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Promoting Pro-Environmental Behavior
Evidence from the Lab and the Field

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”Climate change is really the kind of threat for which we as humans have not evolved to cope with. It’s too distant. It’s too remote. It just is not the kind of urgent mobilizing thing. If there were a meteor coming to earth, even in 50 years, it would be completely different. People could imagine that. It would be concrete. It would be specific. You could mobilize humanity against the meteor. Climate change is different. And it’s much, much harder, I think.”

— Daniel Kahneman, *Council on Foreign Relations (2017)*

Introduction and Summary

Unravelling the Flying Carpet

The quote by Daniel Kahneman on the previous page may seem like a somber introduction to a dissertation that aims to uncover solutions for complex challenges. However, it is the pursuit of elegant solutions that has always captivated me throughout the development of the studies presented herein. As humanity continues to expand the "flying carpet" of CO_2[1] and other greenhouse gases in the atmosphere, many are diligently working towards devising partial solutions. One has to accept that success in this domain comes incrementally.

There is no doubt that technology and policy will have to work hand in hand to avoid the most extreme scenarios outlined in the latest report by the Intergovernmental Panel on Climate Change (IPCC, 2022). However, the report also states that demand-side strategies including pro-environmental behavior (PEB) can potentially reduce greenhouse gas emissions by 40-70% by 2050. Various strategies exist for encouraging pro-environmental behavior at the individual level. One approach is to prohibit certain actions outright, compelling people to adopt more environmentally friendly practices. Alternatively, financial disincentives can be imposed on undesirable behaviors by increasing the explicit costs associated with them. However, these regulations or interventions often face challenges in implementation due to public resistance. More subtle, choice-preserving methods may encounter less opposition and thus be easier to put into practice. Behavioral science provides a toolkit for developing such strategies, leveraging insights into human behavior to promote eco-friendly choices without the need for coercion or punitive measures.

All four studies of this dissertation examine an implementation of choice architecture or *nudging*. The basic idea is to create a decision environment to "alter people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (Thaler & Sunstein, 2021, p. 8). There are many different types of nudges

[1] My own rudimentary calculations suggest a hypothetical layer of approximately 2.5 meters of CO_2 around the Earth's entire surface if it all were concentrated there. This layer is increasing by a few centimeters annually at current global emission rates.

that have been applied to a great variety of contexts. Several meta-analyses have analyzed different aspects of nudge studies. Hummel and Maedche (2019) categorize interventions along different dimensions and find defaults to be the most effective strategy. DellaVigna and Linos (2022) compare effect sizes published in academic literature with those of interventions implemented by so-called "Nudge Units" in the United States and found a considerable difference in the effectiveness of 8.7 percentage point take-up effect for the former compared to 1.4 percentage points for the latter. They attribute the differences to three dimensions: statistical power, characteristics of the intervention (e.g., area or issue at hand and type of nudge), and publication bias.

There have been serious concerns about the methodologies used, e.g., grouping different interventions under the same umbrella to call them "environmental" even though they may be incommensurable (Simonsohn et al., 2022). Especially in the domain of high-impact behavior, it appears advisable to remember that differing interventions will be varyingly effective for different consumer segments (Wolske & Stern, 2018).

In the present dissertation, three out of four studies were conducted as online experiments, while the fourth utilized data from a large Swiss energy provider to analyze behavior in the field. Study 1 examines the impact of decision support, i.e., a simple color coding to make environmentally desirable and undesirable decisions more salient. Study 2 investigates how reference points or the set of possible decisions influence the same trade-off in two different conditions. Study 3 frames achievable donations either in a way that lets participants accumulate them in a *GAIN* treatment or avoid subtracting from the maximum in a *LOSS* treatment. Finally, Study 4 evaluates the effect of small price changes on default adherence to one's energy tariff.

Study 1 by Bregulla (2022)
Real-time decision support promotes pro-environmental behavior

People's actions often fail to meet their desired standards in terms of climate change mitigation. It is plausible that facilitating the alignment of individuals' behavior with their values could serve as a viable approach to address climate change. Our understanding of the psychological mechanisms that underlie decision-making in this context remains incomplete. Enhancing individuals' PEB is thought to rely heavily on self-regulation and, more precisely, self-control (Fujita, 2011; Nielsen, 2017). An avenue worth exploring in addressing this matter involves the creation of choice environments that prioritize long-term objectives over immediate gratification, all while preserving individual choice.

While it is essential to recognize effortful inhibition as a significant component of self-control, it does not encompass the entirety of the concept. There are various methods through which individuals can prioritize their long-term objectives over short-term gratification (Fujita, 2011). In fact, relying exclusively on effortful inhibition to achieve environmental goals might not be the best approach, as forward-thinking strategies could prevent individuals from even encountering situations where resisting temptation is the sole option (Nielsen, 2017). However, when individuals are presented with immediate temptations, effortful inhibition can play a pivotal role in upholding long-term objectives (Nielsen, 2017). That is why designing decision environments that reduce the cognitive effort required to select more sustainable choices has been advised (Langenbach et al., 2019).

In Bregulla (2022), participants face a series of decisions between two options in the *Carbon Emission Task* (CET) by Berger and Wyss (2021). Participants can either decide to emit CO_2 in the range between 0.23 and 19.85 lbs and receive a small payment between 0.2 and 1 GBP, or they can choose to avoid emitting CO_2 but forego the bonus. To provide context regarding the significance of the specified CO_2 amounts, the display also indicates the approximate distance an average car would travel before it emits the corresponding quantity. Overall, participants face twenty different trade-offs for which they have to weigh the personal short-term benefit against the long-term goal of mitigating emissions. By acquiring emission certificates from the European Union Emissions Trading System (EU ETS) and retiring them from the market, it is possible to create an experimental design in which participants' decision-making has actual environmental consequences[2].

The study introduces a relatively simple *decision support* treatment to promote PEB. Both the control and treatment group receive identical numerical data. However, participants in the decision support treatment are guided by a color-coded system that highlights the ratio between potential bonuses and CO_2 emissions (red for relatively low ratios and grey for higher ratios, while the option avoiding emissions remains green). Without having to calculate specific trade-offs quickly, participants receive intuitively understandable information about how large the emissions are compared to the possible bonus. This uncomplicated method increases the average rate of pro-environmental decisions by roughly 8 percentage points, i.e., from 46% percent of pro-environmental decisions in the control condition to 54% in the condition with decision support. Further analyses revealed that particularly large financial incentives overshadow other aspects of a given set of decision variables.

On average, people behave consistently within a subset of decisions concerning the same amount of CO_2 or the same bonus level. They generally choose the pro-environmental option more often when the emissions are higher, and the financial incentives are lower.

[2] There exists a lively discussion on the topic of the effectiveness of the system, the issue of a considerable surplus of allowances within the EU ETS since its inception, and possible tools to counteract the effects of thereof (Rosendahl, 2019). However, this is outside of the scope of this dissertation.

However, there are considerable differences between the average decisions made for similar ratios of the different trade-offs of bonus to CO_2. For instance, people only choose the pro-environmental option in about 20% of decisions when the bonus is GBP 5, and the CO_2 emissions are 1.02 lbs (a ratio of 4.9 GBP/lbs). Compare this to more than twice as many pro-environmental decisions when the bonus is only GBP 1 but the emissions are 0.23 lbs (a ratio of 4.3 GBP/lbs). This shows how strongly people react to the financial incentive.

It is encouraging to observe that even in a highly anonymous online context participants exhibited a significant degree of PEB and responded positively to the decision support treatment. However, this observation cannot overshadow the reality that the larger financial incentives were so influential that participants could not solely depend on effortful inhibition to sustain the level of pro-environmental decisions evident with smaller bonuses. This challenge was evident even among individuals with high self-control scores. Nevertheless, the treatment can serve to accentuate the relative impact or highlight specific trade-offs, especially in scenarios involving environmental implications that might be hard to grasp. It also shows the benefits of offering *transparent* information to decision-makers.

Study 2 by Berger and Bregulla (2023)
Coherently arbitrary pro-environmental behavior

In contrast to the decision-support treatment of the first study, Berger and Bregulla (2023) confronts participants with a treatment hidden in plain sight. The central aim is to examine how individuals in various ”universes” or decision contexts evaluate the same trade-off. This allows us to test a common assumption in environmental psychology: that individuals make decisions to optimize their utility based on fixed preferences (Steg & Vlek, 2009). In experimental research, the measured behavior is then interpreted to reflect these preferences. However, this premise has been critiqued by research in behavioral economics. In certain contexts, valuations can be ”coherently arbitrary.” This means that while initial valuations may rely on arbitrary anchors, subsequent valuations appear consistent within the ”universe” delineated by that anchor (Ariely et al., 2003). However, when comparing different ”universes” starting with different anchors, these valuations differ between conditions, thereby questioning the concept of fixed preferences.

To examine these findings in the domain of PEB, this experiment also uses the CET and implements two treatments that only differ in the range of possible bonuses: In the *low financial stakes* condition, the range is GBP 0.2 to 1 (as in Study 1), while in the *high financial stakes* condition, bonuses range from GBP 1 to 5. The CO_2 emissions are the same in both conditions. Crucially, both conditions contain a potential bonus of GBP 1 in a subset of choices, termed the *target* decisions. This allows for comparison regarding the influence of how the spectrum of trade-offs within a condition influences behavior in the target decisions.

The results show the expected difference between conditions and the expected cost- and benefit sensitivity within one condition. Overall, higher bonuses and lower emissions lead to a lower average of pro-environmental decisions. This is the behavior predicted by economic and psychological theory, according to which people will try to balance their utility maximization with their environmental values. Looking at each condition separately, people make coherent decisions on average. However, by isolating and comparing the *target* decisions, which are objectively equal in both conditions, the significant effect of the decision sets emerges. When the target decision represents the highest possible bonus, as is the case in the low financial stakes condition, people choose the pro-environmental option in only about 33% of cases. In contrast, in the high financial stakes condition the target becomes relatively unappealing, and the proportion of pro-environmental decisions increases to about 62%. Taken together, participants in the study do not differentiate based on the scope of the environmental impact of their decisions.

This finding underscores the limitations of viewing preferences as a fixed construct and highlights the need for caution when generalizing from specific experimental settings to real-world behavior. Notably, participants across all CET conditions receive information on the "car mile equivalents" of the corresponding CO_2 emissions for each decision. Such additional information is apparently insufficient to ensure participants remain sensitive to the scope of their decisions. This presents challenges when promoting PEB in non-financial terms. While the results suggest that framing might be a useful tool, one must remain vigilant about transparency when crafting choice environments.

In a concurrent paper examining various factors influencing PEB (and using the same experimental paradigm as presented in Study 3), evidence of scope sensitivity is found between groups with different incentives (Lange & Dewitte, 2023). This contrasts the scope *in*sensitivity observed in Berger and Bregulla (2023). Importantly, the experimental designs, stakes involved, and types of dependent variables measured differ between the studies. Future research must further investigate under which conditions people display coherent arbitrariness in their PEB and what prompts them to act with scope sensitivity.

Study 3 by Hauser and Bregulla (2023)
Saving the world voluntarily: Experimental evidence of gain-loss framing on voluntary pro-environmental behavior

As shown in Study 2, the framing of a choice set can have a tremendous effect on people's decisions, which is examined in Hauser and Bregulla (2023) by implementing a $GAIN$ and a $LOSS$ frame to measure possible effects on PEB. This study combines research of voluntary PEB and insights on loss framing.

The core idea applied in this study is rooted in the finding that the positive utility of a gain, such as a financial one, is outweighed by the negative utility of an equivalent loss (Kahneman & Tversky, 1979). As there exists no economic distinction between gain and loss frames, the underlying hypothesis posits that due to loss aversion, individuals exert greater effort under a loss frame. This fact has been used to study the effect of loss framing on PEB. However, the PEBs (and intentions) tested vary widely, making it challenging to draw a definitive conclusion regarding a consistent effect. In experimental research, only a limited number of studies have actually measured PEB (see Homar & Cvelbar, 2021 for an overview). Study 3 thus combines insights about loss aversion and incentivizes participants to work on a real-effort task. Distinct from other settings where loss frames were implemented, participants in this study do not gain any immediate personal benefit. They can only generate donations for an environmental cause.

The experimental paradigm used here is the *Work for Environmental Protection Task* (WEPT) by Lange and Dewitte (2022). It consists of 15 pages, each with a number identification task. By completing individual pages, participants generate donations to an environmental organization that plants trees. The tasks vary in the potential donation amount (ranging from GBP 0.1 to 0.3) and the required effort, which is indicated by the number of digits participants must check for specific features (ranging from 40 to 200). Before beginning each page of the task, participants can choose to either work for the specified amount and effort or decline that particular page.

The difference between the $GAIN$ and $LOSS$ treatment in the study is only how the total donation amount is presented. In the $GAIN$ treatment, the total donation accumulates, increasing with every page completed by the amount specified for that page. Conversely, in the $LOSS$ treatment, participants begin with a maximum total donation of GBP 3, which decreases by the specified amount for any page they opt not to complete.

The results reveal a marginally significant effect of increased working effort in the $LOSS$ treatment. In the $LOSS$ treatment, the average number of completed WEPT pages stands at 5.16 (SD = 4.11), in comparison to 4.66 (SD = 4.41) pages in the $GAIN$

treatment. Despite the expected effect being small and the study having high statistical power with a substantial sample size ($N = 897$), there are indications that the random assignment to the two treatment groups did not work as intended. Participants in the $GAIN$ treatment exhibit slightly higher biospheric values in comparison to those in the $LOSS$ treatment. While biospheric values are never perfectly aligned with PEB, they are generally related to it (Katz-Gerro et al., 2017). In regression models that account for biospheric values among other variables, the effect of the $LOSS$ treatment attains conventional significance levels, and the estimated size of the effect even increases to 0.60 and 0.67 pages for the respective models. Interestingly, people with lower biospheric values, determined by a median split of the data, showed a more pronounced reaction to the treatments. This is evidenced by the statistically significant difference between $M = 4.47$ ($SD = 4.06$) pages solved in the $LOSS$ treatment compared to $M = 3.74$ ($SD = 3.72$) in the $GAIN$ treatment.

The context of this online study was highly anonymous, i.e., there was no researcher observing participants as one might find in a lab setting. Even though the task does not closely mimic real-world situations, many are familiar with the anonymous online environment. It remains remarkable how much time and effort participants devoted to mitigating climate change. On average, participants dedicated more than 11 minutes to a task without personal benefit. The $LOSS$ treatment does show a slight effect, and while a 10% increase might seem substantial from a distance, in practical terms it translates to only about half a page more solved in the WEPT. Together with existing research, this result raises doubts about the scalability of such interventions in broader contexts. One conclusion drawn is that beyond the unique design and framing, merely providing people with an opportunity to partake in a simple task, potentially seen as gamification, can access a considerable potential for contributing to climate change mitigation.

Study 4 by Bregulla et al. (2023)
Stability of green default adherence in a costly moment of change

The fourth paper in this dissertation examines field data about the stability of defaults in the Swiss energy sector. Defaults can be characterized as the preset option that, in the absence of an active choice, becomes the automatic selection for an individual. Defaults have been used successfully to increase retirement savings (Madrian & Shea, 2001) and organ donations (Johnson & Goldstein, 2003). However, the literature on the exact mechanisms of defaults and how they interact with price signals remains scarce. For instance, the meta-analysis by Jachimowicz et al. (2019) suggests three primary mechanisms: endorsement, endowment, and ease. Endorsement is in effect when a given default is perceived as the choice architect's recommendation (Jachimowicz et al., 2019).

Endowment refers to the decision-maker interpreting the default as the status quo or feeling a sense of ownership over it (Jachimowicz et al., 2019). Increased perception of endowment results in a stronger reference-dependent interpretation of the options and loss aversion (Kahneman & Tversky, 1979). Ease means a default requires less physical or mental effort than choosing an alternative (Dinner et al., 2011).

While Study 4 cannot distinguish between the exact mechanisms at work, it offers further insights into the interplay between price signals and defaults. In this context, a default is the tariff assigned to household customers when they relocate into the service area of an energy provider. For the customers in this study, this default meant they received electricity from hydropower sources and were placed on a mid-tier pricing tariff out of the three available options. The other tariff options were a cheaper one primarily sourced from nuclear energy and a more expensive tariff derived from solar energy. The data analyzed in this study draws from an event in 2021 when a major energy provider, referred to as *Provider A* due to a non-disclosure agreement, acquired two smaller providers, *Provider B* and *Provider C*. This acquisition resulted in diverse price adjustments for the distinct customer groups of each of the three merged providers.

When an individual's energy provider undergoes an acquisition by another company, it can serve as a potential *moment of change*. Such moments represent brief intervals that can disrupt habitual behaviors, prompting individuals to actively contemplate and possibly alter a specific behavior (Thompson et al., 2011). In the context of this study, the pivotal moment arises when consumers experience a shift in electricity prices due to the acquisition of the energy providers. Such instances can draw customers' attention to their energy contracts and encourage an active deliberation on their preferences.

Upon merging, the tariffs of the previously distinct providers were standardized. As a result, the original customer groups of the previously distinct providers faced varied price changes for their default tariffs. Specifically, customers from Provider A saw a decrease of 4.55%, while those from Provider C experienced an increase of 11.44%. Meanwhile, the tariff for Provider B's customers increased only marginally, by 0.56%. This scenario allows us to study default adherence in a natural experiment setting, where we observe three distinct groups experiencing increasing, stable, and decreasing price changes, respectively.

Utilizing data from 143,313 electricity meters for the period 2019-2022, the results indicate a pronounced effect of defaults on contract selections. For meters adhering to the default tariff from 2019 to 2021, 99.4% continued with this tariff in 2022. The majority of those who transitioned selected the lower-priced tariff. Within the context of the natural experiment, the only statistically significant finding was a slightly higher propensity for Provider A's customers to deviate from the default compared to the reference customer group of Provider B. However, this deviation is of such limited magnitude that its practical relevance is minimal. Notably, meters with higher electricity consumption demonstrated a certain degree of cost sensitivity, with increased usage corresponding to a slightly elevated likelihood of deviating from the default. However, this trend is most likely mitigated by the study's data limitation, capping energy consumption at 10,000 kWh/year. The resulting yearly cost difference between the default and the most economical tariff is CHF 24 for the median energy consumption in the dataset.

In conclusion, this study reinforces the efficacy of defaults in the context of electricity tariffs. It contributes to the literature on choice architecture and behavioral interventions, which currently has a limited number of studies that utilize extensive datasets over prolonged periods (Nisa et al., 2019). While significant price increases have been pinpointed as *the* discernible factor prompting default deviations in previous studies (Berger et al., 2022), this study demonstrates that, for smaller amounts, defaults remain remarkably effective. An open question is the financial tipping point that triggers specific behaviors, and it will have to be answered separately for different contexts. Future research should explore this threshold, especially during moments of change in sectors where individual decisions can have substantial environmental impacts.

Holding the Threads

The studies in this dissertation examine PEB from different perspectives. The results of Study 1 show that even (or especially) in a context where people face an unfamiliar trade-off, a simple decision-support system promotes PEB. In Study 2 it becomes clear that we should not accept people's decisions as their fixed preferences since different sets of possible trade-offs we face – the different "universes" in which we live – can heavily influence how we interpret the objectively same decision. It is possible that more familiarity with the subject matter could alleviate this issue. In the case of carbon emissions, however, it does not appear likely that "carbon literacy" (having a grasp on which actions cause which amount of emissions) will develop soon, especially not on its own. A reaffirmed insight of Study 2 is that unintended nudges may happen more frequently than expected, and it is worth considering that choice architecture is always present in such environments. The question is only whether it is intentional or by accident.

Study 3 applies the concept of loss aversion to effortful PEB and finds only a small effect for the *LOSS* frame compared to the *GAIN* frame. This appears to demonstrate that at least for the context of PEB without an immediate personal benefit, loss aversion may not suffice to meaningfully promote the desired behavior. However, as becomes more clear as this field advances there is no "one size fits all" solution. An intervention may have a considerable effect in one context with a specific population but fail to deliver on its promises in another. Over time, we should update our beliefs and consider whether it is worthwhile pursuing further implementations of a given intervention.

Study 4 reinforced the idea that defaults can significantly influence decisions. In this context, the default was relatively easy to accept both financially and environmentally. It was cost-effective and likely met the majority of individuals' preferences regarding their desired energy source.

When examining the heterogeneous effect sizes in the studies presented and the broader literature, it becomes clear that there is not a single "simple" behavioral solution to address these issues. For problems as complex as climate change, expecting anything else would have been surprising. Addressing such a challenge requires a broad range of interventions, including standard economic methods centered on pricing (Thaler, 2017). However, relying solely on financial incentives is also not always sufficient to ensure people act in their best interest (Benartzi et al., 2017). The efficiency of interventions can be significantly raised by tackling non-financial obstacles to action (Wolske & Stern, 2018). Scientists and policymakers need to collaborate to navigate these challenges, identifying which interventions are most potent for each specific scenario. The fact remains that choice architecture will consistently influence decisions and behavior, whether intended or not. The threads are in our hands, and it is up to us to decide whether we continue weaving the flying carpet or begin to slowly unravel it.

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Study 1

Real-Time Decision Support Promotes Pro-Environmental Behavior

Real-time decision support promotes pro-environmental behavior

Daniel Bregulla

Summary: In this controlled online experiment, I show how a transparent decision support environment promotes people's pro-environmental behavior. Participants complete a validated experimental protocol (i.e., the Carbon Emission Task), where they are asked to trade off financial gains and environmental externalities. In a treatment where participants receive decision support via colored feedback, they engage in more pro-environmental behavior than in a neutral control treatment. Furthermore, pro-environmental values positively correlate with corresponding behavior in both treatments. The data does not support the hypothesis that decision support moderates the relationship between pro-environmental values and pro-environmental behavior, or that the correlation between environmental motivation and behavior is moderated to a lesser extent by self-control under the decision support treatment.

Keywords: pro-environmental behaviour, decision support, carbon emission task, behavioral economics, self-control, biospheric values

Entscheidungshilfe in Echtzeit fördert umweltfreundliches Verhalten

Zusammenfassung: In einem kontrollierten Online-Experiment fördert eine Entscheidungsunterstützung umweltfreundliches Verhalten. Die Teilnehmenden absolvieren eine validierte Versuchsanordnung (den Carbon Emission Task), bei dem sie finanzielle Gewinne und externe Umweltauswirkungen gegeneinander abwägen. In der Treatmentbedingung mit Entscheidungshilfen in Form von farbigem Feedback entscheiden sie umweltfreundlicher als in der Kontrollbedingung. Die umweltfreundlichen Werte der Teilnehmenden korrelieren positiv mit dem entsprechenden Verhalten. Hingegen konnte nicht bestätigt werden, dass die Entscheidungshilfe die Beziehung zwischen umweltfreundlichen Werten und umweltfreundlichem Verhalten moderiert oder dass die Korrelation zwischen umweltfreundlichen Werten und Verhalten in der Treatmentbedingung mit Entscheidungshilfen in geringerem Masse durch Selbstkontrolle moderiert wird.

Stichwörter: umweltfreundliches Verhalten, Entscheidungshilfe, Carbon Emission Task, Verhaltensökonomie, Selbstkontrolle, biosphärische Werte

1 Introduction

Limiting global warming to 1.5 instead of 2 degrees Celsius would have clear benefits for natural ecosystems as well as humans according to the Intergovernmental Panel on Climate Change (IPCC, 2018). Without immediate and substantial climate action, the world is facing considerable and irreversible consequences within a few decades. The reduction of emissions resulting from CO_2 and other greenhouse gases is paramount, and mitigation efforts will involve both the supply as well as the demand side (Creutzig et al., 2022). Mitigating the damage caused by our current behavior will require drastic lifestyle changes on many fronts.

Although many people worldwide believe that humans cause climate change and that it lies in our ability to limit its negative impacts (Carlsson et al., 2021), a discrepancy between people's values and actions has been observed across various domains (Sheeran & Webb, 2016). Research has repeatedly shown that pro-environmental beliefs and values are not always and entirely translated into corresponding behaviors (e.g., Farjam et al., 2019; Wyss et al., 2022). Even though protecting the environment makes people feel good about themselves (Taufik et al., 2015), the context in which people decide can lead them to behave in ways that go against the biospheric values they hold (Steg, 2016). This can explain that although people's environmental values and beliefs have continuously increased since the 1970s, corresponding behavior has often lagged behind (Kennedy et al., 2009). Intriguingly, even people with a relatively high environmental awareness have been shown to behave contrary to their own standards (Juvan & Dolnicar, 2014). This frequently observed attitude-behavior gap has sparked research interest in narrowing or even closing it.

Despite abundant research about the attitude-behavior gap, mitigation efforts have not taken advantage of all available tools for intervention, e.g., by fully integrating the social and behavioral sciences into demand-side solutions (Nielsen et al., 2020). The demand side encompasses the decisions of households and individuals, which account for a considerable share of total emissions. In Switzerland, for example, Rohrer (2021) estimates that about 20 % of the emissions reduction necessary for a sustainable future can be realized by individual behavior change.

In demand-side mitigation, behavioral interventions refer to a class of initiatives that apply a more thorough understanding of the social, cognitive, and contextual factors in decision-making. Behavioral interventions are increasingly part of the policy toolbox (Benartzi et al., 2017). They typically alter the decision environments in an effort also referred to as "choice architecture" to achieve a higher probability of specific options being selected (Weber, 2017).

