps to break down the process by which x affects y. Figure 1 shows the cause and effect chain used

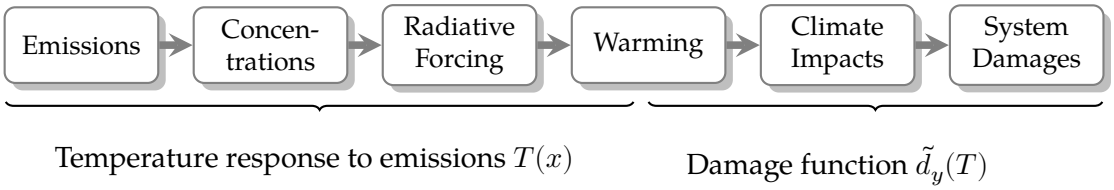


Figure 1: Climate change cause and effect chain

Note: Adapted from IPCC (2021).

by the IPCC (2021, sec. TS.1.3).[18] CO_2 emissions lead to increased CO_2 concentrations in the atmosphere. The same is true for other greenhouse gases. Once they are in the atmosphere, these gases capture a part of the sunlight that is reflected from the earth's surface and emit heat in all directions (radiative forcing), including back to the surface. This heat raises global temperatures (global warming). Global warming then affects the broader climate as well as natural and human systems. To better understand this process, I will break it down into two parts: the response of warming to emissions $T(x)$ and the response of outcomes to warming $\tilde{d}_y(T)$.

In the simplified model shown in Figure 1, the first part of the cause and effect chain – from emissions to warming – is continuous and monotone. Figure B.1 is taken from IPCC (2021, p. 28), including captions. It plots CO_2 emissions against observed and predicted global warming. The caption states that "every tonne of CO_2 emissions adds to global warming". Moreover, the relationship is not just continuous it is "near linear", as captured by the TCRE. Predicted future warming (here until 2050) is shown for several overall emission scenarios and paths. The relationship is also independent of emission scenarios.

The physical process underlying the TCRE is that every ton of CO_2 emitted eventually increases the concentration in the atmosphere. The increase is neither immediate nor one-to-one, due to the carbon cycle and feedback effects. However, after about 10 years the two most important processes – CO_2 decay and thermal inertia – compensate each other, so that warming remains approximately constant (Ricke and Caldeira 2014; Mattauch et al. 2020; IPCC 2021).

At this stage in the cause and effect chain one can already anticipate a potentially large marginal impact. While the usual way of presenting the TCRE may suggest a small effect (4.5×10^{-13} °C/tCO_2), one needs to account for the fact that temperatures rise everywhere and that the earth is large. Looking instead at the preceding step, I find

[18] I split outcomes into climate impacts and system damages. Climate impacts are changes to the climate, whereas system damages are damages to both natural and human systems (Fuglestvedt et al. 2003). For simplicity, the picture excludes the feedback effects that the climate can have on CO_2 concentrations and direct effects of greenhouse gases on system outcomes.

that each ton of CO_2 creates 287 W of radiative forcing.[19] This is the energy-equivalent of having 35 LED light bulbs shining down on earth 24 hours a day forever per ton of CO_2 emitted.[20]

Continuity. The second part of the causal chain – from warming to climate change outcomes – may have discontinuities. For example, after a certain amount of emissions, global warming and melting, the Greenland glacier will reach an atmospheric level at which it will continue to melt completely even if there was no further temperature increase. Crossing this threshold would thus lead to a discrete jump in the amount of glacier ice melting at a distant point in the future. As a result, the predicted amount of glacier ice in any given model $\hat{y}(\mathbf{x}, \boldsymbol{\vartheta})$ may be discontinuous in $\mathbf{x}$.

However, the unconditional damage function will still be continuous due to epistemic uncertainty. Specifically, there are large uncertainties about parameters and initial conditions $\boldsymbol{\vartheta}$. Assuming a continuous distribution for the these parameters implies that $y(\mathbf{x}) \equiv E_{\boldsymbol{\vartheta}}(\hat{y}(\mathbf{x}, \boldsymbol{\vartheta}))$ is also continuous, as is the average over multiple climate-impact models. For example, Figure B.2 shows the relationship between global warming and the probability ratio of extreme heat events. While individual model runs (thin lines) differ and can be volatile, the aggregate result (thick lines) is continuous and smooth.

The continuity argument also applies to other tipping points – thresholds "beyond which a system reorganizes, often abruptly and/or irreversibly" (IPCC 2021, sec. 1.4.4). Notably, in addition to feedback effects in the outcome itself, as described above, there can also be feedback effects on the whole climate system. For example, the disappearance of the Greenland glacier can further increase temperatures, as land and ice absorb more sunlight than snow covers (albedo effect). These feedback loops are not captured in the simplified causal chain depicted in Figure 1. However, epistemic uncertainty is large about all tipping points. Confidence intervals for the level of warming at which global tipping points will be reached are at least 1 °C wide (McKay et al. 2022). Because of this uncertainty, captured in a continuous distribution over temperature thresholds, averaging across different parameters and models again implies continuity of $\tilde{d}_y(T)$ and $d_y(x)$.[21]

[19] Radiative forcing is 0.56 W/m² per 1 $TtCO_2$ (Hsiang and Kopp 2018). The result is obtained by multiplying the former with the earth's surface area ($5.1007 \times 10^{14} m^2$).

[20] A typical household LED light bulb uses 8W of energy. "Forever" assumes that there are no automatic or human corrections to the increased concentration (Matthews et al. 2009).

[21] Note also that the IPCC is very confident that tipping points will not affect global, end-of-century outcomes, which are the focus of this study (IPCC 2021). Instead, tipping points with a global impact (such as the melting of the Greenland and West Antarctica ice sheets) are likely to unfold over several centuries, not this century. Although this conclusion may change as models start using a finer resolution

Montonicity. In addition, for the outcomes considered in this study, there exists no tipping point such that the marginal impact becomes zero afterwards (McKay et al. 2022). This could happen with some local outcomes, such as the Greenland glacier (see above). However, here I consider global outcomes, such as the total amount of glacier ice in the world. None of these outcomes are predicted to be depleted in the global warming range $T \in [0, 5]$ °C. Some micro-level discontinuities may exist (e.g., a chunk of glacier ice falling of), but these are impossible to predict with any degree of certainty and will average out through the expectations operator. This means the impact of a small emission reduction will be positive regardless of whether a given tipping point is reached or not.[22] The following result summarizes the findings.

Result 3.1. *Climate change is a continuous or monotonous public goods game:*

1. *Marginal impact* $m_y(x)$ *is continuous,*
2. $m_y(x) > 0$, *even if tipping points were known exactly.*

3.3 Strategic Substitutability

The extent to which the effect of one person's emission reductions on climate change outcomes depends on others' (overall) emission reductions x^r is governed by the shape of the damage function. By Equation (2), the marginal impact $m_y(x)$ is weakly increasing if and only if $d_y(x)$ is weakly convex. In this case, overall emission reductions weakly decrease the marginal impact. I call this strategic substitutability.[23] Conversely, if the damage function is strictly concave, the marginal impact is strictly decreasing in overall emissions and strictly increasing in overall emission reductions, which I call strategic complementarity.

An analysis of a representative list of outcomes confirms that the marginal impact is weakly increasing for most outcomes. Among the 15 outcomes deemed very important by IPCC (2021) and for which they assess the shape of the damage function, 53% are linear, 33% are convex, and only 13% are concave, see Table B.1. Thus, 87% of outcomes exhibit strategic substitutability. Note that this is in line with the functional form assumption typically made in environmental economics (Hassler and Krusell 2018). The exceptions are mostly outcomes that are approaching their physical limits. In the case of glacier ice, at 2.4 °C warming, nearly half of preindustrial glacier mass will disappear

and include key processes relevant to tipping points (Palmer and Stevens 2019).

[22] Here I am assuming that reaching tipping points is always bad. Some tipping points may decrease overall global warming (McKay et al. 2022). I assume that other drawbacks (e.g., non-reversibility, local effects) dominate the effect of reaching those tipping points on overall utility.

[23] For caveats about this definition, see Footnote 8.

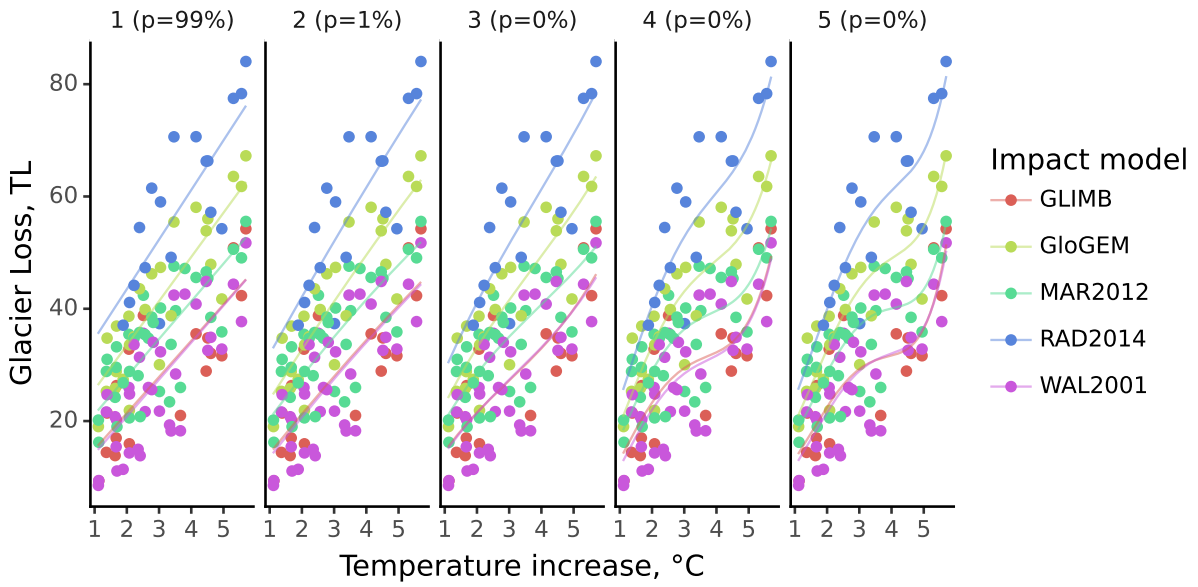


Figure 2: Damage function for glacier ice

Note: Predicted amount of glacier ice melting (in teraliters, TL) as a function of temperature increase, for several impact models and functional forms. Dots: individual model projections for 2100 by impact model (color) from Marzeion et al. (2020). Panels: polynomial of the damage function s (and posterior model probability $p(s|\text{data}_y)$). Lines: model-specific damage functions $\tilde{d}_{yis\hat{\theta}}(T)$ for impact model i, polynomial s and statistical parameters $\hat{\theta}|s = E(\theta|s, \text{data}_y)$, estimated using Equation (16). Results for other outcomes shown in Figures B.3 and B.4

by 2100. In fact, under 4.4 °C warming glaciers in Central Europe, Caucasus, Western Canada and US, North Asia, Scandinavia and New Zealand are predicted to lose ≥80% of their mass (IPCC 2021). As a result, the rate of change decreases as global temperatures increase further. Thus, the marginal impact is decreasing in overall emissions and temperature increase for glacier ice and similar outcomes.

Result 3.2. *For most outcomes y and expected emissions x^e, the marginal impact $m_y(x^e - x^r)$ is weakly decreasing in emission reductions x^r (strategic substitutability):*

$$\frac{\partial m_y(x^e - x^r)}{\partial x^r} \leq 0.$$

3.4 Point Estimates

Figure 2 shows the estimated damage function for glacier ice. Each panel shows one statistical model. The panel title indicates the order of the polynomial and the model posterior probability. The thin colored lines are the damage functions for each climate-impact model combination $\tilde{d}_{yis\hat{\theta}}(T)$, while the thick black line is the overall damage

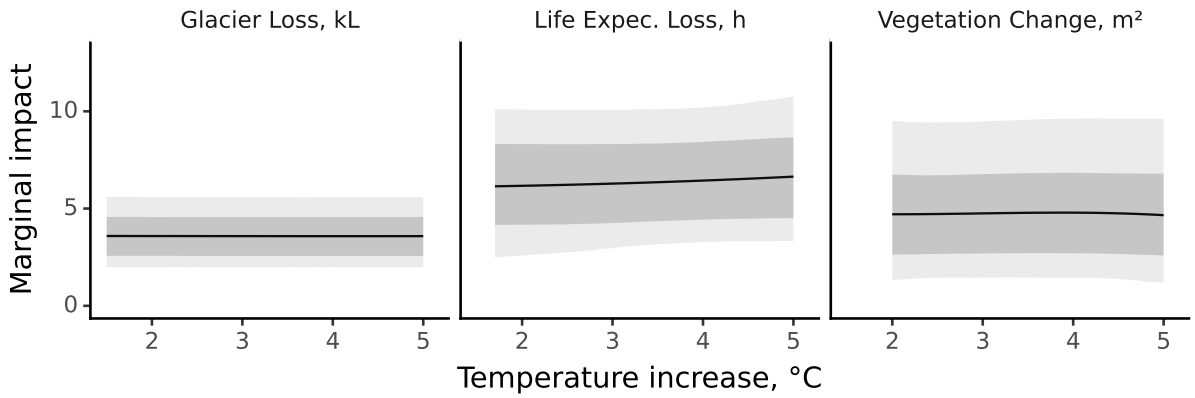


Figure 3: Marginal impact for several outcomes

Note: Marginal impact of reducing emissions by 1 tCO_2 as a function of overall temperature increase for glacier ice loss (in kiloliters, kL), aggregate life expectancy loss (in hours, h) and vegetation undergoing ecosystem change (in square meters, m²) by 2100. Aggregate life expectancy is the life expectancy of everyone who lives until 2100 combined. Estimated using a Monte Carlo simulation for Equation (17) and data from Marzeion et al. (2020), Carleton et al. (2022), and Warszawski et al. (2013). Impact models drawn with equal probability, functional form from the model posterior probability, statistical model parameters from the coefficient posterior probability and the transient climate response to cumulative emissions (TCRE) from the distribution in IPCC (2021). Black line: point estimate. Grey area: 67% (dark) and 90% (light) interval.

function $\tilde{d}_{ys\hat{\theta}}(T)$. The Bayesian procedure does well in terms of preventing over-fitting. The fifth order polynomial, which appears to show signs of over-fitting by visual inspection, has 0% posterior probability for all three outcomes. This also confirms that $n_s = 5$ is sufficiently large.

There is heterogeneity in the best fitting models, but the damage functions are mostly linear or convex, in line with the findings in the previous section. For all three outcomes, the linear damage function receives the highest posterior probability, with lower probabilities given to the second and third order polynomials. For glacier ice melting (Figure 2), the quadratic damage function (second panel) is slightly concave. On the other hand, the damage functions for life expectancy (Figure B.3) and vegetation change (Figure B.4) the higher order polynomials are mostly convex.

Figure 3 shows the predicted marginal impact as a function of temperature. The line is the point estimate, while the gray areas are the confidence intervals resulting from my Monte Carlo simulation. The estimates take into account uncertainty arising from impact models, the damage function's functional form, its parameters and the temperature response to emissions. In line with the mostly convex damage functions for life expectancy and vegetation change, the marginal impact is increasing for these outcomes. However, the non-linearity is small, and I cannot rule out that the marginal

impact is constant as a function temperature for any of the three outcomes.

The estimated marginal impact is statistically significant and tangible for all outcomes. At current expected emissions and global warming of 2.4 °C, the marginal impact is 3.6 (67% CI: 2.6-4.6) kiloliters less glacier ice melting, 6.2 (67% CI: 4.2-8.3) hours longer life expectancy, and 4.7 (67% CI: 2.7-6.7) m² less vegetation undergoing ecosystem change. Thus, in the 67% ("likely" in the IPCC classification) credible interval the order of magnitude remains the same as for the point estimates. The same is true for the 90% ("very likely") credible interval: 2.0-5.6 kL glacier ice, 2.7-10.1 h life expectancy and 1.4-9.4 m² vegetation change.

These estimates are likely conservative. They rely on the standard assumption that cumulative emissions in 2100 are a sufficient statistic for damages in 2100 (see Section 2.2). In Appendix A.2, I show that this assumption will lead to a downward bias for outcomes with delayed effects. In Semken et al. (2025), we confirm that the results are indeed robust to relaxing this assumption: estimates become larger for outcomes with substantial delayed effects (glacier ice), while differences for those without (life expectancy and vegetation change) are not statistically significant. Similarly, the glacier point estimate is also below the 8 kL estimated by Marzeion et al. (2018).[24]

Result 3.3. *At expected emissions x^e – consistent with current national targets and 2.4 °C of global warming – the projected marginal impact $m_y(x^e)$ of reducing emissions by 1 tCO_2 is:*

1. *3.6 (90% CI: 2.0-5.6) kiloliters less glacier ice melting,*
2. *6.2 (90% CI: 2.7-10.1) hours longer life expectancy,*
3. *4.7 (90% CI: 1.4-9.4) m² less vegetation undergoing ecosystem change.*

3.5 Discussion

The objective of this paper is to compare the conventional wisdom on the impact of small emission reductions with the predictions implicit in climate scientists' models. In the conventional wisdom, small emission reductions can have no impact on climate change outcomes. However, as Result 3.1 shows, every tCO_2 matters in expectation. Not only that, but climate models also suggest that the impact on outcomes is tangible, as shown in Result 3.3. Finally, it is commonly believed that one's impact increases the more people reduce their emissions (strategic complementarity). Yet, as Result 3.2 shows, for most climate change outcomes the marginal impact of emission reductions

[24] Marzeion et al. (2018) report the committed glacier mass change per kg of CO_2 emitted (Fig. 2). The study is based on a smaller ensemble and does not include Greenland and Antarctica, leading to an estimate of around 8 kL at 2.4 °C of global warming.

decreases with overall emission reductions (strategic substitutability). Thus, having a meaningful impact does not require the collaboration of others.

None of this is to suggest that collaboration to achieve our global climate change goals is not important. While the impact of small emission reductions may be large in absolute terms it still only affects a fraction of global systems threatened by climate change. Moreover, avoiding tipping points is important, as they could have severe regional consequences in the short-term, severe global consequences in the very long run, and be irreversible (IPCC 2021, sec. 5.4.9). Thus, we should care about tipping points. However, the above results show that the existence of tipping points does not imply that the expected marginal impact is zero. The predicted impact of a 1 tCO_2 emission reduction is tangible, whether or not we reach global targets.

4 Beliefs

4.1 Experimental Design

The first experiment consists of a baseline survey and an obfuscated follow-up survey. The baseline survey contains several parts: introduction and consent, views on climate change, explainers, baseline measures, belief elicitation, information intervention, demographics and feedback. The explainer and belief elicitation are described below. The baseline measures, information intervention and obfuscated follow-up are explained in Section 5.1. Views on climate change and demographics are explained in Section 7.1. The full instructions for the baseline survey are provided in Appendix C.2.

Explainers. The belief survey uses the term "global warming". Participants are provided with a short definition of global warming and a simplified version of the causal chain leading from actions to climate change outcomes (shown in Figure 1).[25] This ensures that all participants have a basic understanding of how climate change works.

Belief order. The order of the questions about the marginal impact is the reverse of Section 3: absolute marginal impact, complementarity and continuity. This order is chosen, first, so that the last marginal impact (vegetation change) may serve as an example in the following questions. Second, nudging people into threshold thinking by asking the continuity question first could bias the results of the other two questions.

[25] I provide the following definition, which is adapted from Andre et al. (2024): "Global warming refers to the fact that the world's average temperature has considerably increased over the past 150 years and will continue to increase in the future."

To avoid this effect, I ask this question last. The point estimate beliefs are elicited separately for each of the three climate change outcomes and their order is randomized.

Point estimate belief. Before eliciting the absolute marginal impact belief, I illustrate 1 tCO_2 and fix key assumptions. To ensure participants have a clear understanding of how much 1 tCO_2 is, I provide them with three actions that emit about 1 tCO_2: (a) driving 10 miles a day for 1 year (with an average diesel car), (b) eating 5 servings of meat per week for 1 year (beef, pork or lamb), and (c) taking 1 long-distance return flight, for example London to New York and back (Jones and Kammen 2011; Ivanova et al. 2020; IPCC 2022b, sec. 5.3.1.2). I provide (a) and (b) as daily amounts during one year, to avoid psychophysical numbing (Heath and Starr 2022). Participants are asked to "assume governments take no actions beyond their current targets, leading to 2.4 °C of warming". Moreover, I highlight that the effect is an aggregate measure ("the sum of all changes in the world") and explain what this means using glacier ice (where the effect "could consist of small amounts of ice melting from each glacier") as an example.

Beliefs over the absolute marginal impact $m_y(x^e)$ are elicited using a novel "augmented staircase" method. First, participants state if emitting 1 tCO_2 will affect the outcome at all. Second, if the answer is yes, they select an order of magnitude using the staircase method (Cornsweet 1962). At each step – explained in more detail below – participants see an amount and choose if the true amount is "less than" or "more than" the amount. The order of these options is randomized. Third, they refine the estimate using a slider, shown in Figure C.3. Above each question, participants see a short explanation of the effect and the unit(s). Additional, on the staircase pages, they see an illustration of the amount in question.

To get a conservative estimate, participants who think the impact is non-zero are anchored with the correct answer. Specifically, the staircase starts with $m_y(x^e)$ derived in Section 3, rounded to one significant digit. The first step is shown for the vegetation outcome in Figure 4. Anchoring effects could be sizable, as participants have probably never thought about the marginal impact, possibly leading to high cognitive uncertainty (Enke and Graeber 2022). To also mitigate possible response-order or primacy effects (Krosnick and Alwin 1987), the order of the options is randomized. Together the two features ensure that these cognitive effects would bias the belief average towards $m_y(x^e)$, making it a conservative measure of misbeliefs.

The augmented staircase spans 18 orders of magnitude, see Table C.1. After the anchor, the next option is six orders of magnitude above or below. The final step is three orders above or below this value. If participants select an interior value (i.e. not

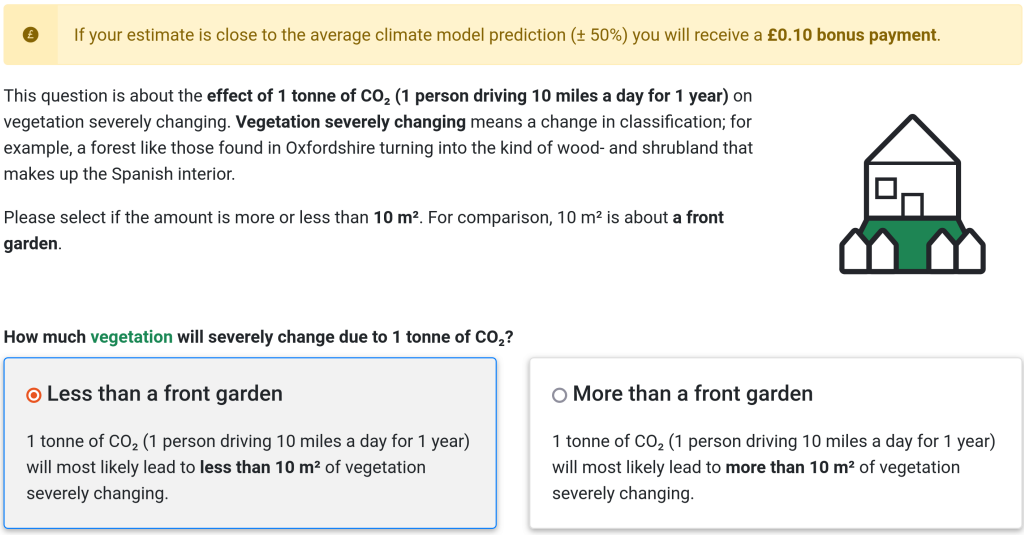


Figure 4: Point estimate elicitation

Note: First staircase step in the marginal impact point estimate belief elicitation for vegetation change. Part of the "augmented staircase" method. Shown to participants who first indicate that 1 tCO_2 has an impact on vegetation change. Shows correct order of magnitude from Result 4.3. Question followed by two more staircase steps and a slider, shown in Figure C.3. The remaining staircase options are shown in Table C.1. Estimate is for the effect of emitting 1 tCO_2, assuming governments implement current pledges and no one else changes their behavior (explained to participants during an instructional video).

less than $m_y(x^e) \cdot 10^{-9}$ or great than $m_y(x^e) \cdot 10^9$), can use the slider to refine their estimate, see Figure C.3. The slider is bound by the previous choices (for example $[m_y(x^e) \cdot 10^{-3}, m_y(x^e)]$ after selecting <, > and >). The final estimate is rounded to one significant figure.

The "augmented staircase" procedure has several advantages. First, all three questions are intuitive to participants. Second, participants can enter an exact zero on an otherwise logarithmic scale. Third, the pictures in the magnitude options make the exponential increase in the amount comprehensible to lay people (Heath and Starr 2022). Fourth, the slider question allows for a precise estimate, on a cognitively less demanding range.[26]

The numeric representations use the typical wording for large numbers (e.g. 10^3 = 1,000 and 10^6 = 1 million) and frequently used units (e.g. mL but not µL). The base units are metric, as in Result 3.3, but for glacier ice I additionally provide a conversion to imperial units. The visual representation is meant to be intuitive for the average participant. For example, the volume of glacier ice melting ranges from a drop of water to the water in Loch Ness (the UK's largest body of water). The visual representations are shown in Table C.1.

[26]Note that while precision increases from the zero to the slider question, confidence and test–retest reliability are likely to decrease.

