How Can Behavioral Economics Enhance Climate Change Policies?

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Abstract

Climate change demands urgent action, mainly to reduce greenhouse gas emissions. However, the effectiveness of public policies aimed at encouraging companies to reduce their emissions may be compromised by individuals' loss aversion. This study proposes an experiment to investigate how loss aversion influences the acceptance and perceived effectiveness of various climate policies. By using an informational treatment to "clean" loss aversion in a treatment group, we compare policy preferences and willingness to support the transition to low-carbon practices between treatment and control groups. The results of this study will provide valuable insights for policymakers on how to design more effective climate interventions, taking into account the anomalous behaviors associated with loss aversion.

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1 Introduction

Climate change represents one of the most pressing and complex challenges of the 21st century, demanding immediate, comprehensive, and effective actions to mitigate its far-reaching impacts (DERVIS, 2007). The global nature of this issue requires coordinated efforts from governments, industries, and individuals worldwide to address the multifaceted consequences of rising temperatures, extreme weather events, and ecosystem disruptions (IPCC, 2018). In response to this urgent threat, governments at various levels - local, national, and international - are implementing a wide array of policies and initiatives aimed at encouraging substantial reductions in greenhouse gas (GHG) emissions (DUBASH et al., 2013). These policies span diverse approaches, including but not limited to:

1. Carbon pricing mechanisms (e.g., carbon taxes and cap-and-trade systems) (BANK, 2018)
2. Renewable energy incentives and mandates (CARLEY, 2011)
3. Energy efficiency standards for buildings and appliances (GILLINGHAM; NEWELL; PALMER, 2009)
4. Transportation sector reforms, including electric vehicle incentives and public transit improvements (SPERLING; GORDON, 2009)
5. Afforestation and reforestation programs (CHAZDON et al., 2016)

While these policy interventions are crucial steps towards mitigating climate change, their effectiveness is not guaranteed and can be significantly influenced by various factors. One critical aspect that may compromise the impact of climate policies is the complex interplay of human behavior and decision-making processes, particularly behaviors exhibited by individuals and organizations that are not suitable for the classic rational decision-making model (STERN, 2016).

Climate policies are typically based on optimization algorithms that assume individuals are rational decision-makers, responding mechanically to price signals (KNOBLOCH; HUIJBREGTS; MERCURE, 2019). This approach stems from traditional economic theory, which posits that people make choices to maximize their utility based on perfect information and consistent preferences. However, insights from behavioral economics have increasingly challenged this view, emphasizing that it is no longer tenable for economists to claim that the self-regarding, rational actor model offers a satisfactory description of human decision-making (GOWDY, 2008).

Behavioral economics, drawing from psychology and neuroscience, has revealed numerous cognitive biases and heuristics that influence human decision-making, often leading to outcomes that deviate from purely rational choices. These include phenomena such as loss aversion, present bias, status quo bias, and social norms, among others. Such findings imply that the real-world impacts of decarbonization policies that rely primarily on price adjustments to reduce greenhouse gas (GHG) emissions could be very different from what would be expected based on rational decision-making models (KNOBLOCH; HUIJBREGTS; MERCURE, 2019).

One particularly relevant concept in this context is loss aversion, a cognitive bias where individuals tend to prefer avoiding losses to acquiring equivalent gains (KAHNEMAN; TVERSKY, 2013). This bias can significantly impact the public's reception of and compliance with climate policies. For instance, policies that frame carbon pricing as a loss (e.g., increased costs) may face stronger resistance than those framed as preserving gains (e.g., maintaining environmental quality for future generations), even if the economic outcomes are identical (KNOBLOCH; HUIJBREGTS; MERCURE, 2019). Loss aversion can lead people to prefer the status quo or perceived less costly options, even when more "costly" alternatives offer potentially greater benefits for climate change mitigation. By better understanding this phenomenon and considering it during optimization, policymakers can develop more effective strategies to promote the transition to a low-carbon economy.

Our research is related to the existing literature on behavioral economics and environmental policies. Several studies have explored how psychological factors influence environmental decisions ((WEBER, 2015); (BREKKE; JOHANSSON-STENMAN, 2008); (MAO et al., 2020); (HE et al., 2019); (KNOBLOCH; HUIJBREGTS; MERCURE, 2019); (GOWDY, 2008); (SHEFRIN, 2023)). These studies have laid a foundation for understanding the complex interplay between human psychology and environmental decision-making.

However, there remains a significant gap in the literature regarding the specific role of loss aversion in climate policy acceptance. While this concept has been extensively studied in other contexts, its application to climate policy preferences has been limited. Our work aims to address this gap by providing experimental evidence on how loss aversion affects preferences for different types of climate policies. By providing experimental evidence, our research contributes not only to the theoretical understanding of behavioral economics in environmental policy but also offers practical insights for policy design. We aim to demonstrate how public policies can be crafted to account for anomalous behaviors associated with loss aversion, potentially increasing their effectiveness and public acceptance.