In the present research, I test the efficacy of a behavioral intervention in a laboratory setting. Using recently established experimental protocols that allow studying personal and environmental tradeoffs, I test the causal impact of real-time decision support, mainly how pro-environmental behavior depends on feedback given at the decision point. I find that real-time decision support promotes pro-environmental behavior on average.

2 Decision support to promote pro-environmental behavior

People's daily consumption decisions offer a considerable chance to alter the trajectory of climate change because of their environmental consequences (IPCC, 2018). A substantial portion of individuals' decisions is shaped by interaction with companies. Oftentimes, companies aim to support their consumers in making pro-environmental or otherwise sustainable choices. For example, consumer labels created by companies assist consumption (Camilleri et al., 2019; Taufique et al., 2022), novel products help people sustain scarce resources such as water (Tiefenbeck et al., 2019), and many customers are offered so-called climate-neutral products via offsetting (Berger et al., 2022). Businesses need to be careful how they communicate well-intended interventions to their clients. For example, people have been shown to take a company's carbon offset program as a moral license to increase consumption (Günther et al., 2020). There is even evidence that recommendations for voluntary behavioral changes can decrease people's willingness to take action to reduce emissions (Palm et al., 2020). Adverse effects can be difficult to predict, but behavioral research offers different methods to deepen our understanding of what factors influence people's decision process.

One of these methods to deepen our understanding is laboratory research, which can serve as a "wind-channel" to test prospective interventions (Bolton & Ockenfels, 2012; Berger & Wyss, 2021). This way of behavioral economic engineering tests prospective interventions in the lab while analyzing certain psychological mechanisms, and then translates findings into field research by studying real-world behavior. Recent work in environmental psychology has shifted the theoretical thinking away from rational choice approaches (e.g., the theory of planned behavior (Ajzen, 1991)) to self-regulation (Nielsen, 2017). This suggests that not only the intention to act pro-environmentally matters, but equally the self-regulation capacity to align intentions and behaviors. Self-regulation has been identified as an important leverage point in pro-environmental behavior (Nielsen, 2017). Neurological evidence exists that activation in brain regions associated with self-regulation and inhibitory control is linked to pro-environmental behavior (Baumgartner et al., 2019). The concept of self-regulation encompasses people's choice of goals, how they intend to achieve these goals, putting one's plans into action, as well as self-control (Fujita, 2011). Self-control is necessary when we are presented with two mutually exclusive options where one delivers instant gratification and the other supposedly helps us to achieve a (primary) long-term goal (Duckworth et al., 2016). Central concepts of self-control are the ability to override or modify our internal reactions and to refrain from acting according to undesired impulses (Tangney et al., 2004). Self-control has different paths through which it can affect how people act in specific situations. People with higher self-control are more likely to exhibit the behavior that enables them to achieve their goal, but they are also more likely to select themselves into environments that support them in the behavior necessary to achieve their goal (Nielsen & Bauer, 2018).

Understanding self-control only as effortful inhibition would be inadequate, however. Effortful inhibition is a critical component of self-control, but there are other ways how people can advance their distal motivations (Fujita, 2011). In fact, effortful inhibition of impulses should be deemed a last resort for people to reach their environmental goals since prospective strategies can prevent us from even being put in a situation with no other option than to try and resist temptation (Nielsen, 2017). Nevertheless, once confronted with a tempting situation, effortful inhibition can help to shield overriding goals from being compromised by short-term temptations (Nielsen, 2017). It has been suggested that policymakers try to support people by constructing choice settings where the required amount of cognitive control necessary to choose the more sustainable option is kept to a minimum (Langenbach et al., 2019).

The intervention used here is designed in this spirit to facilitate decision-making. The decision support treatment directs participants' focus to their long-term goals. However, this process is not intended to work through deliberation but to offer additional information via intuitively understandable colors. The color red is more likely to be interpreted negatively than green (Krzywinski, 2016). Such a categorization is useful to facilitate choosing even in a context where people are not aware of their exact preferences and determining them in monetary terms is difficult.

3 The present study

Different approaches have been taken to tackle the problem of overcoming the attitude-behavior gap by targeting newly gained insights into when psychological factors dovetail with behavior. One type of a relatively simple to implement intervention is a label that informs people about the carbon emissions of their choices. People appear to choose more environmentally friendly when presented with information regarding the greenhouse gas emissions associated with specific food options (Camilleri et al., 2019). Another way to help people become more environmentally friendly is to give them real-time feedback on how much energy they are using at the moment (Tiefenbeck et al., 2019).

In the present study, people make a series of trade-offs between pro-environmental choices and environmentally harmful alternatives including a financial bonus. To test the causal impact of decision support, they are randomly assigned to either a decision support condition with color-coded carbon labels or a neutral control condition without any decision support. The color scheme helps participants immediately recognize the trade-off they have to make between a personal financial gain and a pro-environmental choice.

The central hypothesis of this study is that the presence of decision support increases participants' pro-environmental behavior. The second hypothesis is that biospheric values are positively correlated with participants' pro-environmental behavior.

4 Materials and methods

4.1 Open science and ethical statement

The hypotheses were pre-registered. Data, code of statistical analyses, and pre-registration are available via the Open Science Framework (https://osf.io/grxv5/). The experiment was conducted on Prolific, realized using the software oTree (Chen et al., 2016), and analyzed using R (R Core Team, 2020). Only data that matched a pre-registered inclusion protocol were analyzed. As the experiment was a standardized behavioral study involving simple decisions with minimal risk to healthy adult participants, ethical approval was granted via an expedited protocol of the German Society for Experimental Economics. I report all measures, conditions, data exclusions, and sample size decisions.

4.2 Participants and sampling decision

Per budgetary constraint (Lakens, 2022), I recruited a total of 300 participants via Prolific, in exchange for a flat payment of 1.5 GBP and an additional, choice-dependent bonus. Participants were pre-selected to have at least a 90 % approval rating and fluency in English. They needed on average 15 minutes to complete the study and were timed out after a maximal time of 49 minutes. They were told to receive their choice-dependent bonus via Prolific, typically within 2–5 business days. The pre-registered inclusion protocol was the following: I included all participants who correctly answered the comprehension check, the bot check, and the attention check. Additionally, I included all participants who made at least 75 % (i.e., 30) of the trade-off decisions that marked the central dependent variable. Moreover, people with a red-green vision deficiency were removed from the final dataset since they were not able to draw meaningful information from the decision support treatment. This yielded a final sample of 275 participants from 30 countries (39 % females; mean age: 26.3 years).

4.3 Dependent variable: pro-environmental behavior

I assessed actual pro-environmental behavior through responses in a series of discrete choices, trading off immediate hedonic goals and long-term environmental goals. In the Carbon Emission Task (Berger & Wyss, 2021), a validated experimental protocol to assess pro-environmental behavior, participants face repeated dichotomous trade-offs between a financially rewarding, but environmentally harmful Option A and a financially non-rewarding, but carbon-neutral Option B. This emission is realized through purchases and the retirement of emission certificates from the EU-Emission Trading Scheme, a frequently used method by environmental social scientists to attach actual climate consequences to laboratory behavior (Löschel et al., 2013; Ockenfels et al., 2020; Wyss et al., 2022).

Participants made 40 consecutive choices between the two options. Option A included the emission of 0.23, 1.02, 4.46, or 19.85 lbs. of CO_2 combined with a bonus payment of 1, 2, 3, 4, or 5 GBP. To facilitate the understanding of the amount of CO_2, participants were also shown the approximate distance an average car can drive until said amount is emitted. Option B consisted of no CO_2 emissions and no possible bonus payment. All combinations were displayed twice. One round was chosen at random to determine the actual bonus payment.

4.4 Experimental manipulation

Participants were randomly assigned to one of two conditions, modulating whether or not real-time decision support was given. Participants in the decision support condition were informed that the boxes containing Options A and B would be color-coded. Namely, the color of the box containing Option A indicated how much a specific decision would pollute for a given bonus. Combinations of the lowest possible bonus and the highest possible CO_2 emission featured a red background, whereas the highest bonus combined with the lowest CO_2 value was grey (see Figure 1). Combinations between these two extremes were colored on a linear scale depending on the ratio of each Option A. The box of Option B was always colored green in this condition. Additionally, participants were informed that the accumulated amount of chosen emissions would be displayed by a smoke cloud. A smoke cloud would grow with every choice of Option A. Figure 2 depicts an example of the decision support treatment where the participant has repeatedly chosen the unsustainable Option A, which led to the increase of the cloud. Both options were colored grey in the control condition, and no smoke cloud was shown.

Figure 1: Information provided to participants about the color range from red to grey of Option A in the treatment condition

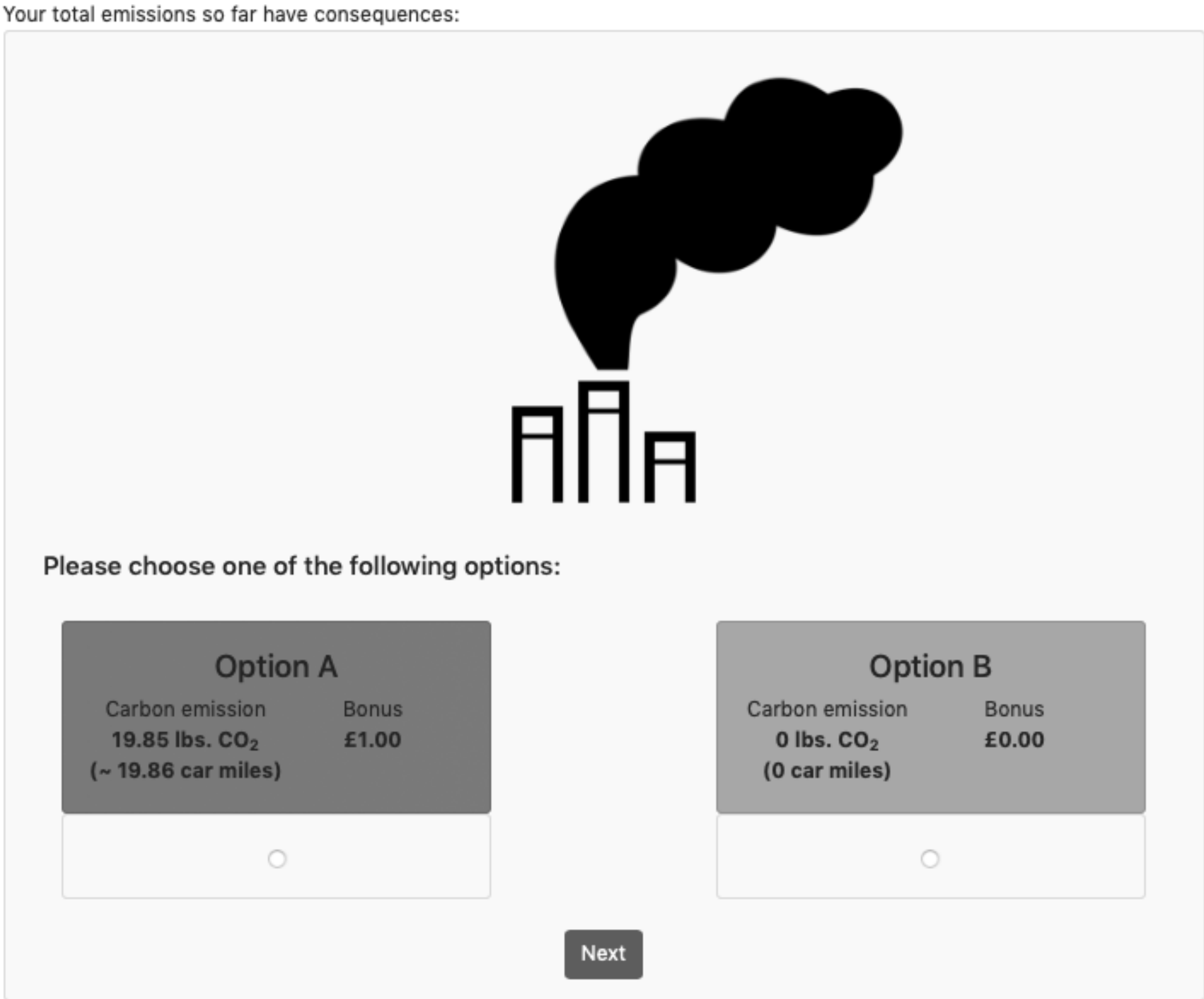

Figure 2: Example of decision support condition with smoke cloud (after choosing Option A repeatedly)

4.5 Post-experimental questionnaire

After the assessment of pro-environmental behavior, participants completed the Social Value Scale (Steg et al., 2012), which includes items reflecting egoistic, hedonic, altruistic, and biospheric values. Biospheric values, which are the relevant dimension for the purpose of this study, were measured with four items: respecting earth, unity with nature, protecting the environment, and preventing pollution. Participants rated the items as "guiding principle in their lives" on a 9-point scale ranging from "opposed to my values" to "of supreme importance". The biospheric values subscale showed a very good internal consistency (Cronbach's alpha =.87). Finally, participants completed a series of demographic questions, reporting their gender, age, level of highest education, employment, household income, as well as their political orientation.[1]

5 Results

In line with the central hypothesis, average pro-environmental behavior was more pronounced in the decision support treatment than in the control treatment. I found that decision support had an increasing effect on the number of participants' pro-environmental decisions. On average, the percentage of pro-environmental decisions in the treatment condition was about 8 percentage points higher than in the control condition (54.2 % compared to 45.9 %), and the effect was statistically significant, $t(269.57) = -2.3325$, $p = 0.0204$ (see Figure 3). Table 1 includes a more extensive model controlling for demographic variables, where the effect remains statistically significant. Subsequently, I also checked the effect for single decisions in a mixed-effects logistic regression for its robustness, where it persisted (see Supplementary Material Table 3).

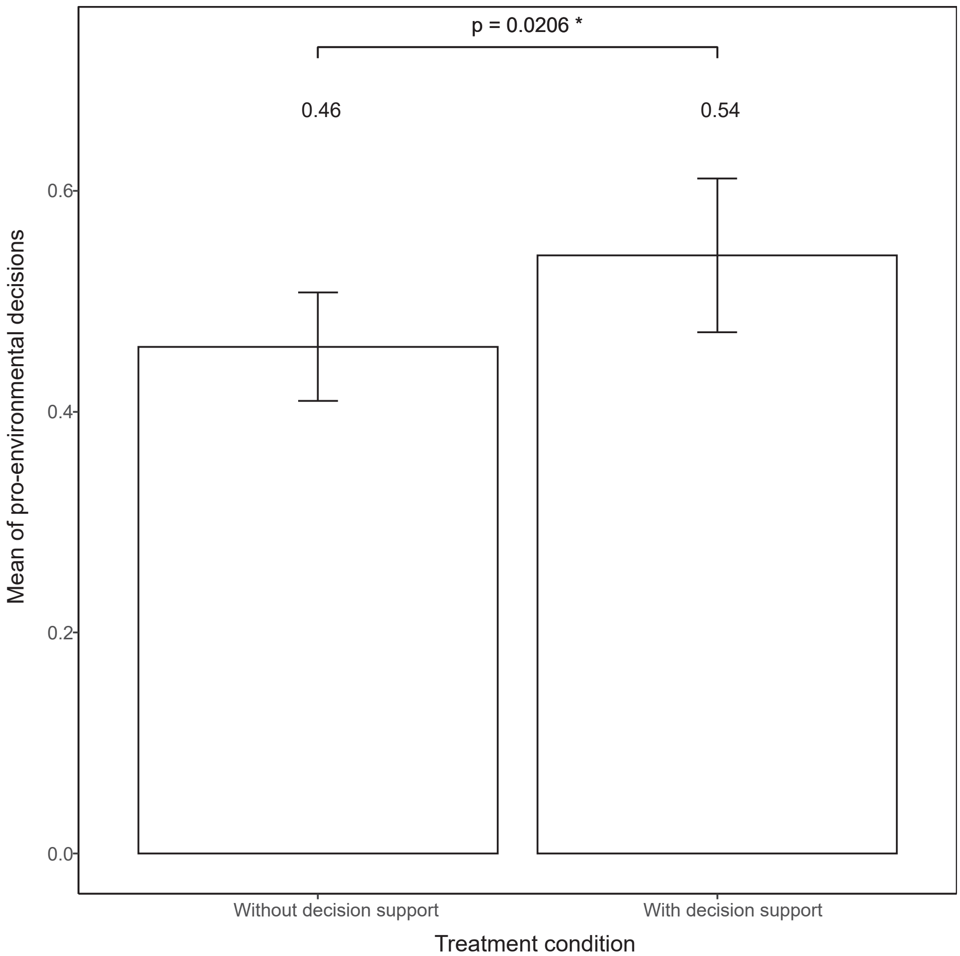

Figure 3: Mean of pro-environmental decisions of participants in the control condition compared to the decision support condition (whiskers indicate 95 % confidence intervals for the simple regression)

1 A scale to measure self-control was also assessed: The Brief Self-Control Scale (Tangney et al., 2004) was administered (Cronbach's alpha = 0.84).

Predictors	Model 1			Model 2		
	Estimates	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.46	0.41–0.51	**<0.001**	0.46	0.02–0.89	**0.039**
Decision support (1 if yes)	0.08	0.01–0.15	**0.021**	0.10	0.03–0.17	**0.005**
Age	*NO*			0.00	-0.00–0.01	0.702
Gender (1 if female)	*NO*			*0.09*	0.02–0.16	**0.011**
Education control	*NO*			*YES*		
Income control	*NO*			*YES*		
Political views control	*NO*			*YES*		
Employment control	*NO*			*YES*		
Observations	275			275		
R^2 / R^2 adjusted	0.019 / 0.016			0.255 / 0.153		

Note. CI = 95 % confidence interval. Estimates represent unstandardized beta coefficients.

Table 1: Simple regression of mean of pro-environmental decisions on treatment condition (Model 1) and multiple regression with added control variables (Model 2)

In the analysis of the single decisions, which included the bonus level and the CO_2 to be emitted as independent variables, the effect of the bonus level on participants' decisions becomes apparent. Figure 4 illustrates the respective means of pro-environmental decisions by bonus level and CO_2 emission for all participants. The x-axis combines bonus and CO_2-levels to a single ratio for easier interpretation. Clearly, people seem to decide (economically) consistently within a subset of decisions of the same CO_2-level such that options with a higher bonus level lead to a less pro-environmental choice. However, the ratio of how high the bonus is compared to the CO_2 is not generally decisive. Especially for a bonus level of at least 3 GBP, people on average act less environmentally friendly for a specific carbon level than would be expected if they based their decisions on specific ratios. This was the case in both the treatment and the control condition (see Figure 5).

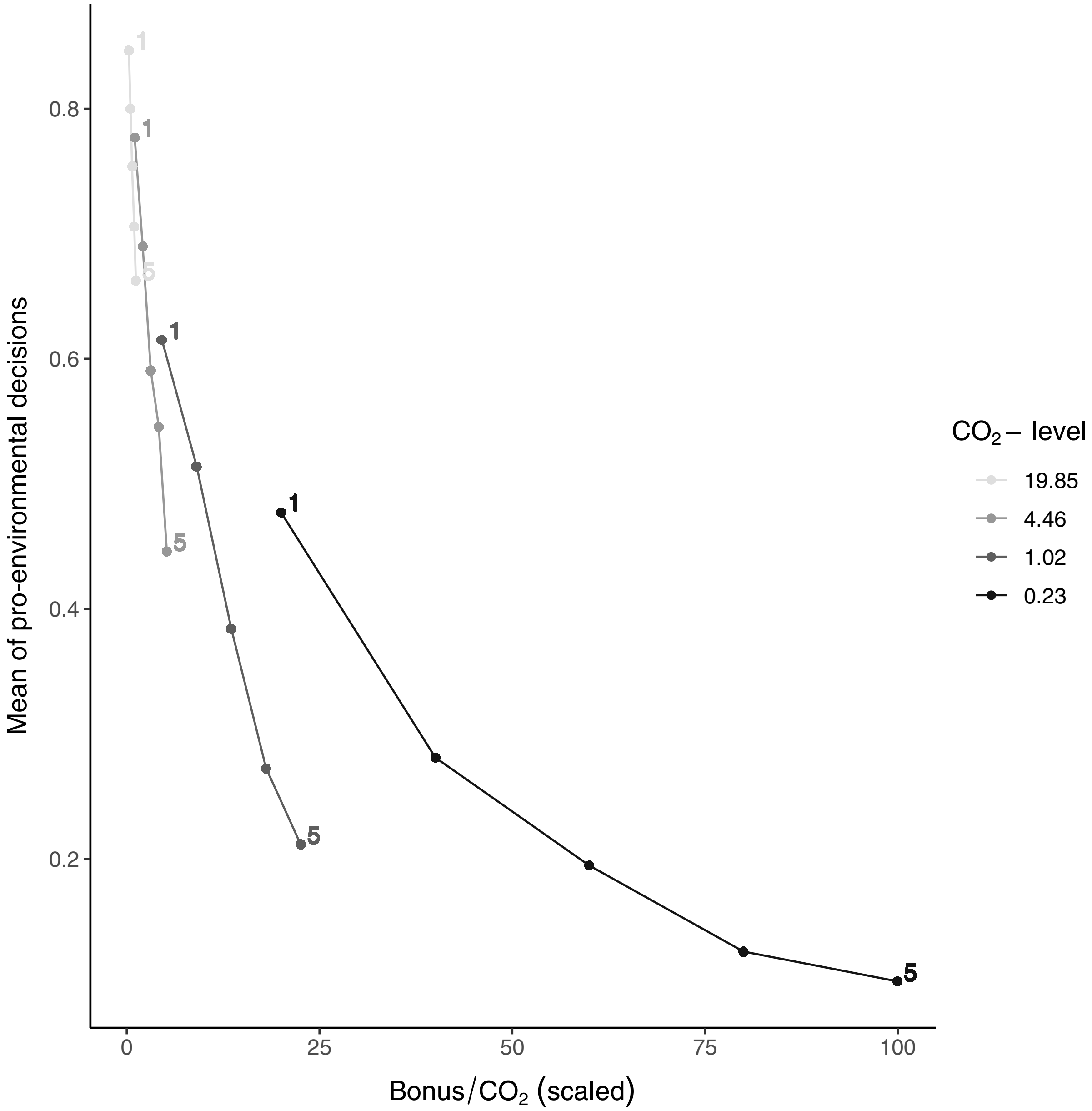

Figure 4: Mean of pro-environmental decisions by bonus in GBP (values 2, 3, and 4 omitted for better readability) and CO_2-level

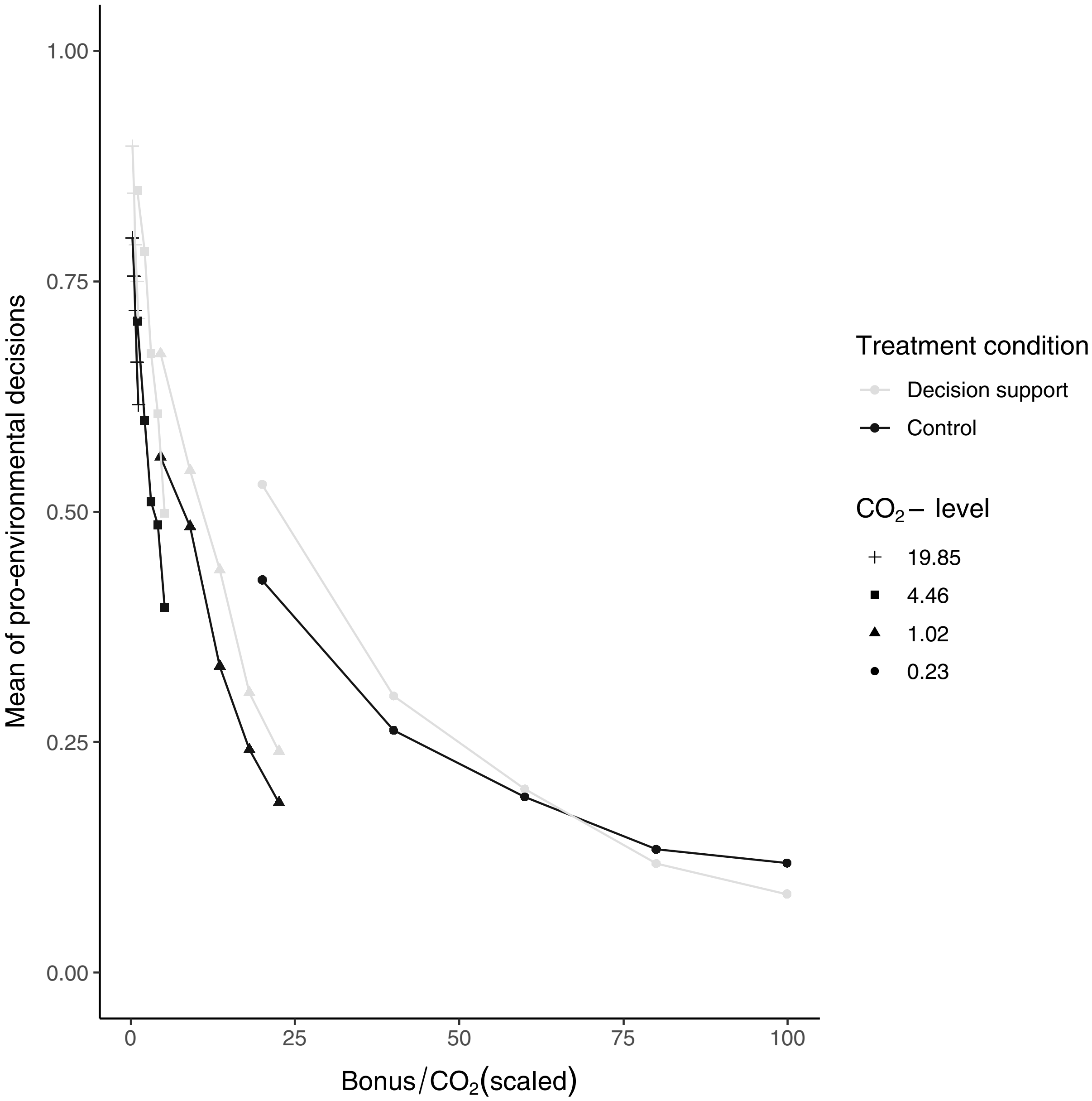

Figure 5: Mean of pro-environmental decisions by bonus (1 GBP to 5 GBP from left to right for each line), CO_2-level, and treatment

As a second hypothesis, I investigated the link of environmental motivation (measured by the biospheric values) with pro-environmental behavior. I find highly significant values for both the simple regression model as well as when controlling for demographic variables (see Table 2). For the respective models, the regression estimates show an increase of 8.4 percentage points (see Figure 6) and a 6.4 percentage point increase in the mean of pro-environmental decisions for an increase in biospheric values of 1. Again, I conducted single decision analyses via mixed-effects logistic regression with participant random effects and bonus and CO_2 fixed effects, adding the controls as above in an additional model (see Supplementary Material Table 4). The effect remains statistically significant.