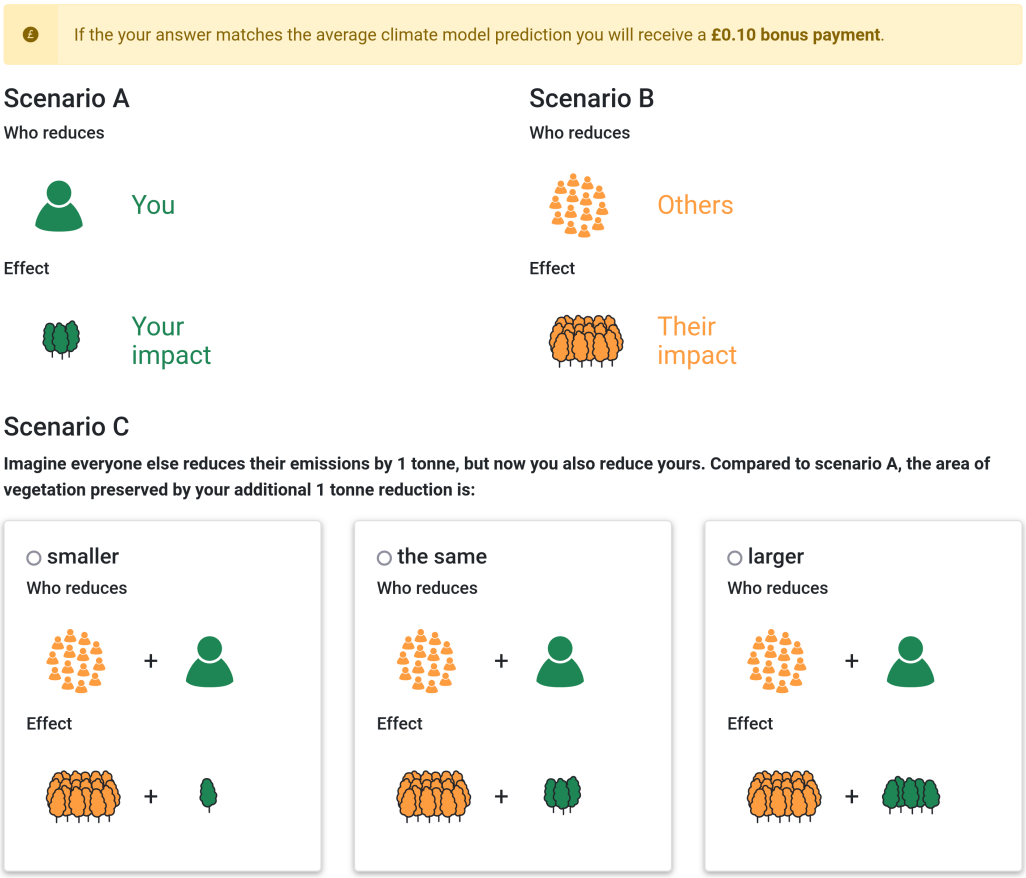


Figure 5: Complementarity elicitation

Note: Belief elicitation for complementarity, i.e. how the marginal impact of a 1 tCO_2 emission reduction changes as a function of others' emission reductions. Green trees: impact of a participants' 1 tCO_2 reduction. Orange trees: impact of everyone else's 1 tCO_2 reduction. Answer "smaller" corresponds to strategic complementarity $[\partial m_y(x^e - r)/\partial r < 0$, where $m_y(\cdot)$ is the marginal impact, x^e are expected emissions and r are overall emission reductions], "larger" to strategic substitutability $[\partial m_y(x^e - r)/\partial r > 0]$ and "the same" to neither $[\partial m_y(x^e - r)/\partial r = 0]$.

Complementarity belief. To test beliefs about the strategic complementarity of emission reductions, I use a hypothetical vignette (Haaland et al. 2023). The question is shown in Figure 5. Participants are asked to compare three scenarios. In the scenario A, they are the only ones reducing emissions by 1 tCO_2 "in addition to what governments have already promised". In scenario B, "everyone else in the world" but not the participant is reducing emissions by 1 tCO_2. Finally, in scenario C, both everyone else and they reduce emissions. The question asks if compared to scenario A, the impact of reducing emissions by 1 tCO_2 on the area of vegetation is saved from ecosystem change is (a) larger, (b) smaller or (c) the same. The impact of both others' and the participants own emission reductions is visualized for all three options. The former is always the same size as in scenario B while the latter is larger, smaller or the same size as in

scenario A. The vegetation outcome was chosen because here the prediction is unambiguously "smaller", as it is for most outcomes (Result 3.2). The order of the answers – whether ascending or descending – is randomized. The question is explained in a video.

Threshold belief. To test beliefs about the relevance of thresholds, participants are asked whether several statements are true or false, see Figure C.11. Specifically, I ask whether: there are "there is a dangerous level of global warming, at which global warming outcomes will become much worse" (*exist*), "we know the temperature at which we will reach dangerous global warming to at least one tenth of a degree (such as 1.5 °C or 2.0 °C)" (*known exactly*), "one person cannot prevent dangerous global warming" (*one cannot prevent*), "one person reducing emissions will not have any direct impact on global warming outcomes, if we cannot prevent dangerous global warming" (*zero after*), and "at current expected emissions, based on current government policies and individual behavior, we will exceed the dangerous level of global warming" (*exceed*). The first question provides a definition. Note that the questions *exist*, *one cannot prevent* and *exceed* may be true or not, depending on ones assumptions. However, *known exactly* and *zero* are inconsistent with the climate scientific Result 3.1. The other questions are included to validate the assumptions of the theoretic model. Participants are told that one question will be chosen for the incentive and the question is always *known exactly*.

Incentives. Participants are incentivized to give answers that match those derived in Section 3. Specifically, they receive a £0.10 bonus when their continuity and complementarity answer matches Result 3.1 and Result 3.2, respectively, and if their absolute marginal impact answer lies within a $\pm 50\%$ range of Result 3.3. Participants are also told that the best feedback is rewarded with a £5 bonus payment. This was found to increase engagement.

4.2 Empirical Strategy

To test for the presence of misbeliefs, I provide the average answers with their 95% confidence interval (CI). For the threshold result, I calculate the percentage of participants who think the *know* and *zero* questions are true. Agreement with the latter question implies that $\exists x : m_y^p(x) = 0 \; \forall \; x > x^*$ where m_y^p is the perceived marginal impact. For the complementarity result, I calculate the percentage of participants who think there is strong strategic complementarity (answer "larger") and weak strategic complementarity (answer "larger" or "the same").

For the point estimate, I report the average misbelief in orders of magnitude. Specifically, I use the median of the log belief relative to the true model value across outcomes:

$$\log_{10}\left(\text{median}\left(\frac{m^p_{yi}(x)}{m_y(x)}\right)\right) \tag{4}$$

where $m_y(x)$ is the estimate obtained in Result 4.3 and $m^p_{yi}(x)$ is the belief of participant i. I use the median because, unlike the mean, it is invariant to the order of the operations and less sensitive to outliers. Additionally, I provide the percentage of people who underestimate the median impact across the three outcomes.

4.3 Sample

The study was carried out on Prolific. Participants are UK residents between 18 and 65 years old. I chose the UK because it is an English-speaking country that is close to the global average in terms of knowledge about and attitudes towards climate change (Hickman et al. 2021; Dechezleprêtre et al. 2025). To make the sample more representative, it is balanced by gender.

I deploy several strategies to increase data quality. First, participants have to have a 95% approval rate and must use a PC or tablet, to guarantee a comparable experience. Second, I appeal to participants' prosociality by mentioning on the first page that the quality of the research depends on them reading the questions carefully and providing honest answers. I try to limit attrition by mentioning upfront that the survey includes questions about how global warming works but that no prior knowledge is required, asking participants to give us their best guess if they are unsure. Third, I include two attention checks, one during the baseline survey and one at the end of the belief section. Participants who fail both attention checks are excluded.

The experiment took place in November and December 2023. In total, 600 participants completed the baseline survey. This sample size was determined using a power analysis for the information provision experiment, see Section 5.3. All participants passed the attention checks. The sample is relatively representative in terms of gender and age, but somewhat higher income, more educated and more environmentalist than the UK population, see column (1) of Table D.1.

4.4 Results

Figure 6 shows the threshold beliefs. A majority of participants think that all statements are true, including the two false statements. First, 77% (95% CI: 73%-80%) of participants think temperature thresholds of tipping points are known with at least one

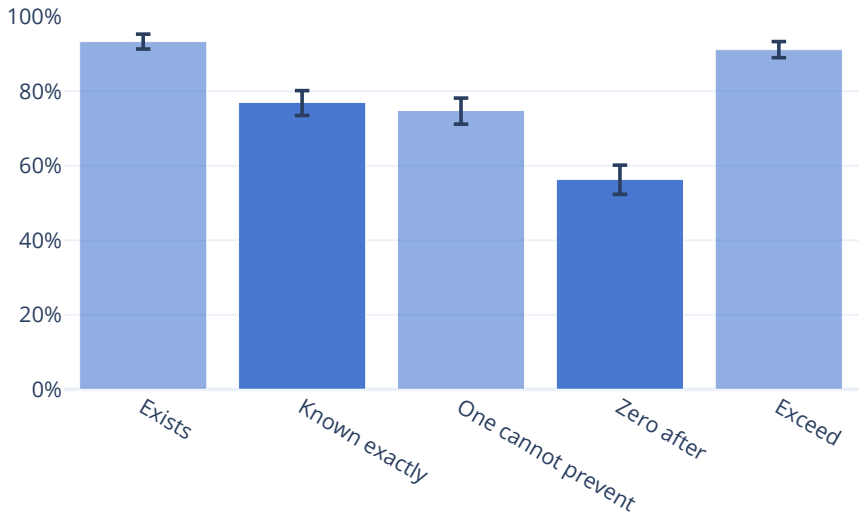


Figure 6: Threshold beliefs

Note: Percentage of participants agreeing with statements about thresholds: whether (a) they exist, (b) they are known to at least a tenth of a degree, (c) they cannot be prevented by one person, (d) the marginal impact is zero after crossing them and (e) they will be exceeded at current expected emissions. Solid colors (answers *known exactly* and *zero after*): agreement is inconsistent with the climate scientific Result 3.1. Error bars: 95% confidence intervals.

order of magnitude greater precision than is the case. Second, 56% (95% CI: 52%-60%) think that the marginal impact is zero after crossing these temperature thresholds. Thus, most participants perceive climate change as a threshold public goods game.

Result 4.1. *Most subjects believe climate change is a threshold public goods game:*

$$\exists x^* : \quad m_y^p(x) = 0 \quad \forall\, x > x^*.$$

In terms of strategic interactions, 93% (95% CI: 91%-95%) of participants think own and overall emission reductions are weak strategic complements. Of those, 67% (95% CI: 63%-71%) believe the marginal impact would be larger if others reduced their emissions (strong strategic complementarity), see Figure 7. Only a small minority believe that emission reductions exhibit strategic substitutability, as predicted by the climate scientific Result 3.2.

Result 4.2. *The perceived marginal impact $m_y^p(x = x^e - x^r)$ is increasing in emission reductions x^r (strategic complementarity):*

$$\left.\frac{\partial m_y^p(x^e - x^r)}{\partial x^r}\right|_{x^r=0} > 0.$$

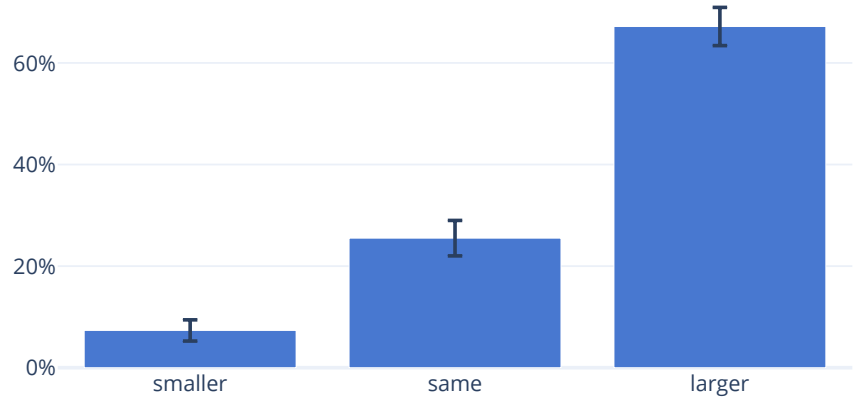


Figure 7: Complementarity belief

Note: Percentage of participants indicating that the marginal impact is "smaller" (strategic substitutability), the "same" or "larger" (strategic complementarity) if everyone else also reduced their emissions. Elicited using the hypothetical vignette shown in Figure 5. "Smaller" is the prediction derived from the average climate model in Result 3.2. Error bars: 95% confidence intervals.

Finally, participants under-estimate the absolute marginal impact. The median participant underestimates it by 1.6 (95% CI: 1.2-2.0) orders of magnitude. Moreover, they underestimate the marginal impact for all outcomes, see Figure 8. Finally, the median estimate is well below even the lower bound of the climate scientific Result 3.3.

Result 4.3. *The average perceived marginal impact is smaller than the projected marginal impact:* $m_y^p(x^e) < m_y(x^e)$.

5 Attitudes and Intentions

5.1 Experimental Design

The second part of the first experiment investigates the effect of providing the climate scientific Results 3.1 to 3.3 on attitudes and intentions. It consists of an information provision section and an obfuscated follow-up survey. The preceding baseline and belief sections of the survey are described in Section 4.1. The last page of the obfuscated follow-up survey, which elicits moral views, is described in Section 7.1. The full instructions are provided in Appendices C.2 and C.3.

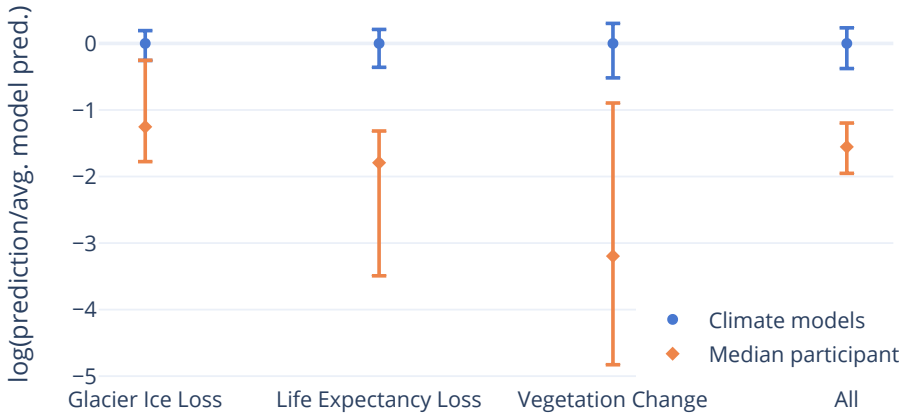


Figure 8: Point estimate error

Note: Median marginal impact belief compared to the climate scientific results for different outcomes, in orders of magnitude, estimated using Equation (4). Unit: log with base 10 of prediction divided by the average climate model prediction (point estimate from Result 3.3). Blue dots: climate scientific Result 3.3 for different outcomes or mean over all outcomes ("All"). Orange diamonds: median perceived marginal impact for different outcomes or median of all outcomes and participants ("All"). A value of $-x$ implies that the prediction is x orders of magnitudes below the average climate model prediction. Beliefs estimated using the "augmented staircase" method, see Figure 4. Error bars: 90% confidence interval from Result 3.3 and Figure 3 (blue, top) and 95% confidence interval of the median perceived value (orange, bottom).

Information provision. The information provision section is a continuation of the belief survey and is structured as follows. Participants are randomly assigned into a treatment and a control group. Treated participants are provided with the continuity, complementarity and absolute marginal impact results from Section 3. This order is chosen to build a coherent narrative. In particular, deriving a meaningful absolute marginal impact requires continuity of $m_y(x)$.

The provision of answers is gamified to increase engagement (Balsters and Evershed 2021). The pages for the continuity and complementarity result have the same layout as the questions, see Figures C.12 and C.13, respectively. The model-based result is highlighted in green with a check mark. If the participant's answer matches the climate scientific result, then it gets a second check mark. Otherwise, the participants answer is highlighted in red with a cross mark. The continuity page also contains a short summary of the explanation from Section 3.2. The three absolute marginal impact results are all shown on one page, see Figure C.14. For each outcome, I show their answer, the climate scientific result and the visualization for the nearest order of

magnitude.

The control group is an active control group. Participants see a reminder of their answer and rate the question. This is done to rule out that the effect is driven by a difference in salience of the estimates or the level of engagement. At the end of the information provision, a 2-minute video summarizes the results. It emphasizes that the marginal results are cumulative. No video is shown to the control group.

Baseline measures. At the start of the belief survey, I elicit baseline attitudes and intentions. Self-efficacy is measured using three statements adapted from the environmental psychology literature (Hornsey and Fielding 2016; Hornsey et al. 2021; Angill-Williams and Davis 2022), such as "I feel able to contribute to tackling global warming". Intentions cover both own emission reductions in the next 12 months and encouraging others to reduce emissions. All of these variables are measured on a 7-item Likert scales and their order is randomized.

Obfuscated follow-up. Three days after the first survey I invite all participants to an obfuscated follow-up survey.[27] This survey is carried with a different researcher name, consent form, layout, coloring scheme, domain and framing (climate change instead of global warming). Leaving three days between the main and the follow-up survey ensures that most participants will have at least one other study, as the majority of Prolific users spends between 1 and 2 hours per week on the platform (Peer et al. 2022).[28]

The follow-up survey measures self-efficacy and intentions to reduce emissions. Self-efficacy is again measured using three questions adapted from the environmental psychology literature (Hornsey and Fielding 2016; Hornsey et al. 2021; Angill-Williams and Davis 2022). I pick different questions and consistently use "climate change" instead of "global warming" to further obfuscate the connection to the first survey. Intentions to reduce emissions are measured using four questions from Hornsey and Fielding (2016). I ask how likely the participant would engage in certain activities "should the opportunity arise in the next 12 months". They are: "switch household appliances off at the wall socket to reduce energy consumption", "take steps to reduce my carbon footprint", "use alternative forms of transport such as walking, cycling, or public transport" and "choose energy efficient appliances and electronic equipment". I also

[27] Participants have a maximum of four days to complete the survey.

[28] While the study was done by Prolific employees with a potential conflict of interest, this result is unlikely to be upward biased. As the authors note themselves, "previous research has suggested that sites where participants' frequency of usage is lower (e.g., Prolific) show higher data quality" (Peer et al. 2022). Thus, the authors would have, if anything, had an incentive to report lower usage numbers.

ask participants whether they would convince others to reduce their carbon footprint and learn more about how to reduce their carbon footprint (7-item Likert scale).

Experimenter demand. Experimenter demand effect is a potential problem in all information provision experiments. Besides the use of an obfuscated follow-up, I follow several other recommendations from Haaland et al. (2023) to mitigate it. To confirm the obfuscation, I ask participants at the end of the follow-up survey what they think the purpose of the study was Bursztyn et al. (2020). I check if they mentioned the baseline survey and additionally provide the results for the subsample of subjects who did not.

5.2 Empirical Strategy

The primary outcomes of the information provision experiments are self-efficacy as well as intentions to reduce emissions. The two measures are averages of the three self-efficacy and four intention questions, respectively. The questions are weighted by the inverse of their covariance (Anderson 2008). Secondary outcomes are the four items that make up the intention scale, intentions to convince others and to learn more about how to reduce ones carbon footprint.

I estimate the local average treatment effect τ on these outcomes using the following regression model:

$$y_i = \tau t_i + X_i'\gamma + \varepsilon_i \tag{5}$$

where y_i is the outcome variable, t_i is a treatment indicator, X_i is a vector of baseline covariates for individual i, and $\varepsilon_i \sim N(0, \sigma^2)$ is a random error. X_i includes the baseline self-efficacy index, intentions to reduce emissions and intentions to convince others. Let r_b^* and r_t^* be the predicted reductions of control and treated participants, respectively. I test the null hypothesis that $r_t^* - r_b^* = \tau \neq 0$ at the 5% significance level using heteroscedasticity robust standard errors. All outcomes and baseline variables are z-scored before the regression to obtain the treatment effect in standard deviations.

I use the full set of baseline participants for the donation outcome and the retained participants for the remaining outcomes. This assumes no selective attrition between the two surveys. I validate this assumption using a test of mean differences between the two treatment groups at the 5% significance level. To gauge experimenter demand effects, I manually code the participants' believes about the purpose of the study, check if they mentioned the first study, and report the total number and percentage of answers that do.

Table 1: Treatment effect – primary outcomes

	Self-efficacy	Intentions	Donation
	(1)	(2)	(3)
Info treatment	0.292***	0.105**	0.259***
	(0.038)	(0.053)	(0.066)
Baseline values	✓	✓	
Observations	545	545	600
R^2	0.660	0.298	0.028
Control mean	0.0	0.0	65.3
Control s.d.	1.0	1.0	54.1

Note: Between subject treatment effect of providing participants with the climate scientific Results 3.1 to 3.3. Information was provided in a seemingly unrelated survey three days before in experiment 1 [columns (1)-(2)], and in the same survey in experiment 2 [column (3)]. Experimental designs are described in Section 5.1 and Section 6.1, respectively. Coefficient: treatment effect τ in standard deviations, estimated using Equation (5) and Equation (6), respectively. Outcomes: (1) perceived self-efficacy index, (2) intentions to reduce emissions index, and (3) donations to reduce global emissions. Baseline values: controls for baseline values of perceived self-efficacy, intentions to reduce emissions and to convince others to reduce emissions. Robust standard errors in parentheses. Control mean and standard deviation (s.d.) in column (3) are calculated before standardization. *p<0.1; **p<0.05; ***p<0.01.

5.3 Sample

The sample size was determined using a Monte Carlo power analysis and data from two pilots. The treatment effect on intentions to reduce emissions, using the pooled pilot data, was 0.16 standard deviations. Based on 1000 simulations of the regression with baseline covariates in Equation (5), a sample size of 500-600 was predicted to detect a treatment effect at the 5% significance level with 85.0-90.7% power.

Of the 600 participants from the baseline survey, 545 completed the follow-up survey. There was no selection into the follow-up survey by treatment (p=0.8877). The sample remains relatively representative in terms of gender and age, but somewhat higher income, more educated and more environmentalist than the UK population, see column (2) of Table D.1.

5.4 Results

Informing participants in the treatment group about the climate scientific Results 3.1 to 3.3 has a large effect on attitudes and intentions. Table 1 columns (1) and (2) show the treatment effect. The information treatment increases perceived self-efficacy and intentions to reduce emissions by 0.29 (95% CI: 0.22-0.37) and 0.11 (95% CI: 0.00-0.21) standard deviations, respectively.

The obfuscation of the follow-up survey worked well. Only 2 participants (0.3%) mention the first survey. The treatment effect is robust to removing these participants, see Table D.2.

The treatment also has an effect on several secondary outcomes. It leads to an increase in intentions to switch off electronic devices and to decrease ones carbon footprint, but not necessarily to use alternative means of transport or more efficient devices, as shown in columns (1)-(4) of Table D.3. Moreover, it increases intentions to convince others and learn about how to reduce one's own footprint, as shown in columns (5) and (6) of Table D.3, respectively.

Result 5.1. *Subjects in the information treatment intend to reduce their emission more than those in the control group:* $r_t^* > r_b^*$.

6 Behavior

6.1 Experimental Design

The second experiment investigates the effect of providing the climate scientific results Results 3.1 to 3.3 on real donations to reduce global emissions. The full instructions are provided in Appendix C.4.

Explainers. The study, like the belief survey in Section 4, begins with views on climate change and explainers. Participants see a definition of global warming and a simplified version of the causal chain leading from actions to climate change outcomes (shown in Figure 1).[29] It explains that actions (such as driving, flying, heating, and dietary choices) increase CO_2 concentrations, which leads to global warming. Global warming, in turn, affects several outcomes (such as glacier ice, life expectancy, and vegetation change). On the following page, I inform participants that 1 tCO_2 is created by driving about 4,000 miles with an average diesel car.

On each of these pages, participants are asked to rate how surprising they found the information on a 4-item Likert scale. This serves to increase engagement and obfuscate the purpose of the survey.

Information provision. Following the explainers, participants are randomly divided into a treatment and a control group. The treatment group sees one page each with the point estimates, threshold and strategic substitutes results, and a video summary.

[29] I use the same definition of global warming as in the belief survey, see Footnote 25.

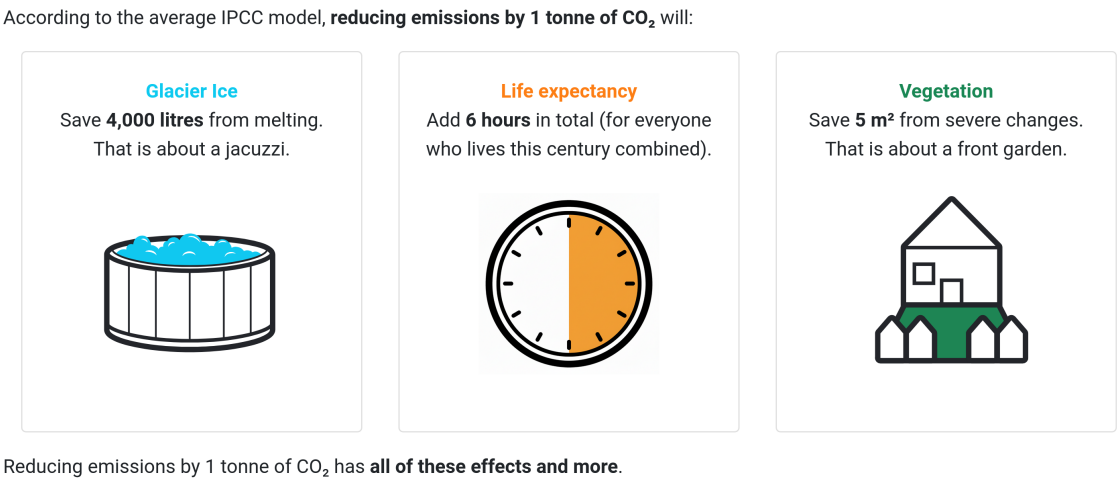


Figure 9: Information treatment

Note: Information treatment in the behavior experiment. Summarizes and visualizes Result 3.3. Shown only to participants in the information treatment group. Participants are asked to rate how surprised they are about this information at the bottom of the page, to increase engagement and obfuscate the purpose of the study. Full screenshot in Figure C.16. Participants also receive information about the threshold Result 3.1 and the strategic substitutability Result 3.2, see Appendices C.4.8 and C.4.9.

