Sections of a Stage 1 Registered Report

Nature Climate Change

Title page

Abstract

Introduction (no subheadings permitted)

Methods

Ethics information

Design

Analysis plan

Sampling plan

Data availability statement

Code availability statement

References

Acknowledgements

Author contributions

Competing interests

Figures & Figure captions

Tables (A Design Table is mandatory)

Supplementary information

Motivated Climate Change Denial

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Abstract

Climate change is arguably one of the greatest challenges of our times. Albeit the scientific consensus that human activities caused climate change, a substantial part of the population downplays or denies human responsibilities. In this registered report, we will present causal evidence on a potential explanation for this discrepancy: motivated reasoning. We conduct a tailored survey experiment on a broadly representative sample of 4,000 U.S. adults to provide causal evidence on how motivated cognition shapes beliefs about climate change and influences the demand for slanted information. We further explore the role of motives on environmentally harmful behavior. Our key design idea is to exogenously vary the possibility to behave selfishly at the expense of the climate. Participants that have the opportunity to act selfishly justify their actions by distorting their beliefs and seeking out slanted information. Further, providing participants with an excuse increases the likelihood of selfish and environmentally harmful behavior.

Introduction

Human activities caused the recent warming of the Earth.[1] Despite the near-unanimous scientific consensus on this matter[2] [3] [4], a substantial part of the population denies or downplays the contribution of humans to climate change. In a 2019 PEW study, 30% of U.S. adults said humans play only a partial and 20 % said no or a minor role in climate change.[5] [6] [a] How can we explain this discrepancy? Various factors affecting beliefs on climate change have been proposed in recent literature.[7] [8] For this project, we focus on the potential explanation that climate change denial stems from motivated reasoning patterns. The literature of motivated beliefs posits that the belief formation process is often guided by the desire to maintain certain convictions or to hold a positive self-view, rather than by a desire for belief accuracy. In the context of climate change, people's beliefs might be shaped by the need to justify their emitting behavior (e.g., driving a big car, enjoying transcontinental flights, eating a meat-rich diet, or being invested in CO2 intensive industries). Intuitively, actions that harm the climate are easier to live with when one downplays the severity of climate change or the role humans play in it. However, causal evidence for the connection of motivated cognition and climate change denial is scarce and the determinants of climate change denial remain poorly understood.[9]

In this project, we will conduct a tailored survey experiment[10] with 4.000 respondents from the U.S. population to shed light on the following three questions: (i) does motivated cognition shape beliefs about climate change? (ii) moving beyond beliefs, does motivated cognition influence how people seek out information about climate change? (iii) does

[a] The 2022 report Climate Change in the American Mind finds similar results: a third of the respondents said that climate change is due to natural changes and is not mostly caused by human activities.

environmentally harmful behavior increase when people anticipate the opportunity to justify their behavior?

To establish the causal role of motivated reasoning for beliefs about climate change and information demand, our key design idea is to exogenously manipulate the motive to form beliefs or seek out information about climate change in a self-serving way. Specifically, our approach relies on experimentally varying the possibility to behave selfishly at the expense of the climate and then measure beliefs about climate change in an incentive-compatible way or the demand for slanted information.

The 4,000 participants will be randomly assigned to one of five treatment conditions: *Belief Main, Belief Control, Demand Main, Demand Control* and *Behavior*. To answer our first research question, 1,600 study participants will be randomly assigned to treatments *Belief Main* and *Belief Control.* In *Belief Main*, participants will have the opportunity to earn additional payments by taking away the money from a donation that helps fighting climate change and keeping it for themselves. Specifically, in the experiment, there is a $20 donation intended to fight climate change. Subjects can decide to take away this donation and instead keep the $20 for themselves. After this decision, and as a surprise, we will elicit beliefs about the scientific consensus on the causes of recent global warming in an incentive-compatible way (see Design Section for an overview of the potential payments). To be precise, we will inform participants about a survey conducted among climate scientists. Participants have to guess how many, out of 100 scientists, doubt that human activities are the main cause of global warming. We can incentivize this question using the actual results from a survey, making it costly for participants to distort their beliefs. In *Belief Control*, we elicit the same climate change belief but remove the opportunity to enrich oneself at the expense of the climate. Instead of keeping money for themselves, participants in the control group can only decide how to distribute 20 dollars between two climate nonprofits. Hence, the only difference between the two conditions is the exogenous variation in the "motive" to manipulate beliefs about the main driver behind climate change. We hypothesize that participants in *Belief Main* distort their beliefs about climate change in a self-serving way. Thus, compared to *Belief Control,* they, on average, state that skepticism among experts is significantly more common.

Moving beyond beliefs, treatments *Demand Main* and *Demand Control* study how motivated reasoning shapes information demand about climate change. Slanted information about climate change pervades both social and traditional media.[11] [12] [13] [14] Arguably, harming the climate might create a self-serving demand for such slanted information. The treatments are identical to *Belief Main* and *Belief Control*, except we replace belief elicitation with an information demand paradigm. Participants can choose between two short clips about climate change. Participants know that they have to watch the selected clip at the end of the experiment. The two clips differ substantially in their perspective on climate change. While one video follows the science on climate change, the other is visibly slanted, downplays climate change and disputes established scientific consensus. We hypothesize that participants in *Demand Main* choose to watch the clip downplaying climate change significantly more often, compared to *Demand Control*.