Predictors	Model 1			Model 2		
	Estimates	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.50	0.47–0.53	**<0.001**	0.46	0.07–0.85	**0.022**
Biospheric values (centered)	0.08	0.06–0.11	**<0.001**	0.06	0.04–0.09	**<0.001**
Age control	*NO*			-0.00	-0.01–0.00	0.685
Gender control	*NO*			*YES*		
Education control	*NO*			*YES*		
Income control	*NO*			*YES*		
Political views control	*NO*			*YES*		
Employment control	*NO*			*YES*		
Observations	275			275		
R^2 / R^2 adjusted	0.115 / 0.112			0.288 / 0.190		

Note. CI = 95 % confidence interval. Estimates represent unstandardized beta coefficients.

Table 2: Simple regression of mean of pro-environmental decisions on biospheric values (Model 1) and multiple regression with added control variables (Model 2)

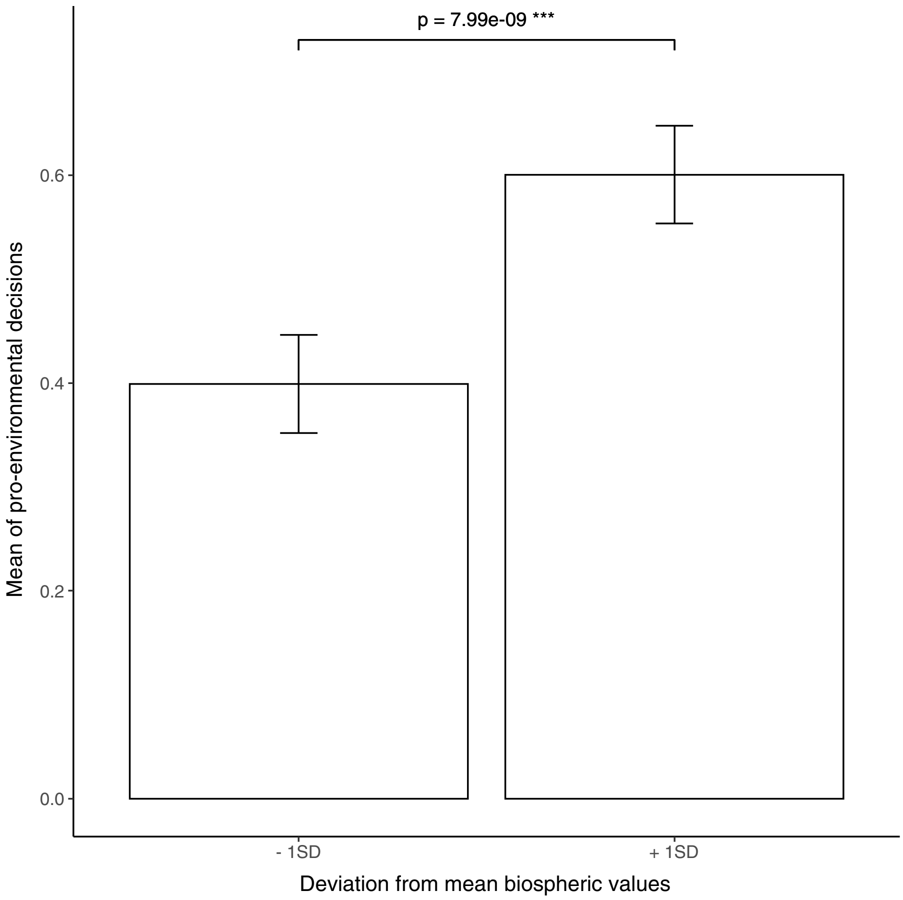

Figure 6: Link of biospheric values and the mean of pro-environmental choices calculated for the simple regression model with one standard deviation below and above the mean of biospheric values, respectively (whiskers indicate 95 % confidence intervals)

Additionally, I pre-registered two more hypotheses, namely that the link of environmental motivation and behavior would be moderated (i.e., higher) in the decision support condition, and that the link of environmental motivation and behavior would be moderated to a lesser extent by self-control under decision support than in the control condition. I do not find evidence for the hypothesized effects (see Supplementary Material Table 5 and Table 6). I will discuss possible implications of these results in the following section.

6 Discussion

While many people show increasing concern about the consequences of climate change, their behavior is often not up to par. Helping people align their actions with their values could prove a promising course for mitigating climate change. Crucially, the psychological mechanisms underlying our decision-making in the environmental context are far from being completely understood. Self-regulation and, more specifically, self-control are considered main targets to improve people's sustainability. One possible avenue to tackle the issue is to design choice environments that support long-term goals rather than short-term satisfaction without taking away people's agency.

In this study, I present a simple intervention that helps participants increase pro-environmental behavior. The numerical information remains the same for both the treatment and the control condition. The main difference is that participants in the decision support treatment are alerted to the ratio of the possible bonus compared to the amount of CO_2 emitted by an easily interpretable color scheme. This simple intervention increases the average amount of pro-environmental decisions by about 8 percentage points. As expected, there is a significant association of biospheric values with pro-environmental behavior in the CET. On average, increased biospheric values are linked to more pro-environmental behavior (about 6.4 percentage points when controlling for demographic variables).

Furthermore, the results of the logistic regressions including the specific CO_2 and bonus values indicate that especially the high financial incentives to behave environmentally harmful (i.e., at least 3 GBP) dominate all other facets of a certain combination of decision variables. Participants appear to no longer consider the exact ratio of bonus to CO_2 emissions with which they are confronted. The bonus values can be considered rather high in this study, since the maximum amount of 5 GBP equals more than triple the amount of the participation fee. This is certainly one aspect to consider when analyzing the link between environmental values and pro-environmental behavior observed in this study. While the overall association is expressed by the results mentioned above, the decision support treatment did not lead to a stronger alignment of biospheric values and the amount of pro-environmental decisions than in the control condition. One possible reason is the comparatively high level of biospheric values in this sample. Overall, the people in the present study showed relatively high pro-environmental values (M = 5.11, SD = 1.2). For example, two out of three samples in the articles by Van der Werff et al. (2013a) (M = 4.79, SD = 1.26, n = 232; M = 5.11, SD = 1.28, n = 50; M = 4.18, SD = 1.46, n = 150), Van der Werff et al. (2013b) (M = 4.73, SD = 1.32, n = 468; M = 5.14, SD = 1.39, n = 138; M = 4.23, SD = 1.28, n = 99) as well as the sample in Nguyen et al. (2016) (M = 2.63, SD = 1.21, n = 682) have significantly lower means (and also larger standard deviations) of biospheric values than the present sample. Thus, while this is by no means conclusive evidence, taken together with the shape of the distribution of biospheric values in my sample (see Figure 7), it appears reasonable to assume that these participants report their biospheric values to be above average compared to the general population. And even though biospheric values are clearly linked with participant's behavior in the CET, the following closer look at a subset does raise some questions: Out of the 17 people who scored the maximum (7) on the items about biospheric values, only two participants always chose the pro-environmental Option B, whereas four people even chose the unsustainable Option A in each round.

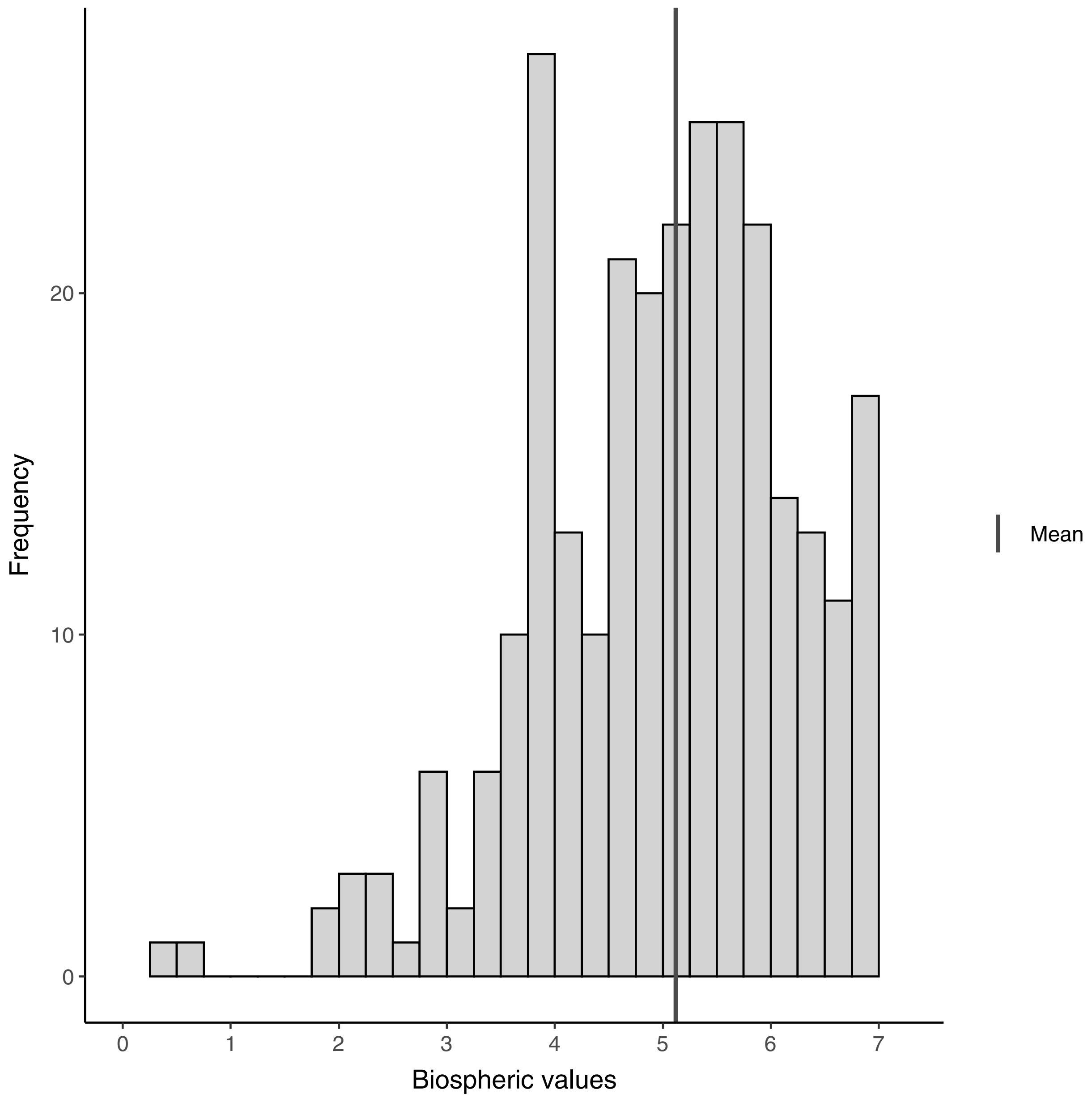

Figure 7: Histogram of biospheric values in the sample

There is no evidence for an effect of self-control on behavior, be it as a main effect or in an interaction. On a purely descriptive level, it can be mentioned that participants with a self-control score above the sample average chose the pro-environmental Option B in about 52.4 % of cases compared to 47.5 % for participants below the sample average. Still, none of the inferential models identify self-control as a statistically significant factor overall. I reckon the possibly small influence of self-control in this setting was overshadowed by the strong financial incentives discussed above.

The theoretical framework on which I based this study suggests that self-control helps people prioritize long-term goals over short-term gratification (Duckworth et al., 2016). There are different ways how this can be achieved. One possibility is the effortful inhibition of impulses when facing a tempting option. However, effortful inhibition has not been recommended as the optimal solution to this issue. It was rather seen as a measure of last resort when all other self-control strategies have failed (Nielsen, 2017). Crucially, in the choice setting of this study there were no other mechanisms through which self-control could function apart from "simply" resisting temptation. Apparently, even people with a high score on the self-control scale found it challenging to always engage in behavior that was in line with their stated values.

Firms interested in supporting their customers in their decision-making can use the tool presented in this study to make pro-environmental options more salient. The decision support treatment presented works in a context where people have to make quick decisions about CO_2 emissions, a measure that is generally not well known. The benefit of implementing it in the CET is the explicitly measurable financial utility. There are undoubtedly other factors contributing to the utility of specific actions, but they can be difficult or even impossible to quantify. While color-coding is common in our daily lives to steer desirable behavior (e.g., at traffic lights), I have shown that even in a more abstract setting participants react to a simple treatment. There were no hidden mechanisms applied. Participants were informed about the meaning of the stimuli. This is crucial for firms to emphasize a high degree of transparency.

6.1 Limitations

Berger and Wyss (2021) already mention limitations of the CET such as reference-dependence and costs of pro-environmental behavior in practice sometimes consisting of money, but also time, effort, or convenience rather than money. They are also aware that pro-environmental behavior can be financially beneficial in some circumstances.

This study shows that financial incentives still have a very strong effect on people's decisions even in an experimental setting. It is difficult to assess the external validity, although this experiment included real-world consequences. In a real-world setting, personal taste and context-specific norms will most likely have just as strong an impact on consumer decisions as the decision support treatment presented here. Additionally, the sample recruited in this study cannot be assumed to represent the general public. As mentioned above, the environmental values of the participants seem high relative to other studies.

7 Conclusion

The conducted study shows how even when confronted with a rather unknown quantity such as CO_2 emissions people can be supported in their pro-environmental behavior by increasing the salience of available options. The statistically significant increase of about 8 percentage points more pro-environmental decisions in the treatment group compared to the control condition is respectable considering the anonymous experimental setting. I find no evidence that self-control affected the decisions made by the recruited participants. The literature suggests that effortful inhibition is only one aspect of self-control and may not be strong enough to help people refrain from yielding to temptation. I believe my findings support this view. If businesses want to support their clients in more pro-environmental behavior without limiting their choices, there are other options than only increasing the salience of environmental consequences. One example is giving people the opportunity to limit the choice set voluntarily before deciding.

7.1 Acknowledgements

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7.2 Data and supplementary material

https://osf.io/grxv5

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Supplementary material

	Model 1			Model 2		
Predictors	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
(Intercept)	1.34	0.77 – 2.33	0.295	5.49	0.03 – 1102.38	0.529
age				1.02	0.96 – 1.07	0.538
CO_2	1.23	1.22 – 1.25	**<0.001**	1.23	1.21 – 1.24	**<0.001**
Control condition	*Reference*			*Reference*		
Decision support	2.43	1.13 – 5.18	**0.022**	2.64	1.31 – 5.32	**0.006**
diverse	*Reference*			*Reference*		
female				0.29	0.01 – 8.19	0.464
male				0.13	0.00 – 3.85	0.238
Bachelor	*Reference*			*Reference*		
Doctorate				3.87	0.30 – 49.88	0.299
HS				0.86	0.37 – 1.98	0.717
Master				0.66	0.23 – 1.89	0.443
no_HS				0.19	0.02 – 2.42	0.203
other				0.00	0.00 – Inf	0.973
<100k	*Reference*			*Reference*		
<10k				0.71	0.02 – 22.63	0.848
<150k				0.28	0.01 – 11.65	0.502
<20k				0.13	0.00 – 4.06	0.246
<30k				0.46	0.01 – 14.93	0.660
<40k				1.44	0.04 – 45.96	0.837
<50k				0.36	0.01 – 12.57	0.574
<60k				0.52	0.01 – 18.34	0.719
<70k				1.22	0.03 – 50.88	0.917
<80k				0.14	0.00 – 8.22	0.341
<90k				0.02	0.00 – 1.22	0.062
>=150k				0.15	0.00 – 83.74	0.552
conservative	*Reference*			*Reference*		
liberal				2.37	0.23 – 24.41	0.468
moderate				0.86	0.08 – 9.05	0.897

none_of_the_above				1.66	0.13 – 21.87	0.698
somewhat_conservative				1.20	0.09 – 16.18	0.893
somewhat_liberal				2.47	0.24 – 25.78	0.449
very_conservative				1.47	0.02 – 92.17	0.857
very_liberal				3.07	0.25 – 38.45	0.384
full_time	*Reference*			*Reference*		
looking_for_work				1.29	0.36 – 4.63	0.699
not_looking_for_work				2.15	0.28 – 16.27	0.458
occasional_gigs				16.47	1.25 – 217.55	**0.033**
part_time				3.66	1.05 – 12.74	**0.042**
Bonus	0.48	0.46 – 0.50	**<0.001**	0.49	0.47 – 0.51	**<0.001**
retired				0.00	0.00 – 0.64	**0.033**
student				1.25	0.43 – 3.67	0.684
Random Effects						
σ^2	3.29			3.29		
τ_{00}	9.85 $_{id}$			7.31 $_{id}$		
ICC	0.75			0.69		
N	275 $_{id}$			275 $_{id}$		
Observations	10961			10961		
Marginal R^2 / Conditional R^2	0.235 / 0.808			0.400 / 0.814		

Note. CI = confidence interval.

Table 3: Hypothesis 1. Replication of the treatment effect on sustainability for single decision data. Mixed-effects logistic regression with participant random effects and bonus and CO_2 fixed effects

	Model 1			Model 2		
Predictors	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
(Intercept)	2.10	1.43 – 3.08	**<0.001**	3.54	0.02 – 633.54	0.633
age				1.00	0.94 – 1.05	0.863
CO_2	1.22	1.21 – 1.24	**<0.001**	1.22	1.21 – 1.24	**<0.001**
diverse	*Reference*			*Reference*		
female				0.45	0.02 – 11.52	0.626
male				0.28	0.01 – 7.33	0.444
Bachelor	*Reference*			*Reference*		
Doctorate				3.13	0.26 – 37.93	0.371
HS				0.92	0.41 – 2.10	0.851
Master				0.98	0.35 – 2.71	0.961
no_HS				0.27	0.02 – 3.13	0.293
other				0.00	0.00 – Inf	0.971
<100k	*Reference*			*Reference*		
<10k				0.64	0.02 – 18.27	0.795
<150k				0.28	0.01 – 10.41	0.487
<20k				0.15	0.01 – 4.31	0.271
<30k				0.48	0.02 – 14.24	0.672
<40k				1.57	0.05 – 45.89	0.793
<50k				0.44	0.01 – 13.92	0.640
<60k				0.67	0.02 – 21.58	0.821
<70k				1.40	0.04 – 52.87	0.855
<80k				0.21	0.00 – 11.54	0.445
<90k				0.03	0.00 – 1.80	0.093
>=150k				0.46	0.00 – 232.74	0.806
conservative	*Reference*			*Reference*		
liberal				4.50	0.46 – 43.59	0.195
moderate				2.08	0.21 – 20.83	0.533
none_of_the_above				3.27	0.27 – 40.40	0.355
somewhat_conservative				3.76	0.29 – 48.47	0.311
somewhat_liberal				5.33	0.54 – 52.91	0.153
very_conservative				4.29	0.08 – 242.69	0.479
Biospheric values	2.28	1.68 – 3.09	**<0.001**	1.92	1.42 – 2.59	**<0.001**

very_liberal				5.26	0.45 – 61.57	0.186
full_time	*Reference*			*Reference*		
looking_for_work				1.16	0.33 – 4.05	0.816
not_looking_for_work				2.11	0.29 – 15.24	0.458
occasional_gigs				7.50	0.60 – 93.93	0.118
part_time				3.15	0.94 – 10.62	0.064
retired				0.02	0.00 – 2.70	0.117
student				1.08	0.38 – 3.10	0.884
Bonus	0.49	0.47 – 0.51	**<0.001**	0.49	0.47 – 0.51	**<0.001**
Random Effects						
σ^2	3.29			3.29		
τ_{00}	8.83 $_{id}$			6.95 $_{id}$		
ICC	0.73			0.68		
N	275 $_{id}$			275 $_{id}$		
Observations	10961			10961		
Marginal R^2 / Conditional R^2	0.275 / 0.803			0.419 / 0.813		

Note. CI = confidence interval.

Table 4: Hypothesis 2. Replication of the association of biospheric values and sustainable choices for single decision data. Mixed-effects logistic regression with participant random effects and bonus and CO_2 fixed effects

	Model 1			Model 2			Model 3			Model 4		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
(Intercept)	0.46	0.41 – 0.51	**<0.001**	0.61	0.10 – 1.12	**0.019**	1.42	0.85 – 2.39	0.184	2.93	0.02 – 484.76	0.680
age				-0.00	-0.01 – 0.00	0.850				1.00	0.95 – 1.05	0.974
CO_2							1.22	1.21 – 1.24	**<0.001**	1.22	1.21 – 1.24	**<0.001**
Control condition	*Reference*			*Reference*			*Reference*			*Reference*		
Decision support	0.08	0.01 – 0.15	**0.018**	0.09	0.03 – 0.16	**0.006**	2.19	1.07 – 4.47	**0.031**	2.48	1.27 – 4.87	**0.008**
diverse	*Reference*			*Reference*			*Reference*			*Reference*		
female				-0.14	-0.46 – 0.19	0.409				0.27	0.01 – 6.73	0.423
male				-0.21	-0.53 – 0.12	0.214				0.15	0.01 – 3.93	0.257
Bachelor	*Reference*			*Reference*			*Reference*			*Reference*		
Doctorate				0.15	-0.10 – 0.40	0.232				3.26	0.28 – 38.01	0.346
HS				-0.00	-0.08 – 0.08	0.920				0.95	0.42 – 2.14	0.908
Master				-0.02	-0.12 – 0.08	0.696				0.83	0.30 – 2.29	0.722
no_HS				-0.10	-0.34 – 0.13	0.394				0.29	0.03 – 3.25	0.312
other				-0.38	-0.93 – 0.17	0.179				0.00	0.00 – Inf	0.972
<100k	*Reference*			*Reference*			*Reference*			*Reference*		
<10k				0.00	-0.33 – 0.34	0.991				1.19	0.04 – 33.67	0.917
<150k				-0.13	-0.50 – 0.23	0.470				0.48	0.01 – 17.66	0.688
<20k				-0.18	-0.51 – 0.15	0.288				0.26	0.01 – 7.10	0.422

<30k				-0.07	-0.41 – 0.26	0.668				0.87	0.03 – 25.10	0.933
<40k				0.05	-0.29 – 0.38	0.780				2.44	0.09 – 69.72	0.601
<50k				-0.09	-0.44 – 0.25	0.593				0.74	0.02 – 22.90	0.861
<60k				-0.04	-0.38 – 0.31	0.834				1.16	0.04 – 36.63	0.934
<70k				0.06	-0.30 – 0.42	0.737				2.64	0.07 – 98.24	0.598
<80k				-0.17	-0.57 – 0.22	0.392				0.28	0.01 – 14.95	0.534
<90k				-0.29	-0.69 – 0.11	0.149				0.05	0.00 – 3.06	0.155
>=150k				-0.19	-0.81 – 0.43	0.544				0.55	0.00 – 261.79	0.847
conservative	*Reference*			*Reference*			*Reference*			*Reference*		
liberal				0.12	-0.10 – 0.34	0.270				3.03	0.32 – 28.98	0.336
moderate				0.04	-0.18 – 0.26	0.730				1.36	0.14 – 13.56	0.791
none_of_the_above				0.08	-0.16 – 0.32	0.507				2.22	0.18 – 26.91	0.532
somewhat_conservative				0.09	-0.16 – 0.33	0.482				2.46	0.19 – 31.23	0.488
Biospheric values	0.08	0.04 – 0.12	**<0.001**	0.06	0.02 – 0.10	**0.006**	2.22	1.41 – 3.49	**0.001**	1.86	1.21 – 2.87	**0.005**
somewhat_liberal				0.15	-0.07 – 0.37	0.184				3.79	0.39 – 37.17	0.252
very_conservative				0.10	-0.30 – 0.49	0.630				2.54	0.05 – 137.54	0.648
very_liberal				0.14	-0.10 – 0.37	0.261				3.60	0.31 – 41.40	0.304
full_time	*Reference*			*Reference*			*Reference*			*Reference*		
looking_for_work				-0.02	-0.14 – 0.11	0.798				1.19	0.35 – 4.07	0.782
not_looking_for_work				0.03	-0.16 – 0.23	0.740				2.32	0.33 – 16.26	0.397
occasional_gigs				0.14	-0.10 – 0.38	0.243				7.14	0.59 – 86.88	0.123

part_time				0.10	-0.02 – 0.22	0.094				3.56	1.07 – 11.82	**0.038**
Bonus							0.49	0.47 – 0.51	**<0.001**	0.49	0.47 – 0.51	**<0.001**
retired				-0.32	-0.75 – 0.12	0.157				0.01	0.00 – 1.79	0.083
student				-0.02	-0.12 – 0.09	0.736				1.06	0.38 – 3.00	0.908
Decision support * biospheric values	0.01	-0.04 – 0.07	0.709	0.01	-0.05 – 0.06	0.745	1.04	0.57 – 1.91	0.898	1.02	0.58 – 1.80	0.940
Random Effects												
σ^2							3.29			3.29		
τ_{00}							8.64 $_{id}$			6.72 $_{id}$		
ICC							0.72			0.67		
N							275 $_{id}$			275 $_{id}$		
Observations	275			275			10961			10961		
R^2 / R^2 adjusted	0.134 / 0.124			0.310 / 0.209			0.285 / 0.803			0.430 / 0.813		

Note. CI = confidence interval.