2 The Experiment

2.1 Hypothesis Testing

To investigate the role of loss aversion in climate policy preferences, we have designed an experiment that simulates policy choices in a simplified economic model. This model considers an economy with only two types of technologies: energy-efficient (sustainable) technologies and fossil fuel technologies. Individuals preferences for these two alternatives are determined by two dimensions: upfront capital cost (i.e., the purchase price and eventual installation costs), and the (discounted) total operating costs during a technology's lifetime. The primary goal of policymakers in this scenario is to promote a massive substitution of carbon fuels by ensuring that low-carbon technologies can financially compete with fossil-fuel alternatives. In this regard, we suppose policymakers face two policy options: (i) include a residential/corporate carbon tax of R\$600/tCO2, which is added to the household/business energy price (option A), or (ii) dispense a technology subsidy of 50%, which is paid on the upfront investment costs of renewable sources of energy (i.e. heat pumps, solar thermal and modern biomass systems) (option B).

Building on the foundation of prospect theory (KAHNEMAN; TVERSKY, 2013) and its assertions about loss aversion, even if the policies were prepared to make them equally profitable[1] (such that rational decision-makers should view these contracts as equivalent and should be indifferent when choosing between them), we should expect people being more willing to accept option B, because they receive greater disutility from losses than utility from equivalent gains. That is, due to loss aversion, the relative disadvantage (loss) of higher upfront costs has a relatively stronger impact on decisions than the advantage in energy costs (gain), when evaluated

[1] The cost to implement the sustainable energy paid in $t = 0$ plus the expected gains for the next years equals to the carbon tax losses for the next years

from the reference point of ongoing fossil-fuel technologies. Thus, there may be unintended consequences associated with penalty contracts and in the real world presumably option B is more efficient than option A, because it may prove more effective for policies to aim at reducing relative disadvantages, than aiming at further increasing relative advantages (KNOBLOCH; HUIJBREGTS; MERCURE, 2019)).

In order to verify those theoretical arguments, we have developed a set of hypotheses to guide our investigation. Our primary testing hypothesis (H1) states that participants will demonstrate a statistically significant preference for the gain-framed policy (Option A) over the loss-framed policy (Option B), even when the economic outcomes are equivalent. This hypothesis directly tests the impact of loss aversion on policy preferences in the context of climate change mitigation.

To provide a more nuanced understanding of the factors influencing policy preferences and outcomes, we have also developed a secondary hypotheses: H2 posits that the strength of preference for gain-framed policies will positively correlate with the decision-maker's level of loss aversion. This hypothesis seeks to explore the relationship between individual loss preferences and sensitivity to policy framing, and to understand what is the turning point from a gain framed policy to a loss framed policy (how much we need to subsidize to make individuals indifferent).

2.2 Experimental Design

To rigorously test our hypotheses regarding the impact of policy framing on sustainable technology adoption, we have designed a Randomized Controlled Trial (RCT) in collaboration with state-level government. This approach allows us to examine the effects of our policy interventions in real-world settings, providing robust evidence for policy recommendations. Our study will span a single state, focusing on cities carefully selected based on their comparability. We will consider factors such as population size, urban-rural composition, economic structures, industrial diversity, and baseline levels of sustainable technology adoption. This selection process ensures that our sample is representative and that the effects we observe can be attributed to our policy interventions rather than pre-existing differences between cities.

Our partnership will be with the state of Sao Paulo, home to some of the cities with the worst air quality in the country (UOL, 2024). We will randomly assign cities to one of three groups: two treatment groups receiving different policy interventions, and a control group maintaining current policies.

The first treatment group will receive an information-based intervention. In these cities, trained agents will conduct individual interviews with a sample of residents. Before asking questions about preferences for energy transition incentives, the interviewers will provide a carefully crafted explanation to raise awareness about decision biases, particularly those stemming from loss aversion. This approach aims to examine how increased awareness of cognitive biases might influence individuals' perspectives on energy transition policies.

This explanation will be based in three questions. Two of these three questions will be problems 11 and 12 of Kahneman and Tversky (2013). The questions will be reformulated so that all individuals are able to understand the question and answer it correctly. The third question will be the same as in Levin (2002) example. That is, treated participants must choose how many ingredients to put or remove from a pizza, following the same forms of the paper. Adding explanations of how the loss aversion influences the responses, it is expected to remove treated individuals' loss aversion bias make their questionnaire responses as close as possible to a rational individual decisions. [2]

The second treatment group will receive an information-based intervention and also be subject to a policy-based intervention. In these cities, they will receive the same treatment as the first group but also local governments will implement a temporary program of financial incentives for households and businesses to adopt cleaner energy sources or improve energy efficiency. This could include subsidies for solar panel installation, tax breaks for electric vehicle purchases, or grants for energy-efficient home improvements.