On the point estimates page, I show all three estimates from Result 3.3 with a visual representation, see Figure 9. I clarify that life expectancy refers to that for everyone who lives this century combined", and emphasize that the effects are cumulative. The threshold Result 3.1 is summarized in one sentence, while the strategic substitutability Result 3.2 is represented using the three scenarios from the belief elicitation, see Figure C.17. Again, participants are asked to rate how surprising they found this information.

Donation. The outcome of this study is a donation to reduce emissions. The donation task is adapted from Andre et al. (2024). Participants can divide £200 between themselves and a charity called atmosfair. The donation is used to reduce global emissions, by buying carbon offsets.[30] It costs about £20 to reduce global emissions by 1 tCO_2. At the end of the study, one participant is randomly selected and their decision is implemented. Participants choose by how much they want to donate using a slider. They can pick any value between £0 and £20. Alternatively, they can pick the amount of emission reductions. The sliders are automatically synchronized, see Figure C.18.

[30]The participants are provided with the following information. The offset program is run by a charity, works transparently, and only finances certified projects (Atmosfair 2024). Independent research has confirmed the effectiveness of the program (Stiftung Warentest 2018).

6.2 Empirical Strategy

The outcome in the donation experiment is the amount donated in pounds. I estimate the local average treatment effect τ on these outcomes using the following regression model:

$$y_i = \tau t_i + \varepsilon_i \tag{6}$$

where y_i is the outcome variable, t_i is a treatment indicator and $\varepsilon_i \sim N(0, \sigma^2)$ is a random error. There are no control variables.[31] The donation outcome is z-scored before the regression to obtain the treatment effect in standard deviations. I test the null hypothesis that $r_t^* - r_b^* = \tau \neq 0$ at the 5% significance level using robust standard errors.

6.3 Sample

The sample size of 600 participants was determined using a Monte Carlo power analysis and data from a pilot. The treatment effect, using the pilot data, was 0.23 standard deviations. Based on 1000 simulations of the regression in Equation (6), the sample size was predicted to detect a treatment effect at the 5% significance level with 91.0% power.

The study was carried out in October 2025 on Prolific. Experimental subjects are UK residents between 18 and 65 years old. The inclusion restrictions are the same as for the first study, see Section 5.3. The sample is relatively representative in terms of gender and age, see column (3) of Table D.1.

6.4 Results

Informing participants about the climate scientific Results 3.1 to 3.3 has a large impact on their real donations to reduce global emissions. Column (3) of Table 1 shows the treatment effect. The treatment increases donations by 0.26 standard deviations (95% CI: 0.13 - 0.39). The treatment is thus predicted to increase donations by £14 or 21%, relative to the control group.

Result 6.1. *Subjects in the information treatment reduce their emission more than those in the control group:* $r_t^* > r_b^*$.

[31] Unlike in the experiment on attitudes and intentions covered in Section 5, I did not elicit a baseline value of the dependent variable. The reason is that this a one-wave survey, and eliciting a baseline value of this unusual task may have led to experiment demand or consistency bias. Other available baseline measures, such as age and gender, were found not to increase statistical power in a pilot.

7 Heterogeneity

7.1 Survey Design

Several variables used for heterogeneity analyses are elicited in the belief and follow-up survey. At the start of the belief survey described in Section 4.1, participants are asked if they think global warming is mainly the result of human activity, if they trust climate scientists, and whether they consider themselves environmentalists (7-item Likert scales). At the end of the survey, participants are asked about whether they have children, their highest level of education and their household income. I further obtain biological sex and age from Prolific.

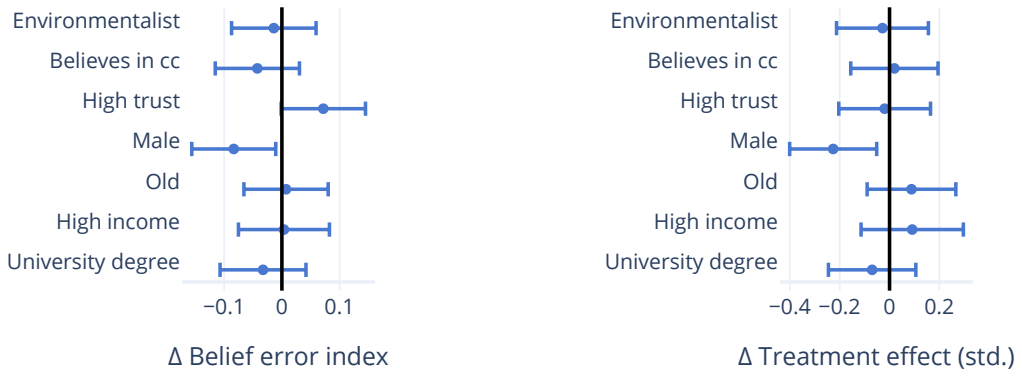
To make sense of the heterogeneity results, I also elicit moral views at the end of the obfuscated follow-up survey described in Section 5.1. I ask when reducing emissions is the "right thing to do". Participants choose their level of agreement (5-item Likert scale) with statements reflecting different moral arguments, which are described in Section 7.4. The order of the statements is randomized.

7.2 Empirical Strategy

To gauge heterogeneity in misperceptions and the treatment effect, I define several subgroup indicators. The subgroups are: environmentalists, believes in climate change, high (above median) trust in scientists, high (above median) income, male, old (above median age) and university educated. Since participants had the option to skip the income question, I only use the subsample that reported it for this subgroup analyses. All other heterogeneity analyses use the same samples as in Section 4.3 and Section 5.3, respectively.

To analyze heterogeneity in misperceptions, I construct an error measure for each of the belief Results 4.1 to 4.3, as well as a composite error index. "Threshold" and "complementarity" errors are defined as answering that we know exactly where thresholds lie and that the marginal impact exhibits strict strategic complementarity, respectively. A point estimate "error" is defined as having underestimated the marginal impact for at least two of the impacts. The motivation for the latter definition is that I expect this type of error, like the previous errors, to lead to lower perceived self-efficacy and thus a larger treatment effect. The error index is the simple average of these three variables. The belief heterogeneity measure is the difference in the average error rate between the subgroup and the remaining sample.

To assess heterogeneity in the treatment effect of correcting misperceptions, I look at the differential treatment effect on perceived self-efficacy, since it shows the largest



(a) Beliefs

(b) Treatment effect

Figure 10: Heterogeneity

Note: Heterogeneity in belief and treatment effect results. Subgroups (y-axis): environmentalist, believes in climate change, high (above median) trust in scientists, high (above median) income, male, young (below median age) and university educated. Error bars: 95% confidence interval. (a) Difference in the average error index between the subgroup and the remaining sample. Error index is the simple average of binary point estimate (underestimating at least two marginal impacts), threshold (we know exactly where thresholds are) and complementarity (strict strategic complementarity) errors, see Figures 6, 7 and 8, respectively. (b) Differential treatment effect, measured in standard deviations among the control group. Regression model: Equation (7). Outcome: perceived self-efficacy, see column (1) of Table 1.

treatment effect, see Section 5. Building on Equation (5), I use the following regression model:

$$y_i = \delta d_i t_i + \beta d_i + \tau t_i + X_i'\gamma + \varepsilon_i \tag{7}$$

where d_i is a dummy variable indicating whether subject i belongs to a given subgroup, and the outcome variable y_i, treatment indicator t_i, control variables X_i and error term ε_i are the same as in Section 5.2. I report δ as a measure of the differential treatment effect.

7.3 Results

The marginal impact belief errors per subgroup are shown in Figure 10a. Perhaps surprisingly, I find no evidence that environmentalists, those who believe in climate change and those with high trust in climate scientists make fewer errors on average. Males have a significantly lower error rate, while I find no evidence for belief difference by age, income or education.

The differential treatment effect on self-efficacy per subgroup is shown in Fig-

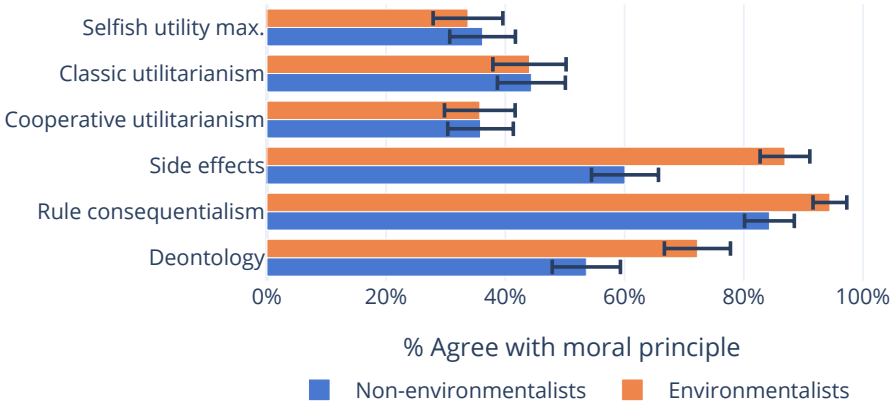


Figure 11: Moral reasoning

Note: Agreement with different moral principles among environmentalists and non-environmentalists. The question asked whether participants agreed with the following statements. One person reducing their emissions is the right thing to do: (1) only if it has larger personal benefits than personal costs ("selfish utility maximization"), (2) only if it has larger societal benefits than societal costs ("classic utilitarianism"), (3) only if everyone else also reduce their emissions ("cooperative utilitarianism"), (4) because it will inspire others to do the same ("side effects"), (5) because if everyone else did it, the world would be a better place ("rule consequentialism"), (6) independently of whether it has an impact on climate change outcomes ("deontology").

ure 10b. They track the results for the belief error index. Again, I find no evidence for a differential treatment effect by environmentalism, belief in climate change and trust in climate scientists. Males show a smaller treatment effect, while I find no significant difference by age, income or education.

7.4 Moral Reasoning

The finding that there is no difference in average misperceptions or the treatment effect between environmentalists and non-environmentalists may be surprising. Environmentalists have a 29% higher score in baseline intentions to reduce emissions than non-environmentalists ($p<0.001$). Thus, one might assume that they think that their emission reductions will have a large impact and that, as a result, the information provision would have a smaller effect.

This suggests that environmentalists reduce their emissions for reasons other than the direct impact on climate change outcomes. Typical moral principles that depend on the direct impact of an action include selfish utility maximization (private benefits > private costs), classic utilitarianism (social benefits > social costs) and cooperative

utilitarianism (social benefits > social costs, up to fair share).[32] However, people may also apply other moral principles in this setting, such as consequentialism with side effects (action inspires others), rule consequentialism (world would be better if everyone did it) and deontology (moral duty).[33] If environmentalists adhere to any of the latter moral principles, they may choose to decrease emissions, even if they do not expect this to have any meaningful direct impact on climate change outcomes.

To test this hypothesis, I ask participants if they agree that reducing emissions is "the right thing to do" for reasons derived from the above moral principles. Figure 11 shows the results for environmentalists and non-environmentalists. There is no discernible difference between the two groups in their agreement with arguments capturing selfish utility maximization, classic utilitarianism or rule consequentialism. By contrast, environmentalists are significantly more likely to agree with arguments capturing rule consequentalism, side effects and deontology.

This result provides suggestive evidence that different moral views can explain the equally large error rates and treatment effect among environmentalists and non-environmentalists. In particular, at baseline, they have the same misperceptions about the marginal impact. However, environmentalists may seek to reduce emissions for moral reasons that are independent of the direct impact on climate change outcomes (e.g, they want to "do their part" or "inspire others"). The treatment then increases their perceived *direct* impact. This gives them an *additional* moral reason to reduce emissions. Thus, both environmentalists and non-environmentalists show a positive treatment effect.

8 Theory

8.1 Threshold Thinking

In this section I provide a simple framework to motivate why subjects' beliefs may differ from the climate model findings. I show that threshold thinking and uncertainty can give rise to misbeliefs about Results 3.1 to 3.3. For simplicity, I consider a single deterministic threshold here. Appendix E.1 extends the results to multiple stochastic

[32] Selfish utility maximization leads individuals to act only if the personal benefits outweigh the personal costs (e.g., Becker 1976). Classic utilitarianism justifies action only if it produces greater societal benefits than societal costs (e.g., Bentham 1834). Cooperative utilitarianism holds that the right action should additionally lead to a fair distribution of responsibility (e.g., Murphy 1993; Murphy 2000).

[33] Side effect reasoning suggests acting because it may inspire others to do the same (e.g., Glover and Scott-Taggart 1975). Rule consequentialism supports action if widespread adherence to the rule would produce the best overall consequences (e.g., Hooker 2002). Deontological ethics argues that one should act based on moral duty, not consequences (e.g., Kant 1797).

thresholds. All proofs are provided in Appendix F.

Let x^p be a subject's belief over the realized value of cumulative anthropogenic CO_2 emissions in 2100. Assume that subjects think there is a threshold of the following kind. Before the threshold, climate change does not happen and, therefore, the damage on any outcome is zero. Crossing the threshold imposes some fixed amount of damage. Hence, subjects think the damage function is discontinuous.

Assumption 8.1. *Subjects perceive the damage function to be:*

$$d_y^p(x^p) = \begin{cases} 0 & \text{if } x^p \leq x^* \\ d_y^* & \text{otherwise,} \end{cases}$$

where $d_y^* > 0$.

Result 8.1. *Subjects believe that climate change is threshold public goods game:*

$$\exists x^* : \quad d_y^p(x) - d_y^p(x-1) = 0 \quad \forall\, x > x^*.$$

Two facts motivate the threshold assumption. First, many people tend to dichotomize or categorize complex phenomena (Berlin 1990; Oshio 2009). Second, when it comes to climate change in particular, the public discourse is often framed in terms of our societal goals. We typically ask if we can still *stop* climate change or *reach* the Paris Agreement target, not what the direct benefit of a particular reduction is. Even the terms used in the academic literature often suggest dichotomies, including "disastrous" (Tavoni et al. 2011) and "catastrophic" (Weitzman 2011) climate change. It is easy to see how such a framing could lead people to believe that climate change is a dichotomous outcome.

However, subjects are uncertain about total emissions. They treat information about total emissions x as a signal for the realized value x^p. Let $G(x^p; x)$ be the subjective CDF over x^p and $g(x^p; x) \equiv G(x^p + 1; x) - G(x^p; x)$ the perceived probability of a 1 tCO_2 reduction being pivotal for staying below x^p. Subjects' perceived marginal impact is the expected damage avoided:

$$\begin{aligned} m_y^p(x) &= P(x^* < x^p \leq x^* + 1|x) d_y^* \\ &= g(x^*; x) d_y^* \end{aligned} \tag{8}$$

Subjects assign the highest probability to expected emissions x. Recall that $x = x^e - x^r$, for some fixed level of expected emissions x^e and reductions x^r. Assume that the expected level emissions is larger than the threshold, i.e. $x^e > x^*$. Any reduction

in overall expected emissions up to $x^e - x^*$ moves us closer to the threshold x^*. Such a reduction can therefore only increase the perceived probability of being pivotal and the perceived marginal impact.

Assumption 8.2. *Current expected emissions are above the threshold: $x^e > x^*$. Moreover, the PDF of x^p is single-peaked with mode x:*

$$\frac{\partial^2 G(x^p; x)}{\partial x^p \partial x} \begin{cases} > 0 & \text{if } x^p < x \\ = 0 & \text{if } x^p = x \\ < 0 & \text{otherwise.} \end{cases}$$

Result 8.2. *The perceived marginal impact $m_y^p(x = x^e - x^r)$ is increasing in emission reductions x^r (strategic complementarity):*

$$\left.\frac{\partial m_y^p(x^e - x^r)}{\partial x^r}\right|_{x^r < x^* - x^e} > 0.$$

The uncertainty assumption is in line with scientific predictions, where the link between emissions and warming comes with large confidence intervals. While the point estimate for the transient climate response to cumulative emissions (TCRE) is 0.45 °C/TtCO$_2$, the 66% confidence interval ranges from 0.27 °C to 0.63 °C (IPCC 2021, sec. 5.5.1). As shown in Appendix E.1, uncertainty about the perceived threshold level of emissions gives the same results. If the threshold belief is at least partly due to the focus on international targets in the public discourse, then people may well have uncertainty about the thresholds. Even among academics there is disagreement as to whether the Paris target of well below 2 °C and towards 1.5 °C constitutes one or two goals (IPCC 2022b; Mace 2016; Rajamani and Werksman 2018).

Finally, I assume that the perceived probability of being pivotal is small. As a result, the perceived marginal impact is smaller than the marginal impact estimated using climate models.

Assumption 8.3. *The perceived probability of being pivotal, given expected emissions $x = x^e$, is small:*

$$g(x^*; x^e) < \frac{m_y(x^e)}{d_y^*}.$$

Result 8.3. *The perceived marginal impact is smaller than the marginal impact derived from climate models: $m_y^p(x^e) < m_y(x^e)$.*

Due to the unboundedness of x and x^p, there must be some $x = x^e$ for which Assumption 8.3 holds. Thus, the assumption can also be interpreted as x^e being sufficiently far away from x^*. Current pledges, targets and policies will likely lead to 2.1

°C, 2.4 °C and 2.7 °C of warming, respectively (see Section 2.3). All of these are above both Paris goals. Moreover, the difference in emissions between 2.1 °C (the best-case scenario) and 2.0 °C (the largest international target) is around 222 $GtCO_2$ (using the TCRE) while global emissions totaled 59 $GtCO_2$ in 2019 (IPCC 2022b). Thus, it seems plausible that subject assume that the probability of being pivotal is small.

8.2 Consumption

What happens when subjects update their beliefs about the marginal impact in the direction of the model-based results? To answer this question, assume that representative consumer has utility

$$U(\mathbf{c}, r) = u(\mathbf{c}) + v(r, x^r) \tag{9}$$

$$\frac{\partial u(\mathbf{c})}{\partial c_j} > 0, \quad \frac{\partial^2 u(\mathbf{c})}{\partial c_j^2} < 0, \tag{10}$$

where $\mathbf{c} \geq 0$ is a consumption vector for J goods, r is the individual's emission reduction compared to some fixed value of expected individual emissions, and u and v are continuous functions. The individual maximizes their utility function subject to

$$\mathbf{p} \cdot \mathbf{c} \leq Y$$
$$r = r(\mathbf{c})$$

where $\mathbf{p} \gg 0$ are prices, $Y > 0$ is income and r is continuous in $\mathbf{c}$.

Equation (9) imposes additive separability of material consumption utility u and utility from emission reductions v. Recall that there is at least a 10-year gap between a change in greenhouse gas emissions and a detectable effect on the climate (see Section 3.2). Thus, it is plausible that changes in emissions at time t do not affect material consumption utility at time t.

Assumption 8.4. *The representative consumer cares about their own expected impact on the climate change outcomes:*

$$v(r, x^r) = w(r) + m^p(x^e - x^r)r$$
$$m^p(x) = \sum_y \gamma_y m_y^p(x)$$

where $m^p(r)$ is a weighted sum of perceived marginal impacts $m_y^p(x)$ with utility-weights $\gamma_y > 0$.

The main result comes from the fact that utility derived from emission reductions depends on the perceived marginal impact. The functional form is chosen for simplicity. Appendix E.2 shows that the results hold for more general utility functions, as long as v is increasing in $m^p(x)$. I thus assume that the representative consumer cares about the well-being of future generations or the environment itself. This is because own emission reductions will have no detectable effect on the individual's own or even their offspring's lives. Instead, the predicted effects of a 1 tCO_2 emission reduction (Result 3.3) are spread all over the whole world. This assumption is consistent with the fact that people care about others (Engel 2011) and the environment itself (Stern and Dietz 1994; de Groot and Steg 2010).

Assumption 8.4 also implicitly assumes that the individual's reduction r has no impact on the curvature of $d_y(x)$. This assumption is motivated by the fact that even the people with the largest individual footprints make up only a small fraction of global emissions.[34]

Assume constant sensitivity of emission reductions to the consumption of each good and the availability of at least one emission reduction technology:

$$\frac{\partial r(\mathbf{c})}{\partial c_j} = \rho_j, \tag{11}$$

$$\exists j', j'' : \rho_{j'} < 0 < \rho_{j''}. \tag{12}$$

Equation (11) places a restriction on how the J goods are defined. For example, if consumers have access to both combustion engine car and electric car technologies, then "transportation by car" cannot be a category, since a dollar spent on electricity generates less CO_2 than a dollar spent on gasoline. An example for an emission technology j'' is carbon capture and storage.

The representative agent consumes some positive quantity of each available good. If they were not then there would be no demand and hence no supply. The solution to the maximization problem fulfills:

$$\frac{\partial u(\mathbf{c}^*(x^r))}{\partial c_j} + m^p(x^e - x^r)\rho_j = p_j\lambda \qquad \forall\ j \tag{13}$$

where $\mathbf{c}^*(x^r)$ is the optimal consumption vector and λ the Lagrange multiplier. Equation (13) implies that increases in the perceived marginal impact of emission reduc-

[34] By several estimates, Roman Abramovich has the world's largest carbon footprint. Wilk (2021) estimates it to be 34 $ktCO_2$ in 2018, while academic estimates are more conservative (Gössling 2019). However, even that is less than one millionth of the world's total annual footprint of around 60 $GtCO_2$ (see above).

tions $m^p(x^r)$ increase the implicit optimal emission reduction $r^*(x^r) \equiv r(\mathbf{c}^*(x^r))$.

Let $m^b(x)$ and $m^t(x)$ be the perceived marginal impact before and after a treatment that informs participants about Results 3.1 to 3.3, respectively. The treatment is limited to a few experimental participants, who do not know each other. Thus, there is no strategic interaction, x remains approximately constant and the perceived complementarity between r and x^r does not affect r^*. Let $r_b^* \equiv r_b^*(0)$ and $r_b^* \equiv r_b^*(0)$ be the optimal reduction before and after the treatment, respectively. Assuming that participants update their perceived marginal impact in the direction of the results, the treatment increases the perceived marginal impact and, by Equation (13), emission reductions.

Result 8.4. *Subjects in the information treatment reduce their emission more than those in the control group:* $r_t^* > r_b^*$.

8.3 Strategic Interaction

This paper investigates how correcting misbeliefs among a few subjects affects individual demand for emission reductions. An important question is what would happen if the information was given to everyone. It is important that a policy intervention still increases mitigation efforts when taking into account strategic interactions. The following results show that under some very simple assumptions, one would still expect an overall reduction in emissions in this case. Appendix E.3 generalizes the results to a generic utility function $v(r, x^r)$ whose cross-derivative has the same sign as the belief over the physical benefit of emission reductions, with increasing or strictly decreasing differences.

There is a continuum of individuals with mass one and typical member $i \in [0, 1]$. Let $x^r \equiv \int_0^1 r di$ be total reduction reductions. An equilibrium are emission reductions and a marginal impact belief (x^r, m^p) fulfilling optimality and consistency, so that $r_p^*(x^r) = x^r$. I compare possible equilibria for the perceived marginal impact before (m^b) and after (m^t) the treatment. Assume that subjects in the treatment group internalize the strategic complementarity assumption.

Assumption 8.5. *The perceived marginal impact after the treatment* $m^t(x = x^e - x^r)$ *is decreasing in emissions reductions* x^r *(strategic substitutability):*

$$\frac{\partial m^t(x^e - x^r)}{\partial x^r} < 0.$$

Result 8.5, shows that there may be several equilibria when individuals think emissions reductions are strategic complements. The reason is that strategic complementarity makes the implicit best response function $r^*(x^r)$ concave. The second main result,

Result 8.6, is that when changing beliefs from strategic complementarity to strategic substitutability, there is a new equilibrium that is strictly better. Intuitively, increasing reductions in the treatment reveals that the increase in the perceived marginal impact dominates free riding concerns.

Result 8.5. *Given baseline beliefs m^b there may be multiple equilibria (r^L, m^b) and (r^H, m^b), such that $r^L < r^H$.*

Result 8.6. *Assume $\exists r^L$ such that (r^L, m^b) is an equilibrium and $r^*(r^L) > r^L$ given m^t. Then $\exists r^{H'} > r^L$ such that $(r^{H'}, m^t)$ is the unique equilibrium.*

If subjects think that emission reductions are strategic complements (Result 8.2), there may be several equilibria. For example, both current emissions ($r^L = 0$) and the Paris goal (r^H) could be equilibria given baseline beliefs. The fact that we have not reached the "internationally recognized social optimum" r^H, despite agreeing that it is preferred to r^L, may suggest a coordination failure.

What will be the equilibrium effect of correcting beliefs in this context? If participants reduce their emissions given current overall reductions, then there is a new equilibrium with strictly higher average emission reductions. Moreover, since $r_t^*(r^L) > r^L$, this equilibrium can be reach without any coordination, by providing everyone with the climate scientific predictions about the marginal impact.