Table 5: Regression models of hypothesis 3. Interaction of treatment condition with biospheric values (in models 1 and 2 the mean sustainability is linearly regressed on the explanatory variables, in models 3 and 4 sustainable choices for single decision data were regressed on the explanatory variables in a mixed-effects logistic regression with participant random effects and bonus and CO_2 fixed effects)

	Model 1			Model 2			Model 3			Model 4		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
(Intercept)	0.47	0.42 – 0.52	**<0.001**	0.57	0.07 – 1.08	**0.026**	1.58	0.93 – 2.67	0.091	2.08	0.01 – 306.29	0.774
age				-0.00	-0.01 – 0.01	0.972				1.01	0.95 – 1.06	0.828
CO_2							1.23	1.21 – 1.24	**<0.001**	1.23	1.21 – 1.24	**<0.001**
Control condition	*Reference*			*Reference*			*Reference*			*Reference*		
Decision support	0.07	0.01 – 0.14	**0.035**	0.08	0.01 – 0.15	**0.023**	2.05	0.99 – 4.21	0.052	2.14	1.09 – 4.20	**0.026**
diverse	*Reference*			*Reference*			*Reference*			*Reference*		
female				-0.12	-0.44 – 0.20	0.446				0.29	0.01 – 6.84	0.445
male				-0.18	-0.51 – 0.14	0.262				0.19	0.01 – 4.45	0.298
Bachelor	*Reference*			*Reference*			*Reference*			*Reference*		
Doctorate				0.17	-0.07 – 0.42	0.170				3.86	0.34 – 43.78	0.275
HS				-0.00	-0.08 – 0.07	0.902				0.94	0.43 – 2.08	0.880
Master				-0.03	-0.13 – 0.07	0.610				0.78	0.29 – 2.10	0.620
no_HS				-0.12	-0.35 – 0.12	0.333				0.26	0.02 – 2.80	0.267
other				-0.40	-0.95 – 0.14	0.147				0.00	0.00 – Inf	0.972
<100k	*Reference*			*Reference*			*Reference*			*Reference*		
<10k				0.01	-0.32 – 0.35	0.934				1.31	0.05 – 34.24	0.870
<150k				-0.13	-0.49 – 0.23	0.477				0.46	0.01 – 15.94	0.669
<20k				-0.17	-0.50 – 0.16	0.307				0.29	0.01 – 7.35	0.449
<30k				-0.07	-0.40 – 0.27	0.686				0.87	0.03 – 23.40	0.933

<40k				0.06	-0.27 – 0.39	0.720				2.73	0.10 – 72.63	0.548
<50k				-0.07	-0.42 – 0.27	0.668				0.86	0.03 – 24.96	0.929
<60k				-0.01	-0.36 – 0.33	0.933				1.41	0.05 – 41.42	0.841
<70k				0.10	-0.26 – 0.46	0.586				3.58	0.10 – 123.58	0.480
<80k				-0.17	-0.56 – 0.23	0.403				0.27	0.01 – 13.58	0.516
<90k				-0.26	-0.66 – 0.13	0.194				0.07	0.00 – 3.84	0.194
>=150k				-0.18	-0.80 – 0.44	0.567				0.66	0.00 – 286.94	0.894
conservative	*Reference*			*Reference*			*Reference*			*Reference*		
liberal				0.13	-0.09 – 0.34	0.248				3.06	0.34 – 27.74	0.321
moderate				0.05	-0.17 – 0.27	0.649				1.51	0.16 – 14.35	0.718
none_of_the_above				0.10	-0.14 – 0.34	0.403				2.75	0.24 – 31.71	0.416
somewhat_conservative				0.10	-0.14 – 0.34	0.417				2.82	0.24 – 33.89	0.413
Self-control	0.01	-0.06 – 0.08	0.722	0.01	-0.06 – 0.08	0.704	1.27	0.62 – 2.64	0.514	1.26	0.63 – 2.52	0.516
Self-control*biospheric values	-0.05	-0.11 – 0.01	0.079	-0.09	-0.15 – -0.04	**0.001**	0.59	0.32 – 1.11	0.100	0.39	0.22 – 0.71	**0.002**
Biospheric values	0.07	0.03 – 0.12	**0.001**	0.05	0.01 – 0.09	**0.020**	2.08	1.31 – 3.31	**0.002**	1.69	1.09 – 2.60	**0.019**
somewhat_liberal				0.17	-0.04 – 0.39	0.115				4.89	0.52 – 45.97	0.165
very_conservative				0.10	-0.29 – 0.49	0.618				2.53	0.05 – 124.55	0.640
very_liberal				0.16	-0.08 – 0.39	0.186				4.44	0.41 – 48.28	0.220
full_time	*Reference*			*Reference*			*Reference*			*Reference*		
looking_for_work				-0.02	-0.14 – 0.10	0.754				1.19	0.35 – 3.96	0.783
not_looking_for_work				0.03	-0.16 – 0.22	0.757				2.34	0.34 – 15.85	0.385

occasional_gigs				0.16	-0.08 – 0.40	0.195				8.10	0.70 – 93.46	0.094
part_time				0.12	0.00 – 0.24	**0.043**				4.29	1.31 – 14.05	**0.016**
Bonus							0.49	0.47 – 0.51	**<0.001**	0.49	0.47 – 0.51	**<0.001**
retired				-0.49	-0.94 – -0.04	**0.032**				0.00	0.00 – 0.33	**0.015**
student				-0.01	-0.11 – 0.09	0.802				1.12	0.41 – 3.09	0.826
Decision support*self-control	-0.00	-0.10 – 0.10	0.943	-0.01	-0.11 – 0.10	0.916	0.84	0.29 – 2.47	0.750	0.86	0.31 – 2.40	0.777
Decision support*self-control*biospheric values	0.03	-0.05 – 0.11	0.419	0.08	0.00 – 0.16	**0.039**	1.31	0.56 – 3.06	0.531	2.03	0.91 – 4.52	0.084
Decision support*biospheric values	0.01	-0.04 – 0.07	0.617	0.02	-0.04 – 0.07	0.548	1.12	0.60 – 2.07	0.729	1.14	0.65 – 2.02	0.642
Random Effects												
σ^2							3.29			3.29		
τ_{00}							8.48 $_{id}$			6.39 $_{id}$		
ICC							0.72			0.66		
N							275 $_{id}$			275 $_{id}$		
Observations	275			275			10961			10961		
R^2 / R^2 adjusted	0.145 / 0.123			0.340 / 0.231			0.293 / 0.803			0.446 / 0.812		

Note. CI = confidence interval.

Table 6: Regression models of hypothesis 4. Interaction of treatment condition, biospheric values, and self-control (in models 1 and 2 the mean sustainability is linearly regressed on the explanatory variables, in models 3 and 4 sustainable choices for single decision data were regressed on the explanatory variables in a mixed-effects logistic regression with participant random effects and bonus and CO_2 fixed effects)

Study 2

Coherently Arbitrary Pro-Environmental Behavior

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Coherently arbitrary pro-environmental behavior☆

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A R T I C L E I N F O

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A B S T R A C T

An accurate understanding of pro-environmental behavior is a key research topic within environmental psychology and a prerequisite for an adequate psychological response to environmental issues. In this study, we present an experiment testing the degree to which decision makers' pro-environmental behavior is "coherently arbitrary". Coherent arbitrariness refers to the phenomenon that behavior in experimental models may only appear rational, *as if* supported by fixed preferences, despite being affected by arbitrary factors unrelated to preferences. Using the *Carbon Emission Task*, the present research extends this behavioral economic finding to pro-environmental behavior research. We find that (a) *objectively* identical trade-offs are evaluated substantially differently depending on the relative rather than absolute price level of comparative choices, and (b) biospheric values correlate robustly with behavior across conditions. This result may also help to explain findings documenting a motivation-impact gap in pro-environmental behavior, as people may find it difficult to objectively and globally assess the costs and benefits associated with their choices.

1. Introduction

Pro-environmental behavior commonly refers to a broad range of behaviors that produce environmental benefits or avoid environmental harms relative to alternative behaviors (Lange, 2022). Several environmental issues – for example, climate change and global biodiversity loss – are caused by human behavior, and an accurate understanding of the factors that promote or inhibit pro-environmental behavior across actors and scales is one of environmental psychology's primary research objectives (Lange and Dewitte, 2019; Nielsen et al., 2021).

One central result which has been reported repeatedly is that the likelihood of engaging in pro-environmental behavior depends on its associated costs as well as its environmental benefits (Andersson and von Borgstede, 2010; Berger and Wyss, 2021a, 2021b; Diekmann and Preisendörfer, 1998; Kaise et al., 2010; Kaiser and Lange, 2021; Lange et al., 2018; Lange and Dewitte, 2021; Rompf et al., 2017; Steg and Vlek, 2009; Wyss et al., 2022). Existing experimental models (i.e., behavioral paradigms) to measure consequential pro-environmental behavior empirically demonstrate how behavior depends on associated costs and benefits (see Lange, 2022, for a review). Costs can be measured in terms of foregone time (Lange et al., 2018), additional effort (Lange and Dewitte, 2021), or financial sacrifice (Berger and Wyss, 2021a; Wyss et al., 2022). Measurements of environmental benefits can range from curbed CO_2, to donations to environmental NGOs, or saved energy.

The existing experimental models share some key methodological features and measure consequential behavior repeatedly within a given person, thereby testing how the same person responds to various incentives, with incentives being manipulated both in terms of personal costs as well as environmental benefits over multiple trials. Prototypical behavioral results seem surprisingly rational and show monotonic *decreases* in pro-environmental behavior as personal costs rise and monotonic *increases* in behavior in rising environmental benefits. In addition, average pro-environmental behavior across trials correlates with existing psychological constructs such as biospheric values or belief in climate change (Berger and Wyss, 2021a; Lange, 2022; Lange et al., 2018; Lange and Dewitte, 2021). In other words, which (average) costs are tolerable and which (average) benefits are sufficient for an individual to engage in pro-environmental behavior seems to depend on that person's fundamental pro-environmental preferences to the degree that average behavior in such paradigms can be interpreted as reflecting stable person characteristics (Lange et al., 2023).

On a broader level, much research in environmental psychology starts with the assumption that individuals make reasoned choices and select decision alternatives maximizing their utility (i.e. maximizing benefits or minimizing cost, Steg and Vlek, 2009). Thus, people's choices

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reveal their fundamental preferences. Because preferences are hard to measure directly, researchers often observe *changes* in behavior that are in line with theoretical predictions (i.e., cost and benefit sensitivity; Ariely et al., 2003, Kaiser et al., 2010; Kaiser and Lange, 2021) – for example, that pro-environmental behavior becomes less likely or less intense when the relative cost is increasing (Diekmann and Preisendörfer, 1998). Research in behavioral economics, however, has challenged this approach, delivering experimental evidence questioning people's rational and objective preferences for consumption goods and hedonic experiences (Ariely et al., 2003).

Here, we present results from a pre-registered experiment that extends these findings to the study of pro-environmental behavior. Despite seemingly rational comparative statics (i.e., decreases in pro-environmental behavior in rising cost, increases in pro-environmental behavior in increasing environmental benefits), we show that behavior in experimental paradigms might not uniquely reflect absolute pro-environmental preferences, but rather relative decision making, arbitrarily dependent to factors external to the decision maker.

1.1. *"Coherent arbitrariness" of pro-environmental behavior*

Consider an environmentally motivated person who is asked if they are willing to walk five minutes to carry a used plastic bottle to a recycling bin. This person may say *yes* or *no*. If they say *yes*, it is quite likely that this same person in a comparable situation would also agree to a three-minute walk, simply based on their initial answer. If five minutes is an acceptable walk, three minutes should be acceptable as well. Conversely, if the person disagrees to walk for five minutes, they would probably also disagree to walk seven or ten minutes if asked immediately afterwards. In terms of environmental benefits, if a person is willing to walk five minutes to carry one single bottle to a recycling station, they should also agree to carry two (or more) bottles.

In such an example, we likely observe behavior that is in line with the theoretical prediction of cost- and benefit-sensitivity, as reported in previous research, but this behavior may in fact also be derived from a preference for consistency. Thus, calibrating behavior off initial choices may reflect fundamental preferences, but may also stem from consistency motives if people *mistakenly* infer preferences from initial choice. Note that this decision example reflects the essence of experimental models such as the *Work for Environmental Protection Task* (Lange and Dewitte, 2021), the *Pro-Environmental Behavior Task* (Lange et al., 2018), and the *Carbon Emission Task* (Berger and Wyss, 2021a), where it is usually interpreted as cost- or benefit-sensitivity.

If the initial choice reflects absolute pro-environmental preferences, calibrating off such initial choices would not be much of an issue. If initial choices, however, are not caused by fundamental preferences alone, but reflect some arbitrary reason unrelated to preferences, we would observe behavior that only appears "orderly", *as if* supported by demand curves grounded in fundamental preferences. This phenomenon has been coined "coherent arbitrariness" within behavioral economic research (Ariely et al., 2003) because behavior only appears *coherent*, although resulting from initial *arbitrariness*. We sought to test this idea in the domain of pro-environmental behavior due to implications for theory-building in pro-environmental behavior research (e.g., the motivation-impact gap) and potential implications (e.g., estimating the effectiveness of price-regulation such as carbon taxation). We use a simple decision-making experiment, as this allows us control over environmental benefits and personal costs of pro-environmental behavior.

2. Method

2.1. *Open science and ethical statement*

This research presents the results of a controlled behavioral online experiment. The experiment was conducted using oTree (Chen et al., 2016), and the data was analyzed using the open source software R. All original data and code is available in the associated OSF project (https://osf.io/2psf4/). The experiment was pre-registered using *As Predicted* within the OSF. Confirmatory tests of hypotheses follow the pre-registration, and exploratory analyses are clearly marked as such. As the experiment was a standardized behavioral study involving simple decisions with minimal risk to healthy adult participants, ethical approval was granted via an expedited protocol through the Society for Experimental Economics in Germany. Participants provided informed consent prior to taking part in the study and received a flat and variable monetary payoff.

2.2. *Participants, data exclusion protocol, and power considerations*

In total, we recruited 300 participants on the platform Prolific. Participants were required to have at least a 90% approval rating and needed to report being fluent in English. The sample size decision was made per rule of thumb (Lakens, 2022), followed by an attempt to conduct a power analysis. Within economics, research has provided various different effect sizes in similar valuation studies, essentially disabling an objective assessment of expected effect sizes (Ariely et al., 2003; Maniadis et al., 2014).

The pre-registered data exclusion protocol was the following: We excluded all participants who failed to correctly answer the comprehension check, the bot check, and the attention check. Additionally, we excluded all participants who did not make at least 75% (i.e., 30) trade-off decisions in the behavioral task. Following this protocol yielded a final sample of 274 participants (36.9% females; mean age: 26 years). A power sensitivity analysis (95% power, 5% error rate, one-tailed in order to test our directional hypothesis) suggests that our sample is sufficiently powered to detect an effect size of Cohen's $d = 0.39$ in our most central between groups comparison (Hypothesis 1).

Participants received the prospect of a behavior-dependent bonus that varied depending on the experimental condition (see below) and, in addition, were awarded a flat payment of one additional GBP. Participants were allowed to take up to 25 min, but the average time in the study was substantially lower (i.e., 15 min). They were informed to receive their choice-dependent bonus via Prolific, typically within 2–5 business days.

2.3. *Behavioral measurement using the carbon emission task*

In order to capture actual and consequential environmental decision-making, we relied on a variation of the *Carbon Emission Task* (CET) (Berger and Wyss, 2021a) as our central behavioral paradigm. The CET can be used to study the individual trade-off between short-term personal gains and long-term environmental goals by directly pitching financial rewards against people's pro-environmental motives to avoid carbon emissions. In the task, people face a series of decisions involving a financial consequence that is paired with an environmental burden that takes the form of an actual carbon emission. The actual carbon emission can be realized through purchases and the retirement of emission right certificates from the EU-Emission Trading Systems. In the CET, participants face repeated dichotomous trade-offs between a financially rewarding *Option A* and a financially non-rewarding but carbon-neutral *Option B*.

Participants completed forty trials with varying costs and benefits that varied between treatments (see below). Throughout the forty trials, participants were always time-restricted and had fifteen seconds to complete each trial in order to align the completion time between participants. Not making a timely decision meant that the bonus opportunity was foregone. However, timing out occurred rarely. In addition to a flat payment of 1 GBP for participation, one trial is randomly selected for payoff.

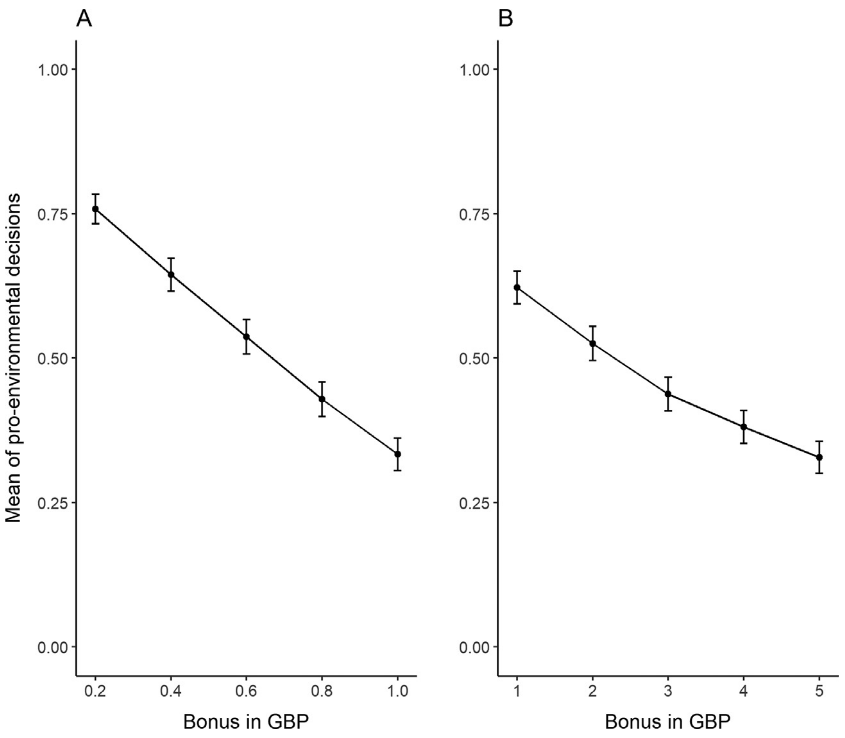

Fig. 1. Average pro-environmental behavior per bonus level, by condition (left: low bonus, right: high bonus)
Note. Average willingness-to-curb CO_2, depending on the prospective bonus amounts. Error bars represent 95% confidence intervals. Panel A shows experimental condition with low bonus prospects, Panel B shows experimental condition with high bonus prospects.

2.4. Self-report measures

In addition to the measurement of behavior in the CET, participants completed the *Social Value Scale* (Steg et al., 2014), which includes items reflecting egoistic, hedonic, altruistic, and biospheric values. Biospheric values, the relevant dimension for the purpose of this study, were measured with four items: respecting earth, unity with nature, protecting the environment, and preventing pollution. Participants rated the items as "guiding principle in their lives" on a 9-point scale ranging from −1 (opposed to my guiding principles) to 7 (extremely important). The biospheric values subscale showed a very good internal consistency (Cronbach's $\alpha = 0.87$). Finally, participants completed a series of demographic questions, reporting their gender, age, level of highest education, employment, household income, as well as their political orientation on the liberal-conservative spectrum, ranging from 1 (very liberal) to 7 (very conservative). In addition, to gather data for a future highly-powered replication and meta-analyses of related work (Wyss et al., 2022), a scale measuring individual differences in self-control was also assessed after the behavioural task, but prior to the assessment of the demographics. Data on people's self-control is included in the provided data set, but not analysed in the context of this study.

2.5. Experimental manipulation and hypotheses

Participants were randomly assigned to one of only two conditions, modulating the prospective financial rewards that come with accepting the bonus and the pollution. In the "high financial stakes" condition, choosing *Option A* was paired with bonus opportunities of 1, 2, 3, 4, or 5 GBP. In the "low financial stakes" condition, *Option A* was 80% less financially attractive, leading to bonus payments between 20 and 100 pence. The associated carbon emissions were the same across conditions and amounted to four different levels (i.e., 0.23, 1.02, 4.46, 19.85 lbs. CO_2). This results in twenty different trade-offs per condition. Each trade-off was presented twice, and all forty trials were presented randomly to participants. Crucially, both experimental conditions include our "target" choice involving the prospective bonus of 1 GBP. This allows inferences about pro-environmental preferences being absolute versus relative – meaning the monetary amount people are willing to forego per unit of CO_2. If target decisions are made identically across conditions, this would support the notion that participants have an absolute preference about trading off money for emissions. If target decisions, however, differ, this would imply relative decision-making, as trials that involve 1 GPB are relatively attractive in the low stakes condition, and relatively unattractive in the high stakes condition.

Hypothesis 1 suggests that average pro-environmental behavior differs between experimental conditions, although the choices problems are factually identical. Trade-offs involving 1 GPB in the high stakes condition are expected to lead to more pro-environmental behavior (i.e. the monetary gains are more frequently forgone), compared to the low-stakes condition. To test Hypothesis 1, we registered a simple regression model with the average PEB of the target decision (i.e., those involving 1 GBP) as the dependent variable and the experimental manipulation as the independent variable. As robustness checks, we registered multiple regressions that control for demographics.

Hypothesis 2 suggests that behavior is correlated with biospheric values, as has been the case with such measurements of behavior in prior validations of such experimental tasks. To test Hypothesis 2, we registered a simple regression using average pro-environmental behavior in the target decision as the dependent variable and biospheric values as the independent variable, also controlling for demographics in robustness checks.

3. Results

Coherently arbitrary decision-making implies that behavior within each experimental condition follows basic economic laws, with higher bonus prospects leading to – ceteris paribus – lower willingness to curb emissions, yet objectively identical trade-offs may provoke different choices depending on the condition. And in fact, despite strong behavioral differences with respect to target decisions, behavior within each condition follows the previously reported dynamics of cost- and benefit-sensitivity. Fig. 1 shows that people's behavior is "locally rational" because higher bonus payments lead to a higher probability of reaping the bonus (and accept the pollution) within each experimental condition, but not across conditions.

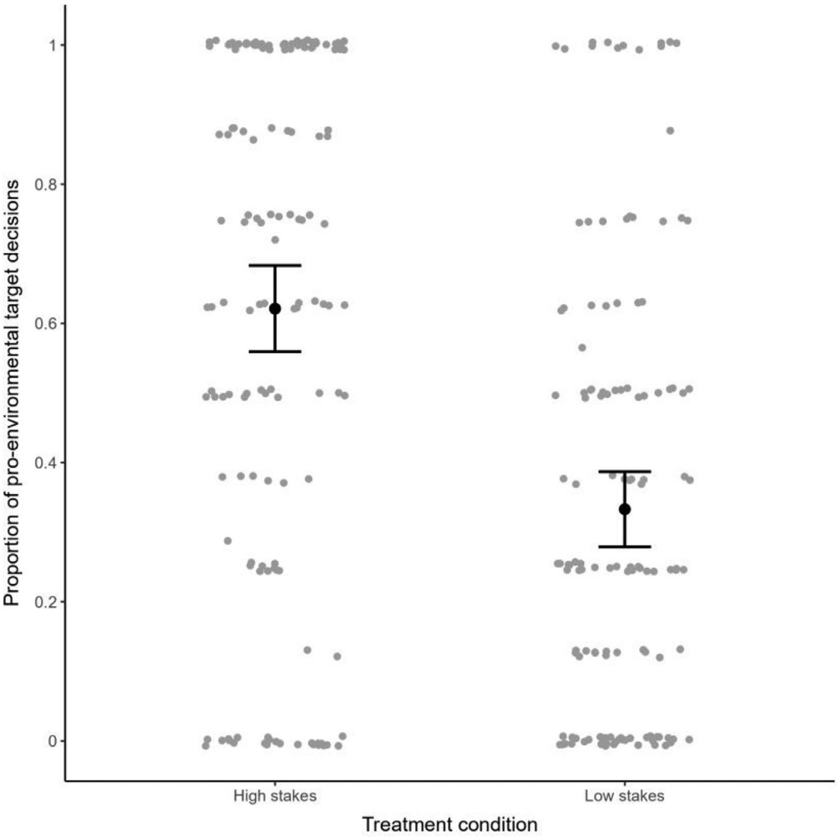

Fig. 2. Difference in average pro-environmental behavior in the target decision (Hypothesis 1)
Note. Difference in mean behavior with respect to the collapsed decisions involving 1 GBP. Error bars represent 95% confidence intervals. Data points reflect average individual decisions made by the participants in the 10 trials involving 1GBP tradeoffs.

