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Promoting energy conservation and environmental protection with behavioral economics

Theory and evidence

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Abstract

This Doctoral thesis studies how nudges can help protect the environment. Three empirical and one theoretical studies investigate applications of green nudges and identify situations where they should, or should not, be used to promote environmental conservation.

In Chapter 1, we explore the interplay between nudges and financial policy instruments using an incentivized online experiment that reproduces daily energy behaviors. We find that these two tools do not perform better when implemented together than individually. Our results suggest that in some situations, displacements between behavioral and financial policy tools are more likely to arise than synergies.

Chapter 2 presents a field study in which a behavioral intervention is used to promote energy conservation in the workplace. Using a difference-in-difference approach, we find a significant reduction in branches' monthly consumption outside the work schedule only, but not on overall consumption. Our findings suggest that nudges that are effective in the household context do not necessarily prompt behavioral change in the working environment.

In Chapter 3, we develop a behavioral model for the usage of in-home displays that provide real-time feedback on energy consumption, focusing on social housing. On top of the cost-benefit analysis between financial and moral utility, on the one hand, and the effort from using them, on the other hand, we add the role of cognitive biases. This study seeks to improve the design of behavioral policies aimed at tackling energy poverty.

Chapter 4 presents an incentivized online experiment that studies moral cleansing in the interpersonal and environmental domains. We find that bad behaviors that impact others trigger costly moral cleansing, whereas those that impact the environment do not even trigger costless cleansing. This empirically shows that people perceive environmental issues differently from other moral issues.

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Introduction

Anthropogenic impact on the environment poses a major threat to natural ecosystems and to the health, economic prospects, and basic resources of people (IPCC, 2014). Its negative effects are already visible, such as in extreme weather events and mass animal extinction, and are expected to become even more severe in the next few years. The primary cause of this disruption is human behavior. But human behavior can also be the way out: if people support green policies, increase the sustainability of their lifestyle, and reduce their consumption, this trend can be altered.

Traditional economic theory describes humans as rational and self-interested, who contribute to environmental conservation only in exchange for personal benefits. Accordingly, market-based policies, which act upon prices to make environmental options convenient (e.g., subsidies on renewables), and regulatory measures, which exclude polluting alternatives from the choice set (e.g., energy-efficiency standards), have been the most commonly used demand-side policy tools.

However, a new view on human decision-making has emerged in recent decades. Behavioral economics has shown that people have cognitive limitations, change preferences depending on decision framing, and care about others. As a consequence, a new category of policy tools has emerged, the so-called nudges (also known as behavioral interventions). A nudge "alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, [an] intervention must be easy and cheap to avoid" (Thaler & Sunstein, 2008, p. 6). They do not change the incentive structure of behaviors or the set of choices. What they change is the underlying choice architecture, for example, by making healthy food more accessible so customers eat more healthfully or by automatically enrolling people in retirement plans.

Thanks to their wide applicability and high impact-to-cost ratio, behavioral interventions have been widely used to promote socially relevant outcomes (OECD, 2017).[1] Many economic applications belong to the domain of energy conservation. Social information, i.e., providing a household with information on how much it consumes relative to similar households, has received the most attention (Allcott, 2011; Allcott & Rogers, 2012; Ferraro, Miranda, & Price, 2011). Another successful strategy involves making green options the default: if people have to opt out, they are more likely to adopt renewable energy plans (Kaiser, Bernauer, Sunstein, & Reisch, 2020) or participate in carbon offsetting programs (Araña & León, 2013) than if they have to opt in.

Yet, some aspects of nudging need further investigation. The ultimate goal of this thesis is to expand the understanding of when behavioral interventions are useful companions in the fight against climate change and the other pressing environmental issues we currently face.

The first Chapter, co-authored by Matteo Ploner and Massimo Tavoni, investigates the interplay between nudges and market-based policy instruments. Although non-pecuniary measures have been widely used to promote socially relevant outcomes, whether they complement or are substitutes for traditional policy instruments remains unclear. As they affect behavior through different mechanisms, many posit that nudges complement traditional policy tools. However, there are also explanations that account for the opposite. A better understanding of the topic would enable policy makers to implement only the combinations of behavioral and market-based tools that give rise to synergies. We conduct an incentivized online experiment where we investigate the effect of a nudge (goal setting and feedback) and a financial reward implemented individually or jointly (versus a control condition) on participants' simulated energy savings. The contribution of this paper is also methodological, as we develop an incentive-compatible task that captures the trade-off of energy conservation between private and societal benefits on one side and personal disutility on the other. More precisely, participants interact with a simulated washing machine. If they reduce their virtual consumption, they receive an economic prize and create positive environmental externalities; however, doing so requires cognitive effort.

Our findings show that integrating the two instruments does not enhance the effect of single policies. Rather, the treatment that combines both interventions affects behavior in the same way as the nudge alone does. Human's limited cognitive resources may explain this result: the

[1] Nudges have also received criticism under different aspects, e.g., because they reduce individuals' autonomy (Hausman & Welch, 2010; Mitchell, 2005), can entail negative distributional consequences (Ghesla, Grieder, & Schubert, 2020) and alter societal self-legislation (Lepenies & Małecka, 2015). Others question their effectiveness (Hummel & Maedche, 2019).

nudge may have diverted participants' attention from the financial incentive, thereby reducing its impact. The implication is that while nudges influence behaviors in a different way than traditional policy tools, there are situations where they reduce (rather than reinforce) their impact. Policy makers should evaluate case-by-case traditional-behavioral mixes and implement only those that generate synergies.

The second Chapter, conducted in collaboration with Giovanna D'Adda and Massimo Tavoni, sheds light on another gap in the application of behavioral interventions to energy conservation, namely, their effectiveness in the workplace. Economists to date have mostly studied non-price measures in the residential sector. However, domestic and non-domestic settings differ in a number of ways, such as the lack of financial incentive and the collective nature of consumption in the latter, which may undermine employees' readiness to make an effort to reduce their consumption and respond to conservation programs. In this study, we partner with an Italian company that implemented a large-scale behavioral intervention consisting of an energy-saving competition among its branches. We assess the impact on branches' monthly energy consumption from mid-2017 to the end of 2019 using a difference-in-difference estimation. We find that the competition generates significant savings outside the working schedule, but this effect is not strong enough to affect total consumption. Reducing inefficiencies is easier outside working hours because employees perform energy-consuming tasks at work and may not be willing to sacrifice their comfort. Our results stress the importance of considering contextual characteristics when implementing behavioral programs and suggest caution in their application in the workplace.

This study also explores the interplay between the energy-saving competition and a traditional policy tool, expanding the investigation of the first chapter. We assess the impact of a retrofit intervention that took place before the study period and involved a subset of highly consuming branches. Our results show a large and significant effect on branches' monthly consumption. As for the energy-saving competition, this effect is higher outside working hours than during the main work schedule. The fact that both interventions act on similar sources of inefficiencies suggests they may displace if they are jointly implemented. Consistent with the previous study, these results identify another situation in which displacements between two instruments are more likely to arise than synergies.

The third Chapter, co-authored by Nives DellaValle, contributes to the emerging literature that proposes behavioral interventions as instruments to fight energy poverty. It studies how cognitive biases affect the decision-making underlying individuals' responses to behavioral interventions. These considerations are particularly important when using nudges to fight energy poverty, as scarcity affects cognitive processes in a way that may undermine policies' impacts. We develop a theoretical model of the decision to interact with in-home displays that provide real-time feedback on households' energy consumption. On the one hand, their usage yields a reduction in energy bills and environmental impact. On the other hand, their usage requires effort. We add the role of present bias and locus of control to this cost-benefit analysis. For both biases, we propose that the higher their severity, the more the equilibrium choice leans toward the non-usage alternative. Our theoretical discussion contributes to informing the design of behavioral policies aimed at tackling energy poverty and stresses, once again, the importance of contextual characteristics when designing and implementing nudges.