The control group cities will maintain their current policies without any additional interventions, serving as a baseline for comparison. By comparing outcomes across these three groups, we aim to assess the relative effectiveness of information-based and policy-based interventions in promoting energy transition and improving air quality in urban areas.

To test our hypotheses comprehensively, we will collect data at multiple levels. At the city level, we will track rates of sustainable technology adoption, energy consumption patterns, and greenhouse gas emissions. For the household level, we will gather survey responses on their loss aversion, relevant demographic information, policy perceptions and preferences, data on actual investments in sustainable technologies, and energy efficiency improvements. But because gathering information about every single individual in each city is too costly and difficult, we will utilize the same population sample used in PNAD to build the experiment. Since the study is São Paulo's state government interest, the partnership with them will be useful to identify the households in the PNAD sample. Thus, the experiment will be done with a representative subpopulation of São Paulo's population, to cheapen and facilitate the intervention. Because PNAD is a representative sample, this selection process ensures the effects we observe can be attributed to our policy interventions rather than pre-existing differences between individuals. Also, taking advantage of available data from PNAD, we will collect data on demographics characteristics of each participant to enrich the baseline survey.

Our data collection will occur at baseline and at regular intervals (6 months, 1 year, and 2 years) after policy implementation. This longitudinal approach will allow us to track both short-term reactions and medium-term effectiveness of the policies, directly addressing our hypothesis about the sustained impact of gain-framed versus loss-framed policies.

2.3 Treatment

Once participants are allocated to either treatment or control groups, the experiment unfolds through a series of seven carefully designed choice scenarios. Each scenario presents participants with two options: one framed as a potential loss and the other as a potential gain (refer to Table 1 for details). This deliberate manipulation of incentive policy framing allows us to test Hypothesis 2 effectively.

The experiment begins with a crucial contextualization phase. Participants are informed that while the scenarios are hypothetical, their responses carry real-world implications. To encourage thoughtful engagement, we've implemented a novel incentive structure: participants will receive a small monetary reward based on one randomly selected choice from their responses. This approach motivates participants to consider each decision independently and carefully, as any choice could be the one that determines their compensation.

It's important to note that at no point will participants be required to make any actual payments. The monetary reward serves solely as an incentive for conscientious participation, not as a financial risk. This methodology allows us to simulate real-world decision-making processes

[2] Rational individual understood as in traditional economic theory

in a controlled environment, providing valuable insights into how framing affects choices in energy transition policies.

Table 1 – Policy Choices

Choice	Carbon Tax (R$ per month)	Subside (total R$ paid for clean energy)*
1	R$7,45	R$3.130
2	R$13,45	R$3.796
3	R$18,27	R$4.330
4	R$22,16	R$4.761
5	R$25,28	R$5.107
6	R$27,8	R$5.386
7	R$29,81	R$5.610

** R$ amount of investment to be made to change the energy source, not the amount of subsidy.*

Table 1 presents the decision scenarios offered to participants. These scenarios are systematically designed to reflect varying cost-benefit timelines for renewable energy adoption:

- The initial scenario presents a three-year payback period for renewable energy investment.
- Each subsequent scenario extends the payback period by one year.
- The final (seventh) scenario features an nine-year break-even point.

The experimental design incorporates several key parameters. First, a Constant Benefit is assumed, with a fixed reduction of R$60,00 in monthly electricity bills as the benefit of renewable energy adoption, projected over the participant's lifetime. Second, a Discount Rate is applied, using a monthly interest rate of 0.91% (based on the SELIC rate as of July 2024) to calculate present values. Third, the Carbon Tax Model is structured as a perpetual increase in residential electricity bills.

This structured approach creates a spectrum of economic trade-offs. In all scenarios the net present value (NPV) of the renewable energy investment exceeds that of the carbon tax option in exactly two years. So, from a normative economic perspective, a purely rational agent would be expected to choose the renewable energy investment in every scenario. Also, while Table 1 does not explicitly detail these long-term implications, participants are provided with this information to inform their decision-making process.

The second treatment group, undergoes a two-stage intervention process. Initially, all participants in this group receive the same informational treatment as the first treatment group, ensuring consistency in the educational component across treatments. Following this, participants in the second treatment group are randomly subdivided into two cohorts for the framed subsidy presentation.