Table 1
Simple and multiple regression results for the effect of the treatment on the mean proportion of pro-environmental decisions.

	Model 1			Model 2			Model 3		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.62	0.56 – 0.68	**<0.001**	0.46	0.41 – 0.51	**<0.001**	0.52	−0.26 – 1.31	0.192
Low stakes condition	−0.29	−0.37 – −0.21	**<0.001**	0.08	0.01 – 0.15	**0.020**	−0.25	−0.33 – −0.17	**<0.001**
Biospheric values (centered)				0.07	0.04 – 0.10	**<0.001**			
Age							0.00	−0.01 – 0.01	0.884
Gender (1 if female)							0.15	0.06 – 0.24	**0.001**
Education control								YES	
Employment control								YES	
Income control								YES	
Political views control								YES	
Observations	274	274	274						
R2 / R2 adjusted	0.149 / 0.146			0.090 / 0.083			0.345 / 0.255		

Note. CI = 95% confidence interval. The data about biospheric values were mean-centered before the analysis.

3.1. Confirmatory tests of pre-registered hypotheses

As predicted, the experimental condition showed a statistically significant and economically relevant effect on the willingness to forego a personal financial profit to curb CO_2 emissions in the target decision. When trade-offs involving 1 GBP are relatively attractive in financial terms (i.e., compared to 0.20–0.80 GBP), the average willingness to curb emissions is substantially lower ($M = 0.3324$, $SD = 0.2921$, $n = 135$) compared to a situation when 1 GBP trade-offs are relatively unattractive ($M = 0.6213$, $SD = 0.3136$, $n = 139$; against 1–5 GBP comparisons), $t_{\text{Welch}}(268.07)=6.9293$, $p<0.001$, 95% confidence interval ranging from 0.2064 to 0.3726, Cohen's $d = 0.835$. Fig. 2 depicts the between-condition differences. The pre-registered regressions are presented in Table 1, supporting the central result, indicated by a significant main effect of the experimental condition in model 1 and 3. The results suggest that factually identical trade-offs lead to observable differences in behavior, in line with non-absolute preferences and scope insensitivity of PEB.

To assess Hypothesis 2, we tested to which extent biospheric values correlate with average pro-environmental behavior in each condition. In both conditions, there is a positive correlation between environmental concerns and willingness to curb emissions, evidenced by a positive (and similar) correlation. Fig. 3 displays the results. Biospheric values correlate with average pro-environmental behaviorin both conditions, without and with controlling for control variables (see Table 2).

4. Discussion

In a simple behavioral experiment involving actual environmental consequences, we found support for "coherent arbitrariness" or scope-sensitivity of pro-environmental behavior. This manifests in objectively identical decisions producing noticeable behavioral differences. Thus, pro-environmental behavior seems to reflect more than fundamental preferences and seems to be scope-insensitive to a certain degree. The results provide several elements for discussion.

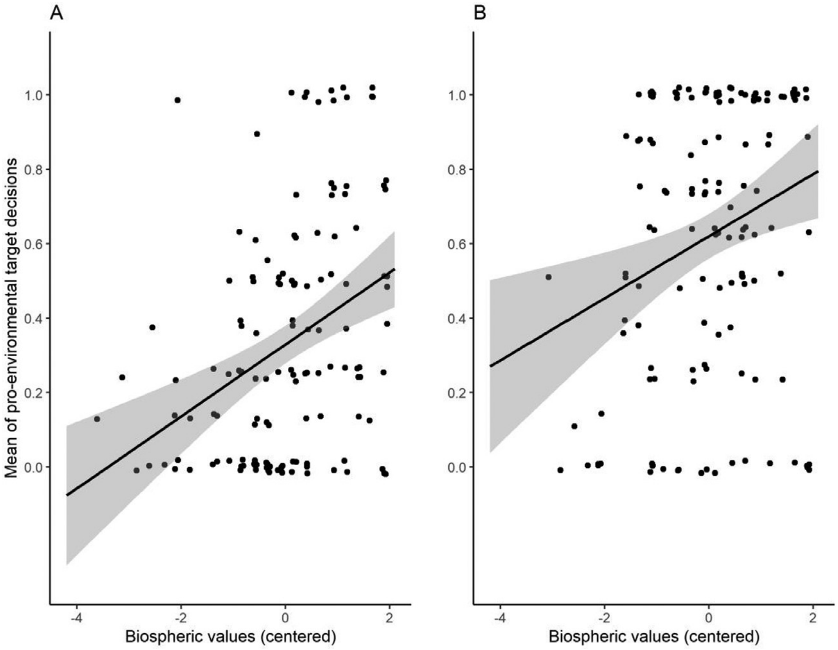

Fig. 3. The correlation between environmental concern (mean-centered) and willingness to curb emissions is positive and significant in both experimental conditions.
Note. Scatterplot with simple regression line. 95% confidence bands are presented in gray. Panel A shows experimental condition with low bonus prospects, Panel B shows the experimental condition with high bonus prospects.

Table 2
Simple and multiple regression results for the effect of biospheric values on the mean proportion of pro-environmental decisions by condition.

	Low stakes condition						High stakes condition					
	Model 1			Model 2			Model 3			Model 4		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.62	0.56 – 0.68	**<0.001**	1.00	0.30 – 1.70	**0.006**	0.33	0.28 – 0.38	**<0.001**	0.66	−0.27 – 1.58	0.161
Biospheric values (centered)	0.08	0.03 – 0.14	**0.002**	0.07	0.01 – 0.13	**0.023**	0.08	0.04 – 0.13	**<0.001**	0.08	0.03 – 0.12	**0.002**
Age				−0.01	−0.02 – 0.00	0.241				0.00	−0.01 – 0.01	0.765
Gender (1 if female)				0.12	−0.02 – 0.26	0.083				0.14	0.03 – 0.26	**0.015**
Education control					YES						YES	
Employment control					YES						YES	
Income control					YES						YES	
Political views control					YES						YES	
Observations	139			139			135			135		
R2 / R2 adjusted	0.065 / 0.058			0.289 / 0.083			0.111 / 0.104			0.425 / 0.245		

Note. CI = 95% confidence interval. Biospheric values scores were mean-centered before the analysis.

First, our experiment is mute on the underlying reasons for the behavioral effects. One plausible explanation is that people lack the skills to accurately translate carbon amounts into monetary units, possibly due to the unfamiliarity with carbon units. However, the fact that experimental participants received information about “car miles equivalents” likely mitigated this risk to some extent. Importantly, prior conclusions about cost sensitivity of pro-environmental behavior have been grounded on similar experimental approaches as well.

Second, empirical results using non-laboratory behavior also seem to be at odds with cost sensitivity. For example, in a dataset of carbon offsets resulting from commercial flights, Berger et al. (2022) found no evidence of cost sensitivity and overall low amounts of pro-environmental behavior. In a similar vein, Nielsen et al. (2022) found that psychological constructs predict psychological measurements of clothing consumption (i.e., self-report scales) but not actual, real-world behavior. Thus, future research could continue to investigate why there is a disconnect between laboratory results and field behavior, especially high-impact behavior (Nielsen et al., 2021). The fact that people respond so scope-insensitively may partially explain why psychological motivation is not a strong predictor of impactful PEBs (Nielsen et al., 2022). This, in turn, could strengthen arguments about the promise that environmental labels can bring (Taufique et al., 2022).

Third, our study can be taken as contributing evidence on the limits of fixed preferences. The most recent IPCC report (Creutzig et al., 2022, 2022) suggests shifting the research focus more to malleable preferences rather than keeping the assumption of fixed preferences in sustainability research. Parting from uniquely fixed preferences broadens the policy toolbox, as policies may transcend the unique manipulation of relative prices as ways to promote environmentally friendly behaviors.

Finally, experimental models with tight control over costs and benefits attached to decision options can serve an important function. Similar to experimental behavioral games used in economic research, rationality assumptions underlying theoretical approaches to understand pro-environmental behavior (e.g., the Theory of Planned Behavior (Ajzen, 1991)) can more readily be tested under clean laboratory conditions. Potential future research, for example, could investigate the extent to which pro-environmental preferences follow other basic rationality assumptions such as transitivity of preferences, thereby informing research and policy about the behavioral foundations of pro-environmental decision-making.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data is openly available via OSF.

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Study 3

Saving the World Voluntarily: Experimental Evidence of Gain-Loss Framing on Voluntary Pro-Environmental Behavior

David Hauser, Daniel Bregulla *

Abstract

Empirical research shows that loss framing appears to be a promising tool to promote pro-environmental behavior. However, only a limited amount of experimental research has examined the effect of loss framing on actual behavior. Here, we use a variation of the Work for Environmental Protection Task (Lange & Dewitte, 2022) to study true voluntary pro-environmental behavior. In an online experiment ($N = 897$), we find a trend of higher working efforts in the *LOSS* frame. However, this effect is small and marginally statistically significant. Interestingly, the effect of *LOSS* framing is stronger and statistically significant for people with low intrinsic motivation to protect the environment. Together, this suggests tailoring the framing of gain and loss specifically to peoples' environmental values.

Keywords: framing, loss aversion, pro-environmental behavior, experiment
JEL classification: C91, D90, Q50

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3.1 Introduction

People's voluntary engagement in pro-environmental behavior (PEB) plays an essential role in future climate change mitigation (Bergquist et al., 2023). Demand-side strategies, including PEB, can potentially reduce greenhouse gas emissions by 40-70% by 2050, according to the latest report of the Intergovernmental Panel on Climate Change (IPCC, 2022). This remarkable potential puts PEB at the forefront of strategies for tackling climate change. One way for governments, companies, or NGOs to promote voluntary PEB is to frame environmental decisions as losses — an approach that has shown potential to boost environmentally friendly behavior (Homar & Cvelbar, 2021). In this paper, we build on the literature of voluntary pro-environmental behavior and loss framing by addressing the following research question: How do gain and loss framing influence people's voluntary working behavior to mitigate climate change?

In our experiment, we measure individual voluntary working behavior to mitigate climate change by applying a variation of the *Work for Environmental Protection Task* (WEPT) (Lange & Dewitte, 2022). In the WEPT, participants can voluntarily work on a WEPT page, a number identification task, to generate a donation to an environmentally friendly organization by the researcher. Alternatively, participants can refuse to work on a given WEPT page. In total, there are 15 randomly presented number identification tasks, and each task varies along the amount donated to the environmentally friendly organization and the required working effort (e.g., size of numbers to be identified). In our *GAIN* frame, participants start with zero donations and can increase their donations to mitigate climate change with every completed WEPT page. In contrast, participants in the *LOSS* frame see the total number of remaining possible donations before deciding whether to work on the task or not. With every WEPT page left incomplete, the total amount of donations decreases.

Our results imply higher working performance under a loss frame for our pre-registered sample. However, the effect size is small (Cohen's $d = 0.12$) and marginally statistically significant ($p = 0.07$, Wilcoxon-Mann-Whitney test). Furthermore, robustness checks including additional data from the pilot study ($n = 50$) suggest a tendency towards an increased working performance under a *LOSS* frame. Interestingly, our *LOSS* framing significantly affects people with low biospheric values ($p = 0.03$, Wilcoxon-Mann-Whitney test). Biospheric values emphasize an individual's intrinsic value of nature and environment (Steg & de Groot, 2012). Additionally, results indicate that age and political ideology drive voluntary working behavior. In line with previous research (Lange & Dewitte, 2022), we find that pro-environmental intentions, environmental concern, and biospheric as well as altruistic values are positively correlated with pro-environmental behavior.

Previous empirical evidence testing the effect of loss framing on PEB is mixed. Some studies suggest a significant effect (e.g., Nabi et al., 2018; Poortinga & Whitaker, 2018), while others find no discernible effect (e.g., Ahn et al., 2015; Essl, Friedrich, et al., 2023). However, experimental designs and the measurement of PEB vary widely across studies. While some are conducted as field experiments, others still measure self-reported willingness to pay or environmental intentions as the dependent variable, and only a limited number of experiments use actual environmental behavior as their outcome measure (Homar & Cvelbar, 2021).

Closely related to our experimental design are experiments testing participants' working behavior under gain or loss contracts. Under a gain-framed contract, people work to receive an incentive, whereas under a loss-framed contract, people work to avoid losing an incentive (Imas et al., 2017). Given that incentives for gain and loss-framed contracts are economically equivalent (i.e., monetary incentives are the same), prospect theory by Kahneman and Tversky (1979) would predict enhanced working effort under a loss contract due to loss aversion around a reference point. Findings from online experiments about gain-loss contracts[1] are mixed, ranging from no effects (DellaVigna & Pope, 2018; Grolleau et al., 2016) to medium (de Quidt, 2018; Goldsmith & Dhar, 2013) or strong effects (Hochman et al., 2014) of loss-framed contracts. The variability in these findings may stem from differences in experimental designs, the nature of real-effort tasks used, or the types of incentives provided (Essl, Hauser, & von Bieberstein, 2023). We advance this research by incentivizing participants to work on a real-effort task to gain donations to mitigate climate change. Hence, participants do not receive any immediate benefit for themselves by working on the task.

3.2 Methods

We pre-registered our study on the Open Science Framework (OSF) and received ethical approvement from the Faculty of Business Administration, Economics and Social Sciences of the University of Bern (serial Number: 292022). We provide a survey template to test gain-loss framing online via Qualtrics, data, and R code to facilitate future analyses of the WEPT on OSF.

[1]See Essl, Hauser, and von Bieberstein (2023) for an overview.

3.2.1 Experimental Design

We designed a between-subject experiment with two parts.[2] In the first part, after giving informed consent, participants familiarized themselves with the number identification task of the WEPT. We decided to use the WEPT because this validated task has been widely used (e.g., Vlasceanu et al., 2023) and allows us to assess PEB through repeated measures, presenting participants with different variations over multiple periods. As a trial page of the WEPT (see Figure 3.1), participants had to identify all numbers out of 20 two-digit numbers with an even first digit and an odd second digit. Participants received feedback if they failed to detect all numbers correctly. No specific knowledge or skills were required to complete the task. After completing the trial page, participants were randomly assigned to a *GAIN* or a *LOSS* treatment and could voluntarily complete up to 15 WEPT pages.

FIGURE 3.1: Trial page of the WEPT task.

Following Lange and Dewitte (Lange & Dewitte, 2022), we varied the quantity of numbers and donations per page to measure different effort levels of participants. The quantity of numbers in the identification task was 40, 80, 120, 160, or 200, and the donations for completing a WEPT page were GBP 0.10, GBP 0.20, or GBP 0.30. All these factors together led to 15 different combinations of WEPT pages that were randomly presented to participants. In the GAIN treatment, participants were informed that "with every complete page, you increase the amount of donations to an international, non-profit forest restoration organization that plants trees to mitigate climate change. If you complete every page, you can achieve possible donations of GBP 3.0." In contrast, participants in the *LOSS* treatment received the following information: "If you complete every page, you can achieve possible donations of GBP 3.0 to an international, non-profit forest restoration organization that plant trees to mitigate climate change. With

[2]See Appendix B for the entire survey questionnaire.

every incomplete page, you reduce the amount of donations to mitigate climate change". In both conditions, participants were instructed that the total amount of donation would be displayed on each WEPT page before deciding to work on it. Additionally, participants were informed about the maximum of 15 WEPT pages and on each page about the quantity of numbers to be checked to trigger a specific donation. The total amount of donation was economically equivalent in both conditions. While in the $GAIN$ treatment, the total amount started with GBP 0, the total amount of donation started with GBP 3.0 in the $LOSS$ treatment. We highlighted that completing a WEPT page is voluntary and that participants' working effort has true consequences for the environment. Furthermore, we emphasized that only pages completed with at least 90% accuracy would result in a donation and that participants would not receive any feedback on their performance. To avoid potential bias, we did not disclose the name of the organization that would receive the donations. Participants were briefed that planting trees is an effective method to mitigate climate change. A comprehension question ensured that participants understood the instructions correctly. Finally, participants could provide their e-mail addresses to receive a confirmation e-mail as soon as we made the donation. In the second part of the experiment, participants completed self-reported questionnaires assessing pro-environmental intentions, environmental concern, value orientation, and belief about climate change. We used the New Environmental Paradigm (NEP) (Dunlap et al., 2000) to capture participants' environmental concern, a 15-item scale ranging from (1) strongly disagree to (5) strongly agree. The 16-item E-SVS scale by Steg and de Groot (2012) was employed to measure biospheric, hedonistic, altruistic, and egoistic values. This scale ranges from (-1), representing opposition to a value, to (7), indicating supreme importance. We also administered a single item introduced by Berger et al. (2023) to measure participants' belief in climate change. As an exclusion criterion, we asked participants about the effectiveness of tree planting to mitigate climate change. The experiment concluded with a questionnaire about gender, age, education, political affiliation, risk attitude, and income.

3.2.2 Theoretical Model and Behavioral Prediction

We present a simple model that aims to explain why people tend to work more when potential environmental donations are framed as losses than as gains. Our model is based on a model by Imas et al. (2017) about working effort under loss contracts and the seminal work on Prospect theory by Kahneman and Tversky (1979). We make three essential assumptions in our model. First, depending on environmental values, people experience a utility of acting environmentally friendly to a reference point. This means that people, depending on their environmental values, derive a positive utility from donating and a negative utility from not donating. Second, we assume that environmental losses (e.g., forgone donation to an environmental organization) loom larger for people than equivalent gains. Third, we assume that the reference point is determined by the status quo. In our context this means that participants update their reference point each time before deciding to accept or reject a working contract.

Consider an individual deciding whether to accept a contract to work on a real-effort task and generate donations d to an environmentally friendly organization or to reject the contract. Let $c(e)$ be the costs (e.g., forgone time) of completing the real-effort task depending on the required effort e. We assume that an individual receives a utility $u(d)$ from generating a donation if she has at least some pro-environmental values p. Taken together, we formalize an individual's utility function V as follows:

$$V = V(e, d, p, r) = e \cdot p[u(d) + \nu(d|r)] + (1 - e) \cdot p[\nu(0|r)] - c(e) \tag{3.1}$$

where an individual receives a utility $u(d)$ of generating a donation $d > 0$ to an environmentally friendly organization depending on environmental values $p \in (0, 1)$ with probability equal to effort $e \in (0, 1)$. We assume that u is an increasing and concave function of d and normalized to $u(0) = 0$. Conversely, an individual generates a donation of 0 with probability $1 - e$. As described below, $v(\cdot|r)$ corresponds to the gain-loss prospect theory value function. Let c be an increasing, convex function of e ($c'(e) > 0$, $c''(e) > 0$). Further, we define the utility derived in relation to reference point r as follows:

$$v(x|r) = \begin{cases} (x - r)^{\alpha}, & \text{if } x \geq r \\ -\lambda(r - x)^{\beta}, & \text{if } x \leq r \end{cases}$$

where $\lambda > 1$ captures the loss aversion parameter, α is the risk aversion parameter in the *GAIN* frame, and β is the risk aversion parameter in the *LOSS* frame. Following Imas et al. (2017), we assume that $\alpha = \beta$. We illustrated this value function $v(x|r)$ in Figure 3.2. In the *GAIN* treatment, participants' reference point of donation displayed on the x-axis is 0, and the value depending on donation and reference point increases with every generated donation. Conversely, participants in the *LOSS* treatment start with the total amount of donation as reference point, and their donation value decreases with every forgone donation.

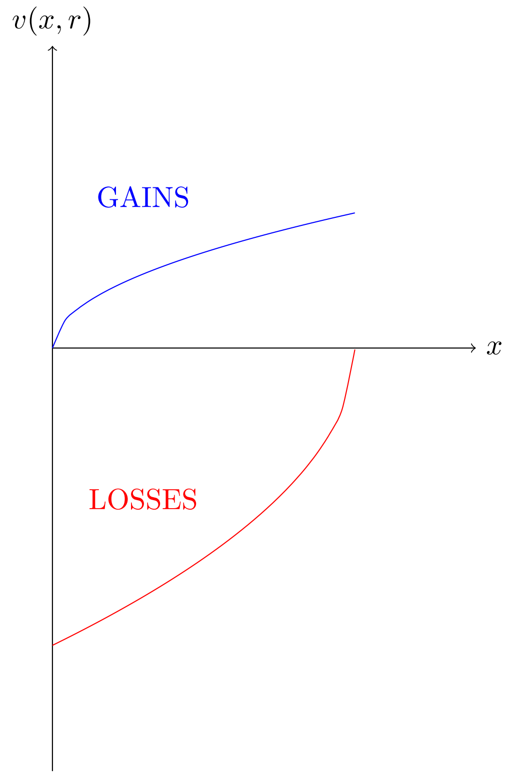

FIGURE 3.2: An individual's value function $v(x|r)$ on the y axis; donations correspond to the outcome measure on the x-axis.

As in Kahneman and Tversky (1979), an individual chooses their optimal effort e^* to maximize overall utility V.

$$\max_e V(e, d, p, r) = \max_e \{e \cdot p[u(d) + \nu(d|r)] + (1 - e) \cdot p[\nu(0|r)] - c(e)\} \tag{3.2}$$

We derive the first-order condition for the optimal effort e_G^* under a $GAIN$ frame $(r = 0)$ and optimal effort e_L^* in a $LOSS$ frame $(r = d)$.

$$c'(e_G^*) = p(u(d) + d^\alpha) \tag{3.3}$$

$$c'(e_L^*) = p(u(d) + \lambda d^\beta) \tag{3.4}$$

Given that $\alpha = \beta$, $\lambda > 1$, and $p \in (0, 1)$ leads to $p(u(d) + d^\alpha) < p(u(d) + \lambda d^\alpha)$. Hence, optimal effort in the $LOSS$ frame will be greater than optimal effort in the $GAIN$ frame, $e_G^* < e_L^*$, if an individual has at least some environmental values $p > 0$. This leads us to our main hypothesis predicted by our model: Participants in the $LOSS$ treatment will exhibit higher effort (e.g., more completed WEPT pages) than participants in the

GAIN treatment if they have some environmental values. Similar to Lange and Dewitte (2022), we assume that the amount of completed WEPT pages is linked to established self-reported environmental measures.

Hypothesis 2: The number of completed WEPT correlates positively with self-reports measuring participants' pro-environmental intentions, environmental concern, belief in climate change, and environmental values (i.e., altruistic, biospheric values).

3.2.3 Data Collection

Overall, we recruited 998 participants on Prolific.[3] We adhered to the protocol in our pre-registration and excluded participants with incomplete responses (n = 63) or who failed crucial attention checks (n = 23). Further, we excluded participants (n = 15) who did not believe that planting trees is an effective way to mitigate climate change since we could not be sure that these participants were incentivized.[4] Beyond our pre-registered criteria, we did not exclude participants who took longer than one hour to complete the survey, as we received e-mails from participants informing us that they required more time to complete the number identification tasks. This left us with a total sample of 897 participants (51% female; mean age: 40.44). See Table 3.1 for a full description of the sample and randomization check. Randomization between *GAIN* and *LOSS* treatment was successful except for the variables income and biospheric values.

Participants received a flat fee of GBP 1.5 for completing the survey. On average, it took participants nearly 18 minutes to finish the survey.

[3] See power analysis in our pre-registration on (OSF).

[4] In a robustness check (see Table 3.8 in Appendix A), we included these participants. Including participants who did not believe that planting trees is an effective way to mitigate climate change improves the statistical significance of our treatment.

TABLE 3.1: Sample characteristics and randomization check

	Sample (n = 897)	Gain (n = 460)	Loss (n = 437)	Gain vs. Loss *p*-values
Demographics				
Gender (% female)	51	52	49	0.27
Age in years (range 18 – 79)	40.44 (SD=13.48)	40.75 (SD=13.30)	40.12 (SD=13.69)	0.41
Political affiliation (% liberal)	49	50	48	0.48
Education (% higher than high school)	78	80	75	0.08
Income (% earn more than GBP 50'000)	35	0.31	0.39	0.01
Risk	4.6 (SD=2.58)	4.63 (SD=2.60)	4.58 (SD=2.56)	0.79
Climate change related variables				
Environmental concern	3.79 (SD=0.55)	3.80 (SD=0.55)	3.78 (SD=0.56)	0.63
Belief in climate change	3.38 (SD=1.87)	3.41 (SD=1.81)	3.34 (SD=1.94)	0.95
Climate change related values				
Biospheric values	5.47 (SD=1.31)	5.55 (SD=1.28)	5.38 (SD=1.36)	0.06
Altruistic values	5.70 (SD=1.10)	5.73 (SD=1.12)	5.67 (SD=1.09)	0.36
Egoistic values	2.75 (SD=1.43)	2.78 (SD=1.43)	2.72 (SD=1.42)	0.55
Hedonistic values	4.94 (SD=1.30)	5.0 (SD=1.34)	4.89 (SD=1.26)	0.11

Notes: The table reports means and standard deviations for continuous variables and percentage frequencies for categorical variables for the full sample and for participants in the *GAIN* and *LOSS* sample. Standard deviations are given in parentheses. For categorical variables, the *p*-values were obtained from a χ^2-test. For continuous variables, the *p*-values were obtained from Wilcoxon-Mann-Whitney tests. Two participants (1 *GAIN* treatment, 1 *LOSS* treatment) are removed for income calculations because they did not state their income.