Taken together, the results of the first three chapters extend the understanding of the situations in which nudges can be used to promote energy conservation. The final Chapter complements these insights by taking a step back to address the following question: Do environmental issues activate human moral intuition in the same way that other moral issues do? This is an open debate in the literature. Many argue that environmental issues are moral problems in themselves insofar as they affect people's lives, while others argue that given their complex, global and unintentional nature, they trigger different moral dynamics to other domains, particularly interpersonal behavior. This question is also of practical relevance in view of the growing interest in studying whether dissonance reduction strategies, such as behavioral change and strategic information avoidance, also arise in the context of environmental protection.

The fourth Chapter, co-authored by John Thøgersen, sheds further light on the topic by exploring moral cleansing, i.e., behaviors aimed at compensating for prior moral transgressions, in different domains of morality. We conduct an incentivized online experiment where participants recall a time they harmed another person or the environment or a neutral event. They are then provided with different moral cleansing options that vary in costliness (high versus low) and beneficiary (humanitarian versus environmental causes). We argue that costly moral cleansing strongly signals one's morality, making it the preferred strategy to reduce the cognitive dissonance caused by bad behaviors with high moral magnitude. Accordingly, we find that participants who recalled interpersonal misbehaviors are significantly more likely to choose costly cleansing. Instead, when the victim is the environment, participants do not even display costless cleansing, showing that "anti-environmental" behaviors do not trigger cognitive dissonance. Our results provide empirical evidence illustrating that environmental problems differ from other moral issues. As a direct policy implication, this study suggests that prompting moral cleansing can be an effective nudge to promote prosocial behavior but only if it is triggered by deeds that are central to people's morality.

The thesis concludes with a summary of the results and their implications, discusses the limitations, and proposes avenues for future research.

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CHAPTER 1

Energy saving in a simulated environment: An online experiment of the interplay between nudges and financial incentives

with Matteo Ploner (University of Trento) and Massimo Tavoni (Politecnico di Milano)[1]

Abstract

Though nudges are gaining attention as complements to financial incentives, evidence of the interplay between these two policy instruments is lacking. Here, we discuss and evaluate how combinations of financial policies and nudges affect behaviors. Through a framed online experiment, we assess the effect of combining financial incentives (monetary reward) with nudges (goal setting and feedback). We introduce an innovative incentive-compatible energy-saving task: participants optimize their virtual energy consumption on a simulated washing machine. Our findings do not show evidence of synergies between traditional and behavioral interventions. On the contrary, the nudge seems to divert participants' attention from the financial incentive.

Keywords: Financial incentive; Nudge; Goal setting; Motivation crowding out; Online experiment; Energy conservation

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[1] *Author contributions:* VF conceived the study, led the collection and the analysis of the data and the writing of the manuscript. MP contributed to the conception and the design of the study, to the preparation of experimental material, and to manuscript writing. MT contributed to the conception and the design of the study, to manuscript writing, and was responsible for the funding.

1.1 Introduction

Nudges seek to change "people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (Thaler & Sunstein, 2008, p. 6). Policy interventions of this kind encompass a broad and heterogeneous set of measures that span from social information (Allcott, 2011), which encourages a specific behavior by signaling that others do it, to default options (Araña & León, 2013), whereby people are automatically enrolled in the socially optimal alternative.

Nudges are growing in popularity as strategies to promote socially relevant outcomes (see Benartzi et al. (2017) and Hummel & Maedche (2019) for reviews). However, little is known about how they interact with market-based policy instruments: existing evidence is scattered and results are inconclusive (Bettinger, Terry Long, Oreopoulos, & Sanbonmatsu, 2012; Chapman, Li, Colby, & Yoon, 2010; Goldin & Lawson, 2016; List, Metcalfe, Price, & Rundhammer, 2017; Mizobuchi & Takeuchi, 2013; Panzone, Ulph, Zizzo, Hilton, & Clear, 2018; Pellerano, Price, Puller, & Sánchez, 2017). A better understanding would enable policy makers to implement only those combinations of financial and behavioral tools that give rise to synergies (rather than displacements). Moreover, when policy makers implement a new nudge, they add it to an existing mix that is likely to influence its effectiveness (Boonekamp, 2006). Considering these interactions, rather than treating policy instruments as orthogonal, increases the chances of achieving policy objectives.

This study sheds further light on the interplay between financial and behavioral policy tools. Drawing on existing literature, we argue that these tools can be combined in two ways. First, the economic incentive is the pivotal mechanism, and the nudge has the ancillary role of conveying it. The underlying idea is that market-based interventions are sometimes ineffective because they entail search and information costs (Chetty, Looney, & Kroft, 2009). Nudges can improve their effectiveness by making financial benefits more accessible. For example, Chapman et al. (2010) find that automatically assigning people to free vaccination appointments significantly increases vaccination rates. Similar results are observed in the field of education, where more readily available financial aids increase college attendance (Bettinger et al., 2012). Hence, this way of combining market-based and behavioral policies is expected to give rise to synergies.

Second, financial and behavioral policies are combined as stand-alone instruments, appealing to extrinsic (i.e., economic) and intrinsic (e.g., moral utility (Allcott & Kessler, 2019; Myers & Souza, 2020)) sources of motivation. For example, to promote green shopping, a supermarket could introduce a carbon tax and remind its clients of their previous pro-environmental behaviors to reinforce their green habits (Panzone et al., 2018). From this perspective, whether positive or negative interactions arise is still unclear. On the one hand, the fact that market-based policies and nudges affect behavior through different channels suggests that they support each other (Benartzi et al., 2017; Larrick, Weber, Ungemach, Johnson, & Camilleri, 2017). On the other hand, previous studies testing this type of combination observe no interactions (Mizobuchi & Takeuchi, 2013; Panzone et al., 2018). Additional evidence is needed to assess whether this approach to combining pecuniary and behavioral policies generates synergies.

This study collects experimental evidence on a new combination of pecuniary (monetary reward) and behavioral (goal setting and feedback) incentive mechanisms. We conduct an online experiment on Prolific in which subjects optimize their virtual energy consumption. More specifically, we develop an innovative incentive-compatible task that captures the essential incentive structure of real energy behaviors. The energy framing is adopted because most field applications of nudging belong to this domain (Andor & Fels, 2018; Buckley, 2020). We investigate the effect of incentives by randomly assigning participants to one policy instrument, their combination, or a control condition. Our results do not show evidence of synergies among alternative policies. Instead, subjects respond in the same way to the combination of instruments as they do to the nudge alone. Our results suggest caution when designing this kind of policy combination.

The remainder of the paper is organized as follows. Section 1.2 outlines the experimental design. The behavioral predictions are derived in Section 1.3. In Section 1.4 we present the results. Section 1.5 discusses the main findings and concludes.

1.2 Methodology

We develop a novel task that of actual energy consumption choices, represented by a trade-off between private and societal benefits on one side and personal disutility on the other. More precisely, personal and societal benefits are captured by payments to the participant and an environmental charity proportional to the virtual energy saving. Personal disutility is proxied by the cognitive effort required to reduce the virtual consumption. We classify our experiment as an "online framed experiment". Namely, participants from a nonstandard subject pool (recruited through the online platform Prolific) (Henrich, Heine, & Norenzayan, 2010) perform a framed virtual task that reproduces the incentive structure of real-life behavior. To the best of our knowledge, no similar task has been used in previous studies: some lack incentive-compatibility (McCalley, de Vries, & Midden, 2011; McCalley & Midden, 2002), others environmental externalities (Casal, DellaValle, Mittone, & Soraperra, 2017), and others the personal return associated with energy savings (Lange, Steinke, & Dewitte, 2018).

1.2.1 Task design

1.2.1.1 Description

We design a task that simulates the use of a washing machine in a virtual setting in the online oTree environment (Chen, Schonger, & Wickens, 2016). The washing machine's virtual control panel includes three parameters, i.e., *temperature*, *program*, and *duration*, that participants can set by pressing the relevant button (Figure 1.1, left). At every round of the task, the washing machine presents a new load of laundry for participants to do, characterized by two parameters: material and level of dirt. We include five materials (A, B, C, D, and E) and two levels of dirt (low and high) for a total of ten combinations. We also create a simplified instruction manual (Figure 1.1, right) that explains how to use the panel and optimize energy consumption depending on load characteristics.