The first cohort, termed the Loss-Frame Cohort, encounters the subsidy framed as a potential loss. For example, they might be presented with a statement such as: "By not adopting renewable energy, you stand to lose $X in potential savings each month." Conversely, the second cohort, designated as the Gain-Frame Cohort, sees the subsidy presented as a potential gain. They might encounter a statement like: "By adopting renewable energy, you can gain $X in savings each month."

All participants, regardless of their group assignment, complete a decision task where they choose whether to accept or reject the presented subsidy. This uniform task allows for direct comparison across all experimental conditions.

3 Empirical Approach

To estimate the impact of loss aversion on policy adherence, we focus on intent-to-treat (ITT) estimates; that is, simple comparisons of averages in treatment and comparison areas, averaged over "rational" (treated) and "irrational" (not treated) participants. The outcome of interest is the chosen option in each scenario.

$$y^j_{ia} = \alpha + \beta_1 \cdot Treat^1_{ia} + \beta_2 \cdot Treat^2_{ia} + \gamma \cdot \mathbf{X}_a + \epsilon_{ia}$$

Where y^j_{ia} is individual's i (located in city a) choice in scenario j, $Treat^1_{ia}$ is an indicator for living in a city that received both treatments, $Treat^2_{ia}$ is an indicator for living in a city that received only the informational treatment, and β is the intent-to-treat effect. $\mathbf{X}_a$ is a vector of control variables, calculated as city level baseline values. Standard errors are adjusted for clustering at the city level.

Because our questionnaire was designed for participants to have incentives to answer it, we expect to minimize the attrition rate.

4 Expected Results

Our study on the influence of cognitive biases, particularly loss aversion, on climate policy decisions is expected to yield complex and nuanced results. We anticipate that the effects of our interventions will manifest in several interconnected ways, reflecting the multifaceted nature of human decision-making in the context of climate change mitigation.

Firstly, we hypothesize that participants who receive information about cognitive biases may initially experience increased skepticism towards their own decision-making processes regarding climate policies. This heightened self-awareness could potentially lead to a temporary reduction in their willingness to adopt energy-efficient technologies or support climate mitigation policies. While this outcome might seem counterintuitive, it aligns with the concept of cognitive dissonance, where individuals may resist information that challenges their existing beliefs or behaviors (FESTINGER, 1957).

However, this initial skepticism is not expected to undermine the broader understanding of climate change urgency. We posit that most individuals recognize the necessity of addressing climate change, despite their cognitive biases. This understanding could serve as a foundation for policymakers to design interventions that enhance people's ability to recognize and mitigate these biases, ultimately encouraging more critical evaluation of decisions related to energy consumption and environmental impact (KNOBLOCH; HUIJBREGTS; MERCURE, 2019).

The framing of climate policies is anticipated to play a crucial role in their acceptance. We expect to observe a significant difference in responses to policies framed as potential losses (e.g., increased costs due to carbon taxes) versus those framed as preserving gains (e.g., maintaining environmental quality for future generations), even when the economic outcomes are identical. This effect may be particularly pronounced in the group that receives information about loss aversion, as their increased awareness of framing influences could amplify their sensitivity to such nuances.

In terms of long-term effects, we hypothesize that the impact of revealing information about cognitive biases may diminish over time. We anticipate no significant difference between control and treatment groups in a follow-up survey, suggesting that while information about biases might influence immediate decisions, long-term behaviors are likely more influenced by deeply ingrained habits and societal norms.

An interesting counterpoint to these expectations comes from the concept of the "bias blind spot" (PRONIN; LIN; ROSS, 2002). This phenomenon suggests that individuals tend to recognize cognitive and motivational biases more readily in others than in themselves. Consequently, we may observe that participants acknowledge the existence of loss aversion and other biases but maintain that their own decisions are largely unaffected by these phenomena.

The effectiveness of our informational treatment is expected to vary based on individuals' pre-existing beliefs about climate change and their level of environmental concern. We anticipate that those with strong pro-environmental attitudes will be more receptive to information about cognitive biases and more willing to adjust their behaviors accordingly. Conversely, individuals with skeptical views about climate change might exhibit resistance to this information, potentially leading to a backfire effect where they become even more entrenched in their existing beliefs (HART et al., 2012).

Lastly, we acknowledge that participants may have prior awareness of cognitive biases, given the popularity of these concepts in contemporary media and education. Therefore, we interpret our estimand as a lower bound for the effect of learning about cognitive biases on people's climate policy preferences and energy-related decisions.

In conclusion, our expected results reflect the complex interplay between cognitive biases, information processing, and environmental decision-making. While we anticipate observing some impact from our interventions, the magnitude and persistence of these effects are likely to vary due to individual differences, pre-existing knowledge, and the intricate dynamics of human cognition in the face of long-term, global challenges like climate change.

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