3.3 Results

Our study aimed to investigate the impact of gain and loss frames on pro-environmental behavior, specifically the completion of WEPT pages. In line with our pre-registered Hypothesis 1, we compare the average number of completed WEPT pages (e.g., a complete WEPT page is defined as correctly identifying at least 90 percent of the numbers on a given page).[5] As presented in Table 3.2, results reveal that the number of completed WEPT pages is greater for participants in the *LOSS* treatment ($M = 5.16, SD = 4.11$) than for participants in the *GAIN* treatment ($M = 4.66, SD = 4.41$). The difference between the *GAIN* and *LOSS* treatment is marginally significant ($p = 0.068$, Wilcoxon-Mann-Whitney test). In contrast, we find no statistically significant difference in total donations generated by individual participants between the two treatment groups. [6]

TABLE 3.2: Descriptive and inferential statistics: WEPT pages

	WEPT Pages (0-15)	
	GAIN (n = 460)	*LOSS (n = 437)*
Mean	4.66	5.16
SD	4.11	4.41

	GAIN vs. LOSS
Cohen's d	-0.12
95% CI	[-0.25, 0.01]
p-value	0.068

Notes: *p*-values were obtained from a one-sided Wilcoxon-Mann-Whitney test.

Figure 3.3 shows the proportion of completed WEPT pages for all 15 combinations of numbers and donations for the *GAIN* and *LOSS* frame.

[5] The total number of pages completed by all participants, meeting the 90% accuracy criterion, is 4,397. For the more lenient 80% accuracy criterion, the sum is 5,541 pages. Including all pages, even those solved incorrectly, the overall total is 6,073. The difference in the proportion of incorrectly solved pages between the treatment groups is marginally significant ($p = 0.06$, Wilcoxon-Mann-Whitney test), the error rate being larger in the *GAIN* group ($M = 0.33$, $SD = 0.31$) than in the *LOSS* group ($M = 0.29$, $SD = 0.29$).

[6] See Appendix Table 3.6 for the analysis of total amount of donation.

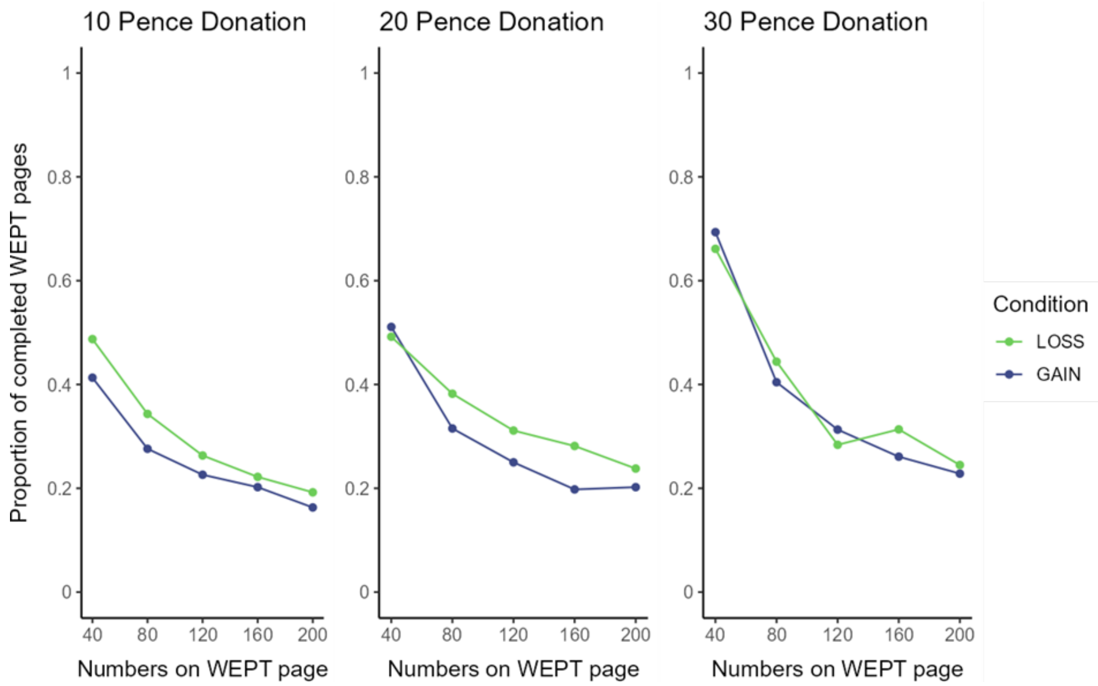

FIGURE 3.3: Proportion of completed WEPT pages as a function of treatment condition, donation amount, and the numbers to be solved on a given WEPT page.

To investigate the effects and the robustness of the results in more detail, we use the following OLS regression model:

$$y_i = \beta_0 + \beta_1 LOSS_i + \beta_2' \mathbf{E}_i + \beta_3' \mathbf{X}_i + \epsilon_i$$

where the dependent variable y_i represents the number of completed WEPT pages by individual i, and $LOSS_i$ is a dummy variable indicating whether the individual was in the $LOSS$ (1) or $GAIN$ (0) treatment, respectively. We also estimate model specifications $\mathbf{E}_i$ to control for factors such as intentions to act environmentally friendly, environmental concern, belief about climate change, and environmental values. $\mathbf{X}_i$ accounts for sociodemographic variables, i.e., age, gender, education, political ideology, income, and risk attitudes. Lastly, ϵ_i is the idiosyncratic error term.

Table 3.3 presents the estimated coefficients of the OLS regression analysis about effects of the $LOSS$ treatment on completed WEPT pages.[7] In Specification 1, the result for the effect of the $LOSS$ treatment is marginally significant for a two-tailed t-test.[8] The treatment coefficient increases and reaches statistical significance at the 5%-level in Specification 2 and Specification 3 when controlling for pro-environmental intentions,

[7] See Table 3.7 in Appendix A for OLS regressions for donation as dependent variable.

[8] However, for our directional hypothesis, the effect of the $LOSS$ treatment is statistically significant for a one-sided t-test (t(882.12) = -1.766, p = 0.039, Cohen's d = -0.12).

environmental concern and values, and sociodemographic variables, respectively. As expected in Specification 2, an increase in pro-environmental intentions and biospheric values leads to a greater number of completed WEPT pages. Furthermore, in Specification 3, we find that an individual's age increases the number of completed WEPT pages.

TABLE 3.3: Effects of *LOSS* treatment on completed WEPT pages: OLS regression

	(1) WEPT pages	(2) WEPT pages	(3) WEPT pages
LOSS treatment	0.50*	0.60**	0.67**
	(0.29)	(0.28)	(0.28)
Pro-environmental intentions		0.49***	0.49***
		(0.16)	(0.16)
Environmental concern		-0.16	-0.15
		(0.19)	(0.20)
Belief in climate change		-0.10	0.00
		(0.17)	(0.18)
Biospheric values		0.62***	0.44**
		(0.20)	(0.21)
Altruistic values		0.19	0.21
		(0.18)	(0.18)
Egoistic values		-0.38**	-0.24
		(0.15)	(0.16)
Hedonistic values		-0.03	0.13
		(0.16)	(0.16)
Female (1 = female)			0.03
			(0.14)
Age			0.67***
			(0.16)
Education (> High school)			-0.37
			(0.34)
Liberal (1 = liberal)			0.26
			(0.30)
Income (> GBP 50,000)			-0.24
			(0.29)
Risk			0.08
			(0.14)
Intercept	4.66***	4.61***	4.82***
	(0.19)	(0.19)	(0.40)
Observations	897	897	895
R-squared	0.00	0.06	0.09

Notes: The table presents estimates from ordinary least squares (OLS) regressions. Robust standard errors are shown in parentheses and all continuous predictors are mean-centered and scaled by 1 standard deviation. Dependent variable is completed WEPT pages according to the 90% criterion. Pro-environmental intentions are measured on a 7-point Likert scale. Environmental concern is assessed on a 5-point Likert scale. Belief in climate change is measured on a scale from -5 ("strongly disagree") to +5 ("strongly agree"). Biospheric, altruistic, egoistic, and hedonistic values are assessed with a scale from -1 ("opposed to my principles") to 7 ("extremely important"). Female indicates being female (1) or not (0), education whether having a higher education than high school (1) or not (0), being liberal (1) or not (0), or having a higher than annual income GBP 50'000 (1) or not (0). In Specification 3, two participants (1 *GAIN* treatment, 1 *LOSS* treatment) are removed because they did not state their income. *, **, and *** document significance at the 10%, 5%, and 1% levels, respectively.

We replicated our findings for different samples in Table 3.4 for Specifications 1-3 considering completed WEPT pages (see Table 3.8 Appendix A for donations). Specifically, we included participants who were skeptical about tree planting and found that results remained robust and are statistically significant at the 5%-level. The same is true if we add data from our pilot study (n = 50), which had exactly the same experimental design as our main study. Contrarily, the effect of the loss framing disappears if we include all WEPT pages without accounting for a minimum of 90% correctly identified numbers. Interestingly, the *LOSS* treatment is more effective for those participants with low biospheric values as determined by a median split (n = 432). Participants with low biospheric values completed 0.73 WEPT pages more in the *LOSS* treatment ($M = 4.47, SD = 4.06, n = 227$) than in the *GAIN* treatment ($M = 3.74, SD = 3.72$, n = 205). This difference is statistically significant ($p = 0.03$, one-sided Wilcoxon-Mann-Whitney test).

TABLE 3.4: Robustness check for different samples

Dependent variable	WEPT pages		
	(1)	(2)	(3)
Main sample	0.50*	0.60**	0.67**
	(0.29)	(0.28)	(0.28)
n	897	897	895
incl. tree planting skeptic	0.56**	0.64**	0.71**
	(0.28)	(0.28)	(0.28)
n	912	912	910
incl. pilot study	0.55**	0.64**	0.72***
	(0.28)	(0.28)	(0.27)
n	927	927	925
incl. all WEPT pages	0.32	0.44	0.53*
	(0.30)	(0.30)	(0.29)
N	897	897	895
Low biospheric values	0.73*	0.77**	0.80**
	(0.37)	(0.38)	(0.38)
n	432	432	432

Notes: The table displays the coefficients of the loss treatment as dummy variable of Specification 1 to 3 of Model 1. Robust standard errors are shown in parentheses. The dependent variable is completed WEPT pages according to the 90% criterion. In Specification 3, two participants (1 *GAIN* treatment, 1 *LOSS* treatment) are removed because they did not state their income (except in sample 'low biospheric values'). In the sample 'including tree planting skeptics', one participant is removed from Specification 1 to 2 because the participant did not state their belief in climate change and two participants are removed because they did not state their income. The sample 'low biospheric values' is based on the median split. Only participants below the median of biospheric values are considered. 'Main sample' is the sample used after the exclusion of participants according to the pre-registered protocol. *, **, and *** document significance at the 10%, 5%, and 1% levels, respectively.

In line with our pre-registered Hypothesis 2, we conducted Spearman correlational analyses, which are presented in Table 3.5. Consistent with the OLS regression analysis, we identified significant correlations between the number of completed WEPT pages and pro-environmental intentions (r = .18, 95% CI [0.12, 0.24], $p < 0.01$), environmental concern (r = .11, 95% CI [0.04, 0.17], $p < 0.05$), biospheric values (r = 0.20, 95% CI [0.14, 0.26], $p < 0.01$), altruistic values (r = .17, 95% CI [0.11, 0.23], $p < 0.01$), but not for the correlation with belief in climate change (r = .08, 95% CI [0.01, 0.14], $p < 0.1$) and egoistic values ($r = -.08$, 95% CI [-.14, -0.01], $p < 0.1$). Overall, we find similar correlations to those reported by Lange and Dewitte (2022).

Table 3.5: Spearman Correlation Table

	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) WEPT	4.93	4.27	1												
(2) PE intentions	5.19	1.21	0.181***	1											
(3) Env. concern	3.79	0.56	0.106**	0.367***	1										
(4) Belief in CC	3.37	1.88	0.080*	0.330***	0.585***	1									
(5) Biospheric	5.47	1.31	0.202***	0.570***	0.490***	0.366***	1								
(6) Altruistic	5.70	1.10	0.166***	0.449***	0.299***	0.386***	0.614***	1							
(7) Egoistic	2.75	1.43	-0.083*	0.005	-0.308***	-0.133***	0.008	0.015	1						
(8) Hedonistic	4.95	1.30	0.001	0.075*	-0.04	0.141***	0.159***	0.275***	0.302***	1					
(9) Female	0.51	0.50	0.039	0.099**	0.151***	0.064	0.112***	0.174***	-0.018	0.053	1				
(10) Age	40.37	13.62	0.164***	0.006	0.032	-0.163***	0.108***	-0.061	-0.222***	-0.327***	-0.054	1			
(11) Education	2.92	0.91	-0.019	0.054	0.066*	0.057	-0.011	-0.001	-0.038	-0.043	-0.007	-0.022	1		
(12) Political Id.	4.40	2.01	-0.028	-0.191***	-0.322***	-0.381***	-0.150***	-0.350***	0.211***	-0.145***	-0.094**	0.269***	-0.085**	1	
(13) Income	4.90	2.62	-0.042	0	-0.005	0.029	-0.034	-0.017	0.171***	0.079*	0.01	-0.052	0.180***	0.059	1

Notes: WEPT are based on 90% accuracy criterion. PE = Pro-environmental. Env. = Environmental. CC = Climate change. Id = Ideology. Pro-environmental intentions are measured on a 7-point Likert scale and environmental concern is measured on a 5-point Likert scale. Belief in climate change is measured on a scale from -5 ("extremely bad") to +5 ("extremely good"). Biospheric, altruistic, egoistic and hedonistic values range form -1 ("opposed to my principles") to 7 ("extremely important"). Besides age, which is a continuous variable, we included the remaining demographical variables as dummy variables. See Table 3.3 for explanation of dummy variables. *, **, and *** document significance at the 10%, 5%, and 1% levels, respectively.

3.4 Discussion

Our experiment examines the effects of a *GAIN* and a *LOSS* frame on voluntary pro-environmental behavior. Results indicate higher levels of pro-environmental behavior under a *LOSS* frame; however, the effect size is relatively small and marginally statistically significant. With our model, we predict that the effect of loss aversion also depends on environmental (e.g., biospheric) values. Interestingly, a robustness check for people with low biospheric values shows that the effect of the *LOSS* frame statistically significantly increases pro-environmental behavior.

Since we observe generally higher biospheric value scores of participants in the *GAIN* frame, their intrinsic motivation to mitigate climate change appears to reduce the difference in the average number of WEPT pages completed across both frames, thereby diminishing the impact of loss aversion. Given that individuals with high biospheric values are already inclined toward pro-environmental behavior, our findings suggest that loss framing could be particularly effective for engaging those with lower biospheric values, even if the effect size is small. Future research could focus on biospheric values to unlock greater improvements in pro-environmental behavior. Additionally, Essl, Hauser, and von Bieberstein (2023) argue that paying participants cash upfront leads to higher effort provision than simply informing participants about an upfront payment, as in our experiment. Together, this evidence may also explain the weak effects of our *LOSS* framing. Although the *LOSS* frame seems to motivate more effort in terms of completed WEPT pages, this does not translate to a corresponding increase in the generated donations. This suggests that participants are not optimizing their choices of which pages to complete based on the potential donations and required effort. To optimize individual choices, a possible variant of our design could be to let participants choose if they prefer a *GAIN* or a *LOSS* frame (Milkman et al., 2021).

We find similar correlation coefficients and statistical significance to Lange and Dewitte (2022) between completed WEPT pages and biospheric and egoistic values, albeit correlation coefficients are smaller for environmental concerns in our study. Overall, these results serve as further evidence of the relationship between specific self-reported and behavioral measures. Because we incentivized a specific form of pro-environmental behavior (e.g., a donation to a tree reforestation organization), we do not expect this behavior to generalize to every pro-environmental behavior (Lange, 2023).

Comparing our results with findings on gain and loss contracts, in particular online experiments, we align with de Quidt (2018) and Imas et al. (2017) by finding weak effects of loss framing on effort provision from a Prolific sample. In comparison to experiments about loss aversion with a focus on energy-saving behavior (e.g., Ghesla et al., 2020) or investments in energy-efficiency (e.g., Heutel, 2019), our experiment was purely based on altruistic incentives. Specifically, participants in our experiment expended effort with no personal financial gain, motivated solely by the prospect of contributing positively to the environment through tree planting. Surprisingly, participants dedicated a substantial amount of time, an average of 11.5 minutes ($SD = 10$ minutes), to complete the real effort tasks to secure an average donation of GBP 1.03.

Lastly, our study is complementary to the broader research landscape on promoting pro-environmental behavior. Many people want to mitigate climate change, but do not exactly know how, do not have the necessary instruments, or are prevented from doing so by psychological barriers. The point is to create the most thriving ground possible to harness the potential of voluntary pro-environmental behavior.

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Appendix A: Additional Analysis

Table 3.6: Descriptive and inferential statistics: Donations

	Donations (in GBP)	
	GAIN ($n = 460$)	*LOSS ($n = 437$)*
Mean	0.99	1.08
SD	0.84	0.89

	GAIN vs. LOSS
Cohen's d	-0.10
95% CI	[-0.23, 0.04]
p-value	0.109

Notes: *p*-values were obtained from a one-sided Wilcoxon-Mann-Whitney test.

Table 3.7: Effects of loss treatment on donation: OLS regression

	(1) Donation	(2) Donation	(3) Donation
LOSS treatment	0.08	0.10*	0.11**
	(0.06)	(0.06)	(0.06)
Pro-environmental intentions		0.10***	0.10***
		(0.03)	(0.03)
Environmental concern		-0.02	-0.02
		(0.04)	(0.04)
Belief in climate change		-0.02	-0.01
		(0.03)	(0.04)
Biospheric values		0.11***	0.08*
		(0.04)	(0.04)
Altruistic values		0.04	0.04
		(0.04)	(0.04)
Egoistic values		-0.08**	-0.05
		(0.03)	(0.03)
Hedonistic values		-0.00	0.03
		(0.03)	(0.03)
Female (1 = female)			0.01
			(0.03)
Age			0.13***
			(0.03)
Education (> High school)			-0.08
			(0.07)
Liberal (1 = liberal)			0.06
			(0.06)
Income (> GBP 50,000)			-0.04
			(0.06)
Risk			0.02
			(0.03)
Intercept	0.99***	0.98***	1.03***
	(0.04)	(0.04)	(0.08)
Observations	897	897	895
R-squared	0.00	0.06	0.08

Notes: The table presents estimates from ordinary least squares (OLS) regressions. Robust standard errors are shown in parentheses and all continuous predictors are mean-centered and scaled by 1 standard deviation. Dependent variable are donations in GBP based on the 90% criterion of correct WEPT pages. Pro-environmental intentions are measured on a 7-point Likert scale. Environmental concern is assessed on a 5-point Likert scale. Belief in climate change is measured on a scale from -5 (“strongly disagree”) to +5 (“strongly agree”). Biospheric, altruistic, egoistic, and hedonistic values are assessed with a scale from -1 (“opposed to my principles”) to 7 (“extremely important”). Female indicates being female (1) or not (0), education whether having a higher education than high school (1) or not (0), being liberal (1) or not (0), or having a higher than annual income GBP 50’000 (1) or not (0). Two participants (1 *GAIN* treatment, 1 *LOSS* treatment) from Specification 2 to 3 are removed because they did not state their income. *, **, and *** document significance at the 10%, 5%, and 1% levels, respectively.

TABLE 3.8: Robustness Check

Dependent variable	WEPT pages			Donations		
	(1)	(2)	(3)	(1)	(2)	(3)
Main sample	0.50*	0.60**	0.67**	0.08	0.10*	0.11**
	(0.29)	(0.28)	(0.28)	(0.06)	(0.06)	(0.06)
n	897	897	895	897	897	895
incl. tree planting	0.56**	0.64**	0.71**	0.09*	0.11*	0.12**
skeptic	(0.28)	(0.28)	(0.28)	(0.06)	(0.06)	(0.06)
n	912	912	910	912	912	910
incl. pilot study	0.55**	0.64**	0.72***	0.09*	0.11**	0.13**
	(0.28)	(0.28)	(0.27)	(0.06)	(0.06)	(0.06)
n	927	927	925	927	927	925
incl. all WEPT pages	0.32	0.44	0.53*	0.05	0.07	0.09
	(0.30)	(0.30)	(0.29)	(0.06)	(0.06)	(0.06)
N	897	897	895	897	897	895
Low biospheric values	0.73*	0.77**	0.80**	0.14*	0.15*	0.15**
	(0.37)	(0.38)	(0.38)	(0.08)	(0.08)	(0.08)
n	432	432	432	432	432	432

Notes: The table displays the coefficients of the loss treatment as dummy variable of Specification 1 to 3 of Model 1. In Specification 3, two participants (1 gain treatment, 1 loss treatment) are removed because they did not state their income (except in sample 'low biospheric values'). While all four samples ('Main sample', 'incl. tree planting skeptic','incl. pilot study', 'low biospheric values') do account for failed attention check, the sample 'incl. all WEPT pages' does not. Robust standard errors are shown in parentheses. The sample 'low biospheric values' is based on the median split. Only participants below the median of biospheric values are considered. In columns (1), (2) and (3) the dependent variable is completed WEPT pages according to the 90% criterion and total generated donation per participant in column (4), (5) and (6). Main sample is the sample used after the exclusion of participants according to the pre-registered protocol. *, **, and *** document significance at the 10%, 5%, and 1% levels, respectively.

Appendix B: Experimental Instructions

Thank you very much for supporting our research!

Please read the study information below and click “I CONSENT” if you want to take part in this study.

Purpose and methodoly of this study:
This study aims to examine the mechanisms of human decision-making in a computer task. Please complete this study on a computer, not on a smartphone. Thank you!

Duration of this study:
In part 1 of this study, you have the opportunity to work on a task. In part 2, we ask you several questions. The study takes about 11 minutes to complete, but may take longer based on participants’ responses. Participants will receive GBP 1.5 for their participation.

Participant rights:
You participate voluntarily in this study. You keep the right to end your participation at any moment during the study by closing your browser and you know that this will not have negative consequences for you. The study does not entail any known risks.

Data confidentiality:
All tasks and questions are for research purposes only. Your decisions and answers will be anonymised and will not influence the terms of any future studies offered to you on Prolific.

Please click ”I CONSENT” (I wish to participate in the study) to start the study.

—Page Break—

Part 1

First, we would like you to complete a number identification task. Below, you see a series of two-digit numbers. Please click the box below each target number. Target numbers are all numbers that consist of an **even first digit** (i.e., 2, 4, 6, 8) and an **odd second digit** (i.e., 1, 3, 5, 7, 9). For example, ”25” or ”83” would be target numbers, but ”17”, ”42”, or ”56” would not be target numbers.

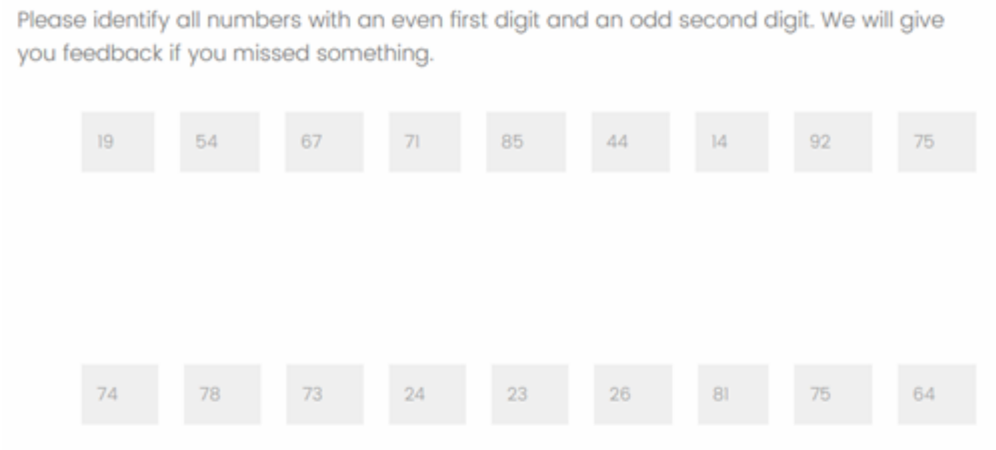

FIGURE 3.4: Trial page of the WEPT task.

—*Page Break*—

In the following, you have the opportunity to complete up to **15 pages** of the number-identification task.

(*GAIN* condition)
With every complete page, you increase the amount of donations to an international, non-profit forest restoration organization that plant trees to mitigate climate change. If you complete every page, you can achieve possible donations of GBP 3.0.

(*LOSS* condition)
If you complete every page you can achieve possible donations of GBP 3.0 to an international, non-profit forest restoration organization that plants trees to mitigate climate change. With every incomplete page, you reduce the amount of donations to mitigate climate change.