Figure 1.1 Simulated washing machine control panel (on the left) and instruction manual (on the right)

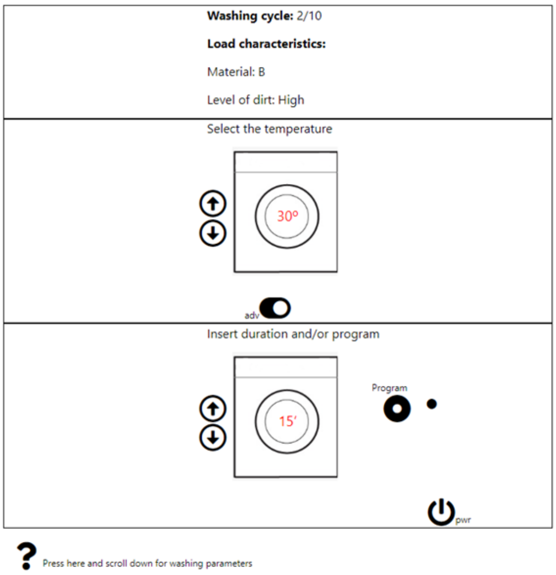


Table 1. Optimal temperature [°C] per material and level of dirt

Material	**A**	**B**	**C**	**D**	**E**
Temperature for low level of dirt	25	40	85	90	70
Temperature for high level of dirt	45	60	95	100	90

*Table 2. Standard program per material. To achieve an **energy saving of 5%**, the standard program must be used in combination with the temperature reported in Table 2 corresponding to the load characteristics.*

Material	**A**	**B**	**C**	**D**	**E**
Standard program	●	▲	■	■	●

*Table 3. Optimized program per material and corresponding temperature reduction [°C]. To achieve an **energy saving of 20%**, the optimized program requires to subtract the temperature reported in Table 4 to the one in Table 2 corresponding to the load characteristics.*

Material	**A**	**B**	**C**	**D**	**E**
Optimized program	✚	◆	▮	●	▲
Temperature reduction	0	15	5	10	10

Table 4. Optimal duration [min] per material in case of high level of dirt.
*To achieve a **10% of energy saving**, the duration must be used in combination with the temperature corresponding to the high level of dirt for the specific material reported in Table 2.*
*To achieve a **15% of energy saving**, the duration must be used in combination with the temperature corresponding to the high level of dirt reported in Table 2, and the standard program reported in Table 3 for the specific material.*
*To achieve a **30% of energy saving**, the duration must be used in combination with the temperature corresponding to the high level of dirt reported in Table 2, reduced by the value reported in Table 4, and the optimized program reported in Table 4 for the same material.*

Material	**A**	**B**	**C**	**D**	**E**
Duration	40	70	80	70	90

The baseline consumption of the washing machine is a function of the temperature required for a specific washing load. The baseline consumption is comparable with that of a washing machine purchased after the year 2000 for a 6 kg load, according to the following formula: $consumption\ (kWh) = 0.0254 * temperature\ (°C) - 0.3786$ (Milani, Camarda, & Savoldi, 2015). Subjects can reduce their virtual consumption by setting specific combinations of temperature, program, and duration (reported in Table 1.1). At every round, the task records participants' percentage of energy-saving, s_{ij} (i: participant, j: round). The mean value represents participant i's final saving: $s_i(\%) = \sum_{j=1}^{10} s_{ij}$.

Table 1.1 Available combinations of washing parameters and related saving

	(1)	(2)	(3)	(4)	(5)
Temperature	X	X	X	X	X
Duration		X	X		X
Standard program	X		X		
Optimized program				X	X
Saving (%)	0.05	0.10	0.15	0.20	0.30

1.2.1.2 Energy-related elements

To ensure incentive-compatibility and increase realism, we include some additional elements in the design, which are summarized in Table 1.2. In the real world, curtailing energy use yields private economic benefits from reduced bills and positive externality on the environment. However, it comes with personal costs, which derive either from the upfront costs of energy efficiency investments, or from the repeated effort of efficiently using the appliances (Barr, Gilg, & Ford, 2005). We incorporate these elements in our task to capture the incentive structure of energy behaviors.

The economic benefits are reproduced with a variable payment proportional to participants' virtual savings. To recreate the positive externality of energy conservation, we introduce a donation to WWF, increasing with participants' savings, according to the following scheme: s_i between 5% and 10% leads to a donation of £0.10, s_i between 10% and 20% a donation of £0.20, and s_i higher than 20% a donation of £0.50. Hence, despite taking place in a simulated setting, behavior in our task has real consequences on the environment. As for the costs, we reproduce the effort of daily energy behaviors. Although this kind of behavior does not embed the highest saving potential, it is the most suitable for a virtual task. Reducing the virtual energy use requires effort in terms of reading and implementing the instructions. Notably, the higher the saving associated with a specific combination of parameters, the higher the difficulty to implement it. For example, setting the correct temperature and the standard program generates 5% of saving, whereas setting the correct temperature, optimized program, and correct duration leads to 30% of saving.

Table 1.2. Summary of the elements of energy behaviors in the field and in the experiment

Feature	Field	Experiment
Economic benefit	Monetary saving in the energy bill	Variable bonus payment proportional to participants' saving
Positive externality	Reduced CO_2 emissions and reduced environmental damage	Donation to an environmental association increasing in participants' saving
Personal cost	Upfront investment costs; search and information costs	Reading and implementing washing machine instructions; greater effort required for higher energy-saving combinations

1.2.2 Treatments

Treatments are implemented with a between-subject design and manipulate the type of incentive implemented. Table 1.3 reports a summary of our experimental conditions.

Pecuniary: Economic reward. Participants are provided with an energy-saving goal, g_i, for the ten rounds. They receive no information on their savings throughout the task. At the end, they receive an economic reward if they achieve the goal.

Our *Pecuniary* treatment belongs to the category of market-based policies. While these often stimulate energy efficiency investments through for instance, grants, rebates and tax credits, our incentive mirrors the idea of a performance-based subsidy (Bertoldi, Rezessy, & Oikonomou, 2013), wherein the economic prize is delivered on the basis of the energy savings achieved by the user. A similar application is studied in Ito (2015), in which California residents were granted a discount in their energy bill if they curbed their electricity usage by 20% compared to the previous year.

Nudge: Goal setting and feedback. Participants are required to set their energy-saving goal, g_i, for the ten rounds. Making participants set their own goals increases nudge's effectiveness because self-set goals strengthen internal commitment (Bénabou & Tirole, 2004) and reflect participants' expectations for their performance (Hsiaw, 2013; Koszegi & Rabin, 2006). As goal setting is more effective when combined with feedback (Abrahamse, Steg, Vlek, & Rothengatter, 2005), at every round, subjects receive feedback that compares the performance of that round with their goal. At the end, they are informed on whether they reach their goal, but they are not awarded an economic prize if they do so.

Our *Nudge* treatment draws on the growing literature that uses non-binding and non-monetary relevant goals to increase performance. Closely related to our setting, Harding & Hsiaw (2014) study the effect of prompting households to set themselves energy conservation goals and let them track their progress through the program's website. Löschel et al. (2020) develop an energy goal-setting app that also provides conservation tips and feedback on households' performance.

Mix: Goal setting, feedback, and economic reward. As in *Nudge*, participants are required to set their energy-saving goal, g_i, and they receive feedback at every round. As in *Pecuniary*, they receive an economic prize if they achieve the goal. Information about the prize is displayed after participants set their goals to avoid them setting low goals and receiving the prize without effort.

Control. Participants perform the task without the energy-saving goal and the economic incentive. They receive no information on their savings throughout the task.

To avoid that treatments differ in terms of energy-saving goals, we assign goals in the *Pecuniary* condition drawing from those that participants set for themselves in *Nudge* and *Mix*. More precisely, we first launch *Nudge* and *Mix* conditions. We then randomly draw goals from these conditions (with replacement) and assign them to subjects in the *Pecuniary* treatment.