To investigate whether participants are also altering their behavior, we will conduct treatment *Behavior*. Treatment *Behavior* is identical to *Demand Main,* except that we change the timing of questions. In *Demand Main*, participants answered the donation decision without being aware of the subsequent question on information demand. In

Behavior both questions are introduced at the same time and are displayed on one single page. Hence, participants make the donation decision having in mind the option to self-servingly deceive themselves via information demand. Research has shown that having such an opportunity for excuses at hand facilitates moral transgressions.[15] We hypothesize that participants in *Behavior* more frequently choose the selfish action compared to participants in *Demand Main.*

Finally, our rich data set allows us to gauge potential heterogeneous treatment effects along socioeconomic characteristics. To avoid data mining, we will focus on one dimension, income. We chose income because the incentive to act selfishly in the donation decision is at the center of our research design. However, not all participants will experience the same temptation when offered 20 dollars for harming the environment. We will hence test how motivated cognition interacts with the household income of the participants. For our first analysis, we dichotomize household income and hypothesize that participants with income below the U.S. median household income distort their climate change beliefs more than participants that are less financially constrained when given the opportunity to take money away from the nonprofit organization. They further exhibit a larger demand for the video downplaying climate change and choose the selfish action more frequently in reaction to our treatment variation. Extending this, we apply a binning estimator and use lasso estimators to address non-linearities and omitted interaction biases.[16] [17] [18]

The proposed experiment tests if motivated cognition can help to explain widespread climate change denial and environmentally harmful behavior. In our experiment, we elicit the participants' belief about the scientific consensus on the role of humans in recent global warming. In a 2020 survey by the Yale Program on Climate Change Communication, only 57

% of the respondents agreed to the statement “most scientists think global warming is happening” when asked about the scientific consensus.[19] [20] Recent literature has also shown that peoples’ beliefs about the human role in climate change and the belief about the consensus predict support for climate policies. [21] [22] Political interest groups opposing climate legislation frequently tried to raise doubt about the scientific consensus about climate change to undermine the support for climate policies, lending further support for the importance of our measure. [23] Hence, the beliefs about climate change in our study can be a powerful rationalizing story that can have real-world consequences.

In the context of climate change, there exists an abundance of slanted and biased information sources.[24] [25] [26] [27] Our study will deliver insights into whether people actively choose biased information for motivated reasons. This relates to recent literature that looks at information demand in the context of political news.[28]

Finally, our analysis of the role of motivated cognition for the donation behavior illustrates how motivated reasoning enables climate-damaging acts. The incentivized donation decision captures a central trade-off of climate action; fighting climate change comes at a personal cost. Recent literature showed how economic preferences, moral values, and social norms predict climate preferences.[29] We add to this by focusing on how motivated cognition affects climate preferences.

Our study also connects with two broader research strands. First, research on motivated reasoning, which has a longstanding tradition in psychology and economics.[30] [31] The central idea of this literature is that the desire for a positive self-view or the preservation of certain convictions drives people to manipulate their beliefs in a self-serving manner. Implications have been studied in diverse contexts, the one closest related to our paper is moral behavior. To rationalize selfish behavior, individuals distort beliefs about other peoples' behavior[32], marginalized groups[33], their risk preferences[34], their fairness preferences[35 36], over investment opportunities[37], or ambiguity preferences[38]. Further, recent evidence suggests that individuals frequently seek out situations in which they have the cognitive flexibility to rationalize selfish behavior.[39] In contrast to the existing literature, we look at beliefs about climate change. As stated before, a prominent explanation for climate change denial in the population is motivated cognition.[40 41] Related to this research strand, our evidence also contributes to the literature on people's demand for information or avoidance of information.[42 43 44 45 46 47 48 49]

Second, in the sphere of beliefs about climate change most research focuses on upholding party identity as the dominant driver behind climate denial.[50 51 52 53 54 55] However, most of the existing evidence cannot distinguish between motivated cognition or other belief formation processes.[56 57] The reason is that party affiliation is not easy to vary exogenously. In contrast to studies on partisanship, we look at a different motive: self-interest. Upholding a positive self-view is a prominent driver of motivated cognition and can be manipulated by exposing participants to situations in which they might behave contrary to their positive self-image.

Methods

Ethics information

Our research complies with all relevant ethical regulations. We obtained ethics approval from the German Association for Experimental Economic Research e.V., Institutional Review

Board Certificate No. m5JjfAbk. Informed consent will be obtained from all participants. Participants will receive a by the survey provider determined fixed payment and a computer program will choose a subset of participants for additional payments which are based on their decisions (for details, see Design Part – Payments).

Design

To study the role of motivated cognition for climate change beliefs, we plan to conduct a large-scale online survey experiment using a broadly representative sample. The experiment will have five different treatment conditions. Figure 1 illustrates the experimental procedure.