For each page, we will tell you how many numbers you will have to check (so that you can estimate the effort) and how much money we will donate if you complete the task. You can then decide, for each page separately, if you want to do this additional effort or not. Doing this task is completely voluntary. You can decide, for each page separately, if you want to do this additional effort or not. If you want, you can decline checking the numbers (by clicking ”no”) every time and go directly to the next part of the study. However, please do not simply close the survey before you have reached the end of it (otherwise we do not know whom to pay for their participation).

Why plant trees to fight climate change?
The climate crisis will have an increasingly negative impact in the coming decades. Carbon dioxide (CO_2) is regarded as a key contributor to climate change, and scientists around the globe agree that climate change can be mitigated only if carbon emissions are dramatically reduced and captured. Trees absorb CO_2, making reforestation one of the most effective carbon capture solutions (Intergovernmental Panel on Climate Change, 2022). Therefore, planting more trees will lead to a great offset of CO_2 emissions and to a great contribution to the fight against climate change. With a donation of GBP 3.0 to the forest restoration organization, 10 trees are planted which leads to a carbon emission offset of 400 kg CO_2 (equivalent to driving an average passenger car 993 km).

The total amount of donations will always be displayed before you decide to work on a page.
The trees for this study will be planted within the next two months. If you would like to receive a confirmation e-mail, you have the opportunity to register yourself below.

Thus, your working effort has real consequences for the environment.

—*Page Break*—

What happens if you decide to complete the page?

- The total amount of donations increases.
- The total amount of donations decreases.
- The total amount of donations stays the same.

What happens if you decide not to complete the page?

- The total amount of donations increases.
- The total amount of donations decreases.
- The total amount of donations stays the same.

Does your behavior have real consequences for the environment?

- Yes.
- No.

Please insert your e-mail if you want to be updated and receive a confirmation that the trees have been planted.

—*Page Break*—

(*GAIN* condition)
Amount of donation: GBP 0

The next page will contain **40 numbers** and **we will add a donation** of **GBP 0.1** to a non-profit forest restoration organization to plant trees if you complete this page.

(*LOSS* condition)
Amount of donation: GBP 3.0

The next page will contain **40 numbers** and **we will reduce the donation** by **GBP 0.1** to a non-profit forest restoration organization to plant trees if you do not complete this page.

(*GAIN* and *LOSS* condition)
If you decide to complete this page, please do so thoroughly because we can only count pages that are at least 90% correct. We will not give you feedback, so please check whether your answers are correct before proceeding to the next page.

Do you want to complete this page?

- Yes.
- No.

—*Page Break*—

Survey

To conclude this study, we ask you to answer a final survey. Please answer honestly; you are reminded that all questions are for research purposes only. Your answers will be entirely anonymised and will not influence the terms of any future studies offered to you on Prolific. At the end, you will receive your completion code. Please make sure to copy the code and enter it on Prolific.

Here, we ask you about your behavior in the forthcoming month. Please rate the following statements on the 7-point scale:
(extremely unlikely / moderately unlikely / somewhat unlikely / neither likely nor unlikely / somewhat likely / moderately likely / extremely likely)

- I will try to reduce my carbon footprint in the forthcoming month.
- I intend to engage in environmentally friendly behavior in the forthcoming month.
- I plan to stop wasting natural resources in the forthcoming month.

—*Page Break*—

Listed below are statements about the relationship between humans and the environment. For each one, please indicate how much you agree with it.
(5 point Likert scale: strongly disagree / somewhat disagree / unsure / somewhat agree / totally agree)

- We are approaching the limit of the number of people the earth can support.
- Humans have the right to modify the natural environment to suit their needs.
- When humans interfere with nature it often produces disastrous consequences.
- Human ingenuity will ensure that we do NOT make the earth unlivable.
- Humans are severely abusing the environment.
- The earth has plenty of natural resources if we just learn how to develop them.
- Plants and animals have as much right as humans to exist.
- The balance of nature is strong enough to cope with the impacts of modern industrial nations.
- Despite our special abilities humans are still subject to the laws of nature.
- Please select ”totally agree”.

- The so-called ecological crisis facing humankind has been greatly exaggerated.
- The earth is like a spaceship with very limited room and resources.
- Humans were meant to rule over the rest of nature.
- The balance of nature is very delicate and easily upset.
- Humans will eventually learn enough about how nature works to be able to control it.
- If things continue on their present course, we will soon experience a major ecological catastrophe.

—*Page Break*—

Below you will find 16 values. Behind each value there is a short explanation concerning the meaning of the value. Please rate how important each value is for you AS A GUIDING PRINCIPLE IN YOUR LIFE? You can use the values in-between to indicate where you fall on the scale. In the following scale: -1 means *opposed to my principles*, 0 means *not important*, 7 means *extremely important.* (nine point Likert scale ranging from -1 to 7)

- EQUALITY: equal opportunity for all
- RESPECTING THE EARTH: harmony with other species
- SOCIAL POWER: control over others, dominance
- PLEASURE: joy, gratification of desires
- UNITY WITH NATURE: fitting into nature
- A WORLD AT PEACE: free of war and conflict
- WEALTH: material possessions, money
- AUTHORITY: the right to lead or command
- SOCIAL JUSTICE: correcting injustice, care for the weak
- ENJOYING LIFE: enjoying food, sex, leasure, etc.
- Please select ”opposed to my principles”
- PROTECTING THE ENVIRONMENT: preserving nature
- INFLUENTIAL: having an impact on people and events
- HELPFUL: working for the welfare of others
- PREVENTING POLLUTION: protecting natural resources
- SELF-INDULGENT: doing pleasant things
- AMBITIOUS: hard working, aspiring

—*Page Break*—

Further questions:

- To what extent do you agree with this statement: The occurrence of climate change is caused by human activities and will bring largely negative consequences. You can use the values in-between to indicate where you fall on the scale. In the following scale: -5 means strongly disagree, 5 means strongly agree.
- How effective do you consider tree planting to be as a climate protection measure? (not effective at all / not very effective / effective / very effective)
- What is your gender? (Female / Male / Prefer not to say / Prefer to self-describe)
- How old are you?
- What is the highest degree or level of education you have completed? (Less than High School diploma / High School or equivalent / Bachelor degree (e.g., BA, BSc) / Master degree (e.g., MA, MS, MEd / Doctorate (e.g., PhD, EdD, DBA / other)
- In political matters, people talk of “the left/progressive” and “the right/conservative”. How would you place your views on a scale of 1 (completely left/progressive) to 10 (completely right/conservative)? You can use the values in-between to indicate where you fall on the scale.
- Are you generally a person who is willing to take risks or do you try to avoid taking risks? In the following scale: 1 means not at all willing to take risks, 10 means very willing to take risks. You can use the values in-between to indicate where you fall on the scale.
- What is your household income per year? Please estimate your answer in British pounds.
- What is your Prolific ID?

—Page Break—

Thank you for participating in our study

With your work in the decision task you generated GBP {amount of generated donations is displayed} of donations to fight climate change. Because we can only count pages that are at least 90% correct, we will correct your pages before we make the donation. Thus, the final amount of donation might deviate.

The flat payment for this survey is GBP 1.5 and will paid in the next days.

To confirm that you have completed this study, please click ”Finish the study” and you will be redirected to Prolific.

Study 4

Stability of Green Default Adherence in a Costly Moment of Change

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Abstract

Green energy defaults in tariff choices have received substantial research and practical attention. In this longitudinal field study, we examine their effectiveness in a potential moment of change that can disrupt routine decision-making. Exploiting a merger in the Swiss energy landscape, we test how a novel branding and a price change affect people's adherence to a green energy default. Our central result – based on 143,313 meters (data 2019-2022) – is that defaults are very stable. Of those 120,150 with strict default adherence 2019-2021, 99.4% also stick with the green energy default after the merger. The minority who change largely move to cheaper, more conventional energy tariffs. The findings provide a novel perspective on energy tariff defaults and offer more evidence for their effectiveness. Our results indicate that while percentage-wise large, objectively moderate price changes do not meaningfully impact the effectiveness of defaults.

Keywords: Default; Natural experiment; Energy tariff; Moment of change; Cost sensitivity

Author note

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4.1 Introduction

Choice architecture – the intentional design of decision environments that align choices with underlying goals – has received considerable research attention in the social and behavioral sciences (Hummel & Maedche, 2019; Jachimowicz et al., 2019; Kaiser et al., 2020; Mertens et al., 2022), including applications to the domain of energy decisions (Composto et al., 2023; Ebeling & Lotz, 2015; Liebe et al., 2021). The recent report of the Intergovernmental Panel on Climate Change (IPCC) summarizes that choice architecture plays a supporting role in the policy mix surrounding energy decisions, as it works "synergistically with price signals, making the combination more effective" (Creutzig et al., 2022, p. 506).

However, this understanding of choice architecture's synergy with price signals stems largely from a meta-study of energy consumption (Khanna et al., 2021), and insights into how price signals interact with choice architecture around tariff choices remain scarcer. In a recent attempt to assess how the costs of defaults relate to default adherence, Berger et al. (2022) find that increased costs of the default are inversely linked to default adherence in the domain of voluntary carbon offsets made by commercial aviation customers. Findings like these contribute to the notion that "there is no average effect of nudging," as highlighted in the discussion of the recent meta-study by Mertens et al. (2022) and following correspondences (Maier et al., 2022; Szaszi et al., 2022).

This leaves behavioral scientists with the research task to carefully study moderators and boundary conditions that affect the effectiveness of choice architecture interventions and to be mindful of the potential domain-specificity of such interventions. Relatedly, most evidence on choice architecture and behavioral interventions highlighted in IPCC work routinely rests on relatively small sample sizes and short durations. For example, in Nisa et al. (2019), one of the largest prominently cited meta-studies in the IPCC reporting, more than 50% of the studies involve fewer than 100 participants per condition. Although the meta-study reports on 84 single studies and 144 effect sizes, half of the studies included only lasted for one week or less, and studies predominantly took place in artificial laboratories. Hence, surprisingly little evidence exists about the (long-term) effectiveness of behavioral interventions in the field. This is particularly concerning given recent calls within environmental psychology to prioritize impact over theory (Nielsen et al., 2021) and to focus on actual, ideally long-term behavior (Lange et al., 2023).

To address these gaps, we contribute novel data from a longitudinal field study intended to augment our evidence base on the effectiveness of choice architecture interventions. Specifically, we rely on a merger and acquisition among energy providers in Switzerland, which resulted in varying price changes and heterogeneous communication for consumers.

We use this context to examine the price sensitivity of default adherence in energy tariff choices during a potential moment of change. A moment of change refers to a considerable change in an individual's life within a short time that potentially interrupts a specific (habitual) behavior and necessitates conscious deliberation (Thompson et al., 2011). In such moments, behavior change may happen more easily. In our study, the change in question is the acquisition of one's energy provider and the associated price change, which alerts customers about their (defaulted) energy contract.

Specifically, we observe the tariff choice behavior of households of three distinctive groups of households. One group received a letter containing information that their energy provider is changing and that prices are rising. Another group received information that their energy provider is changing and that prices stay about the same. A third group received information that prices are falling (i.e., their energy provider did not change). In all three groups, the default green energy choice is a Swiss hydropower-based tariff. After receiving the letter, households could actively change to a relatively cheaper but more conventional tariff (i.e., including nuclear energy) or a relatively greener but more expensive tariff (i.e., consisting of solar energy). This setting allows us to observe changes to the adherence of a green default for similar customers who either experience positive, negative, or no price changes. Additionally, we argue that this context offers a particularly salient moment for customers to reconsider their tariff choices compared to "normal" price changes administered by one's current energy provider. The change in providers coupled with a price change certainly draws attention to the default tariff as such and provides a test of how robust default energy tariffs are.

4.2 Methods

4.2.1 Study Context

In Switzerland's regulated energy market, households and companies who consume less than 100,000 kWh of energy per year cannot freely choose their energy provider. Instead, they are assigned to the local incumbent. Typical providers offer more than one tariff, including one default tariff, which customers automatically receive when they move into the provider's service area (Liebe et al., 2021). In 2021, three previously separate Swiss energy providers serving adjacent areas outside of a large city merged into one (i.e., one provider integrated two smaller providers into their company and brand). To honor a non-disclosure agreement, we refer to them as Provider A, Provider B, and Provider C. Provider A is the company who integrated Provider B and C. Starting in January 2022, the available electricity tariffs were unified, resulting in considerable price changes for customers of two of the formerly distinct customer groups. This created ideal conditions for the analysis of a natural experiment.

Historically, all energy providers offered their customers three electricity tariffs under their own branding. Starting in 2022, the branding changed to Provider A, offering three electricity tariffs in the regulated market: *Conventional* (mainly nuclear power, supplemented with hydropower), *Renewable* (100% renewable energy, mainly Swiss hydropower, default contract), and *Renewable Plus* (100% solar power, with extra certification). This led to price changes for the default tariff *Renewable* (see Table 4.1 for all tariff price changes): The relative price changes compared to 2021 were -4.55% for Provider A and +11.44% for Provider C. The price for Provider B's customers remained almost stable and increased by merely 0.56%.

TABLE 4.1: Percentage Change for Post-Merger Tariff Prices Compared to Pre-Merger Levels by Provider and Tariff

	Price Change in %		
Tariff	Provider A	Provider B	Provider C
Conventional	-4.76	+0.58	+12.06
Renewable (default)	-4.55	+0.56	+11.44
Renewable Plus	-4.14	+0.46	+10.10

To provide context for the new tariff price structure introduced in 2022, Figure 4.1 illustrates the cost differences across the range of energy consumption in our dataset. The median energy consumption per meter across all providers in 2021 was approximately 2,200 kWh. For this consumption level, the resulting costs would be CHF 496 for *Conventional*, CHF 520 for *Renewable*, and CHF 579 for *Renewable Plus*.

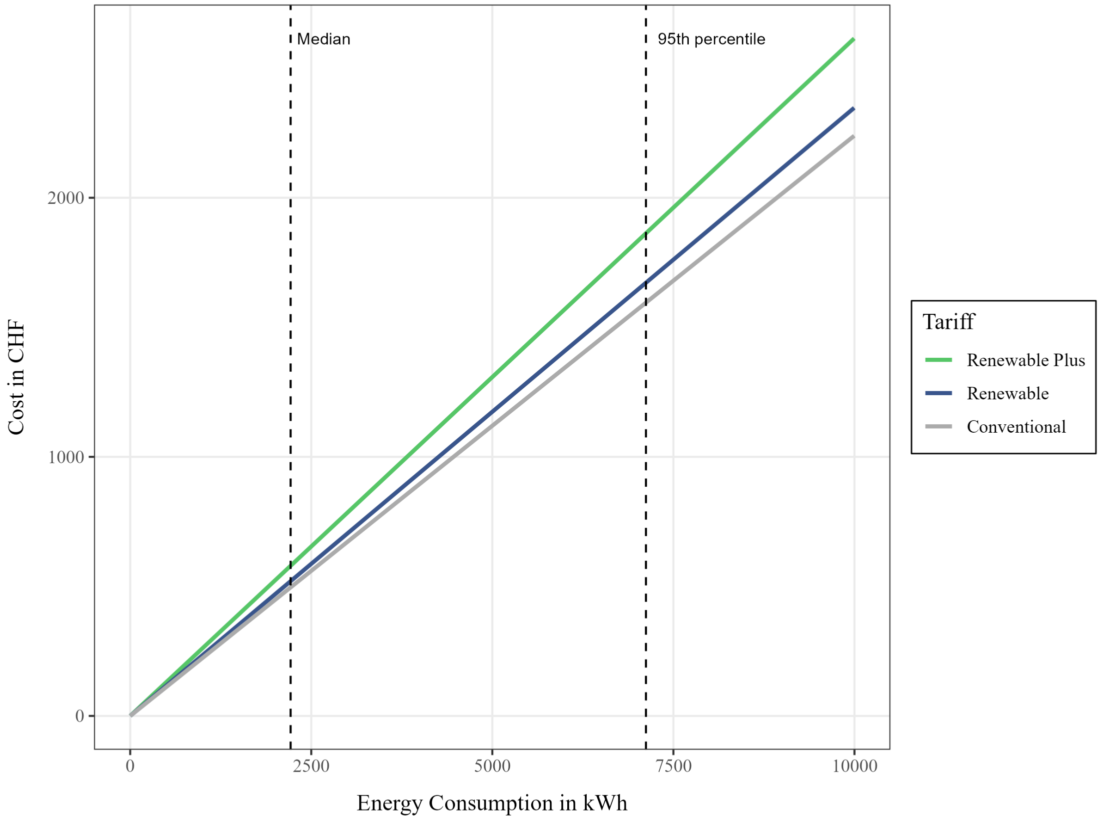

FIGURE 4.1: Visualization of Energy Costs by Consumption for Available Tariffs in 2022

Note. The dashed lines indicate the median and the 95^{th} percentile of consumption in our data for 2021.

4.2.2 Sample Size and Data Inclusion Protocol

We did not pre-register our field study, as many potentially required data exclusions could not have been foreseen and, in fact, only appeared after data collection. Hence, our data inclusion protocol has some degree of arbitrariness. Consequently, we provide Supplementary Material to show that data inclusion decisions did not meaningfully alter any results presented in the results section (see Supplementary Material 1). Our final dataset includes 133,566 active energy contracts, which stem from 141,313 electricity meters (i.e., some contracts include multiple meters) from the three original companies. We excluded 13,974 contracts with more than 10,000 kWh/year consumption as an arbitrary threshold to filter out relatively large business consumers, who consume on average 28,398 kWh/year ($median = 11,985$ kWh/year). Second, due to staggered data collection and billing by the providers, some of the energy consumption data for 2022 is incomplete. To address this, some control models rely on average daily consumption rates rather than annual consumption. Due to the currently limited smart meter rollout, company representatives manually check each meter to record energy consumption throughout the year.

4.2.3 Analytical Approach

Our overall interest is to investigate the stability of default adherence throughout the years 2019-2022. Specifically, we examine the default adherence in the years 2021 to 2022, when the merger happened. To do so, we test if being a customer of Providers A, B, or C before their merger affects the likelihood of switching away from the default tariff (i.e., *Renewable*) after the merger. This allows us to test the degree to which salient changes to the energy tariffs (price, branding) affect default adherence. Besides the descriptive analysis, we employ a standard difference-in-differences approach to investigate the effects in question inferentially. Using a generalized linear mixed model framework, we test how the likelihood of default adherence (i.e., our central dependent variable) depends on three factors: time period (*Pre-Merger 2020*, *Pre-Merger 2021*, and *Post-Merger*), customer group membership (Providers A, B, or C), and energy consumption rate.

4.3 Results

Overall, the implemented default had a large and persistent effect on people's tariff choices. The overwhelming majority of customers across all three providers remained with the default tariff throughout the entire period from 2019 to 2022 (Figure 4.2, left panel). This is consistent with prior findings around default effects in energy tariff choices (Ebeling & Lotz, 2015; Liebe et al., 2021).

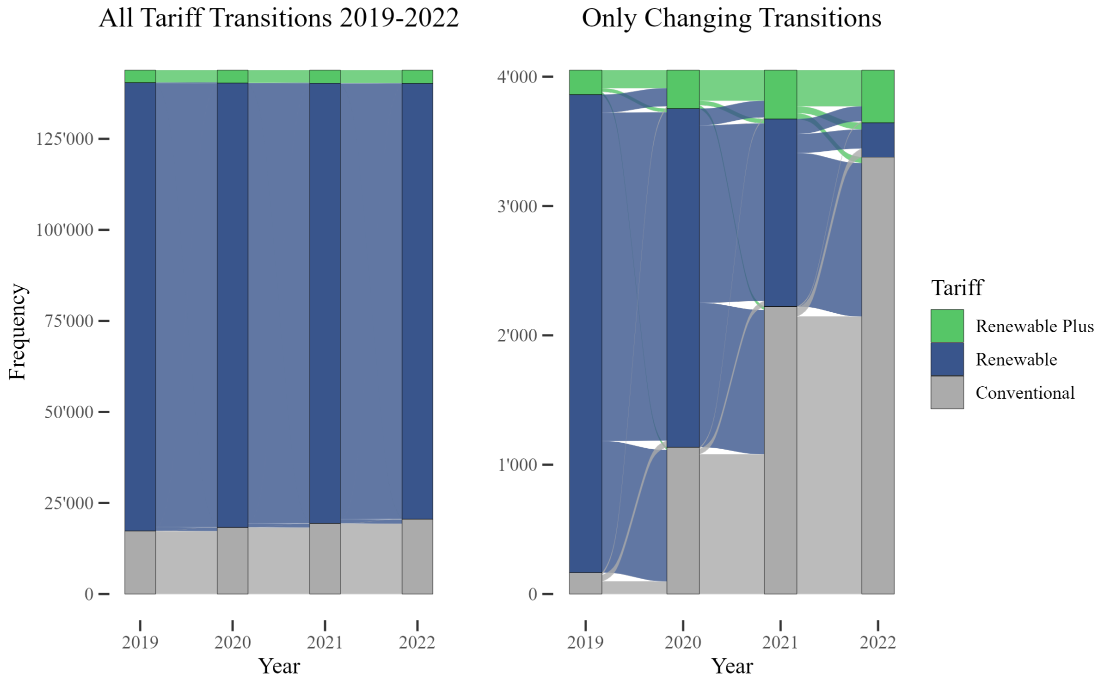

FIGURE 4.2: Graphical Representation of Tariff Transitions for Consumers of All Three Providers 2019-2022 (Left), and the Subset of Transitions Containing at Least One Change in the Same Time Period (Right)

As a novel contribution, we do not find that the heterogeneous price changes and communication associated with the merger had any meaningful effect on default adherence –certainly not in the way one would expect if customers displayed price sensitivity. Statistically, there was one significant effect for the relevant interaction term in the difference-in-differences models. For the time period *Post-Merger*, the customer group of Provider A, compared to Provider B (the reference group), showed a statistically significant lower adherence (*odds ratio* $= 0.54$, 95% CI $[0.30 - 0.95]$, $p = .031$; see Model 1 in Table 4.3). This is surprising when considering that Provider A offered its customers a price decrease for 2022. However, the difference is small in practical terms. The predicted adherence probability for Provider A decreases from 99.90% in 2021 to 99.58% in 2022, a change of -0.32 percentage points. For Provider B, the predicted probability decreases from 99.81% to 99.50%, a barely smaller change of -0.31 percentage points. The interaction of *Post-Merger* and Provider C was not statistically significant (*odds ratio* $= 1.02$, 95% CI$[0.43, 2.41]$, $p = .970$).

Higher energy consumption is associated with slightly lower default adherence (*odds ratio* $= 0.78$, 95% CI $[0.74, 0.83]$, $p < .001$; see Model 2 in Table 3). This finding aligns with previous research, which has shown that higher energy consumption has a small yet negative effect on people's willingness to accept a green default (Ebeling & Lotz, 2015).

Among the tariffs that were actively switched, the majority transitioned from *Renewable* to *Conventional*, a pattern that also aligns with prior research (Liebe et al., 2021). Figure 4.2 (right panel) displays the set of tariffs that were switched at least once for all providers between 2019 and 2022, which depicts the relatively stronger movement to *Conventional* tariffs (i.e., plotted in grey) compared to *Renewable Plus* contracts (i.e., plotted in green). Supplementary Material Tables 4.6 and 4.7 show the distribution for each single provider.

In the subset of tariffs that strictly adhered to the default from 2019 to 2021 and then switched in 2022 ($n = 741$), the same pattern is evident: Table 4.2 shows that there were twelve times as many switches to the cheaper *Conventional* tariff ($n = 685$) compared to the more expensive *Renewable Plus* ($n = 56$). A chi-square test confirmed that a significantly larger proportion of switches to the cheaper option ($\chi^2(1) = 533.93$, $p < .001$). These findings are consistent with the results of Berger et al. (2022), further demonstrating that if customers deviate from a default, they tend to choose options with lower personal costs.

TABLE 4.2: Default Deviations from 2021 to 2022 by Provider and Tariff

Tariff	Provider		
	A	B	C
Conventional	613	39	33
Renewable Plus	52	2	2

To estimate the effect of the cost of adhering to the default more directly, we investigate how the expected energy costs are associated with switching behavior. To do so, we estimate the cost of the default by calculating the expected energy use in 2022 (i.e., the consumption in 2021), multiplied by the additional cost per kWh that comes with sticking to the default compared to the cheapest tariff. In our case, the achievable saving is 0.0108 CHF per kWh and, thus, at most 108 CHF per year for the limit of $10,000$ kWh consumption. The median adherence cost is ~ 24 CHF, and the 95$^{\text{th}}$ percentile is ~ 76 CHF. Regressing default adherence on the expected cost of sticking to the default shows only a minimal effect (see Figure 4.3).