Table 1.3. Overview of treatments

	Pecuniary	Nudge	Mix	Control
Personal benefit	Yes	Yes	Yes	Yes
Environmental benefit	Yes	Yes	Yes	Yes
Goal	Set by experiment	Set by participant	Set by participant	No goal
Feedback	No	Yes	Yes	No
Additional financial incentive	Yes	No	Yes	No

1.2.3 Experimental procedure

We launched the experiment on the online platform Prolific in September 2018. Overall, 574 participants completed the task. Each participant received £1.50 as a fixed participation payment and an additional bonus of between £0 and £1.40, according to the following payoff function:

(1) $\pi_i = a + b * \gamma * s_i + c * prize_i * \delta_i$

where a represents the fixed participation fee; the term $b * \gamma * s_i$ represents the variable bonus payment, proportional to participant *i*'s final percentage of saving, s_i; b is the maximum variable payment from energy saving, equal to £1; γ is a multiplicative factor that serves to normalize the payment, as the virtual saving ranges between 0 and 25 percent; $\gamma = \frac{100}{25}$ so that the variable payment is £0 if $s_i = 0$ and £1 if $s_i = 25$; the term $c * prize_i * \delta_i$ represents the economic reward for achieving the goal, where c corresponds to the monetary reward received in exchange for goal achievement, equal to £ 0.40; $prize_i$ is a dummy for the presence of the economic reward in the experimental condition (1 = yes); and δ_i is a dummy that represents whether participant *i* achieves the energy-saving goal, g_i (1 = $s_i \geq g_i$).

All participants performed the same task. Each subject received written instructions about the experiment and the use of the control panel. Before beginning the task, participants had to correctly answer a comprehension check. Next, they were given two washing trials to familiarize with the control panel and were randomly assigned to one treatment. Then, they performed ten payoff-relevant rounds in which the order of presentation of washing loads was randomized. Repeating the washing task for ten rounds allows us to assess whether and at what pace learning effects occur.

The experiment ended with a short survey measuring participants' universalistic values and cognitive function. Universalistic values were measured with three items (Davidov, Schmidt, & Schwartz, 2008): (i) "This person thinks it is important that every person in the world is treated equally. This person believes everyone should have equal opportunities in life." (ii) "It is important to this person to listen to people who are different from him/her. Even in the case of disagreement, this person wants to understand them." (iii) "This person strongly believes that people should care for nature. Looking after the environment is important to this person." Responses were given on a 6-point Likert scale, from 1 = "Totally disagree" to 6 = "Totally agree." Cognitive function consisted of the cognitive reflection test (CRT) (Frederick, 2005) and three math questions taken from SAT test preparation.

Collecting these measures allows us to control for individual cognitive endowment and gather information about the cognitive effort associated with the task. In particular, universalistic values predict actual sustainable energy choices (Steg, Perlaviciute, & Van der Werff, 2015). A positive correlation between them and virtual energy saving shows that this motivation plays a role also in our task. The same reasoning applies to cognitive function: a positive relationship between the two indicates that, like real conservation behaviors, energy saving is achieved with effort in our task.

1.3 Behavioral predictions

This paper aims to investigate whether combining financial incentives and nudges increases the effectiveness of individual policies. We first focus on the impact of individual treatments. Then, we discuss whether synergies or displacements should arise when treatments are combined.

As predicted by standard economic theory, providing a pecuniary incentive for an activity should enhance performance. Activities require effort, which can be unpleasant, whereas money is viewed as good. In our setting, an economic reward for achieving the goal should induce more effort than no reward, as the latter does not provide any actual incentive to increase effort given the absence of a link between output and rewards. Based on this, we formulate the following hypothesis:

Hypothesis 1: The simulated energy saving will be higher in the *Pecuniary* treatment relative to the control group.

Nudges influence behavior through non-pecuniary drivers. Support for this motivational channel comes from previous studies showing that actual decision-making often departs from what is predicted by standard economic theory (DellaVigna, 2009). In the specific case of goal setting, subjects are provided with non-binding and non-incentivized goals. Those who exhibit reference-dependent preferences (Koszegi & Rabin, 2006) change their behavior to achieve them (Hsiaw, 2013). Indeed, by acting as a reference point, goals divide the space of outcomes into gains and losses. If the comparison between one's performance and the goal is favorable (negative), the individual will perceive a gain (loss) and will derive (dis)utility (Kahneman & Tversky, 1979). Achieving goals also increases intrinsic motivation by leading to a sense of self-achievement (Gómez-miñambres, 2012). The effectiveness of goal setting has been widely documented in a variety of domains, such as performance (Burdina, Hiller, & Metz, 2017; Lent & Souverijn, 2020), healthy lifestyle (King et al., 2013; Samek, 2019), and energy conservation (Harding & Hsiaw, 2014; Loock, Staake, & Thiesse, 2013). Hence, we hypothesize the following:

Hypothesis 2: The simulated energy saving will be higher in the *Nudge* treatment relative to the control group.

Concerning the interaction between the two policy instruments, there is no consensus on the nature of the emerging interplay when combining pecuniary and behavioral interventions as stand-alone instruments. A shortcoming in the literature is the limited evidence available. To the best of our knowledge, only two studies directly compare combinations of financial incentives and nudges with individual policies,[2] and both point to a lack of synergies (Mizobuchi & Takeuchi, 2013; Panzone et al., 2018). Similar to our setting, Corgnet et al. (2015) conduct a laboratory experiment to investigate the effect of goal setting on workers' performance and its interplay with monetary incentives. They find that combining the two instruments leads to better performance than the monetary incentive alone, but only when stakes are high. However, their design does not allow direct testing of the interplay between the two instruments, as the monetary incentive varies the piece-rate payment but does not reward goal achievement.

Moreover, it is unclear why one type of interplay should be predominant. Existing literature accounts for the generation of both synergies and displacements (Bowles & Polanía-Reyes, 2012). Insofar as monetary and behavioral instruments influence decision-making through different channels, they are expected to reinforce each other (Benartzi et al., 2017; Larrick et al., 2017). Consistent with this view, previous evidence has shown that sensitivity to different water conservation programs depends on households' characteristics, with high users being less price-sensitive (Mansur & Olmstead, 2012) but more responsive to social influence (Ferraro & Miranda, 2013; Ferraro & Price, 2013).

Conversely, behavioral sciences suggest that some aspects of human cognition may hinder the creation of the expected benefits. First, according to motivation crowding out, providing an external reward in exchange for a socially desirable behavior may erode the moral and social arguments involved in decision-making (Frey & Jegen, 2001; Gneezy, Meier, & Rey-Biel, 2011). Combining extrinsic and intrinsic sources of motivation may cause the former to

[2] List et al. (2017) show that adding a financial reward to a social comparison increases energy saving. However, in the study, the authors do not compare the effect of the mix with that of the economic intervention alone, making it impossible to conclude that synergies arise in their setting. Petersen et al. (2007) investigate the joint effect of social comparison feedback, economic incentive, and an educational campaign on energy conservation in a student dormitory. The study does not disentangle the effect of individual policies and the marginal gain from combining them.

undermine the impact of the latter. Second, evidence demonstrates that humans have limited cognitive resources, which make them struggle when confronted with too much information (Jacoby, 1984; Malhotra, 1984). A combination of financial incentives and nudges may cognitively overload subjects, inducing them to disregard the message (Iyengar & Lepper, 2000) or focus only on part of it (Shr, Ready, Orland, & Echols, 2019), resulting in substitution effects.

We formulate our prediction in line with the view that tools that affect behaviors through different channels give rise to synergies. In our setting, the *Mix* condition is expected to simultaneously influence subjects who act as predicted by standard economic theory and those who exhibit cognitive biases through the financial incentive and the nudge, respectively. This leads to our third hypothesis:

Hypothesis 3: The simulated energy saving will be higher in the *Mix* treatment relative to the *Pecuniary* and *Nudge* treatments.