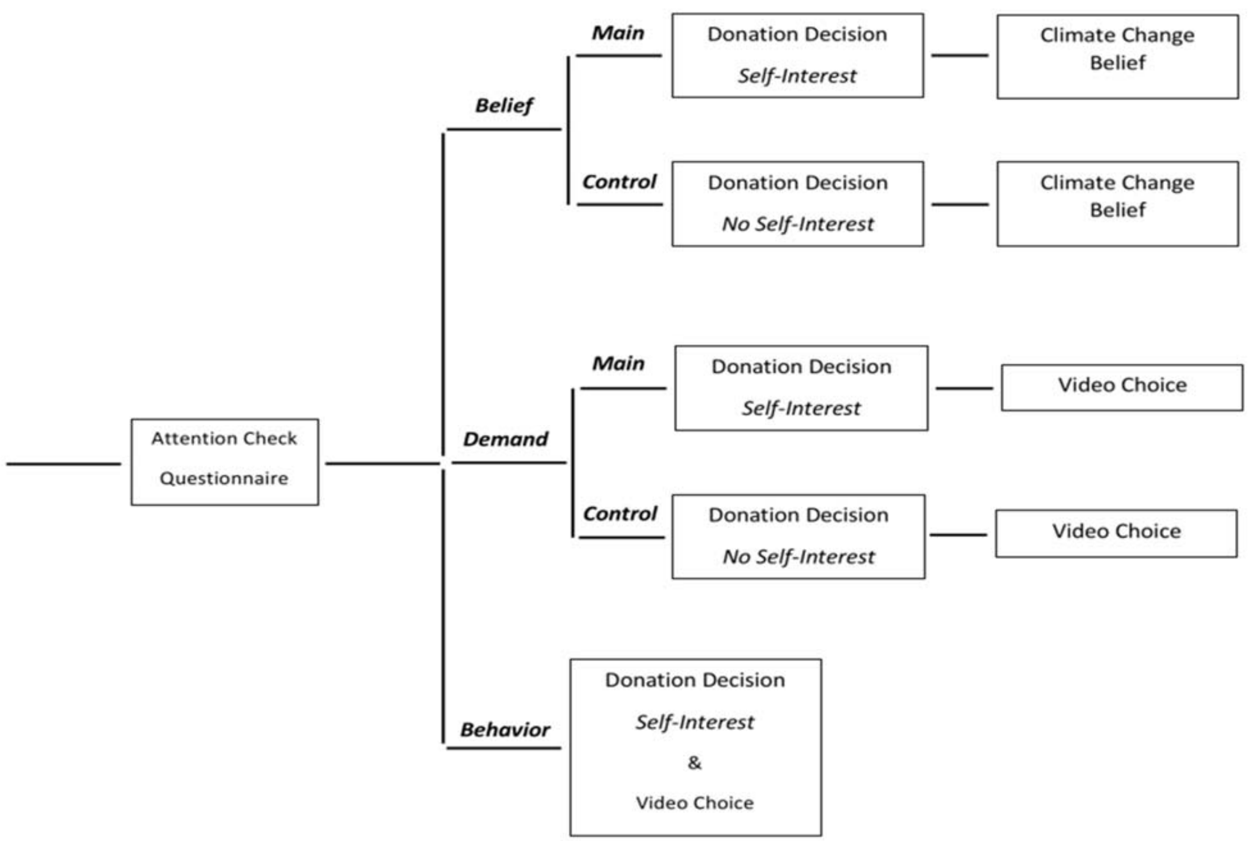

Figure 1: The figure shows our experimental design. After passing an attention check and answering a short questionnaire, participants will be randomly assigned to one of five treatment conditions.

Attention Check, Questionnaire & Demographics

Before each participant is randomly assigned to one of the five treatment conditions, they all have to go through the same set of questions. At the beginning of our experiment, we assure participants that their answers will be anonymized and ask them to sign a consent form. Only respondents who consent to our declaration can move forward. Next, a standard attention check follows. Specifically, participants have to give a prespecified answer to a trivial question. We explain to participants that individuals who click through instructions without reading them are a problem for us. To ensure that they read the questions carefully, we ask them to answer “Very interested” and “I’ve never heard of it” to a question. The exact wording of this question is:

Based on the text you read above, what have you been asked to answer to the following question: How interested are you in Game of Thrones?

Participants now see four response options, two of which are the prespecified ones. Respondents are only allowed to participate if they give the correct answers. Participants that do not pass this stage cannot participate in our survey and are redirected to the survey provider's website.

Participants also have to answer a short questionnaire. We elicit the following demographic information about the participants: age, state of residence, sex assigned at birth, highest level of education, annual household income, area of residency (scale from Farm to large city). Participants that pass this first set of questions are randomly assigned to treatment conditions.

At the end of the survey, all participants answer two questions about their political attitudes (party affiliation and self-placement on a political spectrum). We ask the questions about political attitudes at the end of the survey to not prime party identities.

Payments

After passing the attention check and the questionnaire, participants receive general information about the upcoming decisions, fixed and potential additional payments. We inform participants that they are going to answer questions that can have financial consequences for them. We then explain that a computer program will choose a subset of participants for additional payments. The program will choose one out of ten participants. The likelihood of being chosen is independent of the participant's decision and other respondents' choices. In other words, everyone faces the same likelihood of 10 % of receiving additional payments. Each participant is informed at the end of the survey whether they were randomly chosen or not. If a participant is selected, one of their incentivized decisions gets implemented.[58] In *Belief Main* and *Belief Control*, participants face two decisions with real consequences (Donation decision and Climate Change Belief). To avoid hedging motives between the two decisions, we randomly select one decision for implementation.[59] In the other conditions, the donation decision is implemented.