9 Policy Implications

9.1 Information Provision

An immediate policy implication of the experimental results is that correcting misperceptions about the marginal impact could be a cost-effective "demand-side mitigation strategy" (IPCC 2022b). To assess this, I estimate the Marginal Value of Public Funds (MVPF) – the benefit per dollar spent (Hendren and Sprung-Keyser 2020) – of a public information campaign.[35] I assume that the effect on emissions is 10% of the donation treatment effect from Section 6, and lasts one year. Under these assumptions, the intervention would reduce emissions in the UK by 92 tCO_2/capita.[36] I monetize these

[35]The MVPF is defined as the ratio of the willingness to pay for a policy to its costs (Hendren and Sprung-Keyser 2020). For environmental policies, Hahn et al. (2024) separate the willingness to pay into a monetary value to the consumer and an environmental benefit. Since this policy is a pure information provision, prices are not affected and I set the willingness to pay equal to monetized environmental damages. I do not include (dis-)utility from the updated mental model. I assume that the only costs are those coming from running the campaign. I do not quantify changes in tax revenues, which depend on which goods consumers substitute to.

[36]The average UK and US carbon footprints are 5.1 and 14.8 tCO_2/capita (Friedlingstein et al. 2022). The treatment increased donations to reduce emissions by 21%, see Section 6.

benefits using the EPA's (2023) social cost of carbon of \$193 per tCO_2. For the costs, I use the upper estimate for community-based public health campaigns from Khavjou et al. (2018) of \$2.39 per person reached.[37]

I estimate the MVPF to be well above that of many climate policies, given the assumptions above. For the UK, providing people with the marginal impact information has an MVPF of 8.8. The intervention could potentially be even more cost-effective in high polluting countries, assuming a similar treatment effect. For example, the MVPF would be 12.8 in the US, even if the treatment effect (as a percentage reduction of the total footprint) was only half as large. These MVPFs are well above that of existing policies such as electric vehicle (1.5), solar (1.45-3.86) and wind subsidies (3.85-5.87; Hahn et al. 2024). As shown in Section 8.3, giving the information to everyone reduces emissions even in strategic equilibrium under mild assumptions.

9.2 Reframing Policy Impacts

However, while the effect on individual behavior is substantial, there remains a need for systemic change through policies (Chater and Loewenstein 2023), and the marginal framing can be a catalyst to achieve such change. Currently, the benefits of climate policies are typically advertised in terms of CO_2 reductions, percentage reductions or contributions to a net-zero (or other) target. However, as discussed in Section 1, people do not intrinsically care about carbon emissions, making the first two measures unfit for purpose. On the other hand, the net-zero framing may actually contribute to threshold thinking (see Section 8.1), and thus decrease support, as described in the next subsection. Instead, the marginal impact can be used to frame the benefits of policies in terms of climate change outcomes that voters are more likely care about directly.

As an example, I quantify the impact of the Inflation Reduction Act (IRA) in 2023-24 on glacier ice, mortality and vegetation change. Bistline et al. (2023) estimate that in this period the IRA reduced emissions by 288 $MtCO_2$.[38] Even for national policy analyses, one can simply multiply the point estimates from Result 3.3 by the above emission reductions.[39] The estimated impact of the IRA in 2023-24 is: 1.0 (95% CI:

[37] To be consistent with (Hahn et al. 2024), I use EPA's social cost of carbon for 2020. Khavjou et al. (2018) estimate costs of \$1.00-2.30 per person reached. I adjust the upper bound for CPI inflation from 2018 to 2020 (BLS 2025), to get \$2.39 per person reached.

[38] Bistline et al. (2023) report emission reductions for 2025, 2030 and 2035. I use the figure for 2025 for both 2023 and 2024. The mean prediction of emissions reductions in 2025 is 144 $MtCO_2$/year (range across models: -82 to 538 $MtCO_2$/year).

[39] For the IRA, the error of this method *vis-à-vis* integrating the marginal impact as a function of temperature – using the mean TCRE from IPCC (2021) of 0.45 °C/$TtCO_2$ (see Appendix A.1) – is less than 10^{-12}%. The reason for this is the near linearity of both the response of temperature to emissions and of outcomes to temperature (see Section 3.3). As with the impact of 1 tCO_2, it is important to present

0.6-1.6) trillion liters less glacier ice melting, 200,000 (95% CI: 89,000-330,000) years more aggregate life expectancy, and 14 (95% CI: 4-27) million acres less vegetation undergoing ecosystem change.

9.3 Mental Model

Another way in which the marginal impact results can be used to increase policy support is through a change in peoples' mental model. The mental model from Section 8.1 predicts that voters will underestimate the impact of policies in their country. Specifically, if subjects believe we are far enough away from the threshold or that their country is small enough, national policies will not be pivotal in "avoiding climate change". Thus, at baseline, they will assume that policies in their country have no impact on climate change outcomes, unless other countries also reduce their emissions.

There is ample evidence suggesting that the threshold public goods game framing plays an important role in the discourse about policies. Those opposing national climate policies frequently argue that they have "literally zero" impact.[40] In Switzerland, one of the main arguments against the "glacier initiative" – a referendum to increase the Swiss climate goals – was that its impact on the amount of glacier ice melting would be "literally zero" (Gut 2023). The referendum ultimately failed.

Hence, providing information about the marginal impact of emission reductions – especially the fact that climate change is not a threshold public good (see Section 3.2) – is likely to be a catalyst for policy support. Because the misperceptions about the impacts of individual and collective climate actions are the same, information provision has the potential to increase both. The positive treatment effect on the willingness to convince others to do more about climate change found in Section 5.4 provides some evidence that the information is also effective in increasing collective action. Thus, rather than crowding-out (Maniates 2001; Chater and Loewenstein 2023), we may expect crowding-in of support for systemic change.

the impact in units that people can perceive correctly (see Sections 1 and 3). I follow the same rules for units outlined in Section 3.1.

[40] Recent examples include: Australian prime minister Scott Morrison ("the suggestion that... the individual actions of Australia are impacting directly on specific fire events... that doesn't bear up to credible scientific evidence" The Guardian 2019), US Representative Mario Díaz-Balart ("If we literally go to zero fossil fuels in the United States... it will have zero effect" Politico 2024), and Australian minister Keith Pitt ("there is literally zero impact on the temperature of the planet [of net-zero emission targets]", The Australian 2024).

10 Conclusion

In this paper, I define and derive the marginal impact of emission reductions for tangible climate change outcomes, document important misperceptions and show how they affect behavior. I show that the impact of small emission reductions is tangible, without requiring the collaboration of others. Contrary to these findings, subjects believe the marginal impact is small, exhibits strategic complementarity and is affected by thresholds. Showing the climate model findings to participants increases perceived self-efficacy, intentions to reduce own emissions and real donations to reduce global emissions. The findings are consistent with a simple model of threshold thinking, that predicts a positive effect of providing everyone with this information.

In some sense, the intervention can be seen as a reframing of the debate on climate impacts from societal to individual impacts. Presenting climate change as a collective problem – without emphasizing the fact that everyone can have an impact – may lead people to think in terms of their contribution to achieving the societal goal rather than their direct impact. Moreover, we are not well-equipped to perceive small, abstract numbers correctly (Dehaene 2011). Thus, any presentation in terms of impacts relative to the total anthropogenic damages (on the order $1/8bn$) may reduce perceived efficacy. By contrast, presenting the absolute impact on tangible climate change outcomes leads to high perceived efficacy and emission reductions.

This has important implications for how to communicate climate change issues. First, the marginal impact should be presented in appropriate units. As argued above, absolute impacts are better than relative impacts. Moreover, the unit should be chosen to get an estimate that people can properly perceive and imagine. Second, social goal information should be accompanied by marginal impact estimates. Societal goals may be useful as reference points or to solve coordination problems at the international level. Yet, I argue that they can also have the side effect of leading to lower emission reductions through misperceptions. Communicating both the goal and the marginal impact solves this problem. This strategy is frequently used by aid organizations, who set a fundraising goal but also emphasize the impact of every single donation.

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A Climate Scientific Framework

A.1 Point Estimate Methodology

Climate-impact models. To estimate Equation (1), I use ensemble studies. In these, outcomes are projected using multiple impact models. Each model makes a deterministic prediction of outcome y, given emissions $\mathbf{x}$ and a large vector of parameters and initial conditions $\boldsymbol{\vartheta}$:

$$\hat{y}(\mathbf{x}, \boldsymbol{\vartheta}).$$

These models are often complex and computationally expensive. The ensemble data consists of $\hat{y}$ values for a selection of $(\mathbf{x}, \boldsymbol{\vartheta})$ values. Because the emission paths needed to estimate Equation (2) are not covered, the estimates have to be interpolated.

Decoupling. Instead of estimating the response of outcomes to emissions directly, I estimate the response of temperature to emissions and of outcomes to temperature separately. The reason is that some climate models are known to "run hot". That is, the temperature response is too sensitive to emissions, compared to historical observations (Meehl et al. 2020; Hausfather et al. 2022). To avoid this problem, the damage function is estimated for anthropogenic global mean surface temperature (GMST) change T (in °C) instead of cumulative emissions x. The temperature response to emissions by contrast, is the transient climate response to cumulative emissions (TCRE), taken from IPCC (2021, sec. 5.5.1). Unlike the predictions of some climate models, this TCRE estimate is compatible with historical observations. By decoupling the temperature response from its downstream effects on other climate change outcomes, I avoid the "hot models" problem and abstract from differences in the temperature sensitivity between models.

I denote damages as a function of temperature $\tilde{d}_y(T)$, the marginal impact as a function of temperature $\tilde{m}_y(T)$, and the response of temperature to emissions $T(x)$. In this study, I focus on likely temperature increases of $1 \leq T \leq 5$. In this range, the TCRE is approximately constant. Moreover, the temperature response to emissions is stable after about 10 years (IPCC 2021). Since I focus on the effect of changes in emissions today on outcomes in well over 10 years, I do not model the dynamic response. Let ρ be the TCRE (measured in °C/tCO$_2$), so that $T(x) = \rho \cdot x$. Then,

$$\tilde{d}_y(T(x)) = \tilde{d}_y(\rho \cdot x) = d_y(x), \tag{14}$$

$$\tilde{m}_y(T) = \tilde{d}_y(T) - \tilde{d}_y(T - \rho). \tag{15}$$

Statistical model. Calculating the marginal impact requires estimating a damage function that is conditional on temperature only, integrating out parameters and initial conditions ϑ. I assume this function is smooth, which I motivate in more detail in Section 3.2. Many studies assume a linear or quadratic function. I relax this assumption by fitting polynomials up to order $n_s = 5$ and sample them according to how well they fit the data (see below). By setting n_s large enough, the damage function can be approximated arbitrarily well (Stone 1948). I verify the adequacy of n_s by checking that $s = n_s$ has low posterior probability. I further assume that the functional of the damage function is the same for all impact models and that their coefficients are hierarchical. The statistical model of order s for data point j and impact model i is thus:

$$d_{jyis} = \sum_{k=0}^{s} \beta_{yis}^{(k)} T_j^k + \varepsilon_{jyis}, \tag{16}$$

where $\beta_{yis} = (\beta_{yis}^0, ..., \beta_{yis}^s) \sim N(\beta_{ys}, \Sigma_{ys})$ and $\varepsilon_{jyis} \sim N(0, \sigma_{ys}^2)$.

I fit the statistical model using the ensemble data and use the results construct predicted damage functions. The models are fitted via Hamiltonian Monte Carlo using Stan with 10,000 draws. Due to the potential time-dependence of $d_y(x)$, I only use damages for the year 2100. For the marginal impact estimate, I sample parameters from their posterior distribution, as described below. However, to visualize the damage function I construct a coefficient point estimate $\hat{\theta} = E(\theta|\text{data}_y)$. The predicted damage functions given s and θ per impact model i:

$$\tilde{d}_{yis\theta}(T) \equiv \sum_{k=0}^{s} \beta_{yis}^{(k)} T^k.$$

From the fitted results, I obtain posterior probabilities for both the statistical models and their parameters. I denote these by $p(s|\text{data}_y)$ and $p(\theta|s, \text{data}_y)$, respectively, where data_y is the ensemble data. I use uninformative coefficient priors, following (Gelman and Hill 2007).[41] In addition, I use a uniform model prior, so that the posterior model probability can be approximated by a transformation of the Bayesian Information Criterion (BIC; Schwarz 1978):

$$p(s|\text{data}_y) \approx \frac{e^{-\frac{1}{2}\text{BIC}(s,\, \text{data}_y)}}{\sum_{s'=1}^{n_s} e^{-\frac{1}{2}\text{BIC}(s',\, \text{data}_y)}}.$$

[41] For the generalization of Gelman and Hill (2007, sec. 13) to a case with s coefficients, I follow Stan Development Team (2021, sec. 1.13). Specifically, the priors are $\beta_{ys}^{(k)} \sim N(0, 5)$ and $\Sigma_{ys} = \text{diag}(\tau_{ys}) \times \Omega_{ys} \times \text{diag}(\tau_{ys})$, respectively, with scale parameters $\tau_{ysi} \sim \text{Cauchy}(0, 2.5)$ and correlation matrix $\Omega_{ys} \sim \text{LKJCorr}(2)$.

Sources of uncertainty. To quantify the uncertainty in my marginal impact estimates, I explicitly account for several sources of uncertainty. I estimate damages for several impact models i. The model-specific damage function is estimated using several statistical models s with parameters θ. I model (i, s, θ) as random variables, where $p(i, s, \theta)$ is the probability that they jointly describe the true damage function. The TCRE ρ is also modeled as a random variable. Indexing on all random variables, the marginal impact becomes

$$\tilde{m}_{yis\theta\rho}(T) \equiv \tilde{d}_{ytis\theta}(T) - \tilde{d}_{yis\theta}(T - \rho).$$

I assume or estimate a probability distribution for each of the random variables. First, following the IPCC, I apply "model democracy" to impact models. That is, I assume a uniform distribution and give equal weights to all models. Impact models are weighted equally – in favor of weights based on historical fit – due to limited data availability and quality, as well as the lack of a universal, robust method (IPCC 2021, sec. 1.5.4.8). Let n_{yi} be the number of impact models available for outcome y. Then, for all models present in data_y,

$$p_y(i) = \frac{1}{n_{yi}}.$$

For the distribution of statistical models s and statistical model parameters θ, I use their Bayesian posterior probabilities $p(s|\text{data}_y)$ and $p(\theta|s, \text{data}_y)$.

Finally, for ρ I use the estimate from the IPCC's sixth assessment report, which gives a point estimate of 0.45 °C/TtCO$_2$ and a 90% confidence interval of [0.27, 0.63] °C/TtCO$_2$ (IPCC 2021, p. 749). Consistent with the symmetry of the confidence interval, I assume a normal distribution with a mean of 0.45 and standard deviation of 0.11. I convert these values into °C/tCO$_2$ by multiplying them by 10^{-12}:

$$p(\rho) = 10^{-12} \cdot N(0.45, 0.11).$$

The marginal impact for outcome y as a function of warming T is its expected value given the ensemble data:[42]

$$\begin{aligned} \tilde{m}_y(T) &= E(\tilde{m}_{yis\theta\rho}(T)|\text{data}_y) \\ &= \sum_{i,s} \iint \tilde{m}_{yis\theta\rho}(T) p_y(i) p(s|\text{data}_y) p(\theta|s, \text{data}_y) p(\rho) \text{d}\rho\text{d}\theta. \end{aligned} \tag{17}$$

[42]The random variable θ is a vector, so the integral with respect to θ is higher-dimensional. I write θ non-bold and use a single integral sign to simplify the notation. During the Monte Carlo simulation (described below), I draw n_{sim} values directly from the joint distribution of θ, which is a direct output of the estimation procedure (described above).

Monte Carlo simulation. I estimate Equation (17) through a Monte Carlo simulation. For each outcome, each impact model and temperatures $T = 1.0, 1.1, ..., 5.0$, I sample n_{sim} =10,000 values of s, θ and ρ from the distributions above. Since all variables are distributed according to the assumed distributions in the simulated data, my estimator for the marginal impact given y and T is the simple average over all simulated values j:

$$\frac{1}{n}\sum_{j=1}^{n}\tilde{m}_{jyis\theta\rho}(T).$$

I also provide 67% and 90% credible intervals, which are the central intervals containing 67% and 90% of all simulated values, respectively. For example, the 90% credible interval is:

$$[q_{0.05}(\tilde{m}_{jyis\theta\rho}(T)), q_{0.95}(\tilde{m}_{jyis\theta\rho}(T))],$$

where q_z is a z-quantile.

Data. Data come from ensemble studies used by the IPCC. The main outcomes presented in this study are: glacier ice (Marzeion et al. 2020; IPCC 2021), life expectancy (Carleton et al. 2022; IPCC 2022a) and vegetation change (Warszawski et al. 2013; IPCC 2022a).

To construct the glacier damage, I subtract the volume of glacier ice in the first year available for each climate-impact model. I sum world-wide glacier mass, excluding the Greenland and Arctic peripheral glaciers, for all glacier models with simulations for all climate models, forcings and years considered by Marzeion et al. (2020).

Carleton et al. (2022) estimate the heat mortality effect of climate change for different age groups and create a measure of life years lost using the groups' respective life expectancy.[43] I use this measure to calculate the life expectancy damage, summing over all lost life years until 2100 for a given emission scenario and model run. Following Carleton et al. (2022), I focus on the socio-economic scenario SSP3.

The vegetation change damage in fractions of vegetation undergoing ecosystem change (biome shift) is obtained directly from Warszawski et al. (2013). The archived data provided by Warszawski et al. (2013) has some differences compared to the original paper.[44] However, the amount of vegetation undergoing ecosystem change of 12%

[43] Carleton et al. (2022) only use one impact model. They sample from distribution of statistical parameters for the temperature-mortality relationship, but only have one simulation per draw. Hence, it is not possible to treat these as separate impact models. Instead, I treat the results for two different GDP trajectories as the impact model, since the results are sensitive to this input.

[44] Several forcings are missing for impact-climat models VISIT-MIROC (RCPs 6.0, 4.5), ORCHIDEE-HadGEM (RCP 4.5) and LPJmL-IPSL (RCPs 4.5, 6.0, 8.5). For impact model JULES, the data additionally include RCP 8.5.

at 2° and 30% at 3° warming are similar to the paper (13% and 28%, respectively).

For the point estimate, I pick familiar units, such that the numerical part of the point estimate is a whole, small, and round number, see Section 3.1. Glacier ice loss is originally provided in teratonnes (Tt) of glacier mass.[45] I convert it into kiloliters (kL) using the weight-to-volume conversion rate for solid ice.[46] Life expectancy loss is originally given in years, which I convert to hours (h). Vegetation change is originally measured in fractions of global vegetation at high risk of undergoing ecosystem change.[47] I convert the value into square meters (m^2) by multiplying it with the area of habitable land on earth.

A.2 Sensitivity to Sufficient Statistic Assumption

In Section 2 I make the simplifying assumption that end of century emissions x are a sufficient statistic for the end of century outcome $y(\mathbf{x})$, where $\mathbf{x}$ is the full series of anthropogenic emissions. As discussed in the main text, this assumption approximately holds for climate change outcomes that instantaneously adjust to temperature, since the temperature response stabilizes within 10 years (Mattauch et al. 2020). In this section, I argue that the assumption leads to conservative estimates for other variables.

Many climate change outcomes, rather than adjusting instantaneously, have delayed effects. Figure A.1 illustrates this for the case of glacier ice. The figure shows the evolution of glacier ice loss for different emission scenarios for one climate-impact model combination. In the low emission scenario RCP2.6, emissions and temperature stop rising in the middle of the century. Yet, glacier ice loss keeps increasing, as illustrated by the red line. This is because global glacier mass react slowly to climate change: it takes about 200 years reach near-equilibrium (Marzeion et al. 2018).

Results obtained using the estimation strategy outlined in Appendix A.1 are likely conservative because it mainly uses the variation between emission scenarios to estimate the damage function. For example, I only use the last prediction of the sequence from Figure A.1, corresponding to the amount of glacier ice melting in 2100, to es-

[45] Considered are all glaciers, including Greenland's and Antarctica's periphery (but not their sea ice). The variable is also sometimes measured as contributions to sea-level rise (in m).

[46] 1,088 kL per ton.

[47] The authors create a proxy for the risk of ecosystem shift Γ. The proxy is an average of changes in functional strategies of the vegetation and various measures of biogeochemical stocks and fluxes. An ecosystem is considered to be at severe risk of ecosystem change if $\Delta\Gamma > 0.3$. For comparison, the kind of forest that we see in the south of England shifting to the kind of shrubland that makes up the Spanish interior implies a $\Delta\Gamma = 0.35$. $\Delta\Gamma = 0.35$ is implied by a shift from the average Temperate Broadleaved Deciduous Forest to the average Temperate Woody Savanna, Woodland & Shrubland (Warszawski et al. 2013, Fig. S1). These are the ecosystems of parts of the English interior, including Oxfordshire, and the interior of Spain, respectively (Ostberg et al. 2013, Fig. S3b).

timate damage function for this climate-impact model.[48] Higher emission scenarios have higher overall emission but also had more of their emissions (and temperature increase) in the recent past. As a result, higher emission scenarios include relatively less delayed effects and the slope of the damage function is attenuated.

To illustrate this logic, consider the simple difference between scenarios RCP8.5 and RCP4.5 in Figure A.1, scaled by the transient climate response to cumulative emissions (TCRE) ρ, as an estimator for the slope of damage function:

$$\rho\frac{\Delta d}{\Delta T} = \rho\frac{d_{8.5} - d_{4.5}}{T_{8.5} - T_{4.5}} \approx \rho\frac{7.0TL}{1.5°C} = \rho \cdot 4.7\frac{TL}{°C}.$$

Let $\mathbf{T} = (T_{20s}, T_{30s}, ..., T_{90s})$ be decadal temperature increases – such that, for example, T_{20s} is the temperature increase from 2020 to 2029. In the scatter plot, the difference in the damage d between $T = 3.4$ and $T = 1.7$ is the difference in d resulting from $\mathbf{T}_{8.5}$ under RCP8.5 and $\mathbf{T}_{4.5}$ under RCP4.5. Here, the temperature increase of $\Delta T = 1.5$ corresponds to $\Delta\mathbf{T} = (0.0, 0.2, 0.0, 0.3, 0.3, 0.1, 0.4, 0.1)$. Interpolating this difference, $\Delta T = \rho$ would correspond to $\Delta\mathbf{T} = \rho \cdot (0.0, 0.1, 0.0, 0.2, 0.2, 0.1, 0.3, 0.1)$. However, we really want to use $\Delta\mathbf{T} \approx \rho \cdot (1, 0, 0, 0, 0, 0, 0, 0)$. Instead, my methodology implicitly assumes that most of the temperature increase due to 1 tCO_2 happens later in the century. Thus, it underestimates the effect, by containing less of the delayed effect than it should.

[48] I also pool over the different climate models, leading to approximately $n_c \times n_f$ observations per damage function, where n_c is the number of climate models and n_f is the number of forcing scenarios.

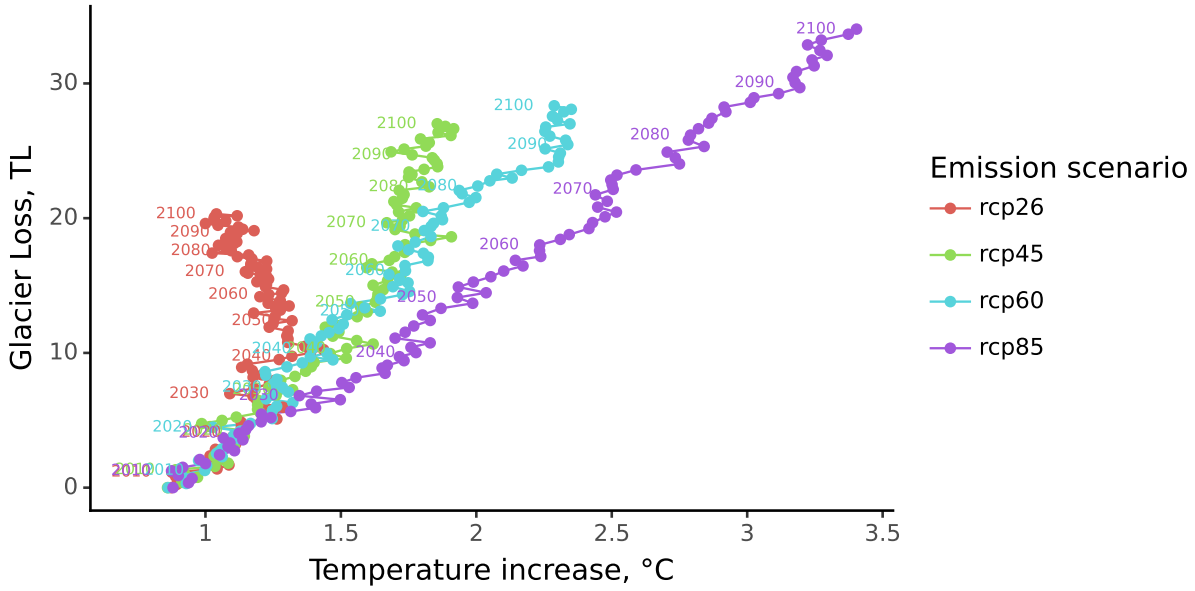


Figure A.1: Time dependence of glacier ice damage

Predicted glacier ice loss for climate model GISS-E2-R and impact model MAR2012. X-axis: temperature increase vis-à-vis industrial times. Y-axis: glacier ice loss vis-à-vis 2006 in teraliters (TL). Color: emission scenarios or Representative Concentration Pathways (RCP). Dots: individual model predictions. Data source: Marzeion et al. (2020).