1.4 Results

1.4.1 Descriptive statistics

Table 1.4 reports the participants' characteristics. From the initial sample of 574, we eliminated 6 participants who had missing socio-demographic characteristics and 2 who had a problem with completing the task.[3] Our final sample comprises 566 participants. Overall, 45.9% of participants are female, the age ranges between 18 and 69, and 48.4% achieved a graduate degree as the highest educational level. Gender is unbalanced across the experimental conditions, with a share of males that is lower in the *Pecuniary* treatment than in the *Mix* condition. To avoid confounding effects from unbalanced demographics, we control for them throughout our analysis. Participants' universalistic values take the unweighted average of the answers to the three items; the average value measures 4.94 (out of 6), which is quite high. This mirrors the current growing concerns about environmental issues. Cognitive function sums up the number of correct answers on the CRT and the math test. Participants answered around half of the questions correctly.

[3] Due to our experimental design, we conducted the experimental sessions in different rounds. We first launched *Nudge* and *Mix* conditions. Unfortunately, while running this session we had a problem with the database and some participants could not finish the task. We excluded partial answers from the analysis. We also excluded two participants who could complete the task during the problem and reported slow processing time. Data collection was completed with a second session.

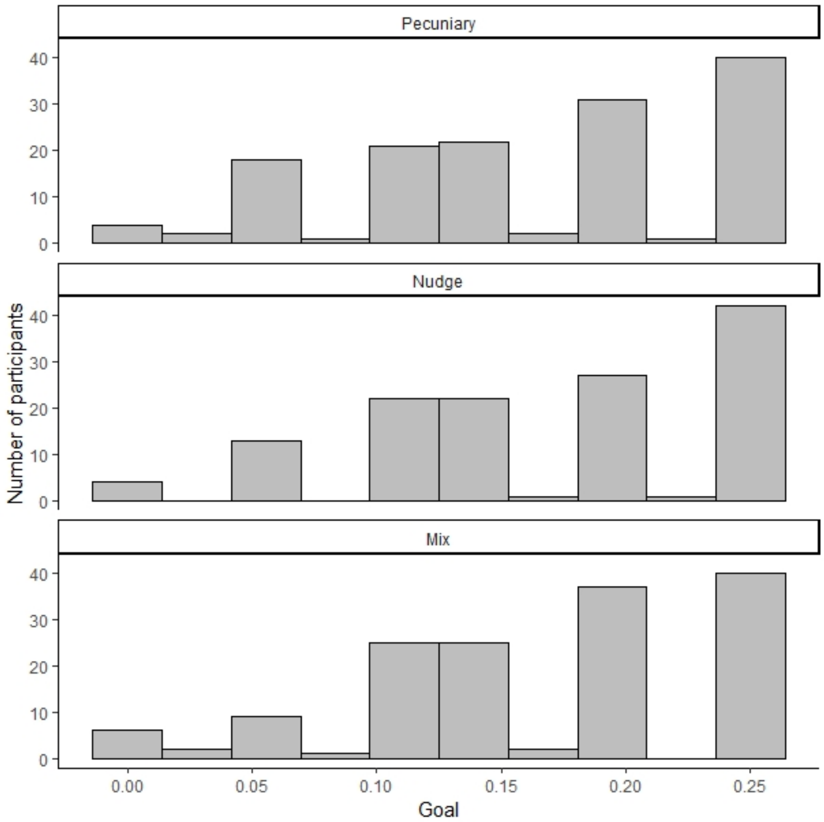
Table 1.4 also reports preliminary results. In particular, *Goal* represents the average goal for the experimental conditions with a target, namely *Pecuniary, Nudge,* and *Mix*. Goals span between 0 and 25 percent, as depicted in Figure 1.2. A chi-square test confirms that goal distribution is balanced across treatments (p > .90). Since goals have the same distribution across conditions, we can rule out that between-treatments variations are due to differences in goals.

Table 1.4 Participants' characteristics and responses per experimental condition

	Pecuniary	Nudge	Mix	Control
N	142	132	147	145
Male (%)	**0.437**	0.583	**0.639**	0.503
Age (years)	30.8	30.5	28.4	31.7
	(10.6)	(11.3)	(8.84)	(11.1)
Graduate (%)	0.535	0.409	0.456	0.535
Universalistic	4.920	4.980	4.960	4.910
	(0.790)	(0.828)	(0.750)	(0.775)
Cognitive	3.820	3.560	3.843	3.841
	(1.350)	(1.450)	(1.320)	(1.400)
Goal	0.163	0.17	0.167	NA
	(0.076)	(0.074)	(0.073)	NA
Energy saved (%)	0.153	0.148	0.156	0.136
	(0.098)	(0.101)	(0.096)	(0.101)
Goal achieved (%)	0.514	0.417	0.503	NA
	(0.502)	(0.495)	(0.502)	NA

Note: *Universalistic* denotes universalistic values, *Cognitive* denotes cognitive function. Values in bold indicate statistically significant differences between the two groups based on Scheffe's multiple comparison test, at the 0.05 level. Standard deviations in parenthesis when applicable.

Figure 1.2. Goal distribution per experimental condition



Even if goals have the same distribution, how they are defined differs across conditions. Goals are endogenous in *Nudge* and *Mix* (as they are set by participants at the beginning of the task) and exogenous in *Pecuniary* (as they are randomly assigned by the experiment). To test whether endogenous goals mirror personal expectations, we regress goals in the *Nudge* and *Mix* conditions on participants' characteristics. The results reported in Table 1.5, Column 1 show that participants set their goals according to their willingness to contribute to the common cause (i.e., their universalistic values) and their ability to do so (i.e., their cognitive skills). This is consistent with self-set goals reflecting personal expectations on future outcomes (Hsiaw, 2013; Koszegi & Rabin, 2006). As goals are randomly assigned in the *Pecuniary* treatment, there is no relation between participants' characteristics and goals for that condition (Column 2). This result reinforces the idea that, by better matching subject characteristics, self-set goals should have higher motivational power than externally imposed targets, such as those of traditional financial incentives.

Table 1.5. Goal level on participants' characteristics by experimental condition

	(1)	(2)
	Goals	
	Self-set	*Experiment-set*
Universalistic	0.012*	-0.011
	(0.006)	(0.008)
Cognitive	0.012***	-0.007
	(0.003)	(0.005)
Constant	0.062	0.257***
	(0.035)	(0.054)
Demographic controls	Yes	Yes
Observations	279	142
R2	0.061	0.051
F statistic	3.547 (df = 5; 273) ***	1.450 (df = 5; 136)

Note: Linear regression. Column (1) includes participants in *Nudge* and *Mix* treatments, Column (2) in *Pecuniary* treatment. *Universalistic* denotes universalistic values, *Cognitive* denotes cognitive function. Standard errors in parentheses. *p < .05, **p < .01, ***p < .001

Finally, the descriptive statistics reported in Table 1.4 do not support our hypotheses about treatment effects. In particular, the percentage of energy savings and goals achieved does not significantly differ across the experimental conditions. Directional observations reveal that all the manipulations lead to higher energy saving compared to the control group, with a higher value for the *Mix* treatment. Average energy savings are lower than average goals for all experimental conditions, leading to an overall percentage of goals achieved of 47.5%.

1.4.2 Treatment effect on energy saving

To investigate our hypotheses about incentives, we assess treatment effect on virtual energy consumption. The multiple individual-level observations are taken into account with the following linear mixed model, with a random intercept at the individual level (Moffatt, 2015):

(2) $s_{ij} = \beta_0 + \sum \beta_i * treat_i + \beta_4 * univ_i + \beta_5 * cogn_i + \beta_6 * round_j + \beta_7 * X_i + u_i + \varepsilon_{ij}$

where s_{ij} denotes the saving achieved by participant i at round j; $treat_i$ is a dummy for the random exposure to each of the treatments; $univ_i$ stands for universalistic values; $cogn_i$ represents cognitive function; $round_j$ represents a continuous variable for the washing cycle; X_i indicates a set of demographic variables, including gender, education, and age; u_i is the subject-specific term that allows the intercept to vary across individuals. The error term is represented by ε_{ij}. Because we perform multiple hypothesis testing (List, Shaikh, & Xu, 2019), we control for the family-wise error rate using a single-step method (Bretz, Hothorn, & Westfall, 2010).