Importantly, the payment regime is identical across the conditions we compare. In *Belief Main* and *Control*, participants can receive up to 4 dollars for the belief decision and have to decide how to allocate a 20 dollars donation. As explained below, the only difference is that in *Belief Main* the decision is between a 20 dollars donation and 20 dollars for the participants instead of allocating 20 dollars between two climate nonprofits. If a participant in *Belief Main* or *Belief Control* is selected for an additional payment, one of these two decisions will be randomly implemented. In the remaining three conditions, the only payment-relevant choice is the donation decision.

Treatment Conditions

Participants will be randomly assigned to one of five treatment conditions: *Belief Main, Belief Control, Demand Main, Demand Control* and *Behavior*.

Belief Main: After the questionnaire and receiving general information about the upcoming decisions, participants are introduced to the donation decision. In the donation decision, participants have the opportunity to take all money away from a donation to a nonprofit organization that fights climate change. In detail, we inform participants that a computer will randomly select one of two climate nonprofits for a 20 dollars donation and that the money would help to fight the climate crisis. Participants receive information about the two climate nonprofits.[b] They are informed that "both climate nonprofits are very established and are committed to the fight against climate change. They fund projects that reduce human-made greenhouse gas emissions. We will randomly select one of the two organizations for the donation." However, they can decide to take the money away from the donation and keep the 20 dollars for themselves instead.

We inform participants about two climate nonprofits to keep the number of organizations identical to the control condition (*Belief Control*), where participants can allocate money

[b] The two companies are Clean Air Task Forceand Industrious Labs. Both organizations are recommended by Giving Green. Giving Green is an initiative that uses scientific methods to recommend organizations that effectively help to reduce atmospheric greenhouse gases.

between these two nonprofits. Participants in *Belief Main* will be told which organization was randomly selected to be the recipient of the donation prior to their choice.

After the donation decision, we elicit beliefs about the scientific consensus on the human role in climate change. Literature has shown that this belief is an important predictor for peoples' support of climate action.[60] We, therefore, argue that deciding to take away money from a climate nonprofit for personal benefit can be rationalized by a more skeptical outlook on the scientific consensus. Importantly, participants will only learn about this question after they made their donation decision. We will inform participants that an academic journal recently published a paper with findings from a survey conducted among climate scientists.[-61] Among other things, they asked the scientists what role humans play in global warming. We ask participants to estimate the beliefs of the scientist who were surveyed. The phrasing of the question reads as follows:

"What do you think: Out of 100 climate scientists, **how many doubt that human activities are the main cause of global warming** over the last decades?"

Incentive compatibility is ensured via a quadratic scoring rule. Participants can earn up to 4 dollars for their answers. The closer their estimate is to the true value the more money they can receive.[c]

The intuition underlying treatment *Belief Main* is that the choice to take away money from a donation that would have helped to save the environment induces a motive to downplay or

[c] The exact formula is:

$$payment = max\{0\,;\; 4 - 40\left(\frac{guess}{100} - true\ value\right)^2\}$$

Where the true value is 0.013 - meaning 1.3 % of the surveyed climate scientists stated that human activities are not the main driver of climate change.

doubt climate change. To establish causality in the relation of motivated reasoning and beliefs about climate change, we will conduct treatment *Belief Control*.

Belief Control is identical to *Belief Main*, except that participants cannot receive any money for themselves in the donation task. Specifically, participants in *Belief Control* have to decide how to distribute 20 dollars between the two climate nonprofits. They can distribute all the money to either of the two organizations. Afterward, participants state their belief about the scientific consensus on the human role in climate change.

Hence, while participants in *Belief Main* can enrich themselves at the expense of the environment, such a motive doesn't exist in *Belief Control*. In other words, *Belief Control* removes the motive for self-deception and measures beliefs absent motivated cognition.

Treatments *Demand Main* and *Demand Control* are analogous to *Belief Main* and *Belief Control,* except that we replace the belief question with an information demand paradigm. Specifically, after facing the same allocation decisions as in *Belief Main* and *Belief Control*, respectively, participants in *Demand Main* and *Demand Control* have to decide between two videos to watch. Both videos focus on the extent to which humans are responsible for the recent climate change, but they differ starkly in their perspectives. The participants will watch the video at the end of our experiment. While one of the two videos reflects the scientific consensus, the other video plays down the role of humans and provides slanted information. The video choice will be elicited as follows.

"Which of the following videos do you want to watch?"

- What they Haven't told You about Climate Change

Since time immemorial, our climate has been and will always be changing. The video explains why “climate change”; far from being a recent human-caused disaster, is, for a myriad of complex reasons, a fact of life on Planet Earth.

- Causes and Effects of Climate Change
    - What causes climate change (also known as global warming)? And what are the effects of climate change? Learn the human impact and consequences of climate change for the environment, and our lives.

The selected video will be shown to participants directly after they answered the two political attitudes questions.[d]

Hence, *Demand Main* allows us to measure demand for slanted information when a motive for self-deception is present, whereas *Demand Control* gives us a benchmark for information demand when that motive is removed.