B Supplementary Climate Scientific Results

B.1 Continuity

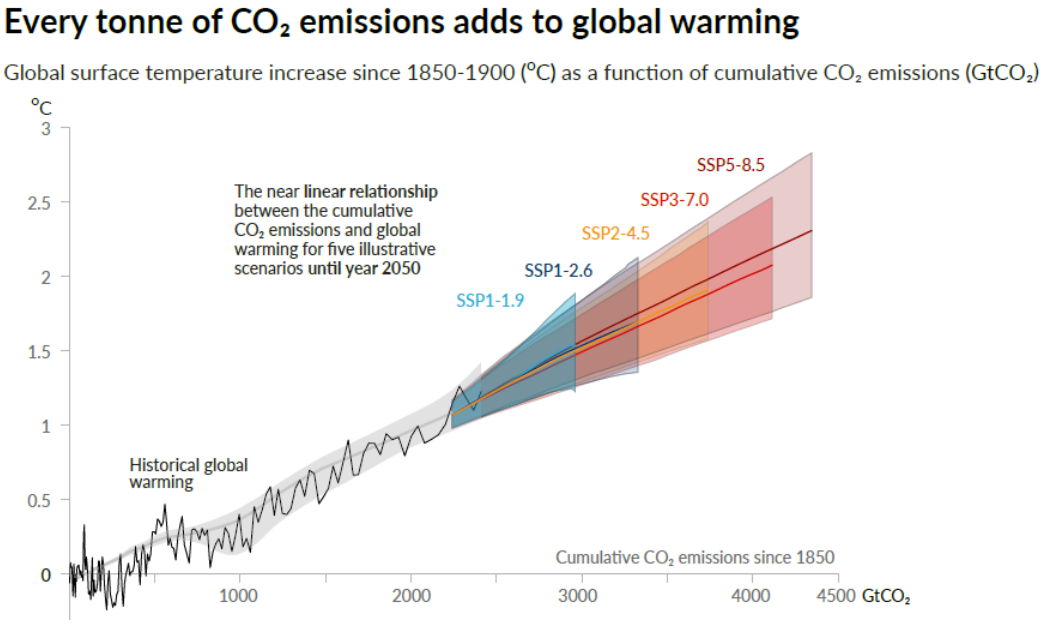


Figure B.1: Relationship between CO_2 emissions (x-axis) and global warming (y-axis). Source: IPCC (2021).

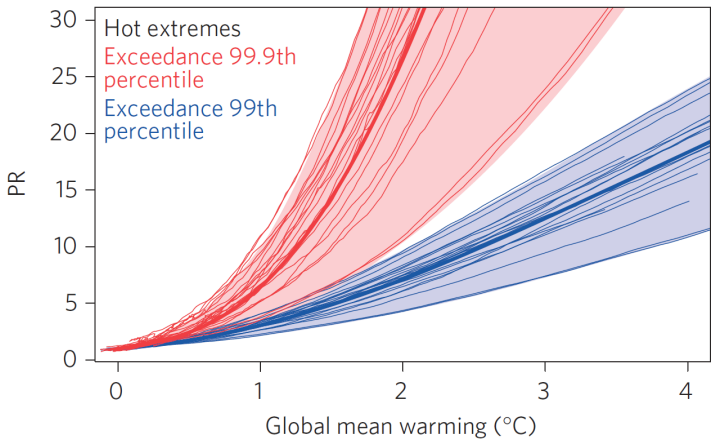


Figure B.2: Relationship between global warming (x-axis) and the probability ratio of extreme heat events (exceeding the 99^{th} or 99.9^{th} percentile of preindustrial daily maximum temperatures; y-axis). Source: IPCC (2018) and Fischer and Knutti (2015).

B.2 Strategic Substitutability

#	Outcome	Shape $\tilde{d}_y(T)$	Source
1	Hot and Cold extremes (frequency)	Convex	IPCC (2021), CCB 12.1 Tab. 1
2	Extreme precipitation events (frequency)	Convex	IPCC (2021), CCB 12.1 Tab. 1
3	Droughts (frequency)	Convex	IPCC (2021), Fig. 11.18
4	Inland floods	N/A	
5	Tropical Cyclones	N/A	
6	Marine Heatwaves (frequency)	Linear	IPCC (2021), Box 9.2 Fig. 1
7	Concurrent Events in Time and Space	N/A	
8	Fire Weather trends	N/A	
9	Air Pollution weather	Linear	IPCC (2021), Fig. 6.14
10	Patterns of mean warming	Linear	IPCC (2021), CCB 12.1 Tab. 1
11	Arctic Warming trends	Linear	IPCC (2021), CCB 12.1 Tab. 1
12	Patterns of Precipitation Change	Linear	IPCC (2021), CCB 12.1 Tab. 1
13	Sea Surface Temperatures (SST) warming	Linear	IPCC (2021), CCB 12.1 Tab. 1
14	Ocean Acidification/pH	N/A	
15	Droughts (Standardized precipitation evapotranspiration index; SPEI) Global	Convex	IPCC (2021), CCB 12.1 Tab. 1

#	Outcome	Shape $\tilde{d}_y(T)$	Source
16	El Niño-Southern Oscillation (ENSO) Variability	N/A	
17	Sea-Ice Loss	Convex	IPCC (2021) Tab. 9.2
18	Permafrost Thaw	Linear	IPCC (2021), CCB 12.1 Tab. 1
19	Sea-Level Change over the 21st century	Concave	IPCC (2021), Tab. 9.10
20	Sea-Level Change Commitment (2,000 years after peak GWL)	N/A	
21	Northern Hemisphere Spring Snow Cover	Linear	IPCC (2021), Fig. 9.24b
22	Mass Loss of Glaciers	Concave	IPCC (2021), Tab. 9.9

Table B.1: Outcomes y and shape of $\tilde{d}_y(T)$

Note: Outcomes are extreme events (1-7) and trends (8-22) identified as driving Representative Key Risks (RKRs) and Reasons for Concern (RFCs) in IPCC (2021, Cross-chapter Box 12.1 Table 1). Convexity, linearity and concavity of $\tilde{d}_y(T)$ imply increasing, constant and decreasing $\tilde{m}_y(T)$, respectively. When primary data was used to assess the shape of $\tilde{d}_y(T)$ and the function had inflection points, the shape was assessed between 1.5 °C and 2.4 °C warming.

B.3 Damage Functions

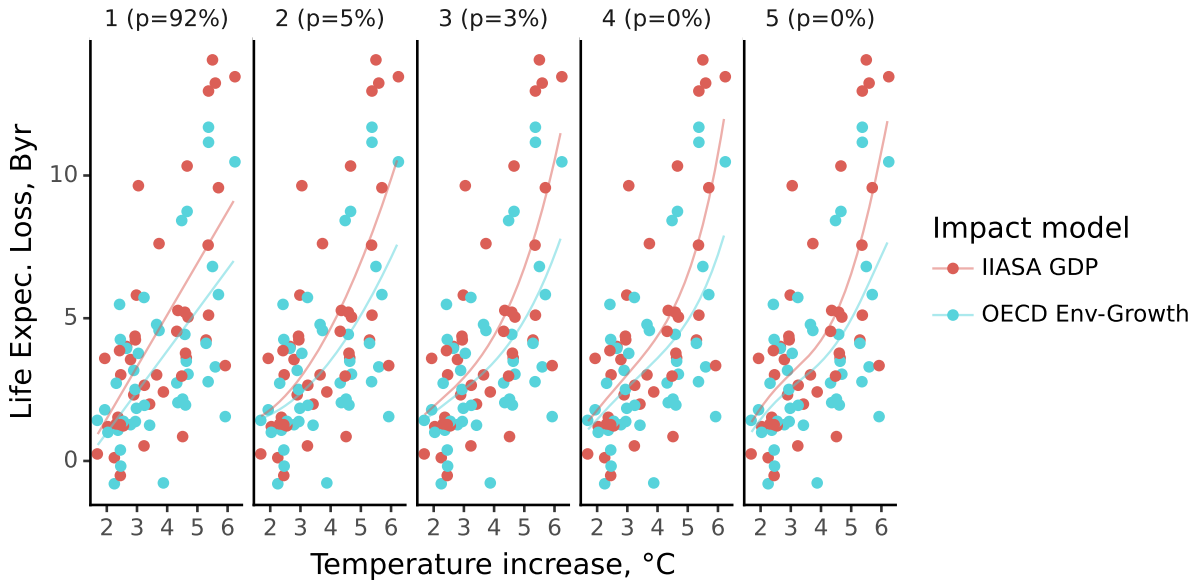


Figure B.3: Damage function for life expectancy. Y-axis: life expectancy decrease (in billions of years). Other features as in Figure 2.

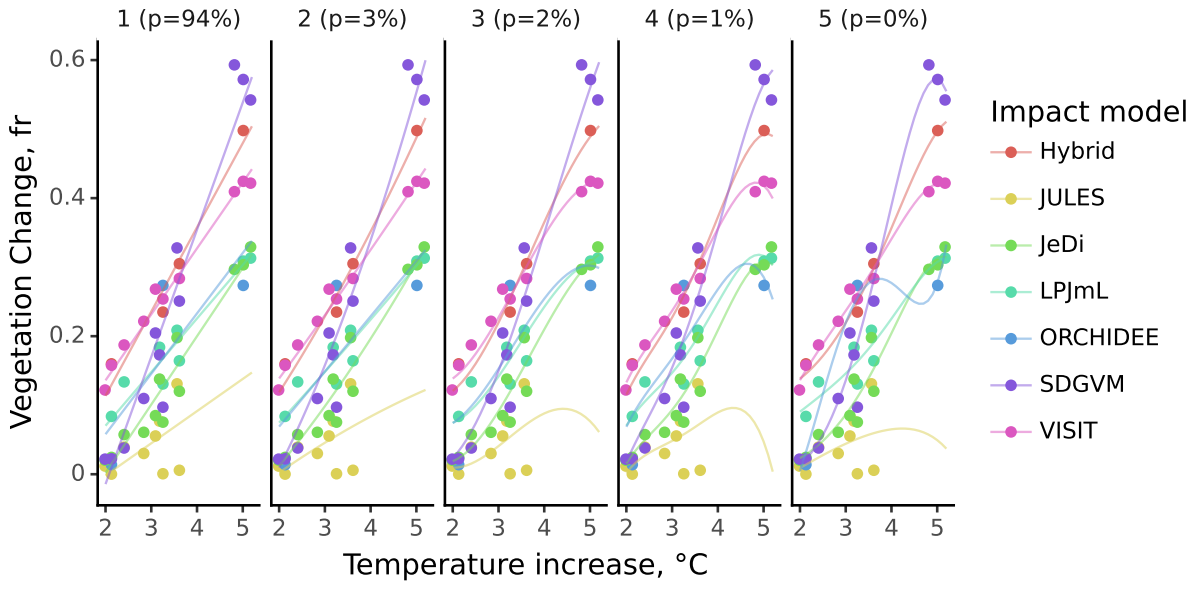
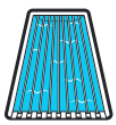


Figure B.4: Damage function for vegetation change. Y-axis: vegetation undergoing ecosystem change (in fractions of global vegetation). Other features as in Figure 2.

C Instructions

C.1 Point Estimate Options

	Glacier ice		Life expectancy		Vegetation change	
Option	Amount	Reference	Amount	Reference	Amount	Reference
E-9	0.004 mL	10th of a drop 	0.02 ms	Micro-seconds	0.005 mm²	Orchid seed 
E-6	4 mL	10th of a shot 	20 ms	Milli-seconds	5 mm²	Grass culm 
E-3	4 L	Large jug 	20 seconds	Seconds	50 cm²	Shrub 
E0	4,000 L	Jacuzzi 	6 hours	Hours	5 m²	Front garden 
E3	4 million L	Olympic pool 	1 year		5,000 m²	Football field 

	Glacier ice		Life expectancy		Vegetation change	
Option	Amount	Reference	Amount	Reference	Amount	Reference
E6	4 billion L	Small lake 	1,000 years		5 km²	Hyde park 
E9	4 trillion L	Loch Ness 	1,000,000 years		5,000 km²	Norfolk county 

Table C.1: Point estimate staircase options

Note: Options shown at various staircase steps of the point elicitation method. "Option" refers to the value by which the scientific Result 3.3 is multiplied, in scientific notation. For example, E-9 means the amount shown is $m_y(x^e)E-9 = m_y(x^e)\cdot 10^{-9}$, or 9 orders of magnitude below the scientific point estimate. The first staircase step is always E0. The second step is E-6 or E6 if "less" or "more" where selected, respectively. The final staircase step is E-9, E-3, E3 or E9, as explained in Section 4.

C.2 Belief Survey

C.2.1 Welcome

Thank you for participating in this survey about **global warming**.

It is very important for the quality of our research that you read the questions carefully and **answer honestly**.

Besides opinion questions, the survey also includes several questions about how you think global warming works. However, **no prior knowledge is required**. If you are unsure, just give us your best guess.

[Bonus box] Several questions in this survey are about **real money**. These are marked

with a box like this one that explains how the bonus payment works.

[Bonus box] At the end of the survey you will be able to **provide feedback**. We will send the most useful comment a **bonus of £5**.

C.2.2 Informed consent

Title of the research project: Global Warming

Principal Investigator: Christoph Semken

Institution: Universitat Pompeu Fabra

Funding agency: This project is funded by the Spanish government and "la Caixa" foundation.

Objectives and duration of the project: The goal of this study is to understand how people think about global warming. The duration of this project is 1 month. We may invite you to a follow-up study on Prolific.

Methodology and participation: You will be asked a number of questions about your views on global warming and participate in interactive tasks. The entire experiment is carried out online.

Privacy: Only pseudomised data (in which you are identified through your Prolific ID) will be collected. It may be stored for up to 5 years. After this time and in the event of data publication, only anonymous data (with your Prolific ID removed) will be published. Anonymised data may be hosted or published in a public repository.

Compensation: Your participation will be compensated via Prolific's payment system. You will receive the compensation indicated in the Prolific invitation (at least £8 per hour). You may not receive your compensation if you fail quality checks, in accordance with Prolific's rules.

Risks and benefits: Participating in this study does not entail any risks. We cannot and do not guarantee that you will receive any benefits from this study.

Voluntary nature of participation: Your participation in this study is on a voluntary basis and you may withdraw from the study at any time without having to justify why.

Contact information: If you have any question about this study, you may contact the principle investigator (Christoph Semken) through the Prolific messaging system.

If you have doubts, complaints, or questions about this study or about your rights as

a research participant, you may contact UPF's Institutional Committee for the Ethical Review of Projects (CIREP) by phone (+34 93 542 21 86) or by email (secretaria.cirep@upf.edu). CIREP is not part of the research team and will treat any information you send confidentially.

In accordance with the General Data Protection Regulation (GDPR) 2016/679 (EU), we provide the following information:

Data controller: Universitat Pompeu Fabra. C. de la Mercè, 12. 08002 Barcelona. Tel. +34 93 542 20 00. You can contact UPF's Data Protection officer by sending an email to dpd@upf.edu.

Purposes of the processing: Carrying out the above-mentioned research project. Anonymised data may be kept indefinitely.

Legal basis: Data owner's consent. You can withdraw your consent at any time.

Recipients: Your personal data will be processed by Universitat Pompeu Fabra. Anonymised data may be published in an open science repository.

Rights: You can access your data; request their rectification, deletion, and in certain cases their portability; you may object to their processing and apply for their limitation by following the procedures described at www.upf.edu/web/proteccio-dades/drets. You can contact UPF's Data Protection officer (dpd@upf.edu) for any queries or if you feel that your rights are not properly respected. Should you not be satisfied, you may file a complaint with the Catalan Data Protection Authority.

I HEREBY CONFIRM that:

- I have read the information sheet regarding the research project,
- I have been able to formulate questions on the project,
- I have received enough information on the project,
- I am between 18 and 65 years old.

I UNDERSTAND that my participation is voluntary and that I can withdraw from or opt out of the study at any time without any need to justify my decision.

I GIVE MY CONSENT to participate in this study.

C.2.3 Warm-up survey

How much do you agree with the following statements?

Global warming is mainly the result of human activity.

I trust scientists who do research on global warming.

I consider myself an environmentalist.

[Options: Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

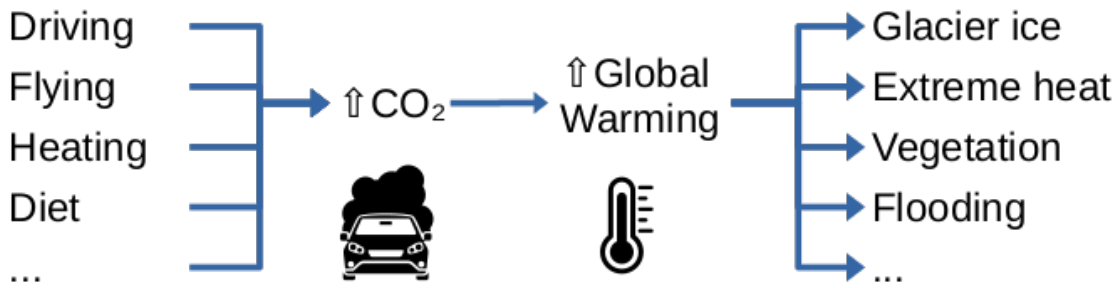
C.2.4 Causal chain

Please pay attention to the information below. We will ask you some questions about it on the next page.

This survey is about global warming and carbon dioxide (CO_2) emissions.

Global warming refers to the fact that the world's average temperature has considerably increased over the past 150 years and will continue to increase in the future.

The **figure below** shows how CO_2 emissions affect global warming outcomes, according to the Intergovernmental Panel on Climate Change (IPCC), a United Nations body made up of leading climate scientists.



Many of **your actions** (including driving, flying, heating and your diet) require the burning of fossil fuels, mostly oil and gas. The burning of fossil fuels releases CO_2 into the air. These **CO_2 emissions** accumulate there.

Through the greenhouse effect, the CO_2 in the air creates **global warming** (an increase in global temperatures). This, in turn, affects many important **global warming outcomes**. For example, global warming leads to glaciers melting, life expectancy decreasing, vegetation severely changing and changes in incomes.

C.2.5 Baseline variables

On a scale from 1 (strongly disagree) to 7 (strongly agree), how much do you agree with the following statements?

[Order randomised]

My actions have an influence on global warming.

I feel able to contribute to tackling global warming.

Individuals like myself can make a difference with respect to global warming.

I would like to reduce my emissions in the next 12 months.

I would like to encourage people close to me to reduce their emissions.

I believe it is important to pay attention to this study. Please choose 'strongly agree'.

[Options: 1 (strongly disagree), 2, 3, 4, 5, 6, 7 (strongly agree)]

C.2.6 Point estimate introduction

In the next task, you are asked to estimate the effect of **1 tonne of CO_2** on different global warming outcomes. Examples of actions that create about 1 tonne of CO_2 are:

- Driving 10 miles a day for 1 year (with an average diesel car)
- Eating 5 servings of meat per week for 1 year (beef, pork or lamb)
- Taking 1 long-distance return flight (for example London to New York and back)

We are interested in the expected **effect** this century on different outcomes of **1 person emitting 1 extra tonne of CO_2**. You can assume that no one else changes their behaviour and governments take no actions beyond their current targets, leading to approximately 2.4°C of warming. The effect is the sum of all changes in the world. For example, the effect on glacier ice could consist of small amounts of ice melting from each glacier.

[Bonus box] We will compare your answer to the predictions derived from climate models. The models are used by the Intergovernmental Panel on Climate Change (IPCC), a United Nations body made up of leading climate scientists. For each outcome, you will **earn £0.10** for an estimate that is within 50% of the average climate model prediction.

C.2.7 Point estimate: vegetation, zero

[The order of the outcomes is randomised.]

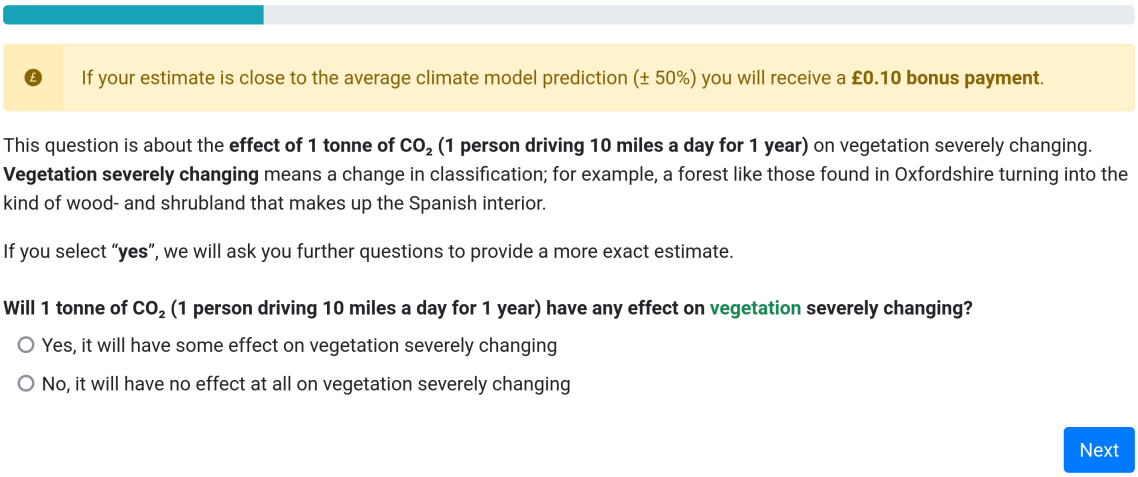


Figure C.1

[Skip next 4 pages if "no" is selected.]

C.2.8 Point estimate: vegetation, staircase 1

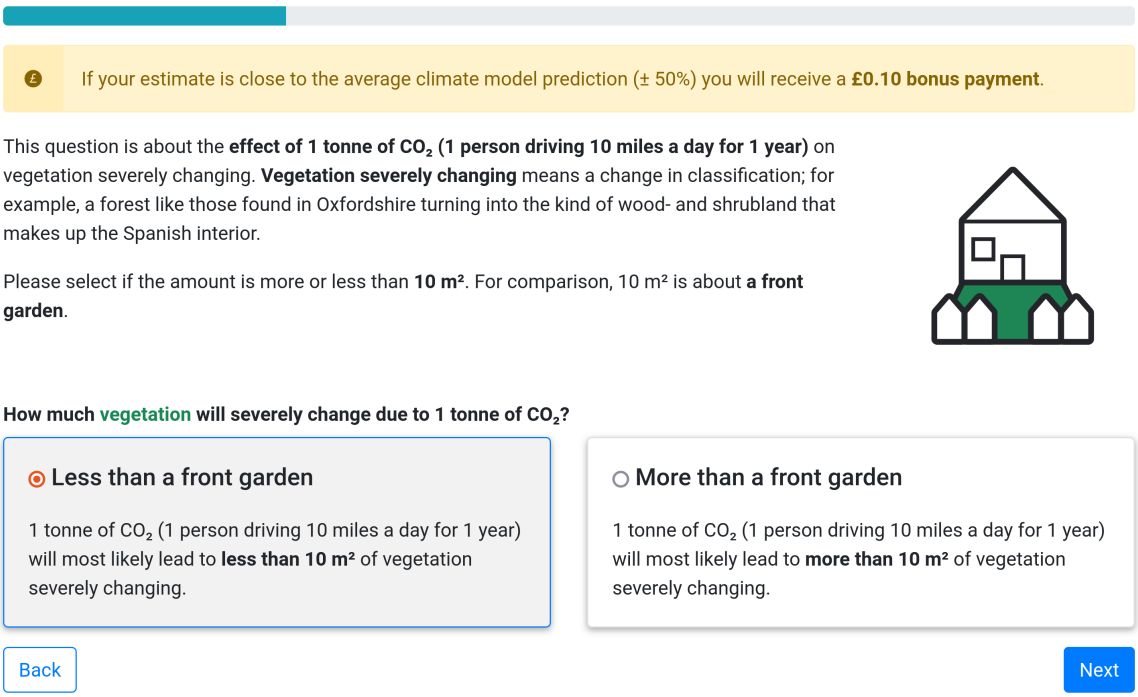


Figure C.2

[Order randomised]

C.2.9 Point estimate: vegetation, staircase 2

[Same as staircase 1, for the option 6 orders below/above the previous option if "less"/"more" was selected.]

C.2.10 Point estimate: vegetation, staircase 3

[Same as staircase 2, for the option 3 orders below/above the previous option if "less"/"more" was selected.]