Regression results are reported in Column 1, Table 1.6. First, they show that universalistic values and cognitive function affect performance as expected. Specifically, we observe a significant and positive relationship between both constructs and virtual energy saving. This finding (and the fact that it is robust throughout the analysis) shows that the task captures the essential elements of actual energy consumption choices: (i) similarly to conservation behaviors, saving virtual energy correlates with universalistic values; (ii) reducing the virtual energy use entails personal costs, as does energy conservation.

Second, Column 1, Table 1.6 shows that none of the treatment dummies differ significantly from zero. All experimental conditions achieve an energy saving of the same magnitude as the control condition. This finding is in contrast with Hypothesis 1 and 2, which foresee a positive effect of the economic incentive and the nudge.

We then turn our investigation to the synergy hypothesis (Hypothesis 3). We test whether the financial incentive and the nudge complement each other by comparing the coefficient of *Mix* with those of individual treatments. For both comparisons, the difference is non-significant (p-values corrected for multiple testing are equal to 1). Hypothesis 3 is therefore not supported by our results.

Further exploration of the results reveals that, despite the lack of significance across experimental conditions, their impact on behavior differs over time. Figure 1.3 shows that the experimental conditions without feedback (*Pecuniary* and control) display higher variance than those with feedback (Levene's test: $p = .031$). Moreover, participants in these conditions achieve lower energy savings at the beginning of the task, but their performance improves over rounds. The opposite pattern arises among participants in *Nudge* and *Mix*: they conserve energy from the beginning, but their saving remains constant. Formal support for these dynamics is provided in Column 2, Table 1.6, which reports the result of Eq. (2), including interactions between treatment dummies and rounds.

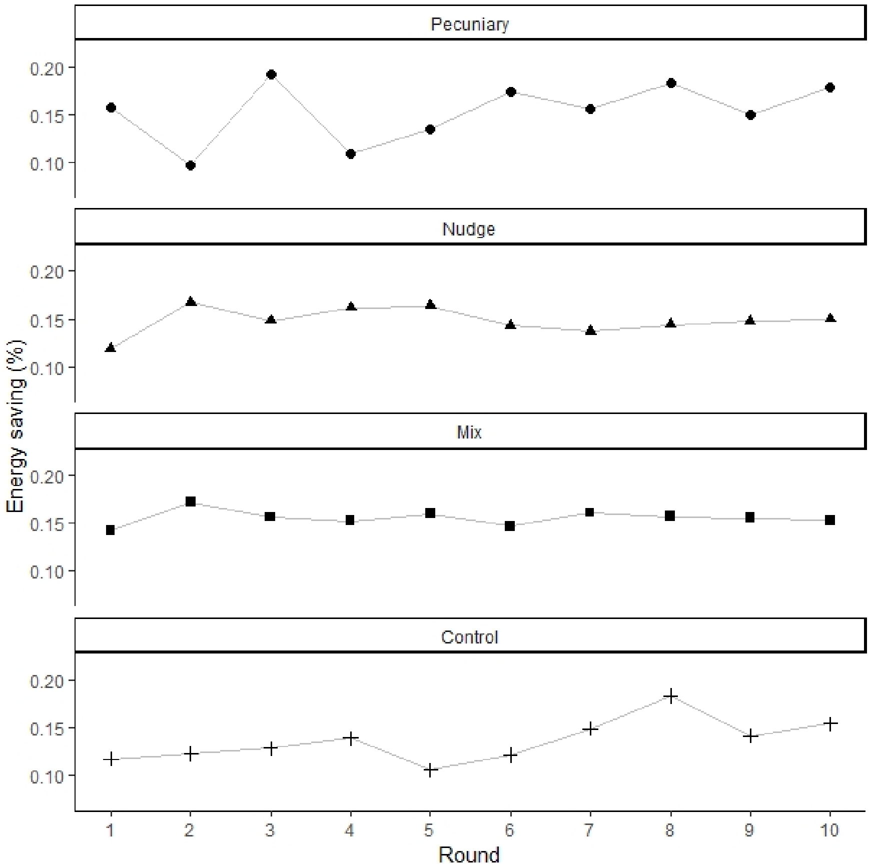
To summarize, even if the absolute treatment effect is the same across experimental conditions, how this result is achieved differs significantly across treatments. Results suggest that feedback prompts learning from the beginning of the task. Learning still occurs in the conditions without feedback but only in the second half of the task. Finally, the saving profile of the *Mix* condition is closer to that of *Nudge* than *Pecuniary*, suggesting that the main driver of behavior in *Mix* is goal setting and feedback (rather than the financial incentive).

Table 1.6. Treatment effect on energy saving

	(1)	(2)
	Energy saving	
Pecuniary	0.015	0.018
	(0.011)	(0.012)
Nudge	0.017	0.042**
	(0.011)	(0.012)
Mix	0.014	0.040**
	(0.011)	(0.012)
Universalistic	0.017**	0.017**
	(0.005)	(0.005)
Cognitive	0.026***	0.026***
	(0.003)	(0.003)
Round	0.002***	0.005***
	(0.0004)	(0.001)
Pecuniary x Round	-	-0.0005
		(0.001)
Nudge x Round	-	-0.005***
		(0.001)
Mix x Round	-	-0.005***
		(0.001)
Constant	-0.002	-0.016
	(0.031)	(0.031)
Demographic controls	Yes	Yes
Observations	5,660	5,660
Subject ID	566	566
Log Likelihood	5,560.612	5,560.797

Note: Linear mixed model, random intercept at individual level. Baseline: control group. *Universalistic* denotes universalistic values, *Cognitive* denotes cognitive function. Standard errors in parentheses. Significance levels adjusted for multiple hypothesis testing. *p < .05, **p < .01, ***p < .001

Figure 1.3. Energy saving per round and experimental condition



1.4.3 Exploratory analyses

1.4.3.1 Heterogeneity based on goal level

In this section, we investigate whether there is heterogeneity in treatment effect depending on goal level. Performance is indeed affected by goal level, with detrimental effect for low values (Locke & Latham, 2002). Table 1.4 shows that this mechanism may be at work in our setting, as the average saving achieved by the control group (13.6%) is close to the average goal set in the other conditions (16.67%). If the lack of treatment effect is due to low goals, only participants with high goals should reduce their virtual consumption.[4]

Participants in *Nudge* and *Mix* set their goals according to their universalistic values and cognitive functions (see Section 1.4.1), which also affect task performance. As these constructs may act as confounders, we include them in the analysis. After controlling for universalistic values and cognitive function, we find a positive and significant relationship

[4] In our setting, goals are constrained by the experimental design. We do not consider the situation in which participants set overly optimistic and non-attainable goals for themselves. For related literature, see Harding & Hsiaw (2014) and Loock et al. (2013).

between goals and energy savings (B = .256, SD = .059, $p < .001$). Hence, goals influence participants' behavior, and low goals may reduce performance relative to the control group. We shed further light on this effect by splitting participants depending on whether their goal is lower (*Low goal*) or higher (*High goal*) than the average and re-estimating Eq. (2) for each subgroup. To compare whether subjects with low versus high goals perform differently from the control condition, we include it in both subgroups. Multiple hypothesis testing is addressed as in Section 1.4.2 through a single-step procedure (Bretz et al., 2010).

We report the results in Table 1.7, with Column 1 for *Low goal* and Column 2 for *High goal*. In the *Low goal* subset, no experimental condition differs significantly from the control group. Goals that are lower or close to the standard performance –namely, the saving in the control group– do not improve performance. In the *High goal* subset, participants in *Nudge* and *Mix* conditions achieve higher energy savings than those in the control group. Hence, those who set high goals for themselves are also more likely to conserve energy. Overall, these results are in line with previous studies: while low goals do not prompt significant saving, realistic self-set goals result in significant energy conservation (Harding & Hsiaw, 2014; Loock et al., 2013). Yet, they shed new light on the difference between self-set and externally imposed goals. By better matching subject type, self-set goals may have higher motivational power than those dictated by traditional policies.