Treatment *Behavior* is identical to *Demand Main*, with one key difference. In *Demand Main* (and all other treatments introduced so far), participants make the allocation decision without being aware of the content of the subsequent question. Instead, in *Behavior,* the two questions (donation decision and information demand) are introduced simultaneously.

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[d] We erased all source names or parts that give away the origin from the two videos and the short descriptions. To mitigate the ethical concern about showing some participants a video casting skepticism about climate change by presenting factually wrong information, we added a short debriefing for all participants at the end of the experiment. The briefing reads:
“The Current scientific consensus on climate change:
- The current warming is happening at a rate not seen in the past 10,000 years.
- The influence of human activity on the warming of the climate system has evolved from theory to established fact

Sources: NASA Global Climate Change, Intergovernmental Panel on Climate Change (IPCC)“

Participants receive all the relevant information before their two decisions. Both decisions will be displayed and answered on the same decision screen.

Hence, in treatment *Behavior*, participants know that they will have a chance to self-servingly deceive themselves when making their donation. In other words, their behavior in the donation decision might be affected by the anticipation of a possible excuse, making it easier to act selfishly. Comparing the donation behavior between *Behavior* and *Demand Main* provides causal evidence on the role of motivated reasoning for behavior.

We will upload the instructions of our Survey to the Open Science Framework (see Sections Data availability and Supplementary Information).

Design discussion

Opportunity vs. actual behavior: It is important to note that our identification rests on an average treatment effect (ATE). We do not measure the direct effect of behaving selfishly on beliefs and demand, but instead compare how the opportunity to act selfishly leads to distorted beliefs about climate change and increased demand for slanted information on the group level. Not every person will behave selfishly and not every person will need an ‘excuse’ in form of our video or belief in our Main treatments. We hence compare the belief and information demand of participants that had the opportunity to act selfishly and damage the climate versus participants that were not able to do so. This allows us to cleanly identify the causal role of motivated cognition for climate denial. Notice that this type of identification strategy is frequently used in the literature on motivated cognition.[62] [63]

Lower Bound: As stated above, not every participant in our Main treatments will behave in a self-interested manner or will feel the need for an excuse for their selfish behavior. It might be even possible that participants who leave the donation untouched in the Main treatments are motivated to reinforce their belief in human-made climate change. While the latter channel seems unlikely given our design, it would work against the proposed hypothesis.

Generalizability: The present study provides causal evidence of the role of motivated cognition for climate change denial. The decisions in our study have real stakes and consequences. We believe that our experimental design mimics real-world decisions in which there exists a fundamental trade-off between actions that might be individually profitable but have negative climate externalities and actions that have a neutral or positive impact on the climate but require individuals to forgo a personal benefit. At the same time, we acknowledge that the stylized nature of our experiment might limit the generalizability of our results for some domains of climate-related behavior, and that more empirical work is needed to fully understand the role of motivated cognition for climate denial.

Representativness: Respondents are stratified to match the respective U.S. adult population on the following dimensions: age, sex, income, region, and education. The survey platform indicated that it is feasible to recruit such a sample for the USA. If the final sample size might not be fully representative of some of these categories, we will explicitly note any deviation in the final results section. Recent work on online panels showed that while they generally support a broad spectrum of most demographics, they sometimes do not support the full distribution of characterizes. For example, extremely high incomes or people in more rural areas.[64] [65] Differences in socio-demographics between our sample and the general population will not affect the causal interpretation of our results. We will carefully check for differences and discuss them and their implications in the final results section.

Analysis Plan

1. Average Treatment Effect: Beliefs (*Belief Main* and *Belief Control*)

Comparing the climate change belief between *Belief Main* and *Belief Control* enables us to causally identify the role of motivated cognition for beliefs about climate change. To test if participants distort their belief about climate change in *Belief Main*, we first run the following regression:

$$Y_i = \alpha + \beta_1 treat_{belief} + \gamma \text{ Controls}_\text{i} + \epsilon_i \quad (\mathbf{1})$$

where Y_i denotes our dependent variable climate change belief. Our variable of interest, $treat_{belief}$, is a dummy variable indicating whether participants were randomly allocated to *Belief Main* or *Belief Control*. The dummy variable takes the value of 1 if the participant was in *Belief Main* and 0 if the participant was randomly assigned to a control condition.

We run two OLS regressions - one without and one with control variables. The controls added to the OLS regression are dummies for age groups, sex, education, income, state and area of residence, post-materialism, self-placement on a left-right political spectrum and party affiliation (the construction of these variables is described in the Sampling Plan section).

Hypothesis I (Beliefs): Participants distort their beliefs about the scientific consensus on climate change in a motivated manner when previously given the opportunity to act in a selfish manner ($\beta_1 > 0$).

2. Average Treatment Effect: Information Demand (*Demand Main* and *Demand Control*)

Focusing on the participants in *Demand Main* and *Demand Control*, we now want to test whether participants that had the opportunity to act selfish show a demand for slanted information. Analog to before we run the following regressions:

$$Y_i = \alpha + \beta_2 treat_{demand} + \gamma \text{ Controls}_\text{i} + \epsilon_i \quad (\mathbf{2})$$

This time Y_i denotes our dependent variable video choice. Additional to the two OLS regressions – one with and without controls – we run a probit regression with controls.