C.2.11 Point estimate: vegetation, slider

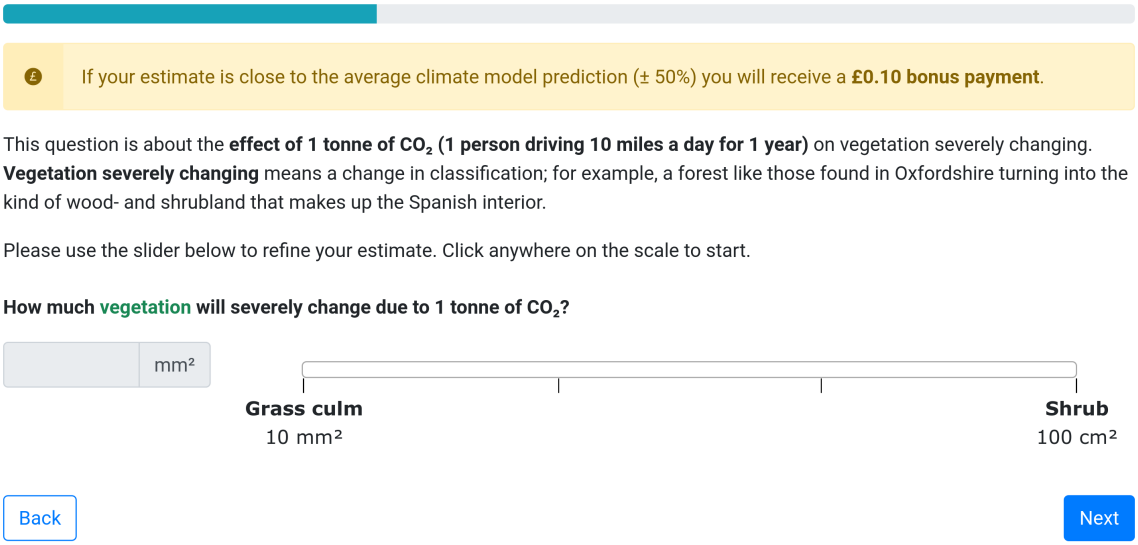


Figure C.3

[Not shown if the previously selected option is E-9 or E9]

[Lower and upper bound determined by previous options, see text]

C.2.12 Point estimate: life expectancy, zero

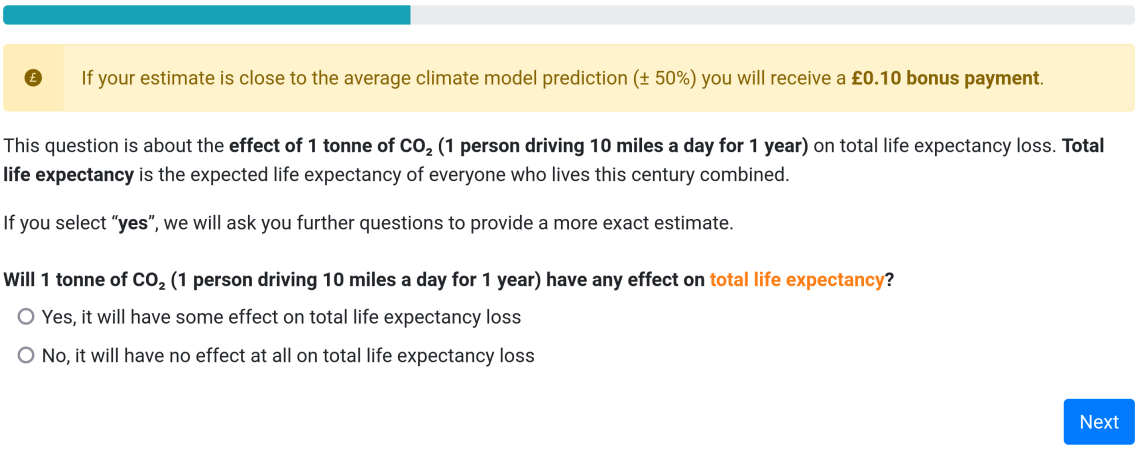


Figure C.4

[Skip next 4 pages if "no" is selected.]

C.2.13 Point estimate: life expectancy, staircase 1

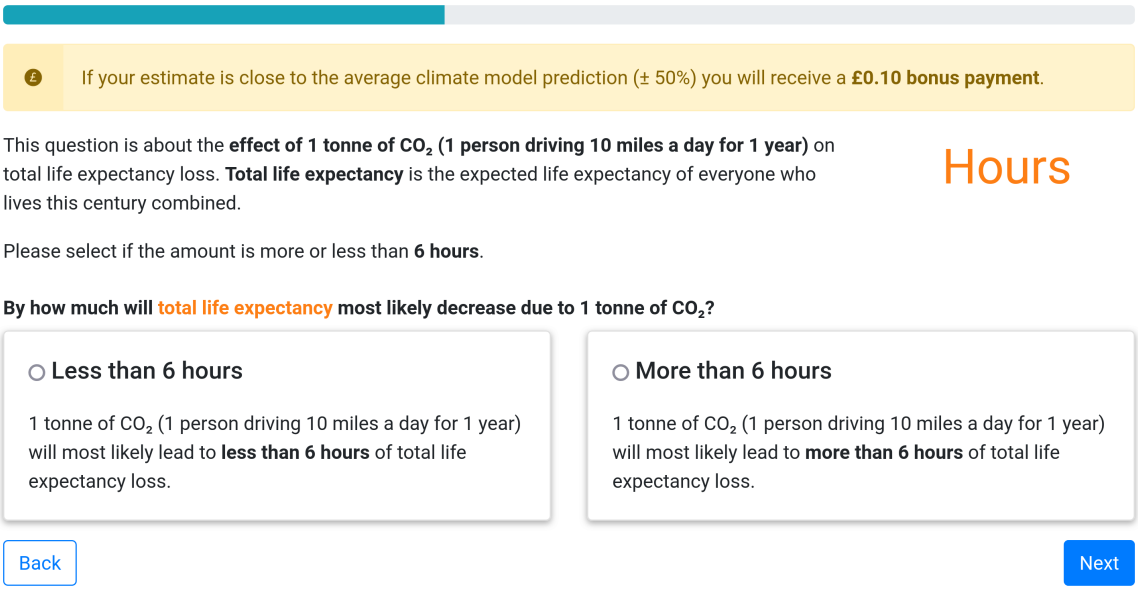


Figure C.5

[Order randomised]

C.2.14 Point estimate: life expectancy, staircase 2

[Same as staircase 1, for the option 6 orders below/above the previous option if "less"/"more" was selected.]

C.2.15 Point estimate: life expectancy, staircase 3

[Same as staircase 2, for the option 3 orders below/above the previous option if "less"/"more" was selected.]

C.2.16 Point estimate: life expectancy, slider

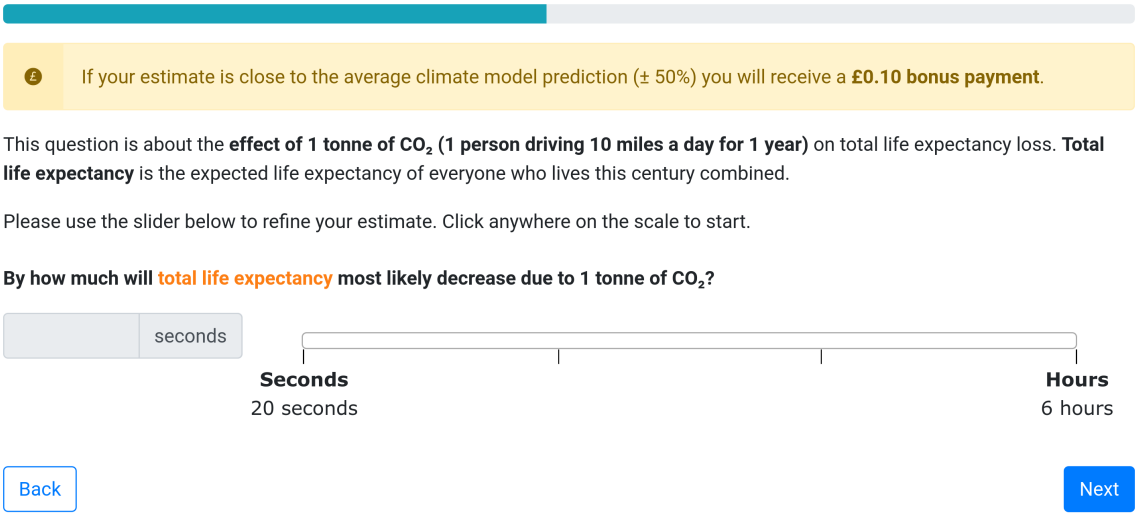


Figure C.6

[Not shown if the previously selected option is E-9 or E9]

[Lower and upper bound determined by previous options, see text]

C.2.17 Point estimate: glacier, zero

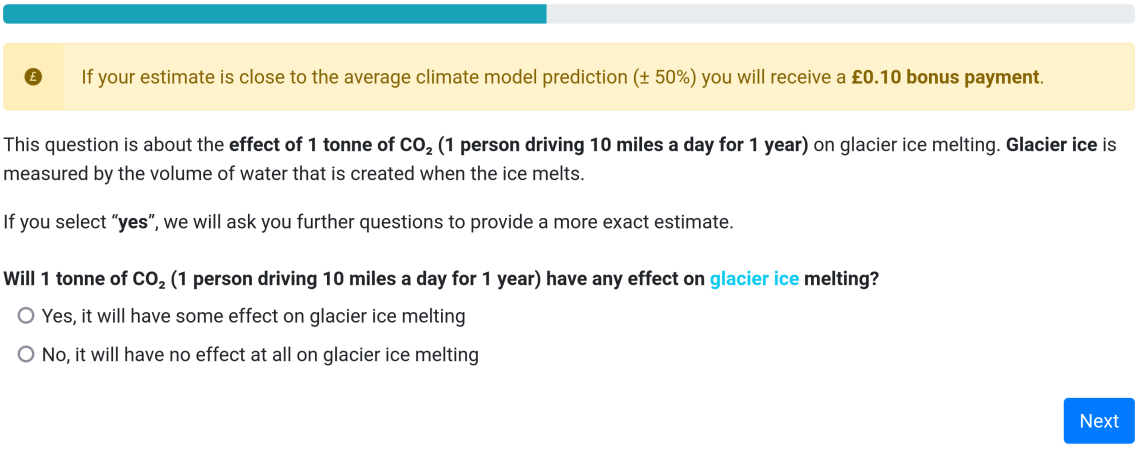


Figure C.7

[Skip next 4 pages if “no” is selected.]

C.2.18 Point estimate: glacier, staircase 1

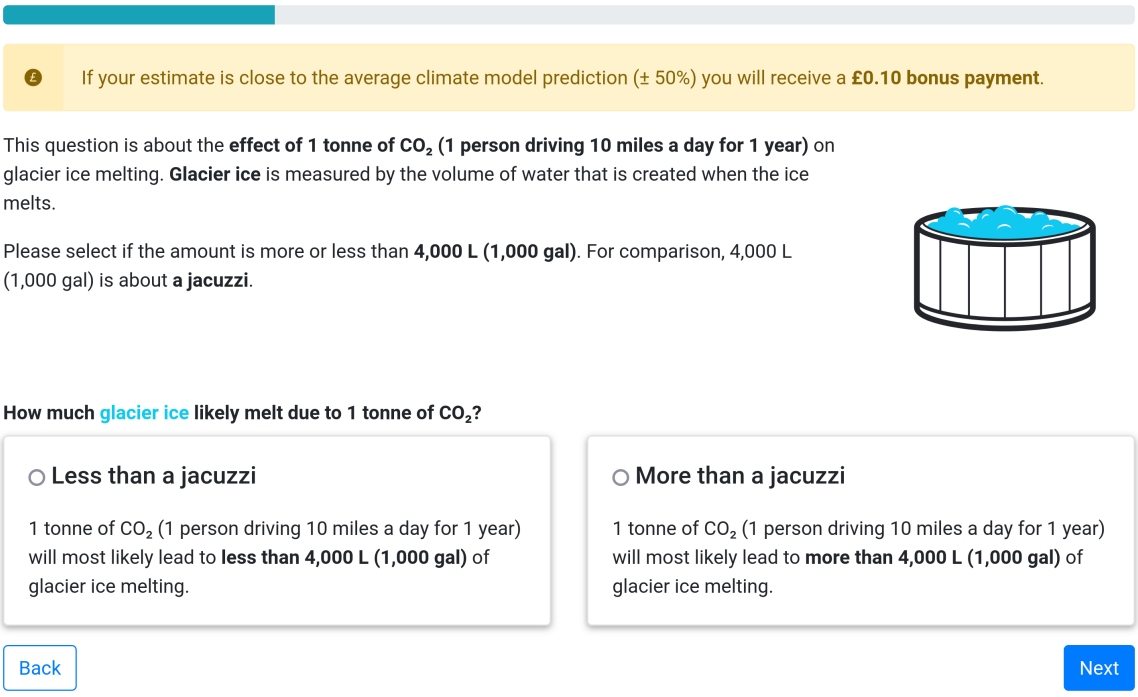


Figure C.8

[Order randomised]

C.2.19 Point estimate: glacier, staircase 2

[Same as staircase 1, for the option 6 orders below/above the previous option if “less”/“more” was selected.]

C.2.20 Point estimate: glacier, staircase 3

[Same as staircase 2, for the option 3 orders below/above the previous option if “less”/“more” was selected.]

C.2.21 Point estimate: glacier, slider

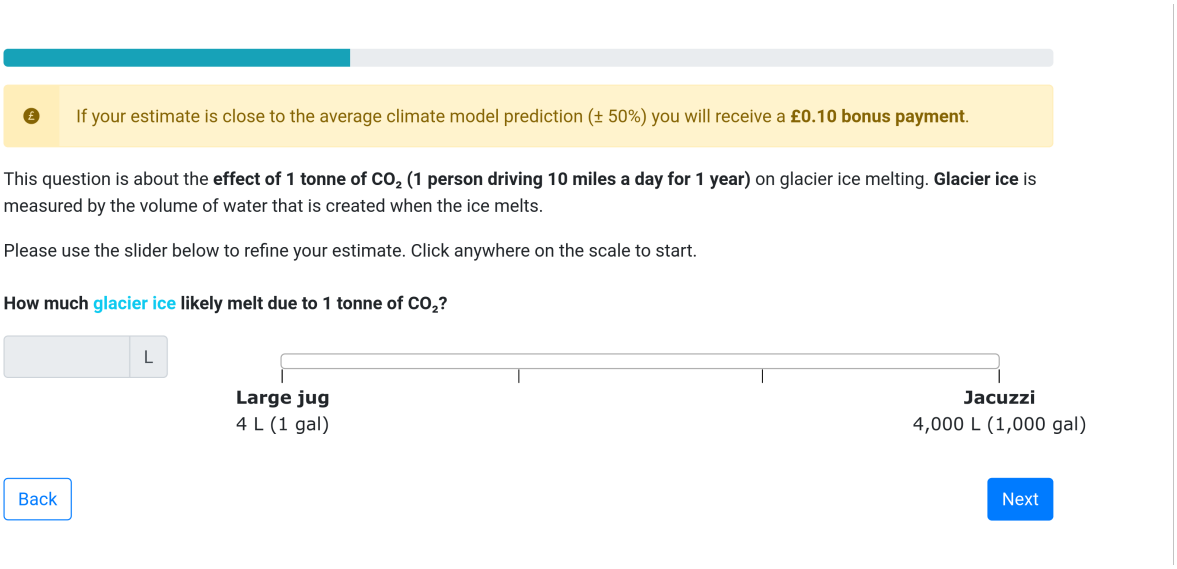


Figure C.9

[Not shown if the previously selected option is E-9 or E9]

[Lower and upper bound determined by previous options, see text]

C.2.22 Complementarity instructions

Please watch the video instructions below to proceed to the next page.

[Video transcript]

In the next question, you are asked to estimate how your impact depends on what others do. By "preserving vegetation" we mean that it will not be severely changed.

There are 3 scenarios. In scenario A, you reduce your emissions by 1 ton of CO_2, while others make no extra effort. The green trees represents the area of vegetation that is preserved by your reduction, however small or large.

In scenario B, everyone else in the world reduces their emissions by 1 ton of CO_2, while you make no extra effort. The orange trees represent the area of vegetation preserved by everyone else's reduction, however small or large.

Finally in scenario C, everyone else already reduces their emissions by 1t of CO_2. Now you also reduce your emissions. Your reduction of 1 ton of CO_2 is added to everyone else's reduction.

We ask you to compare the area of vegetation that your reduction preserves in this scenario, compared to when you are the only one reducing your emissions. Specifically, compared to scenario A, is the area of vegetation preserved by your additional 1 ton reduction smaller, the same or larger?

[End transcript]

[Different parts of the page are highlighted during the video]

[Participants can only proceed if video is watched until the end]

C.2.23 Complementarity

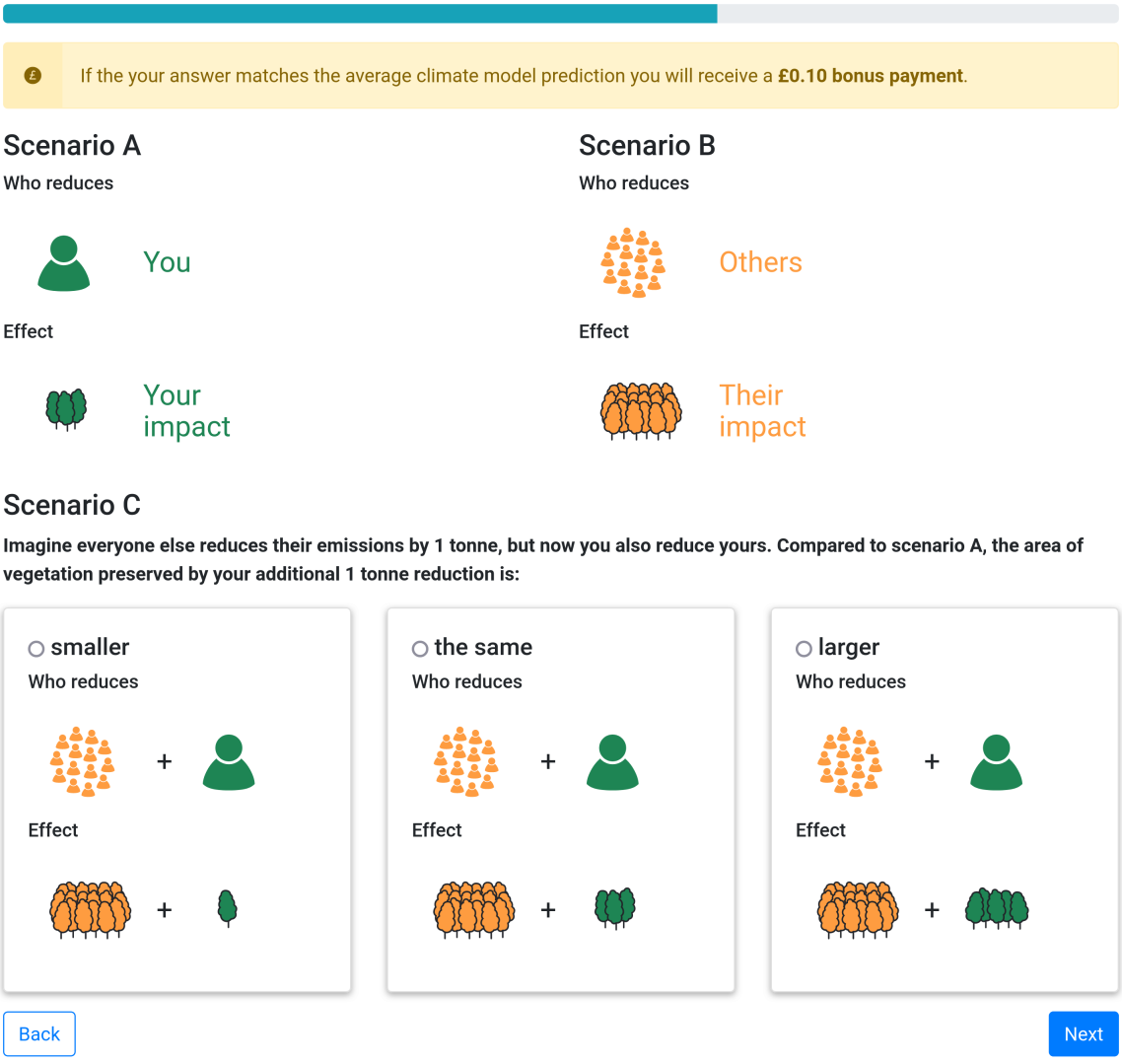


Figure C.10

[Order randomised]

C.2.24 Thresholds

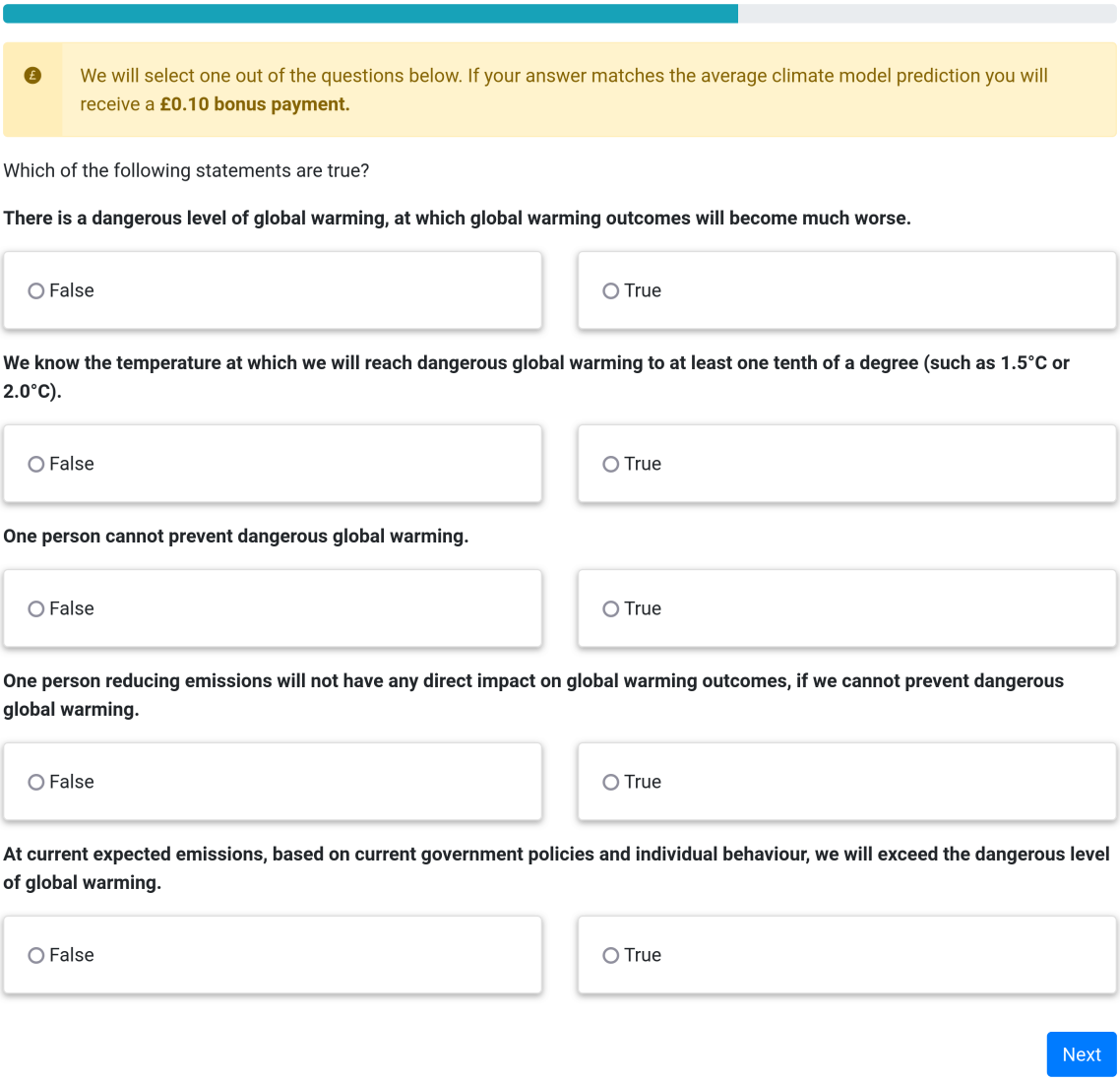


Figure C.11

C.2.25 Attention check 2

The question below is related to the following problem. In survey like ours, there are sometimes a few people who do not carefully read the questions they are asked and just "quickly click through the survey". These answers are problematic because they

compromise the results of the studies. In order to show that you read our instructions carefully, please answer "Purple" at the question below.

Based on the text above, what would you say the colour of grass is?

- Green
- Purple

C.2.26 Info: Introduction

[Treatment group] We will now show you the answers to the estimation questions coming from the Intergovernmental Panel on Climate Change (IPCC), a United Nations body made up of leading climate scientists. For each question we will show you both your and their answer.

[Control group] We are interested in how well-designed you think some of our questions were. In the following pages, you will be reminded of the questions and your answers. We then ask you to rate each question.

C.2.27 Info: Thresholds

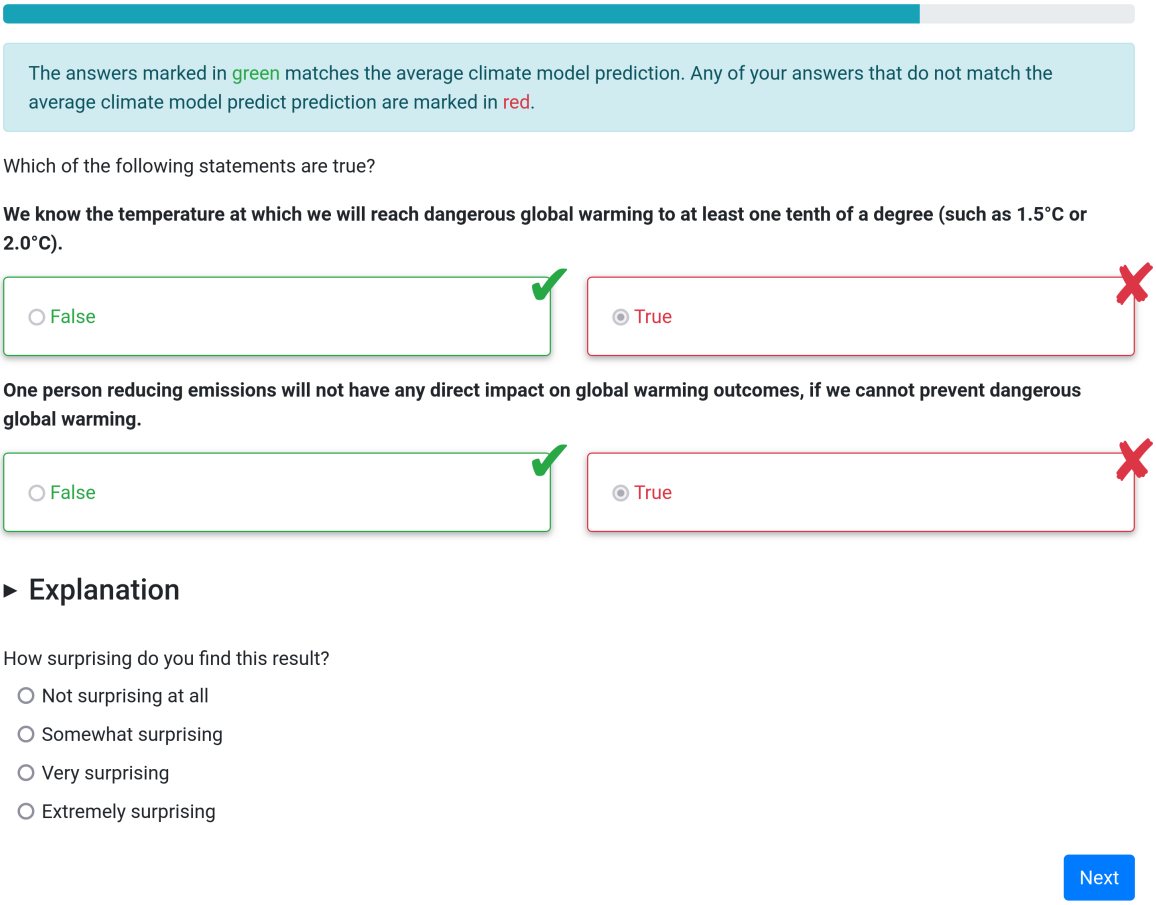


Figure C.12

Explanation [shown if clicked] There may be some dangerous levels of global warming, depending on ones definition. Namely, "tipping points" are levels of global warming with abrupt or irreversible changes.