We further explore Hypothesis 3 by examining whether, among subjects with high goals, the *Mix* condition leads to better performance compared to individual treatments. We compare the coefficient of *Mix* with the other treatment dummies for the *High goal* subgroup. We find that *Mix* is marginally higher than *Pecuniary* ($p = .06$) but does not differ from *Nudge*. It seems that for high goals, providing an economic incentive is not enough to motivate energy saving. What seems more motivating is the possibility of setting a personal goal and receiving feedback. Accordingly, also *Nudge* performs better than *Pecuniary* ($p = .005$). In sum, this analysis provides additional evidence against the synergy hypothesis.

Table 1.7. Energy saving per goal level

	(1)	(2)
	Energy saving	
	Low goal	*High goal*
Pecuniary	0.028	0.005
	(0.013)	(0.012)
Nudge	-0.024	0.053***
	(0.014)	(0.012)
Mix	-0.017	0.041**
	(0.013)	(0.012)
Universalistic	0.014	0.019**
	(0.006)	(0.006)
Cognitive	0.026***	0.026***
	(0.004)	(0.003)
Round	0.004***	0.002**
	(0.0005)	(0.0005)
Constant	-0.003	0.006
	(0.039)	(0.035)
Demographic controls	Yes	Yes
Observations	3,430	3,680
Subject ID	343	368
Log Likelihood	3,424.737	3,628.373

Note: Linear Mixed Model, random intercept at individual level. Baseline: Control group. *Universalistic* denotes universalistic values, *Cognitive* denotes cognitive function. Standard errors in parentheses. Significance levels adjusted for multiple hypothesis testing. *p < .05, **p < .01, ***p < .001

1.4.3.2 Motivation crowding out

This section explores whether appealing to economic incentives crowds out the intrinsic motivation to improve task performance. In our setting, if the lack of synergies is due to motivation crowding out, participants with stronger environmental attitudes are expected to save less energy when a monetary incentive is also present.

We investigate whether, in the treatments with the financial incentive (*Pecuniary* and *Mix*), participants' values play a less important role than in the other conditions. To this aim, we re-estimate the model reported in Eq. (2), adding interactions between treatment dummies and participants' universalistic values. The results of this exercise are reported in Table A1. No significant interaction between treatments and universalistic values is detected, suggesting that the pecuniary incentive does not undermine participants' intrinsic motivation. We, therefore, tend to exclude that motivation crowding out is the likely explanation for the lack of synergies observed in our study. This finding is consistent with earlier work on financial-behavioral combinations (Mizobuchi & Takeuchi, 2013), where no motivation crowding out was found when jointly implementing social comparison and economic reward.

1.5 Discussion and conclusion

Despite the widespread adoption of nudges, their interplay with traditional policy instruments is still unclear. Through a framed online experiment that simulates energy behaviors in an incentive-compatible way, this study investigates individuals' responses to a pecuniary intervention (economic reward) and a nudge (goal setting and feedback) implemented individually and jointly.

We find that incentives do not significantly affect participants' virtual energy saving individually. Several reasons could drive this result. A ceiling effect may be at work. We designed the task so that reducing the virtual energy use required cognitive effort. However, our sample is characterized by highly educated and smart participants. For them, the cognitive costs of reducing the virtual energy use may have been too low for not using the washing machine efficiently, leaving little room for policies to affect performance. A similar message is found in Löschel et al. (2020), in which an energy-saving app leads to zero energy savings, likely because the users who self-selected into using it exhibited low baseline consumption and limited cognitive biases. An alternative explanation is that energy saving goals were very close to the savings achieved by the control group. Since goals affect performance, low goals may have failed to motivate additional effort (Locke & Latham, 2002). Our heterogeneity analysis points to this direction: differences in energy savings are significant among participants with high goals. To sum up, there needs to be some "slack" in resource usage that policies can act upon (Tiefenbeck et al., 2018), which may be missing in our study. Building on our task, future work could vary the costs and benefits associated with the virtual energy saving, in order to reduce such ceiling effect and leave more space for policy evaluation.

Our findings suggest that integrating the two instruments does not enhance the effect of single policies. One possible explanation for this is that the incentives do not affect the policies individually. Yet, our additional analyses show that the treatment combining both policies affects behavior in the same way as the nudge alone does. We propose that a mechanism for this result is "attention crowding out" from the behavioral to the economic incentive. By diverting participants' attention from the market-based policy, the nudge reduces its impact and hampers the creation of the expected benefits. This interpretation is consistent with the notion that individuals have limited cognitive resources (Jacoby, 1984; Malhotra, 1984): in a context characterized by stimuli abundance, sensitivity to a specific aspect depends on how much attention is allocated to it (Pachur, Schulte-Mecklenbeck, Murphy, & Hertwig, 2018). Motivation crowding out could be an alternative explanation (Frey & Jegen, 2001; Gneezy et al., 2011). This mechanism may play a role in our setting because we added an extrinsic incentive to a nudge that appeals to intrinsic motivation. Since our results do not point in this direction, we posit that the attention crowding out explanation is more likely.

A few policy implications can be drawn from our results. First, consistent with earlier evidence (Mizobuchi & Takeuchi, 2013; Panzone et al., 2018), our study shows that combining financial incentives and nudges as stand-alone instruments gives rise to displacements rather than synergies. Hence, policy makers should carefully evaluate whether implementing this type of combination. Second, our findings show that feedback ensures quick learning. In complex environments, characterized by limited information and difficult tasks, learning is slow (Grimm & Mengel, 2012; Weber, 2003). Traditional financial incentives may be less effective than feedback-based nudges in contexts where learning requires time and effort. Finally, we show that high goals have higher motivational power when they are self-set than when they are externally imposed, as they better match subject type. In this respect, nudges have an advantage compared to traditional policies because they allow setting personalized goals without having pre-existing information about subject motivation and ability.

Some limitations of this study should be acknowledged. First, our study was performed in a virtual setting. Although the task captures the incentive structure underlying energy behaviors, external validity considerations call for caution. The stakes involved in our task are of much lower magnitude than those involved in real-world consumption choices. Moreover, our task focused participants' attention on energy saving, while conservation behaviors usually drift in the background of the routine. Second, the experimental setting leaves little room for cost-effective analysis. As a key feature of nudges is their high return for the money invested, future empirical work is needed to investigate how combinations of financial and behavioral policies perform under a cost-adjusted perspective and not only in terms of absolute impact. Finally, we examined some drivers of the lack of synergies, but we did not directly test them. More work is needed to investigate the channels through which financial incentives and nudges interact.