Hypothesis II (Information Demand): Participants in *Demand Main* choose to watch the "What they haven't told you about Climate Change" Video significantly more often ($\beta_2 > 0$).

3. Average Treatment Effect: Donation Behavior (*Demand Main* and *Behavior*)

To show that participants' behavior towards the environment is affected by the opportunity to justify their decision, we now compare the donation decision between *Demand Main* and *Behavior*. While participants in *Demand Main* make their decision unaware of the belief question, the respondents in the other condition are aware of it. We run the following regressions:

$$Y_i = \alpha + \beta_3 treat_{behavior} + \gamma \text{ Controls}_\text{i} + \epsilon_i \quad (\mathbf{3})$$

where Y_i denotes our dependent variable donation decision $treat_{behavior}$ is a dummy variable indicating whether participants were randomly allocated to *Demand Main* or *Behavior*. The dummy variable takes the value of 0 if the participant was in *Demand Main* and 1 if the participant was randomly assigned to *Behavior*.

We run two OLS-regressions - one without and one with control variables – and a probit regression with controls. The control variables are similar to before.

Hypothesis III (Donation Behavior): Giving participants the opportunity to excuse their behavior *while* making their decision increases the rate of the selfish and environmentally unfriendly decisions in the donation decision, i.e. participants take the 20 dollars more frequently in *Behavior* ($\beta_3 > 0$).

We will further compare the *climate change belief* between these two conditions. A significant difference between the beliefs would indicate that ex-post rationalizations are not the same as on-the-spot excuses.

4. Heterogeneity – Income

We explore how the income of the participants affects our results.

4.1 Median split

We start by dichotomizing our income variable along the median income of American households in the year 2021. Our sample is going to be representative of income for this split. Thus, the groups are going to be balanced. We run the following three regressions:

$$Y_i = \alpha + \beta_4 treat\ x\ low\ income + \delta\ treat\ + \sigma\ low\ income\ + \gamma\ \mathrm{Controls_i} + \epsilon_i\ (\mathbf{4.1})$$

$$Y_i = \alpha + \beta_5 treat + \gamma \, \mathrm{Controls_i} + \epsilon_i \, if \;\; low \; income \; = \; 0 \;\; (\mathbf{4.2})$$

$$Y_i = \alpha + \beta_6 treat \; + \; \gamma \, \mathrm{Controls_i} + \epsilon_i \, if \;\; low \; income \; = \; 1 \; (\mathbf{4.3})$$

where Y_i denotes our dependent variable. $treat$ is a dummy variable indicating to which treatment condition a participant was randomly assigned to. $low \; income$ is a dummy variable, indicating whether participants are of low income or not. See the measures part in our sampling plan, for a more detailed description. We first run a regression with an interaction term and in two subsequent regressions, we look at the subsamples separately.

We check whether participants' financial situation affects their motivated reasoning about the climate change beliefs. To test this, we will run the regressions (4.1) to (4.3) with the following specifications: Y_i denotes the climate change belief. $treat_i$ is a dummy variable indicating whether participants were randomly allocated to *Belief Main* or *Belief Control*.

We also check whether the average treatment effects for the information demand vary with the income of the participants. Y_i denotes the video choice, $treat_i$ is a dummy variable indicating whether participants were randomly allocated to *Demand Main* or *Demand Control.*

We hypothesize that the income of participants also affects their behavior in the donation decision. To test this, we run (4.1) to (4.3) using the following specification: Y_i denotes the donation decision, $treat_i$ is a dummy variable indicating whether participants were randomly allocated to *Demand Main* or *Behavior.*

For all three cases, we run two OLS regressions – one with and one without controls. Analog to before, we run probit regressions (with controls) for our binary outcome variables (video choice and donation decision).

Hypothesis IV (low income): Participants with a lower income distort their belief about the scientific consensus on climate change more than participants with a more relaxed financial situation. They further exhibit a larger demand for the slanted information and choose the selfish action more frequently.

4.2 Binning estimator & adaptive Lasso

We extend our analysis of the interaction between our treatment and income in two ways. We implement a binning estimator to study the non-linear interaction effect. [66] For the binning estimator we discretize the income variable into three bins. The three bins correspond to the three terciles of the income distribution in our sample. We estimate two models; one without and one with our controls from (i). In both, we include interactions between the bin dummies and our treatment variable. While the Median split analysis is based on the nationwide distribution of household incomes, the binning estimator focus on the within-sample distribution of income. We further utilize the adaptive lasso estimator to account for covariates that are correlated with income and have a nonlinear impact on our outcome variables.[67] [68]

5. Robustness

As described in the Sampling Plan Section of this report, our benchmark sample drops those respondents that simply clicked through the survey. We will run the same regressions using all observations. This allows us to show that dropping the slowest respondents does not affect our results systematically.