However, we do not know well where such tipping points will occur. Global targets such as 1.5°C or 2°C are arbitrary from a climate scientific perspective.

Moreover, reducing emission will have a direct impact on global warming outcomes, regardless of whether we can prevent any given tipping point. Therefore, one person's emission reductions have an impact on global warming outcomes, even if other people do not reduce their emissions.

[End explanation]

[Control group sees only their own answer, without coloring or the explanation, and the question: How clear do you think this question was? Options: Not clear at all, Somewhat clear, Mostly clear, Perfectly clear]

C.2.28 Info: Complementarity

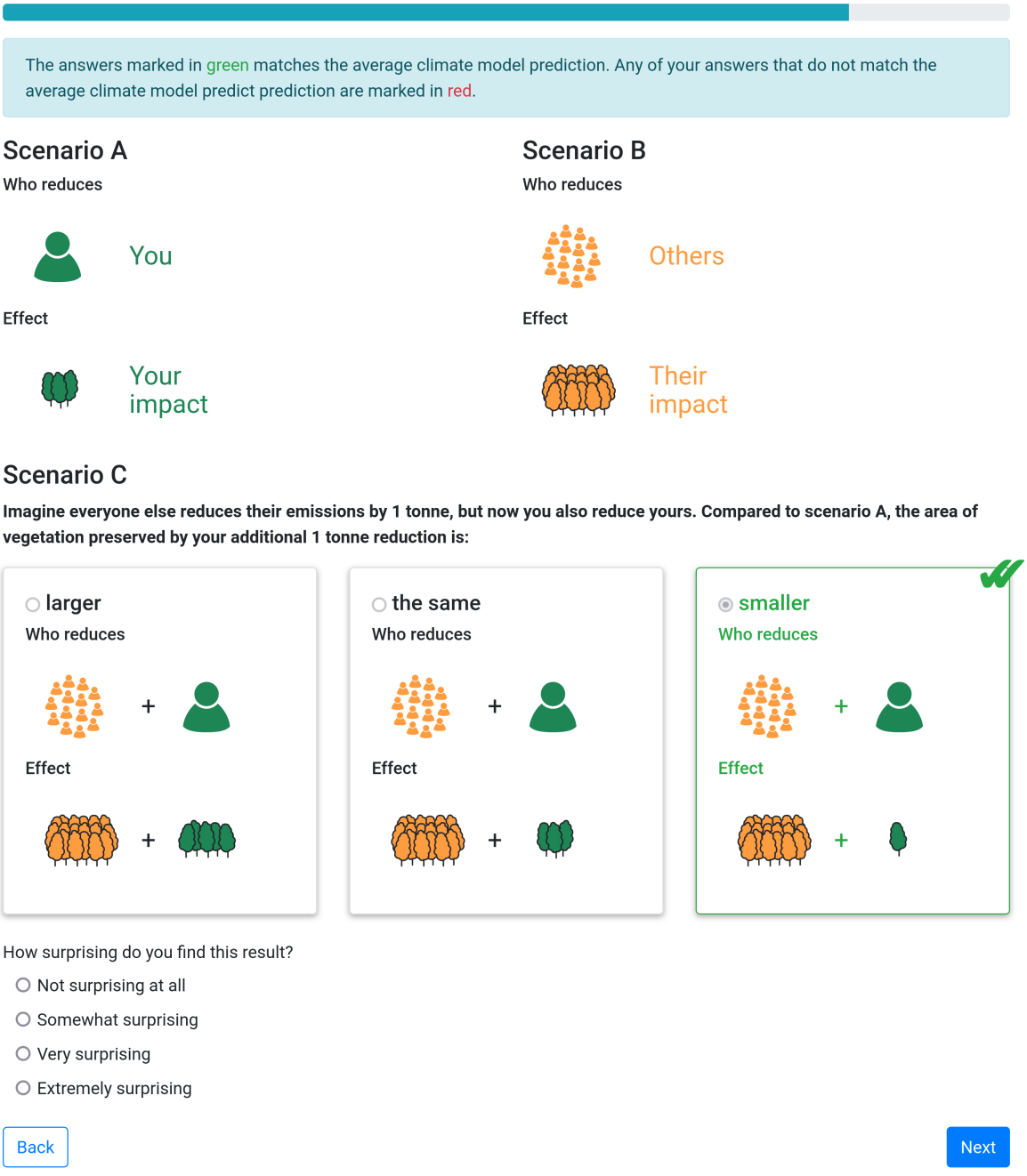


Figure C.13

[Control group sees only their own answer, without coloring, and the question: How clear do you think this question was? Options: Not clear at all, Somewhat clear, Mostly clear, Perfectly clear]

C.2.29 Info: Point estimate

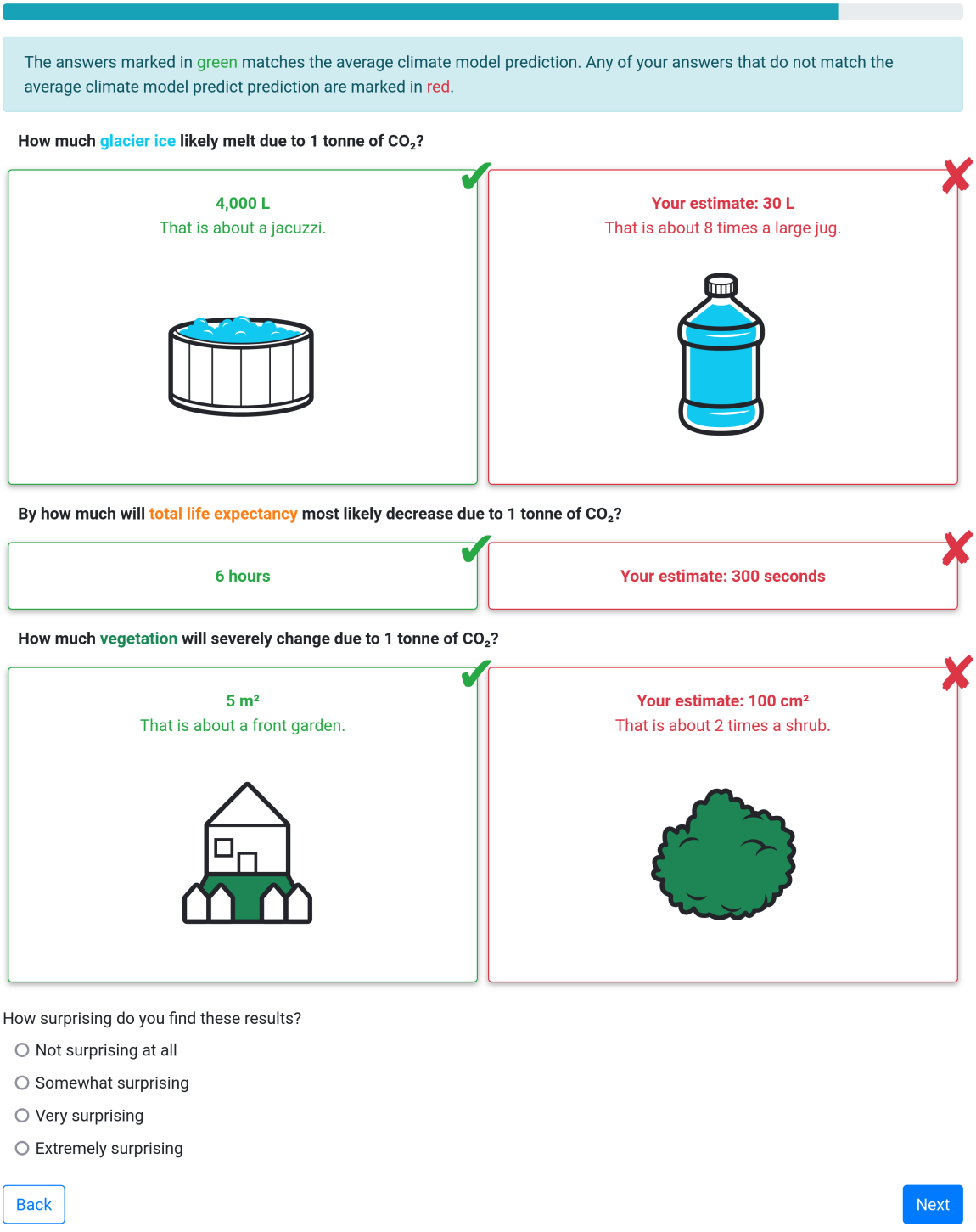


Figure C.14

[Control group sees only their own answer, in full width, without coloring, and the

question: How clear do you think this question was? Options: Not clear at all, Somewhat clear, Mostly clear, Perfectly clear]

C.2.30 Info: Summary

[Page only shown to treatment group]

Please watch the video instructions below to proceed to the next page.

[Video transcript]

Let us summarise the information you have received.

Many actions increase CO_2 emissions. For example, 1 tonne of CO_2 is emitted by:

- driving 10 miles a day for 1 year,
- eating 5 servings of meat a week for 1 year,
- or taking 1 long-distance flight.

Reducing emissions by 1 tonne of CO_2 can be expected to:

- prevent 4,000 litres of glacier ice from melting,
- increase total life expectancy by 6 hours,
- and prevent 5 square metres of vegetation from severely changing.

Importantly, reducing your emissions has all of these effects and more.

You also learned that your emission reductions have an impact, whether or not we reach dangerous levels of warming.

Moreover, for a typical global warming outcome like vegetation, your impact is larger now than if everyone else also reduced their emissions.

Together, these two points mean that you can have an impact on global warming without the collaboration of others.

In summary, the impact of every tonne of CO_2 saved is tangible, even if other people do not reduce their emissions.

[End transcript]

[Participants can only proceed if video is watched until the end]

C.2.31 Demograhpics

Do you have any children?

- Yes
- No

Which of these is the highest level of education you have completed?

- No formal qualifications
- Secondary education (e.g. GED/GCSE)
- High school diploma/A-levels
- Technical/community college
- Undergraduate degree (BA/BSc/other)
- Graduate degree (MA/MSc/MPhil/other)
- Doctorate degree (PhD/other)
- Don't know / not applicable

What is your total household income per year, including all earners in your household (after tax) in GBP?

- Less than £10,000
- £10,000 - £15,999
- £16,000 - £19,999
- £20,000 - £29,999
- £30,000 - £39,999
- £40,000 - £49,999
- £50,000 - £59,999
- £60,000 - £69,999
- £70,000 - £79,999
- £80,000 - £89,999
- £90,000 - £99,999
- £100,000 - £149,999
- More than £150,000
- Rather not say

C.2.32 Feedback

[Bonus box] Your feedback is very valuable at this point. We will send the most useful comment a **bonus of £5**.

Thank you for participating. Do you have any comments on the design of the study?

[Text box]

C.3 Attitudes and Intentions Survey

C.3.1 Informed consent

Welcome to this research study. We appreciate your participation. This study contains real choices and questions regarding climate change.

Requirements

You must be a U.K. resident to participate in this study. You must also be between 18 and 65 years old.

Objectives and methodology

We wish to understand your views on climate change. We will ask you several questions. The survey is carried out online.

Voluntary participation

It is voluntary to participate in the project, and you can at any time choose to withdraw your consent without stating any reason.

Confidentiality

Researchers will at no point have access to any information that could be used to personally identify you. Only pseudomised data (in which you are identified through your Prolific ID) will be collected. It may be stored for up to 5 years. In the event of data publication, only anonymous data (with your Prolific ID removed) will be published. Anonymised data may be hosted or published in a public repository.

Your answers may be linked to a study you have previously participated in, where a second study was announced in the consent form. If you would like to know the name of the study, you can contact us though the Prolific messaging system. You can at any time choose to withdraw your consent to link the two studies without stating any

reason.

Compensation, risks and benefits

Your participation will be compensated via Prolific's payment system. You will receive the compensation indicated in the Prolific invitation (at least £8 per hour). You may not receive your compensation if you fail quality checks, in accordance with Prolific's rules.

Participating in this study does not entail any risks. We cannot and do not guarantee that you will receive any benefits from this study.

Questions about the Survey

If you have questions about this study or your rights, please get in touch with us through the Prolific messaging system.

Data privacy contact information

If you have doubts, complaints, or questions about this study or about your rights as a research participant, you may contact UPF's Institutional Committee for the Ethical Review of Projects (CIREP) by phone (+34 93 542 21 86) or by email (secretaria.cirep@upf.edu). CIREP is not part of the research team and will treat any information you send confidentially.

In accordance with the General Data Protection Regulation (GDPR) 2016/679 (EU), we provide the following information:

- Data controller: Universitat Pompeu Fabra. C. de la Mercè, 12. 08002 Barcelona. Tel. +34 93 542 20 00. You can contact UPF's Data Protection officer by sending an email to dpd@upf.edu.
- Purposes of the processing: Carrying out the above-mentioned research project. Anonymised data may be kept indefinitely.
- Legal basis: Data owner's consent. You can withdraw your consent at any time.
- Recipients: Your personal data will be processed by Universitat Pompeu Fabra. Anonymised data may be published in an open science repository.
- ***Rights***: You can access your data; request their rectification, deletion, and in certain cases their portability; you may object to their processing and apply for their limitation by following the procedures described at www.upf.edu/web/proteccio-dades/drets. You can contact UPF's Data Protection officer (dpd@upf.edu) for any queries or if you feel that your rights are not properly respected. Should you not be satisfied, you may file a complaint with the Catalan Data Protection

Authority.

Project information

Title of the research project: Climate Change

Principal Investigator: [PI]

Institution: Universitat Pompeu Fabra

Funding agency: Spanish government and "la Caixa" foundation

I have received and read the above information about the project, have been able to ask questions, know that my participation is voluntary and that I can withdraw from or opt out of the study at any time without any need to justify my decision. I consent to participate in the study.

- Yes
- No

C.3.2 Warm-up survey

Do you believe in climate change?

- Yes
- No
- Don't know

Generally speaking, how concerned are you about environmental issues?

- 1 (Not at all concerned)
- 2
- 3
- 4
- 5 (Very concerned)

C.3.3 Introduction

Climate change is the long-term shift in temperatures and weather that is caused by **greenhouse gas emissions**. Burning fossil fuels generates greenhouse gas emissions

that act like a blanket wrapped around the Earth, trapping the sun's heat and raising temperatures. The most important greenhouse gas that causes climate change is **carbon dioxide (CO_2)**.

A person's **carbon footprint** measures the amount of greenhouse gases they are responsible for, in tonnes of CO_2. The average UK citizen's carbon footprint is about 8 tonnes of CO_2 per year. It breaks down how much of your emissions come from driving, flying, eating, heating, etc. Your carbon footprint allows you to know and reduce your impact on climate change.

C.3.4 Self-efficacy

On a scale from 1 (strongly disagree) to 7 (strongly agree), how much do you agree with the following statements?

[Order randomised]

If I tried to behave in a climate-friendly way, that would have a positive effect on climate change.

I can personally help to reduce climate change by changing my behaviour.

I personally feel that I can make a difference with regard to climate change.

[Options: 1 (strongly disagree), 2, 3, 4, 5, 6, 7 (strongly agree)]

C.3.5 Intentions to reduce

On a scale from 1 (extremely unlikely) to 7 (extremely likely), how likely are you to engage in the following activity should the opportunity arise in the next 12 months?

[Order randomised]

Switch household appliances off at the wall socket to reduce energy consumption

Take steps to reduce my carbon footprint

Use alternative forms of transport such as walking, cycling, or public transport

Choose energy efficient appliances and electronic equipment

[Options: 1 (extremely unlikely), 2, 3, 4, 5, 6, 7 (extremely likely)]

C.3.6 Other outcomes

On a scale from 1 (strongly disagree) to 7 (strongly agree), how much do you agree with the following statements?

[Order randomised]

I want to convince my friends and family to reduce their carbon footprint.

I want to learn more about my carbon footprint and how to reduce my emissions.

[Options: 1 (extremely unlikely), 2, 3, 4, 5, 6, 7 (extremely likely)]

C.3.7 Ethical reasoning

How much do you agree with the following statements?

One person reducing their emissions is the right thing to do...

[Order randomised]

...only if it has larger personal benefits than personal costs.

...only if it has larger societal benefits than societal costs.

...only if everyone else also reduce their emissions.

...because it will inspire others to do the same.

...because if everyone else did it, the world would be a better place.

...independently of whether it has an impact on climate change outcomes.

[Options: Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

C.3.8 Study purpose

If you had to guess, what was the purpose of this study?

[Textbox]

C.4 Donation Survey

C.4.1 Welcome

Thank you for participating in this survey about **global warming**.

It is very important for the quality of our research that you read the questions carefully and **answer honestly**.

[Bonus box] Several questions in this survey are about **real money**. These are marked with a box like this one that explains how the bonus payment works.

[Bonus box] At the end of the survey you will be able to **provide feedback**. We will send the most useful comment a **bonus of £5**.

C.4.2 Informed consent

Title of the research project: Global Warming

Principal Investigator: Christoph Semken

Institution: Universitat Pompeu Fabra

Funding agency: This project is funded by the Spanish government and "la Caixa" foundation.

Objectives and duration of the project: The goal of this study is to understand how people think about global warming. The duration of this project is 1 month. We may invite you to a follow-up study on Prolific.

Methodology and participation: You will be asked a number of questions about your views on global warming and participate in interactive tasks. The entire experiment is carried out online.

Privacy: Only pseudomised data (in which you are identified through your Prolific ID) will be collected. It may be stored for up to 5 years. After this time and in the event of data publication, only anonymous data (with your Prolific ID removed) will be published. Anonymised data may be hosted or published in a public repository.

Compensation: Your participation will be compensated via Prolific's payment system. You will receive the compensation indicated in the Prolific invitation (at least £8 per hour). You may not receive your compensation if you fail quality checks, in accordance with Prolific's rules.

Risks and benefits: Participating in this study does not entail any risks. We cannot and do not guarantee that you will receive any benefits from this study.

Voluntary nature of participation: Your participation in this study is on a voluntary basis and you may withdraw from the study at any time without having to justify why.

Contact information: If you have any question about this study, you may contact the principle investigator (Christoph Semken) through the Prolific messaging system.

If you have doubts, complaints, or questions about this study or about your rights as a research participant, you may contact UPF's Institutional Committee for the Ethical Review of Projects (CIREP) by phone (+34 93 542 21 86) or by email (secretaria.cirep@upf.edu). CIREP is not part of the research team and will treat any information you send confidentially.

In accordance with the General Data Protection Regulation (GDPR) 2016/679 (EU), we provide the following information:

Data controller: Universitat Pompeu Fabra. C. de la Mercè, 12. 08002 Barcelona. Tel. +34 93 542 20 00. You can contact UPF's Data Protection officer by sending an email to dpd@upf.edu.

Purposes of the processing: Carrying out the above-mentioned research project. Anonymised data may be kept indefinitely.

Legal basis: Data owner's consent. You can withdraw your consent at any time.

Recipients: Your personal data will be processed by Universitat Pompeu Fabra. Anonymised data may be published in an open science repository.

Rights: You can access your data; request their rectification, deletion, and in certain cases their portability; you may object to their processing and apply for their limitation by following the procedures described at www.upf.edu/web/proteccio-dades/drets. You can contact UPF's Data Protection officer (dpd@upf.edu) for any queries or if you feel that your rights are not properly respected. Should you not be satisfied, you may file a complaint with the Catalan Data Protection Authority.

I HEREBY CONFIRM that:

- I have read the information sheet regarding the research project,
- I have been able to formulate questions on the project,
- I have received enough information on the project,
- I am between 18 and 65 years old.

I UNDERSTAND that my participation is voluntary and that I can withdraw from or opt out of the study at any time without any need to justify my decision.

I GIVE MY CONSENT to participate in this study.

C.4.3 Warm-up survey

On a scale from 1 (strongly disagree) to 7 (strongly agree), how much do you agree with the following statements?

[Order randomised]

Global warming is mainly the result of human activity.

I feel able to contribute to tackling global warming.

[Options: 1 (strongly disagree), 2, 3, 4, 5, 6, 7 (strongly agree)]

C.4.4 Information intro

We will now show you some **information about global warming**. The information summarises the average prediction of models used by the Intergovernmental Panel on Climate Change (IPCC), a United Nations body made up of leading climate scientists

We are interested in **how surprising** you think the results are.

C.4.5 Causal chain

Please pay attention to the information below. We will ask you some questions about it on the next page.

This survey is about global warming and carbon dioxide (CO_2) emissions.

Global warming refers to the fact that the world's average temperature has considerably increased over the past 150 years and will continue to increase in the future.

The **figure below** shows how CO_2 emissions affect global warming outcomes, according to the Intergovernmental Panel on Climate Change (IPCC), a United Nations body made up of leading climate scientists.

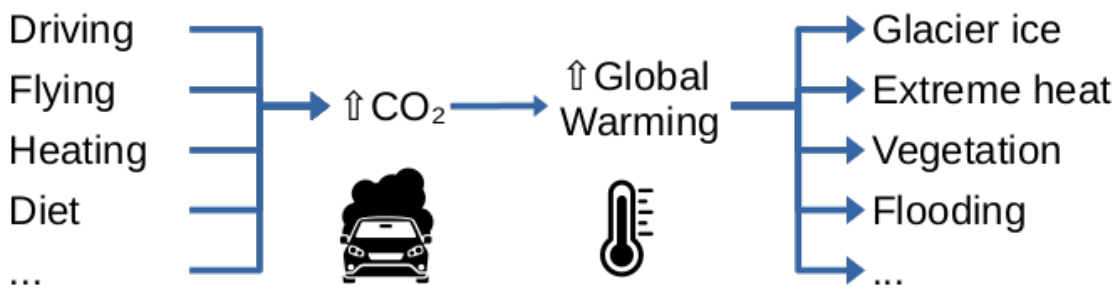


Figure C.15

Many of **your actions** (including driving, flying, heating and your diet) require the burning of fossil fuels, mostly oil and gas. The burning of fossil fuels releases CO_2 into the air. These **CO_2 emissions** accumulate there.

Through the greenhouse effect, the CO_2 in the air creates **global warming** (an increase in global temperatures). This, in turn, affects many important **global warming outcomes**. For example, global warming leads to glaciers melting, life expectancy decreasing, vegetation severely changing and changes in incomes.

How surprising do you find this information?

[Options: Not surprising at all, Somewhat surprising, Very surprising, Extremely surprising]

C.4.6 Measurement

Emissions are measured in **tonnes of CO_2**.

An example of action that creates about 1 tonne of CO_2 is **driving 10 miles a day for 1 year** (with an average diesel car).

How surprising do you find this information?