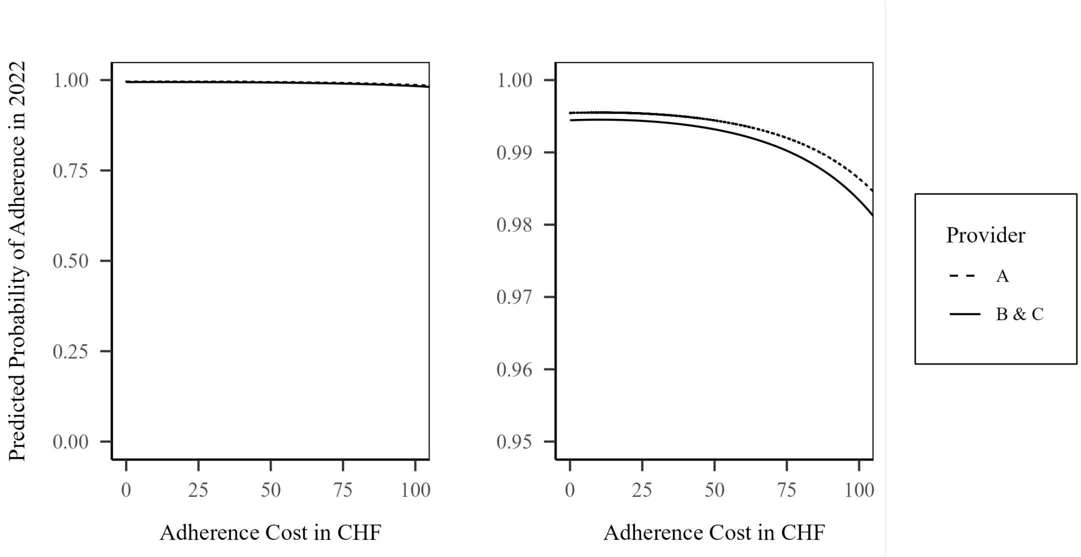

FIGURE 4.3: Impact of Default Adherence Cost on Predicted Adherence Probability for 2022

Note: The figure shows the predicted probability of adhering to the default tariff depending on the associated cost, relative to the cheapest tariff *Conventional*. Both panels are derived from the same underlying model. The panel on the right zooms in on the probability range of [0.95, 1] to offer a more detailed view. The model predicts no discernable difference for Providers B and C. Thus, they are shown as one category. Estimates were obtained from a logit regression with default adherence as the dependent variable and the default adherence cost as the independent variable. The independent variable is an estimate of the cost attached to the default. It was calculated by multiplying the tariff difference (*Renewable* minus *Conventional*) with the energy consumption in 2021. The 95% confidence intervals are virtually identical to the lines in the plot. The corresponding regression results are displayed in Supplementary Table 4.5, the figure is based on Model 2.

Table 4.3: Regression Results for the Relationship Between Customer Group Membership (Provider A, B, or C) and Default Adherence 2021-2022

	Model 1			Model 2			Model 3		
Predictors	Odds Ratios	95% CI	P- Value	Odds Ratios	95% CI	P- Value	Odds Ratios	95% CI	P- Value
Pre-Merger 2020 Provider B (Intercept)	2512.89***	1477.17 – 4274.80	<0.001	2703.47***	1586.45 – 4606.99	<0.001	2749.69***	1594.75 – 4741.06	<0.001
Pre-Merger 2021	0.21***	0.12 – 0.36	<0.001	0.22***	0.13 – 0.37	<0.001	0.22***	0.13 – 0.37	<0.001
Post-Merger 2022	0.08***	0.05 – 0.14	<0.001	0.08***	0.05 – 0.13	<0.001	0.08***	0.05 – 0.13	<0.001
Provider A	2.23**	1.27 – 3.90	0.005	2.09*	1.19 – 3.67	0.010	2.06*	1.16 – 3.65	0.014
Provider C	1.32	0.57 – 3.10	0.516	1.25	0.53 – 2.91	0.612	1.26	0.53 – 2.98	0.600
Pre-Merger 2021 x Provider A	0.86	0.49 – 1.50	0.596	0.84	0.48 – 1.48	0.554	0.84	0.48 – 1.48	0.547
Pre-Merger 2021 x Provider C	1.39	0.59 – 3.27	0.446	1.38	0.59 – 3.23	0.462	1.38	0.59 – 3.24	0.459
Post-Merger x Provider A	0.54*	0.30 – 0.95	0.031	0.56*	0.32 – 0.99	0.046	0.56*	0.32 – 0.99	0.047
Post-Merger x Provider C	1.02	0.43 – 2.41	0.970	1.02	0.43 – 2.43	0.955	1.02	0.43 – 2.42	0.965
Std. Energy Consumption Rate				0.78***	0.74 – 0.83	<0.001	0.76*	0.59 – 0.97	0.030
Std. Energy Consumption Rate x Provider A							1.04	0.80 – 1.35	0.765
Std. Energy Consumption Rate x Provider C							0.91	0.60 – 1.38	0.663
Random Effects									
σ^2	3.29			3.29			3.29		
τ_{00}	24.85 meter_{id}			24.73 meter_{id}			24.77 meter_{id}		
ICC	0.88			0.88			0.88		
N	121354 meter_{id}			121354 meter_{id}			121354 meter_{id}		
Observations	364062			364062			364062		
Marginal R^2 / Conditional R^2	0.054 / 0.889			0.056 / 0.889			0.056 / 0.889		

Note. Results stem from a generalized linear mixed model with a logit link function. The model includes random intercepts for electricity meters and was fitted using maximum likelihood estimation with Adaptive Gauss-Hermite Quadrature (nAGQ = 0). Provider B is the reference group. Std. Energy Consumption Rate is the standardized energy consumption per day in each year. Since the data only contain complete energy consumption for the year 2022, a per-day rate was used instead of absolute consumption. CI = confidence interval.

* $p<0.05$ ** $p<0.01$ *** $p<0.001$.

4.4 Discussion

Through a longitudinal field study, this research investigated the stability of green energy defaults in a potential moment of change. Building on past research suggesting that defaults work over time (Liebe et al., 2021), we tested their robustness in a potential moment of change (Thompson et al., 2011). In our case, this event consisted of an acquisition of two smaller energy providers by a larger provider and accompanying price changes.

There is now increasing evidence about the stickiness of defaults in the domain of tariff choice. We find that even relatively hefty price rises (> 10%) do not meaningfully alter behavioral responses. When customers do switch, they predominantly move to cheaper options, which aligns with prior research (Ebeling & Lotz, 2015). Additionally, higher energy consumption was linked to lower default adherence, suggesting a minor level of cost sensitivity among consumers.

Our study makes a contribution by adding another large field dataset to a domain primarily informed by laboratory studies (Berger et al., 2022; Liebe et al., 2021; Nisa et al., 2019). The longitudinal data allows us to examine behavior over an extended period, providing a more realistic understanding of how choice architecture interventions function in real-world settings and how they unfold over time.

Our findings present relatively strong differences compared to the study by Berger et al. (2022). While their research indicates that higher prices significantly reduce the effectiveness of defaults, almost rendering them ineffective at very high prices, our study suggests a more nuanced picture. It remains an open question how much of a price increase would be ”too high” to maintain the effectiveness of default energy tariffs, and further research is needed to explore this. In fact, the price range of Berger et al. (2022) is much larger than the price range of the present research.

While our field study design does not allow for a perfect manipulation of prices, it offers high external validity. A more controlled laboratory design could have disentangled the effects of price and branding more cleanly but at the cost of real-world applicability. Our difference-in-differences design has its limitations in terms of causal inference. Despite our checks for issues like parallel trends (as detailed in Supplementary Material 2), the design does not fully eliminate the possibility of confounding variables affecting our results.

While our data may include some small businesses in addition to private households, economic arguments should theoretically apply to both. Individuals with high pro-environmental attitudes would be inclined to choose the same contract for their private as for their professional electricity consumption. Liebe et al. (2021) have shown that both private and business consumers generally behave similarly.

In terms of future research, one promising avenue would be to investigate the effects of behavioral science interventions during moments of change more carefully and across various domains. While our study focuses on energy tariff choices, extending this research to more significant behaviors would be interesting. For example, future studies could explore how moments of change impact the uptake of solar panels, the installation of heat pumps, or even shifts in modes of transportation like transitioning from car usage to public transport.

Data availability

The data were obtained by a Swiss electricity provider and are anonymized and part of non-disclosure agreements. Upon request and depending on consent from the provider, the data can be made available for replication.

Code availability

The code used in this study is available from the authors upon request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT based on OpenAI's GPT-4 and DeepL SE's DeepL Translator in order to enhance clarity of the English writing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Supplementary Material 1

Table 4.4: Regression Results for the Relationship Between Customer Group Membership (Provider A, B, or C) and Default Adherence 2021-2022

	Model 1			Model 2			Model 3		
Predictors	Odds Ratios	95% CI	P- Value	Odds Ratios	95% CI	P- Value	Odds Ratios	95% CI	P- Value
Pre-Merger 2020 Provider B (Intercept)	2130.24***	1359.08 – 3338.96	<0.001	2160.68***	1376.38 – 3391.89	<0.001	2125.09***	1353.10 – 3337.53	<0.001
Pre-Merger 2021	0.20***	0.13 – 0.31	<0.001	0.19***	0.12 – 0.31	<0.001	0.20***	0.12 – 0.31	<0.001
Post-Merger 2022	0.08***	0.05 – 0.13	<0.001	0.08***	0.05 – 0.12	<0.001	0.08***	0.05 – 0.12	<0.001
Provider A	2.42***	1.50 – 3.91	<0.001	2.43***	1.50 – 3.92	<0.001	2.45***	1.52 – 3.96	<0.001
Provider C	1.29	0.62 – 2.69	0.499	1.29	0.62 – 2.70	0.502	1.22	0.58 – 2.55	0.603
Pre-Merger 2021 x Provider A	0.86	0.53 – 1.38	0.531	0.86	0.53 – 1.38	0.531	0.85	0.53 – 1.38	0.518
Pre-Merger 2021 x Provider C	1.49	0.71 – 3.12	0.292	1.49	0.71 – 3.13	0.291	1.48	0.70 – 3.11	0.302
Post-Merger x Provider A	0.48**	0.29 – 0.78	0.003	0.48**	0.30 – 0.78	0.003	0.49**	0.30 – 0.79	0.004
Post-Merger x Provider C	1.02	0.48 – 2.15	0.961	1.02	0.48 – 2.16	0.961	1.04	0.49 – 2.20	0.918
Std. Energy Consumption Rate				0.96*	0.94 – 0.99	0.013	0.19	0.03 – 1.17	0.073
Std. Energy Consumption Rate x Provider A							5.19	0.83 – 32.58	0.079
Std. Energy Consumption Rate x Provider C							0.36	0.03 – 4.49	0.426
Random Effects									
σ^2	3.29			3.29			3.29		
τ_{00}	23.57 meter_{id}			23.76 meter_{id}			23.70 meter_{id}		
ICC	0.88			0.88			0.88		
N	135,940 meter_{id}			135,940 meter_{id}			135,940 meter_{id}		
Observations	407820			407820			407820		
Marginal R^2 / Conditional R^2	0.060 / 0.885			0.060 / 0.886			0.060 / 0.886		

Note. *** p<0.001, ** p<0.01, * p<0.05; CI = Confidence Interval.

As in the main text, the implemented default had a large and persistent effect on people's tariff choices. We do not find that the differing price changes caused by the merger of the three providers had any practically meaningful effect on default adherence. However, there was a significant effect for the interaction terms of time period Post-Merger and the customer group of Provider A compared to Provider B (for Provider A: *odds ratio* = 0.48, 95% CI $[0.29, 0.78]$, $p = .003$). However, the effect is small in practical terms. The predicted adherence probability decreases from 99.89% to 99.49% for Provider A from 2021 to 2022, a change of -0.39 percentage points. For Provider B, the predicted probability decreases from 99.76% to 99.41%, a slightly smaller change of -0.35 percentage points. The interaction of Post-Merger and Provider C was not statistically significant (*odds ratio* $= 1.02$, 95% CI $[0.43, 2.41]$, $p = .970$). The interaction was not statistically significant for Provider C (*odds ratio* $= 1.02$, 95% CI $[0.48, 2.15]$, $p = .961$; see Model 1 in Table S1).

As in the main text, the likelihood of adhering to the default does slightly decrease from 2020 to 2021 and from 2021 to 2022, but the effects are quite small in practical terms (i.e., for the customers of Provider B in 2021: *odds ratio* $= 0.2$, 95% CI $[0.13, 0.31]$, $p < .001$; for 2022: *odds ratio* $= 0.08$, 95% CI $[0.05, 0.13]$, $p < .001$; see Model 1 in Table S1) compared to the overall adherence.

As in the main text, the customer group of Provider A exhibited higher odds of default adherence (*odds ratio* $= 2.24$, 95% CI $[1.50, 3.91]$, $p < .001$) compared to the customers of Provider B (Model 1, Table S1).

As in the main text, higher energy consumption is associated with slightly lower default adherence (*odds ratio* $= 0.96$, 95% CI $[0.94, 0.99]$, $p = .013$; see Model 2 in Table 4.4).

TABLE 4.5: Logit Regression with Default Adherence as the Dependent Variable and the Default Adherence Cost as the Independent Variable

	Model 1			Model 2		
Predictors	Odds Ratios	95% CI	P-Value	Odds Ratios	95% CI	P-Value
Intercept	267.67***	195.20 – 377.30	<0.001	219.02***	155.16 – 316.95	<0.001
Adherence Cost	0.99***	0.99 – 0.99	<0.001	1.00	0.99 – 1.01	0.561
Provider A	0.81	0.58 – 1.10	0.191	0.82	0.59 – 1.11	0.210
Provider C	1.00	0.64 – 1.58	0.993	1.00	0.63 – 1.58	0.992
Adherence Cost Squared				1.00**	1.00 – 1.00	0.006
Observations	120,150			120,150		
R^2 Tjur	0.000			0.001		

Note. The independent variable is an estimate of the cost attached to the default. It was calculated by multiplying the tariff difference (*Renewable* minus *Conventional*) with the energy consumption in 2021.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Figure 4.4 shows the descriptive values of median energy consumption by provider, year, and tariff 2019-2021 (total consumption for 2022 is incomplete for parts of our data). The simplified pattern would suggest that cheaper energy is consumed more. The only "irregular" trend is the one for tariff *Conventional* for Provider B, which breaks this pattern. Additionally, Provider B's customer base generally seems to consume slightly more than the other two. Another observation particular to this observation period is that the pandemic caused by the coronavirus does not seem to have influenced energy consumption (with subsequent lockdowns, e.g.) in the customer groups equally (if at all). This fact lends robustness to our analysis, as large increases in consumption could have already heightened consumer sensitivity to electricity prices, thereby complicating the interpretation of our 2021-2022 natural experiment.

Figure 4.5 shows the median daily consumption rate by provider, year, and tariff for 2019-2022. To account for only having data of partial consumption in year 2022, the figure shows the median daily consumption rate. Generally, consumption is the highest for the cheapest tariff *Conventional*. Customers of Provider A show a clearly lower daily consumption pattern for tariff *Renewable Plus* compared to *Renewable*, while for Providers B and C this order is reversed, and consumption is lower for tariff *Renewable* than for*Renewable Plus*.

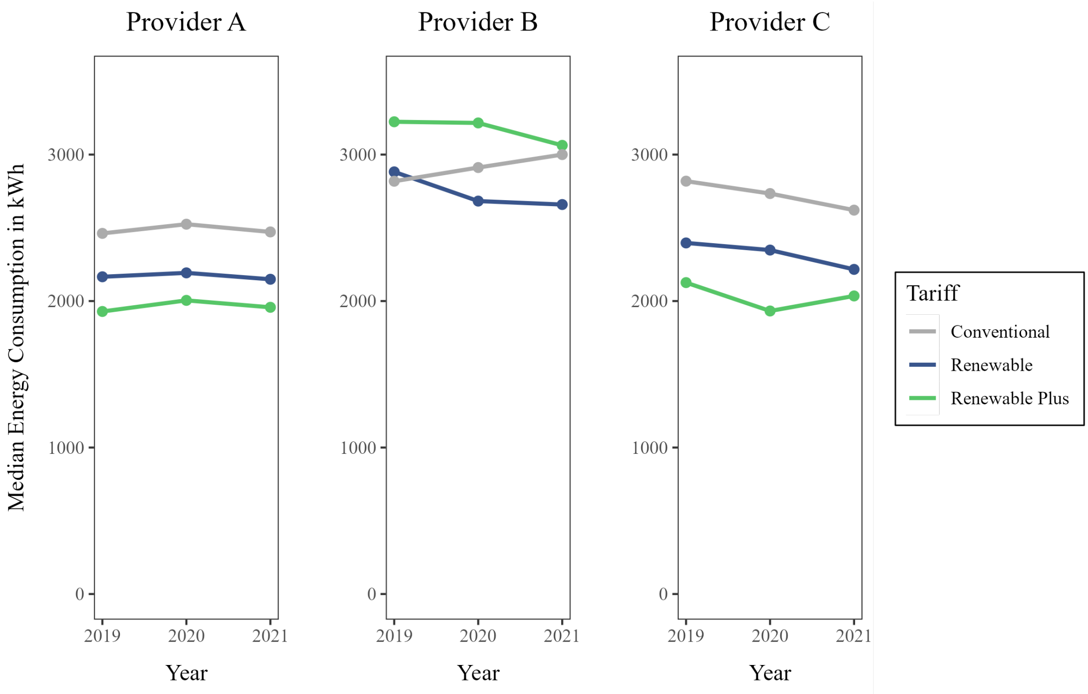

FIGURE 4.4: Comparison of Median Electricity Consumption by Provider, Year, and Tariff

Note. Our dataset only includes complete consumption data for the years 2019-2021.

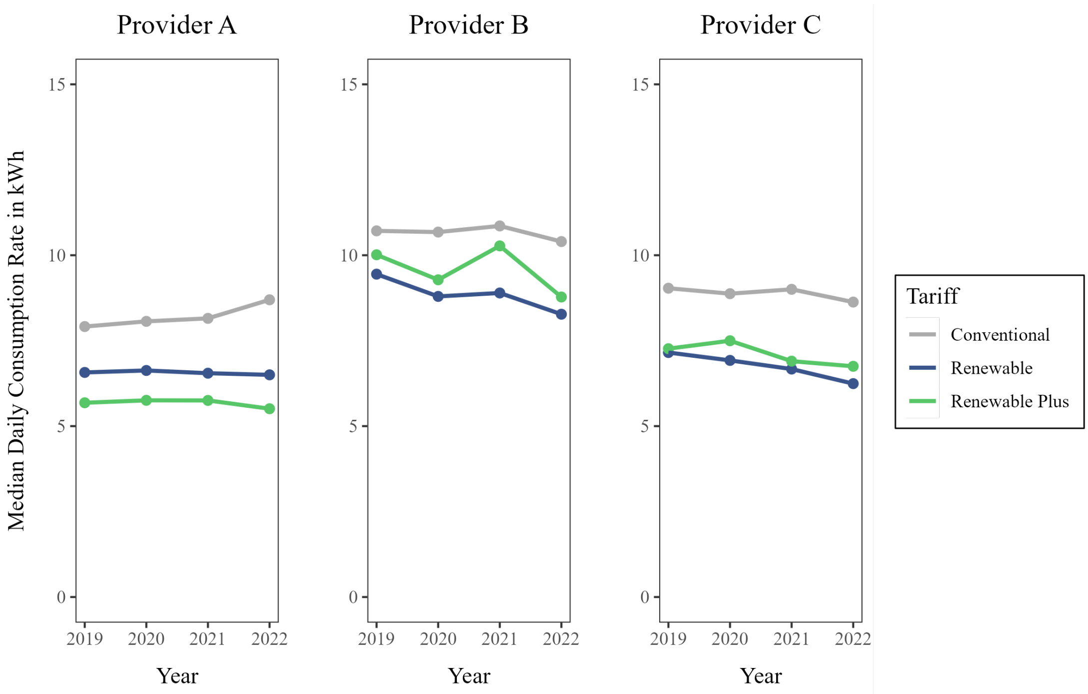

FIGURE 4.5: Comparison of Median Daily Electricity Consumption Rate by Provider, Year, and Tariff

Note. To account for variations in billing periods across customers in 2022, energy consumption is adjusted by dividing it by the number of days billed, thereby generating a standardized energy consumption rate.

Supplementary Material 2

Parallel trends assumption

To identify the effects in our analysis, we rely on the assumption that default adherence in all customer groups followed parallel trends before the merger. To verify, we examine the trends of default adherence for all three customer groups prior to the implementation of the merger. As illustrated in Figure 4.6, the default adherence rates for each customer group followed parallel (decreasing) trajectories until 2021, providing strong evidence that the assumption holds. However, as stated above, the price changes had no apparent influence on default adherence. This is qualitatively reflected in the same figure, as the trends of the three customer groups continue seemingly unaffected after the merger. Tables 4.6 and 4.7 provide exact values for the tariff distributions for all providers in 2021 and 2022.

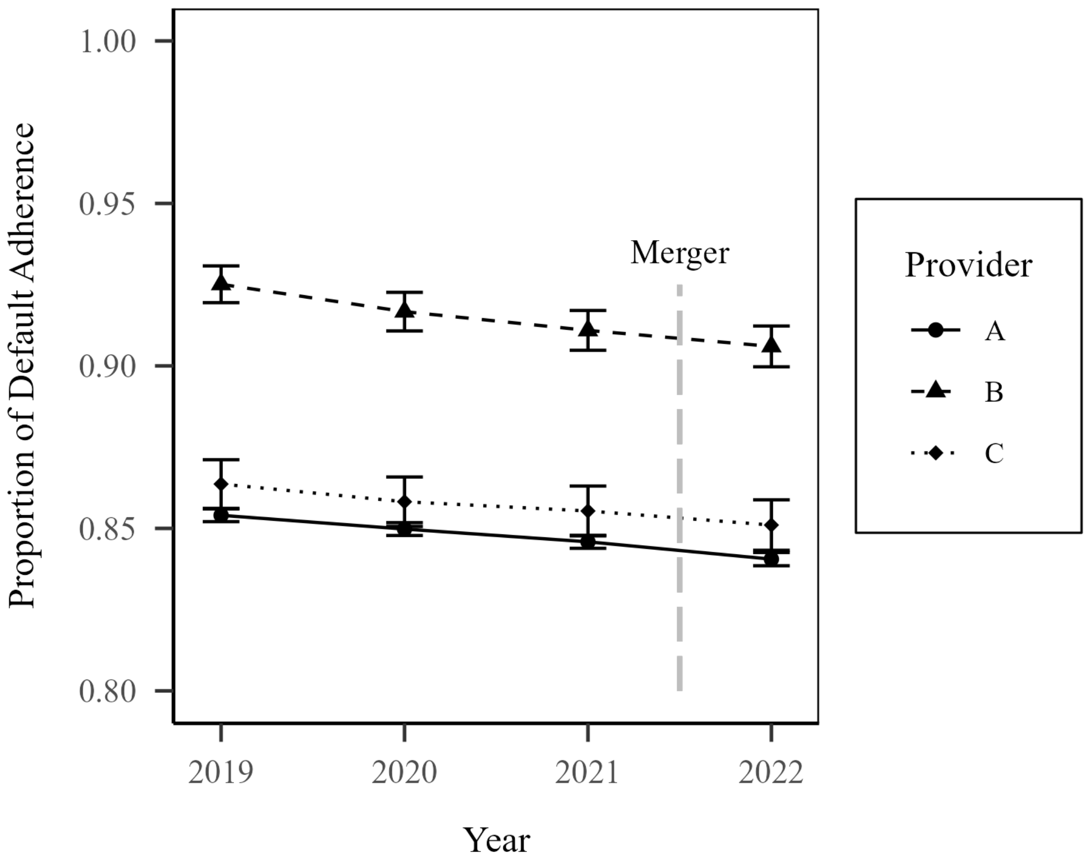

FIGURE 4.6: Default Adherence Trends (to Tariff Renewable) by Provider from 2019 to 2022

Note. Whiskers indicate 95% confidence intervals.

TABLE 4.6: Energy Tariff Distribution by Providers in 2021

	Provider			
Tariff	A	B	C	Total
Conventional	17,350 (14%)	851 (9.9%)	1,193 (15%)	19,394 (13%)
Renewable	106,246 (84%)	7,658 (89%)	6,958 (85%)	120,862 (84%)
Renewable Plus	3,501 (2.8%)	52 (0.6%)	67 (0.8%)	3,620 (2.5%)
Total	127,097 (100%)	8,561 (100%)	8,218 (100%)	143,876 (100%)

Note. The overall number of tariffs differs between 2021 and 2022 due to customers switching from and to other tariffs not analyzed in this study.

TABLE 4.7: Energy Tariff Distribution by Providers in 2022

	Provider			
Tariff	A	B	C	Total
Conventional	17,040 (15%)	958 (11%)	1,345 (15%)	19,343 (14%)
Renewable	97,053 (83%)	7,887 (89%)	7,341 (84%)	112,281 (83%)
Renewable Plus	3,177 (2.7%)	62 (0.7%)	78 (0.9%)	3,317 (2.5%)
Total	117,270 (100%)	8,907 (100%)	8,764 (100%)	134,941 (100%)

Note. The overall number of tariffs differs between 2021 and 2022 due to customers switching from and to other tariffs not analyzed in this study.

Selbstständigkeitserklärung

Ich erkläre hiermit, dass ich diese Arbeit selbstständig verfasst und keine anderen als die angegebenen Quellen benutzt habe. Alle Koautorenschaften sowie alle Stellen, die wörtlich oder sinngemäss aus Quellen entnommen wurden, habe ich als solche gekennzeichnet. Mir ist bekannt, dass andernfalls der Senat gemäss Artikel 36 Absatz 1 Buchstabe o des Gesetzes vom 5. September 1996 über die Universität zum Entzug des aufgrund dieser Arbeit verliehenen Titels berechtigt ist.

Bern, 31. Oktober 2023

Daniel Bregulla