Sampling plan

Using the internet panel of PureProfile, we will administer a survey to 4,000 respondents. Respondents are stratified to match the respective U.S. adult population on the following dimensions: age, sex, income, region, and education. To achieve representativeness along these dimensions, we exploit our initial sociodemographic questions. For each dimension, we obtained quotas based on the American Community Service Survey (Census). We construct buckets in the following way: age is divided into four intervals (18 -24, 25 – 39, 40 – 59, > 60), sex is binary, income is divided based on the median income (below 70 000 and above), education is binary (university / professional degree or not), region is divided into four intervals (Northeast, Midwest, West, South). If a representativeness quota is already fulfilled, a new participant in this category will be redirected to the survey company's website and is not allowed to participate in the survey.[e]

<u>Exclusions and data quality:</u> Ensuring data quality is of utmost importance for survey studies. A key concern is inattentiveness among survey respondents.[69] We employ several measures to alleviate this concern and to ensure the highest possible data quality. Our survey includes one attention check that tests whether participants read the instructions. We ask participants to give a prespecified answer to a trivial question. If the attention check is answered incorrectly, the respondent immediately gets screened out of the survey. These

[e] The survey platform indicated that it is feasible to recruit such a sample for the USA. However, due to imponderables, the final sample size might not be fully representative for some categories. If this issue arises, we will prioritize statistical power over representativeness quotas. We, of course, will explicitly note any deviation in the final results section.

screen-outs are not included in the sample size stated above. We further will keep track on the time spent by the respondents. In each condition separately, we will drop participants that finish the survey under one-third of the median duration. Together with the attention check, this should eliminate participants that rush through the survey inattentively. We will also not include respondents in our sample that do not finish the survey, do not consent to our subject information and consent form, or start the survey and belong to an already filled representative quote.

Sample Size & Power Analysis: Our sample size is determined based on a cost-benefit analysis. We aim to collect the largest sample possible with resources available and ascertain whether this sample would detect effect sizes that are theoretically informative. As our main measures are unique, we can't derive feasible expected effect sizes from other studies. For this reason, we asked a small number of people to answer the climate change belief question, the information demand and the donation decision (the data will be made available, see supplementary information). Both, the climate change belief and the information demand question, were elicited without the context of a self-interested donation decision. However, there are several caveats to this approach: The size of the test sample (around 60 observations per variable) is very small, making it quite likely that the standard deviation in our actual sample will be significantly smaller.

We flag and exclude participants that rushed through the survey. In detail, we measure the median time in each condition. Participants that finish the survey under one-third of the median time in their condition will not be used in our main analysis. This makes it a priori impossible to say how many participants will be in each sample. As a conservative approximation, we assume that about 5 % of participants will be dropped from every condition.

We use the mean and standard deviation of the small test sample plus a sample of 1,520 participants[f] in our power analysis. Using these numbers, we determine the smallest effect size we would be able to detect with 95 % power and an α-Level of 0.01, for our three main hypotheses separately (for details see the subsequent analysis). Power analysis was conducted using Stata. First, we look at the average treatment effect on the climate change belief[g]. We estimate that an impact sample of 1,520 participants would provide over 95 % power to detect an effect size of d = 4.257, i.e. a 15.64 % increase in the belief that more scientists doubt that humans caused recent climate change. Second, we consider the effect on the video choice[h], i.e. the demand for biased information. We estimate that an impact sample of 1,520 participants would provide over 95 % power to detect an effect size of d = 0.089. Third, we look at the donation decision[i], i.e. the comparison between *Demand Main* and *Behavior*. An impact size of 1,520 participants would provide 95 % power to detect an effect size of d=0.106. We conclude that our study will detect useful effects and that our sample is sufficient to test the below-stated hypotheses. Before outlining our planned analyses, we first discuss our measures.

<u>Outcome Measures</u>: Climate change belief is a continuous variable that can take values between 0 and 100.[j] A higher number indicates that participants assume more scientists do

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[f] We test each hypothesis using the participants of two conditions. Each condition has 800 respondents and we subtract the slowest participants for our main analysis. As we do not know the number of participants finishing the survey faster than one-third of the median, we assume it to be not more than 5 %.
[g] Climate Change Belief – test sample: Mean = 27.31; Std. Dev. = 19.64.
[h] Video Choice – test sample: Mean = 0.21; Std. Dev.= 0.41
[i] Donation Decision – test sample: Mean = 0.64; Std. Dev. = 0.49
[j] For the Power Analysis, we harmonized this measure with the other two outcomes by dividing it with 100.

not think that humans played a pivotal role in recent climate change. Video choice is a binary variable measuring the demand for slanted information. "0" indicates that participants choose the video which represents the scientific consensus on the topic. “1” indicates that participants choose to watch the biased video. Donation decision is binary, where "0" indicates a 20 dollars donation to the climate nonprofit and "1" indicates that the participants choose to pocket 20 dollars. We use the donation decision as an outcome measure when comparing *Demand Main* and *Behavior*.