[Options: Not surprising at all, Somewhat surprising, Very surprising, Extremely surprising]

C.4.7 Info: Point estimate

[Only shown to treatment group]

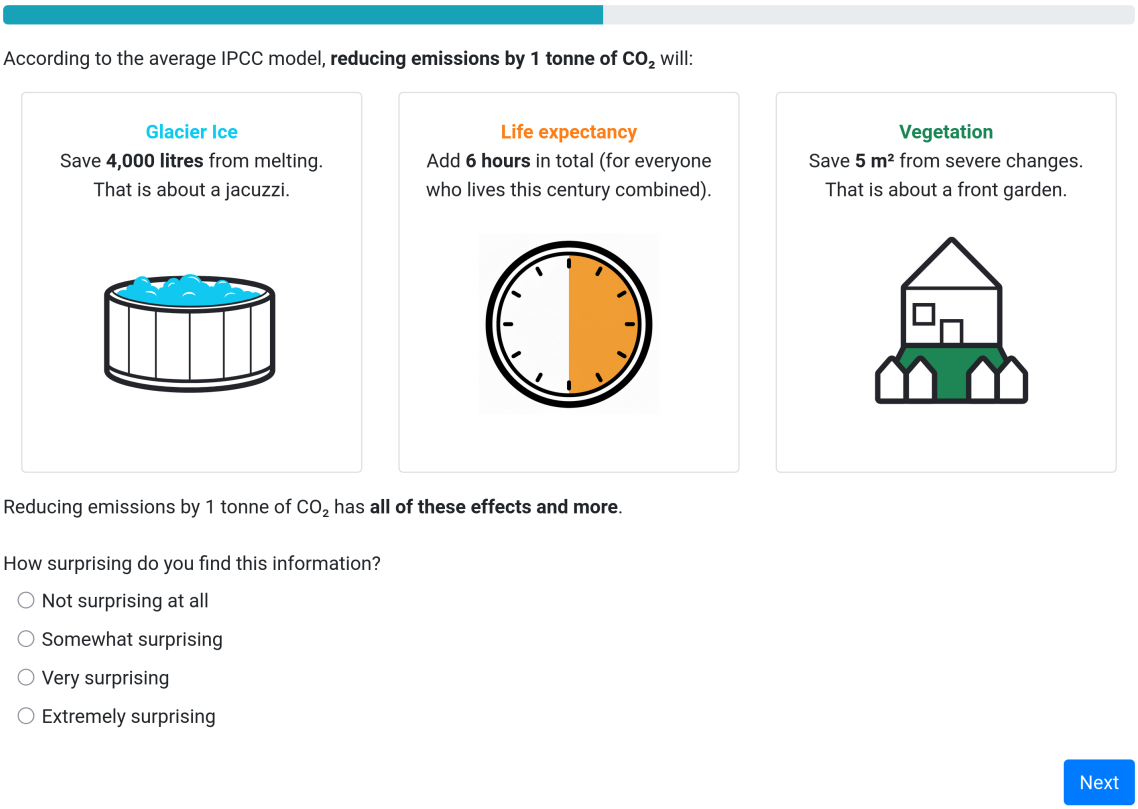


Figure C.16

C.4.8 Info: Complementarity

[Only shown to treatment group]

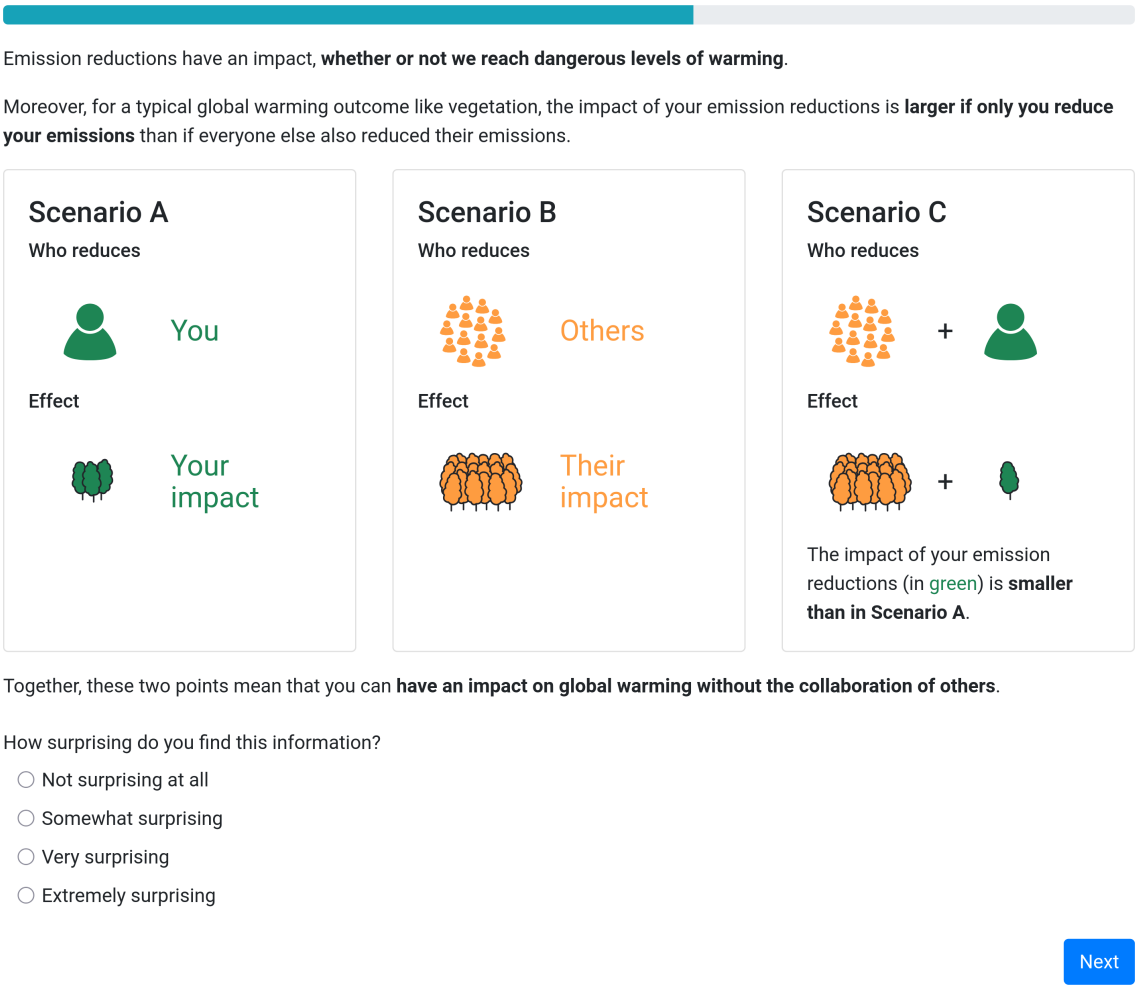


Figure C.17

C.4.9 Info: Summary

[Page only shown to treatment group]

Please watch the video instructions below to proceed to the next page.

[Video transcript]

Let us summarise the information you have received.

Many actions can generate 1 tonne of CO_2, including driving, your diet, and flying.

Reducing emissions by 1 tonne of CO_2 can be expected to:

- prevent 4,000 litres of glacier ice from melting,

- increase total life expectancy by 6 hours,
- and prevent 5 square metres of vegetation from severely changing.

Importantly, reducing your emissions has all of these effects and more.

In addition, our emission reductions have an impact, whether or not we reach dangerous levels of warming.

And, for a typical global warming outcome like vegetation, your impact is larger now than if everyone else also reduced their emissions.

Together, these two points mean that you can have an impact on global warming without the collaboration of others.

In summary, the impact of every tonne of CO_2 saved is tangible, even if other people do not reduce their emissions.

[End transcript]

[Participants can only proceed if video is watched until the end]

C.4.10 Donation instructions

[Bonus box] Please pay special attention to this question, in which you will make a decision about money. We will randomly select 2 respondents. If you are among them, your decision will be a real decision. The decision will be implemented and **you can receive up to £200**.

The second part of this survey consist of a donation task. In this task, you can **receive up to £200**.

You can donate as much as you want of the money to **reduce global CO_2 emissions** (or compensate your CO_2 emissions), for example by funding renewable energy projects. It costs about £20 to reduce emissions by 1 tonne of CO_2 in this way.

The amount that you **keep** will be added to your bonus.

About the programme [shown if clicked] The compensation will be bought from atmosfair. Atmosfair finances solar power, hydro power and other projects that would not happen otherwise. It is a nonprofit, works transparently and only finances projects certified under the highest available standard. Independent research has confirmed

the effectiveness of its compensations. You can find more information about atmosfair here.

C.4.11 Donation

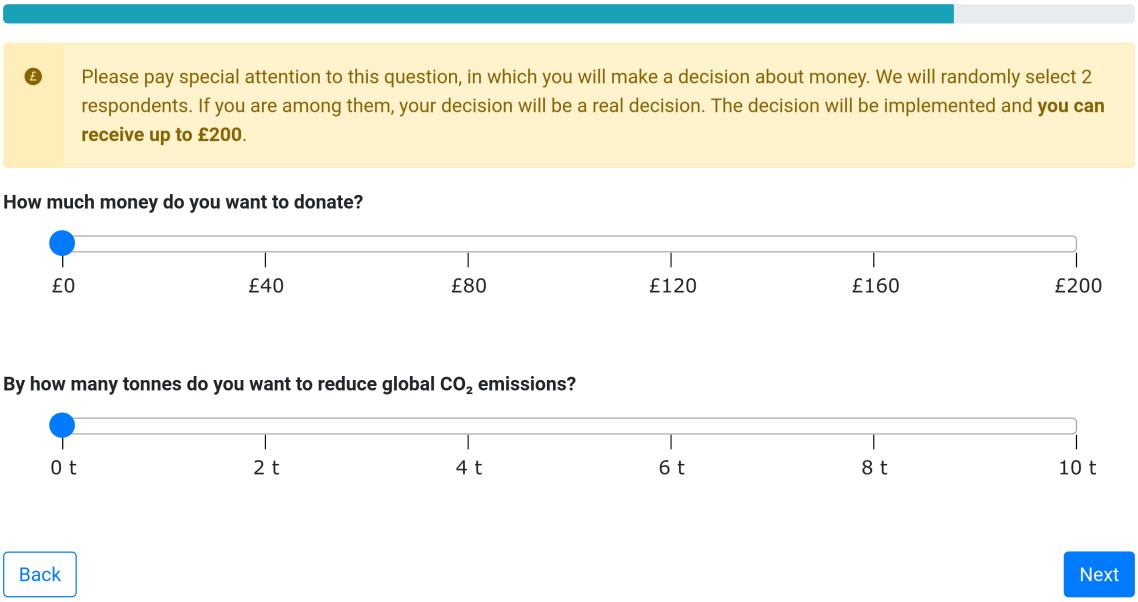


Figure C.18

[Sliders synchronise automatically]

C.4.12 Feedback

[Bonus box] Your feedback is very valuable at this point. We will send the most useful comment a **bonus of £5**.

Thank you for participating. Do you have any comments on the design of the study?

[Text box]

D Supplementary Survey Results

D.1 Sample Characteristics

Table D.1: Sample characteristics

	(1) Beliefs	(2) Intentions	(3) Behavior	(4) UK
Male (%)	50.0	50.3	49.7	49.0
Age (yr)	40.0	41.0	41.0	40.7
Income (k£)	40-49	40-49		32.0
University degree (%)	59.8	60.7		33.8
Environmentalist (%)	46.3	46.2		42.0
N	600.0	545.0	600.0	67M

Note: Shown are average of demographic variables for the (1) belief, (2) attitude and intention and (3) behavior samples, as well as (4) the UK population. Values are the median for age and income, and the mean for all other variables. Income, education and "environmentalist" were only elicited in experiment 1, the sample used for the heterogeneity analysis in Section 7. All samples come from the same population, see Sections 4.3, 5.3 and 6.3. Source for the UK population estimates are: ONS (2022) for gender, age and total population, ONS (2023a) for income, ONS (2023b) for education (England and Wales only), and YouGov (2021) for environmentalists.

D.2 Obfuscation Robustness

Table D.2: Treatment effect – obfuscation robustness

	Self-efficacy	Intentions
	(1)	(2)
Info treatment	0.288***	0.106**
	(0.038)	(0.053)
Baseline values	✓	✓
Observations	543	543
R^2	0.658	0.299
Control mean	0.0	0.0
Control s.d.	1.0	1.0

Note: Treatment effect of experiment 1 without subjects who mentioned the first survey in the purpose field of the obfuscated follow-up. See notes for columns (1)-(2) of Table 1. *p<0.1; **p<0.05; ***p<0.01.

D.3 Secondary Outcomes

Table D.3: Treatment effect – intentions

	Switch off	Footprint	Transport	Devices	Others	Learn
	(1)	(2)	(3)	(4)	(5)	(6)
Info treatment	0.150***	0.114***	-0.017	0.078	0.115***	0.126***
	(0.052)	(0.043)	(0.062)	(0.054)	(0.040)	(0.040)
Baseline values	✓	✓	✓	✓	✓	✓
Observations	545	545	545	545	545	545
R^2	0.159	0.529	0.115	0.148	0.578	0.527
Control mean	4.7	4.1	4.1	4.7	3.5	4.0
Control s.d.	1.5	1.5	1.8	1.3	1.8	1.8

Note: Between subject treatment effect of providing participants with the climate scientific Results 3.1 to 3.3, following the experimental design described in Section 5. Coefficient: treatment effect τ in standard deviations, estimated using Equation (5). Outcomes are intentions to (1) switch of devices at the wall socket, (2) reduce the carbon footprint, (3) use alternative forms of transport, (4) choose energy efficient devices, (5) convince others to reduce their footprint, and (6) learn more about how to reduce the carbon footprint. Robust standard errors in parentheses. Control mean and standard deviation (s.d.) are calculated before standardization. *p<0.1; **p<0.05; ***p<0.01.

E Model Extensions

E.1 Belief Model Extensions

Subjects think there are $K > 0$ thresholds at which there is a discrete jump in climate change outcome y. As a result, the discontinuity result still holds.

Assumption E.1. *Subjects perceive the marginal impact to be:*

$$m_y(x) = \begin{cases} m^*_{y,k} > 0 & \text{if } x^*_k < x \leq x^*_k + 1 \qquad \forall\ 1 \leq k \leq K \\ 0 & \text{otherwise.} \end{cases}$$

Proposition E.1. *Subjects believe $d_y(x)$ is discontinuous in x.*

However, subjects have uncertainty about both the level of emissions and the thresholds x_k^*. Let f_k be the PDF of x_k^*. Then the perceived marginal impact becomes

$$\begin{aligned} m_y^p(x) &= \int g(x^*; x) \sum_{k=1}^{K} m_{y,k}^* f_k(x^*) dx^* \\ &= \int g(x^*; x) m_y^*(x^*) dx^* \end{aligned}$$

where $m_y^*(x^*) \equiv \sum_{k=1}^{K} m_{y,k}^* f_k(x^*)$.

Assume that $\partial m_y^p(x)/\partial x|_{x=x^e} < 0$. Intuitively, if $m_{y,k}^* = m_{y,k'}^* \; \forall k, k'$, this assumption means that x^e is to the right of the nearest threshold. Also let $x^* \equiv x^e + \min\{x^r : \partial m_y^p(x^e - x^r)/\partial x^r = 0, x^r > 0\}$. It is easy to show that the complementarity result still holds.

Assumption E.2. *Current expected emissions are above the threshold: $x^e > x^*$. Moreover, the PDF of x^p is weakly single-peaked with mode x:*

$$\frac{\partial^2 G(x^p; x)}{\partial x^p \partial x} \begin{cases} \geq 0 & \text{if } x^p \leq x \\ \leq 0 & \text{otherwise} \end{cases}$$

and

$$\int g(x^*; x^e) m_y^*(x^*) dx^* \leq 0.$$

Proposition E.2. *The perceived marginal impact $m_y^p(x = x^e - x^r)$ is weakly increasing in emission reductions x^r (strategic complementarity):*

$$\left. \frac{\partial m_y^p(x^e - x^r)}{\partial x^r} \right|_{x^r < x^* - x^e} \geq 0.$$

Finally, assume g and f_k are small at x^e. As a result, the point estimate underestimation result still holds.

Assumption E.3.

$$\int g(x^*; x^e) m_y^*(x^*) dx^* < m_y(x^e).$$

Proposition E.3. *The perceived marginal impact is smaller than the projected marginal impact: $m_y^p(x^e) < m_y(x^e)$.*

E.2 Consumption Model Extensions

The treatment effect result can be generalized to any consumer whose marginal utility from own emission reductions is increasing in the perceived marginal impact for the

treated climate change outcomes. The argument remains the same.

Assumption E.4.

$$\frac{\partial^2 v(r, x^r)}{\partial r \partial m_y^p} > 0$$

Proposition E.4. *Subjects in the information treatment reduce their emission more than those in the control group:* $r_t^* > r_b^*$.

E.3 Strategic Interaction Model Extensions

Let $b^p(r, x^r)$ be the perceived physical benefit of emission reduction r. For example, $b(r, x^r) = m^p(x^e - x^r)r$ in Section 8.2. An equilibrium (r, b^p) is now a perceived physical benefit b^p such that $r_p^*(x^r) = x^r$. Assume that

$$v, b \text{ are twice continuously differentiable} \tag{18}$$

$$\frac{\partial^2 v}{\partial r \partial x^r} \geq 0 \iff \frac{\partial^2 b^p}{\partial r \partial x^r} \geq 0 \quad \forall r, x^r \tag{19}$$

Assumption (19) describes the way in which v and b^p are linked. It implies that if own and total emission reductions are strategic complements in terms of physical benefits b^p, they are also strategic complements in the utility function. Conversely, if they are strict strategic substitutes in b^p they are also strict strategic substitutes in v.

Also assume that believes about the physical benefit of mission's reductions exhibit either increasing differences or strictly decreasing differences. If they exhibit increasing differences then:

$$b^p(r_i^H, r^H) - b^p(r_i^L, r^H) \geq b^p(r_i^H, r^L) - b^p(r_i^L, r^L) \quad \forall r_i^H > r_i^L, r^H > r^L \tag{20}$$

If, by contrast, believes exhibit strictly decreasing differences then:

$$b^p(r_i^H, r^H) - b^p(r_i^L, r^H) < b^p(r_i^H, r^L) - b^p(r_i^L, r^L) \quad \forall r_i^H > r_i^L, r^H > r^L \tag{21}$$

As shown in Lemma F.1, Equation (20) implies that r and x^r are strategic complements, whereas Equation (21) implies that they are strategic substitutes.

Assumption E.5. *The perceived physical benefit before the treatment* b^b *exhibits increasing differences, whereas the perceived physical benefit after the treatment* b^t *exhibits decreasing differences.*

Proposition E.5. *Given baseline beliefs* b^b *there may be multiple equilibria* (r^L, b^b) *and* (r^H, b^b)*, such that* $r^L < r^H$.

Proposition E.6. *Assume $\exists r^L$ such that (r^L, b^b) is an equilibrium and $r_t^*(r^L) > r^L$. Then $\exists r^{H'} > r^L$ such that $(r^{H'}, b^t)$ is an equilibrium.*

F Proofs

F.1 Result 8.1

Proof. Subjects' belief over $d_y(x)$ is $d_y^p(x)$. By Assumption 8.1,

$$\lim_{x \to x^{*-}} d_y^p(x) = 0 \neq \lim_{x \to x^{*+}} d_y^p(x) = d_y^*.$$

□

F.2 Result 8.2

Proof. Assumption 8.2 implies that

$$\frac{\partial g(x^p; x)}{\partial x} < 0 \qquad \text{if } x^p < x$$

Hence,

$$\frac{\partial g(x^*; x)}{\partial x} < 0 \qquad \forall\ x > x^*.$$

By Equation (8), this implies

$$\begin{aligned} & \frac{\partial m_y^p(x)}{\partial x} < 0 && \forall\ x > x^* \\ \iff & \frac{\partial m_y^p(x^e - x^r)}{\partial(-x^r)} < 0 && \forall\ x^e - x^r > x^* \\ \iff & \frac{\partial m_y^p(x^e - x^r)}{\partial x^r} > 0 && \forall\ x^r < x^* - x^e. \end{aligned}$$

□

F.3 Result 8.3

Proof. By Equation (8),

$$\begin{aligned} g(x^*; x^e) &< \frac{m_y(x^e)}{d_y^*} \\ \iff g(x^*; x^e) d_y^* &< m_y(x^e) \\ \iff m_y^p(x^e) &< m_y(x^e) \end{aligned}$$

□

F.4 Result 8.4

Proof. I will proof that $\frac{\partial r^*(x^r)}{\partial m^p(x)} > 0$. The proposition then follows from the fact that $m^t(x) > m^b(x)$.

We have $\frac{\partial r^*(x^r)}{\partial x^r} = -\sum_j \rho_j \frac{\partial c_j^*(x^r)}{\partial x^r}$, where $c_j^*(x^r)$ is implicitly defined by (13). Consider the following cases for product j.

1. $\rho_j = 0$. $\partial c_{ij}^* / \partial m^p = 0$ by (13).
2. $\rho_{j'} < 0$. An increase in m^p requires an increase in $\partial u(c^*)/\partial c_{j'}$ by (13). By (10), this requires an increase in $c_{j'}$. By assumption, $\rho_{j'} < 0$ and thus $\partial r^* / \partial c_{j'} > 0$.
3. $\rho_{j''} > 0$. An increase in m^p requires a decrease in $\partial u(c^*)/\partial c_{j''}$ by (13). By (10), this requires a decrease in $c_{j''}$. By assumption, $\rho_{j''} > 0$ and thus $\partial r^* / \partial c_{j''} < 0$.

By (12), j' and j'' exist. Therefore, $\frac{\partial r^*(x^r)}{\partial m^p(x)} > 0$. □

F.5 Result 8.5

Proof. Consider a consumer with the following beliefs, choice constraints and preferences:

$$x^e = 1 \qquad x^* = 0 \qquad d_y^* = 1 \qquad g(x^*; x) = \begin{cases} \frac{-3x^2}{4} & \forall |x| \leq 1 \\ 0 & \text{else} \end{cases}$$

$$j \in \{+, -\} \qquad p_+ = p_- = 1 \qquad \rho_+ = \rho \qquad \rho_- = -\rho \qquad Y = 1$$

$$\gamma_y = \frac{1}{\sum_y 1} \qquad u(c_+, c_-) = \ln c_+ + \ln c_-$$

The consumers optimal reduction is:

$$r^*(x^r) = \sqrt{\rho^2 m^p (x^e - x^r)^2 + 1} - 1$$
$$m^p(x) = g(x^*; x) = \frac{-3x^2}{4}$$

The parameter ρ determines the number of equilibria. At $\rho = \frac{1}{6}\sqrt{71 + 17\sqrt{17}}$, there are two. A stable equilibrium (r^L, m^p) and an unstable equilibrium (r^H, m^p) with $r^H = \frac{1}{2}(\sqrt{17} - 3) > r^L = 0$. □

F.6 Result 8.6

Proof. I begin by proving two intermediate results.

(i) $m^p(x)$ continuous $\Rightarrow$ $r^*(x^r)$ continuous.

Continuity of m^p_y implies continuity of m^p by Assumption 8.4. By (10), $\partial u(\mathbf{c}^*(x^r))/\partial c_j$ is also continuous. Thus, by (13), $\mathbf{c}^*(x^r)$ is continuous. Finally, $r^*(\mathbf{c}^*(x^r))$ is continuous in $\mathbf{c}^*(x^r)$ by assumption.

(ii) $\frac{\partial m^p(x)}{\partial x} > 0 \Rightarrow \frac{\partial r^*(x^r)}{\partial x^r} < 0$.

Note that x^r enters $r^*_i(r)$ only through $m^p(x = x^e - x^r)$. The result is then a simple corollary of the fact that $\frac{\partial r^*(x^r)}{\partial m^p(x)} > 0$, which was proven in the proof of Result 8.2.

By Assumption 8.5, $m^t(x)$ is continuous and increasing. By (i) and (ii), $r^*_t(x^r)$ is continuous and decreasing, as is $r^*_t(x^r) - x^r$. By assumption $r^*_t(r^L) - r^L > 0$. By the fixed point theorem, there is a point $r^{H'} > r^L$ such that $r^*_t(r^{H'}) - r^{H'} = 0$. By definition, this point is an equilibrium. □

F.7 Lemmas

Two results simplify the next two proofs. First, Lemma F.1 shows that the shape of the belief function – whether (20) or (21) holds – determines if own and average emissions reductions are strategic complements or strategic substitutes. Second, Lemma F.2 shows that this, in turn, determines the shape of r^*.

Lemma F.1. *Assume* (18). *Then,*

1. $\frac{\partial^2 b^p(r, x^r)}{\partial r \partial x^r} \geq 0 \; \forall r, x^r \iff$ (20) *and*
2. $\frac{\partial^2 b^p(r, x^r)}{\partial r \partial x^r} < 0 \; \forall r, x^r \iff$ (21).

Proof. Rearranging (20), $b^p(r_i^H, r^H) - b^p(r_i^H, r^L) \geq b^p(r_i^L, r^H) - b^p(r_i^L, r^L) \iff \partial(b^p(r_i, r^H) - b^p(r_i, r^L))/\partial r_i \geq 0 \iff \partial b^p(r_i, r^H)/\partial r_i \geq \partial b^p(r_i, r^L)/\partial r_i \iff \partial^2 b^p(r_i, r)/\partial r_i \partial r \geq 0 \iff \partial^2 b^p(r, x^r)/\partial r \partial x^r \geq 0$, which proves part 1. Replacing $\geq$ with $<$ throughout proves part 2. □

Lemma F.2. *$r^*(x^r)$ is continuous. Moreover,*

$$\frac{\partial^2 v(r, x^r)}{\partial r \partial x^r} < 0 \Rightarrow \frac{\partial r^*(x^r)}{\partial x^r} < 0.$$

Proof. $\mathbf{c}^*(x^r)$ is implicitly defined by

$$\frac{\partial u(\mathbf{c}^*(x^r))}{\partial c_j} + \frac{\partial v(r, x^r)}{\partial r}\rho_j = p_j \lambda.$$

$\partial u(\mathbf{c}^*(x^r))/\partial c_j$ and $\partial v(r, x^r)/\partial r$ are continuous by assumption. Thus, $\mathbf{c}^*(x^r)$ is continuous. Finally, $r^*(\mathbf{c}^*(x^r))$ is continuous in $\mathbf{c}^*(x^r)$ by assumption, which proves the first part of the statement.

For the second part, note that x^r enters $r^*(x^r)$ only through $v(r, x^r)$. By the same argument given in Appendix F.2, $\frac{\partial^2 v(r,x^r)}{\partial r \partial x^r} < 0$ implies $\frac{\partial r^*(x^r)}{\partial x^r} < 0$. □

F.8 Result E.5

Proof. Consider the example given in the proof of Result 8.5. Let $b^b(r, x^r) = m^p(x^e - x^r)r = g(x^*; x^e - x^r)r$ and assume $x^r \in [0, 1]$. Then $b^b(r, x^r) = -(3/4)(1 - x^r)^2 r$. $\frac{\partial^2 b^b(r,x^r)}{\partial r \partial x^r} = (3/2)(1 - x^r) \geq 0$. Thus, by Lemma F.1, b exhibits increasing differences. The rest of the proof is given in Appendix F.5. □

F.9 Result E.6

Proof. By Lemma F.1, $\partial^2 b^t/\partial r \partial x^r < 0$ and, by Equation (19), $\partial^2 v^t/\partial r \partial x^r < 0$. By Lemma F.2, $r_t^*(x^r)$ and, thus, $r_t^*(x^r) - x^r$ are strictly decreasing. Given that $r_t^*(r^L) - r^L > 0$, by continuity $\exists r' > r^L$ such that $r_t^*(r^{H'}) - r^{H'} = 0$. $(r^{H'}, b^t)$ is an equilibrium and $r^{H'} > r^L$. □