<u>Control Variables:</u> We divide age into the following four intervals (18 - 24, 25 - 39, 40 - 59, > 60), and include dummies for each interval in our analysis. Sex is a binary variable indicating whether a person was identified as male or female at birth. Education is an ordinal variable with four categories from "No high school graduation" to "Graduate or professional degree". In our Analysis, we include dummies for each category. Income is an ordinal variable that captures the annual household income before taxes. It contains 10 categories from “Below 10,000” to “More than 100,000”.[k] In the Analysis parts 1 to 3, we include dummies for each category. For Analysis part 4 (heterogeneity), we create a dummy variable low income based on the median income of American households (below 70 000 and above). Low income equals 0 indicates that the participant has an income above the median income and 1 indicates that the household income of a participant is below the median. And construct dummies for the three bins in our binning estimator. We also collect data on the location of the participants. State of residence is an ordinal variable with a category for each state. We divide all states into four regions (Northeast, Midwest, South, West) and include a dummy for each region in our regression. Further, we ask participants

[k] After participants clicked on of the ten categories, the following questions will ask them to write down the exact number. Thus, we elicit the income as an ordinal and continuous variable.

to describe their area of residence. The area is a categorical variable with 6 variables: Farm, Village, Smaller City (more than 5.000 people), Suburbs, City (more than 100.000 people), Large city (more than 1 million). We include a dummy for each category in our regressions below. We elicit post-materialism using the 4-item post-materialism index from The European Values Study (EVS). We include a dummy for each category (Materialist, Mixed, Post-materialist). Party preference indicates the party that the respondents identify with. It is a variable containing seven categories from "Strong Republican" to "Strong Democrat". We further ask participants to self-place them on a 10-point scale from "Very liberal" to "Very conservative" and include dummies for each category in our analysis.

Data availability

All data and materials will be openly available on the Open Science Framework (OSF) website at this link: https://osf.io/etsf2/?view_only=08631f7d777140a0a6167e846cf567cd

Code availability

All analysis code (completed in STATA) will be openly available on the Open Science Framework (OSF) website at this link:
https://osf.io/etsf2/?view_only=08631f7d777140a0a6167e846cf567cd

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Author contributions

All authors contributed to the paper equally. L.S.S. and F.Z. both formalized and contributed to the research goals, designed the survey experiment, prepared the manuscript with feedback from each other, and L.S.S. conducted the power analysis in consultation with F.Z., and F.Z. developed the outcome measures in consultation with L.S.S. L.S.S and F.Z. contribute to data collection, will analyze the data and will review and approve the final manuscript together.

Competing interests

The authors declare no competing interests.

Table 1. Design Table

Question	**Hypothesis**	**Sampling plan (e.g. power analysis)**	**Analysis Plan**	**Interpretation given to different outcomes**
1. Does motivated cognition shape beliefs about climate change?	Participants that are given the opportunity to behave selfishly at the expense of the environment distort their beliefs about climate change in a self-serving way. Compared to *Belief Control*, participants in *Belief Main*, on average, state that skepticism among experts is significantly more common.	Power analyses suggested that our planned sample size for this comparison (N = 1,520) would be sufficient to achieve 95% power to detect an effect size of d = 4.257.	We will run two OLS-regressions - one without and one with control variables. The dependent variable is participants' climate change beliefs. Our variable of interest is a dummy variable indicating whether participants were randomly allocated to *Belief Main* or *Belief Control*. The controls added to the OLS regression are dummies for age groups, sex, education, income, state and area of residence, self-placement on a left-right political spectrum and party affiliation.	A significant positive treatment effect will be interpreted as causal evidence that motivated cognition shapes beliefs about climate change
2. Does motivated cognition influence how people seek out information about climate change?	Participants that are given the opportunity to behave selfishly at the expense of the environment seek out information that	Power analyses suggested that our planned sample size for this comparison (N = 1,520) would be sufficient to achieve 95% power	We will run two OLS regressions - one without and one with control variables - plus a probit regression. The dependent variable is the participant's video choice. Our variable of interest is a dummy	A significant positive treatment effect will be interpreted as causal evidence that motivated cognition affects peoples' demand for slanted information.

	justifies their behavior. Participants in *Demand Main* choose to watch a clip downplaying climate change significantly more often than participants in the control group.	to detect an effect size of d = 0.089	variable indicating whether participants were randomly allocated to *Demand Main* or *Demand Control*. Controls are identical to the ones above.	
3. Do environmentally harmful actions increase in number when people anticipate the opportunity to justify their behavior?	Participants that are aware that they can justify their actions by choosing slanted information are more likely to behave selfishly. Compared to participants in *Demand Main*, participants in *Behavior* choose the selfish and for the environment harmful action more frequently.	Power analyses suggested that our planned sample size for this comparison (N = 1,520) would be sufficient to achieve 95% power to detect an effect size of d = 0.106	We will run two OLS-regressions - one without and one with control variables - plus a probit regression. The dependent variable is the participant's donation decision. Our variable of interest is a dummy variable indicating whether participants were randomly allocated to *Behavior* or *Demand Main*. Controls are identical to the ones above.	A significant positive treatment effect will be interpreted as causal evidence that the knowledge of an opportunity to justify selfish actions increases the likelihood of environmentally harmful behavior.

Supplementary information

To run our power analysis, we asked a small test sample to answer our main outcome variables. Importantly, this is not a pre-test as the questions were asked without the context of the experiment. The sole purpose was to provide a basis for our power analysis. We will upload the data and also upload the instructions of our Qualtrics Survey. Both can be found under the following Link:

https://osf.io/etsf2/?view_only=08631f7d777140a0a6167e846cf567cd