Appendix

Appendix A. Motivation crowding out

Table A1. Heterogenous treatment effect based on universalistic values

	(1)	(2)
	Energy saving	
Pecuniary	0.048	-
	(0.067)	
Nudge	0.020	0.020
	(0.067)	(0.067)
Mix	0.077	-
	(0.069)	
Economic	-	0.062
		(0.058)
Universalistic	0.022	0.022
	(0.010)	(0.010)
Cognitive	0.026***	0.026***
	(0.003)	(0.003)
Round	0.002***	0.002***
	(0.0004)	(0.0004)
Pecuniary x Universalistic	-0.007	-
	(0.013)	
Nudge x Universalistic	-0.001	-0.001
	(0.013)	(0.013)
Mix x Universalistic	-0.013	-
	(0.014)	
Economic x Universalistic	-	-0.010
		(0.012)
Constant	-0.025	-0.025
	(0.051)	(0.051)
Demographic controls	Yes	Yes
Observations	5,660	5,660
N Subject ID	566	566
Log Likelihood	5,550.689	5,557.576

Note: Linear Mixed Model, random intercept at individual level. Baseline: Control group. Universalistic denotes universalistic values, Cognitive denotes cognitive function, Economic is a dummy variable equal to 1 if the treatment has the economic incentive (Pecuniary and Mix), 0 otherwise. Standard error in parentheses. Significance levels adjusted for multiple hypothesis testing. *p < .05, **p < .01, ***p < .001

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CHAPTER 2

Behavioral intervention to conserve energy in the workplace

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Abstract

This study investigates the effect of a large-scale behavioral intervention to conserve energy in the workplace, consisting of an energy-saving competition among a bank's branches. More than 500 branches were involved for a period of one year. Using a difference-in-difference estimation, we find that the competition significantly reduces monthly electricity consumption outside the work schedule (by 7 percent), but that overall energy use does not change significantly (reduction of 2.5 percent). Branch characteristics do not lead to differentiated program response, in stark contrast with the residential sector. In the same setting, we also evaluate a technological intervention automating building energy management. The retrofit leads to significant energy savings (of 18 percent), also concentrated outside the main work schedule. Our results stress the importance of considering contextual characteristics when implementing behavioral programs and show potential overlaps with smart technology investments.

Keywords: Behavioral intervention; Energy conservation; Workplace; Difference-in-difference; Energy efficiency

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[1] *Author contributions:* VF led the collection and the analysis of the data, and the writing of the manuscript. GD contributed to the data analysis and to manuscript writing. MT contributed to manuscript writing and was in charge of overall direction and planning.

2.1 Introduction

In the last years residential energy use has reduced in Europe whereas commercial consumption has increased (ODYSSEE-MURE, 2018). Commercial buildings are therefore a critical lever to achieving global sustainability goals (Güneralp et al., 2017). Human behavior is one of the primary sources of energy waste in buildings (Y. Zhang, Bai, Mills, & Pezzey, 2018), especially in the workplace, where market failures lead to the inefficient use of appliances (Giraudet, 2020). The most relevant market failures are principal-agent problems –namely, the misplaced incentive between those who consume energy (the employees) and those who pay for it (the company)– and imperfect information –i.e., the lack of knowledge about one's energy consumption and the related operating costs.

There are different strategies to reduce energy consumption in the workplace. Based on traditional economic theory, employees act as rational and selfish agents who, in the presence of market failures, do not make any effort to save energy. They save energy if the company incentivizes them to do so, for instance by introducing bonuses and gifts. Alternatively, the company can take it upon itself to control its employees' energy consumption, such as by installing smart appliances or automating the peak load management. In this case, no effort is required from employees to reduce their consumption, and their passive compliance with the installed technology will generate energy savings for the company.

Other possibilities are offered by the growing body of research in behavioral economics. Behavioral economics shows that people systematically deviate from traditional economic predictions and that such deviations can be harnessed to promote resource conservation (Thaler & Sunstein, 2008). For example, individuals tend to reduce their energy consumption if they discover that they consume more than others do (Allcott & Rogers, 2012) or that their actions have negative environmental and health consequences (Asensio & Delmas, 2015). With this type of intervention, a company can foster its employees' active engagement in energy-saving practices while leaving the incentive structure or the physical environment unchanged.

This study investigates the impact of a large-scale behavioral intervention implemented by an Italian bank to save energy. The core of the program is an energy-saving competition among the bank's branches. Every month, the three branches that save the most are announced through the company's newsletter. Winners gain social recognition along with a small material reward in the form of an eco-gadget. The competition is reinforced by additional incentives, such as informational materials and individual challenges. The program involves more than 500 branches and lasts one year (January-December 2019).

We assess the impact of the behavioral intervention on branches' monthly electricity consumption using a difference-in-difference (DID) approach from mid-2017 to the end of 2019. As control, we use a subset of branches that are not directly involved in the competition as they are part of a precedent retrofitting program. Our dataset's long time coverage enables us to determine whether the parallel trend assumption holds in the pre-intervention period, proving the reliability of our empirical investigation.

We find that the behavioral intervention reduces average monthly energy consumption by 2.5 percent, but this effect is not statistically significant. In terms of magnitude, the impact is at the lower end of results achieved in the residential sector (Buckley, 2020; Delmas, Fischlein, & Asensio, 2013). However, energy consumption outside the main work schedule significantly reduces by around 7 percent. This result confirms previous evidence (Orland et al., 2014) and is easy to explain: while at work, employees need to use appliances for work-related activities and may not be willing to sacrifice their comfort to conserve energy (Buchanan, Russo, & Anderson, 2015). On the other hand, keeping appliances and lights switched off overnight only requires employees to switch them off when leaving the office.

The reason for the overall non-significant effect of the behavioral intervention is likely attributable to the characteristics of consumption in the workplace. First, employees are not charged for their energy consumption. Environments in which users do not pay their bills have shown mixed responsiveness to behavioral interventions (Myers & Souza, 2020; Tiefenbeck, Wörner, Schöb, Fleisch, & Staake, 2019). The absence of bills also reduces the salience of energy consumption, which is usually relegated to the background relative to work-related tasks. Moreover, the company may consider employees' energy consumption as a proxy of their productivity, which creates a barrier for conservation efforts. Second, the workplace's energy consumption is the product of many people's actions, and disentangling personal contribution is almost impossible. Employees may experience that their personal efforts to save energy have little effect on the company's final consumption (Carrico & Riemer, 2011), thereby renouncing to change their behavior. The energy-saving competition fails to address this issue, because it targets branches' rather than individuals' consumption and does not clarify the link between one's effort and the corresponding savings achieved by the company. Finally, even if employees want to save energy, they can do so only by changing their behavior, whereas in the residential sector landlords can also invest in energy efficiency improvement (Brandon et al., 2017). Considering the foregoing, our study claims for caution when generalizing the results of behavioral interventions from a specific context to another (in this case, from home to work).

We use branches' characteristics to explore possible sources of heterogeneity in program effect and inform similar future efforts. Contrary to our expectations, we find that none of the characteristics investigated (pre-treatment energy consumption, heating type and size) influence the behavioral intervention. This result is striking for two reasons. First, findings from the residential sector show that households with higher pre-treatment consumption save more in response to behavioral interventions than those with lower pre-treatment consumption (Allcott, 2011; Bonan, Cattaneo, D'Adda, & Tavoni, 2019; Byrne, Nauze, & Martin, 2018; List, Metcalfe, Price, & Rundhammer, 2017; Tiefenbeck et al., 2018). This result is not replicated for the branches that used more energy. Second, prior research suggests that the workplace is a good environment for implementing behavioral interventions because employees are subject to peer effects (Staddon, Cycil, Goulden, Leygue, & Spence, 2016). Peer effects should be prominent when energy consumption is apportioned to existing small to medium-sized groups that the employees identify with (Bedwell et al., 2014). We therefore expected a stronger treatment effect among smaller branches. However, no interaction is observed between the number of employees (or surface) and the behavioral intervention. Ex-post survey data show that employees did not speak about the competition, suggesting that the targeted unit (i.e., the branch) is too large and heterogeneous to trigger any peer effect.

Our study makes two main contributions to the literature on energy conservation. First, research on conservation in the workplace is relatively scarce (Stern et al., 2016). While psychological and engineering studies provide early insights into the effect of behavioral interventions on employees' energy use (see Staddon et al. (2016) for a review), economists to date have paid more attention to the residential sector (Andor & Fels, 2018; Ramos, Gago, Labandeira, & Linares, 2015). A few notable exceptions exist, though. Brown et al. (2013) show that changing the default settings on office thermostats significantly reduces internal temperature. Handgraaf et al. (2013) and Ornaghi et al. (2018) find that social influence effectively prompts behavioral change when it is tailored to an employee and addresses a specific source of inefficiency, such as office windows left open overnights (Ornaghi et al., 2018). This type of feedback is generally the most effective because it highlights the link between one's action and a given outcome (Tiefenbeck et al., 2018). Finally, Charlier et al. (2021) find that only combinations of nudges prompt employees' conservation efforts. We extend this literature by investigating whether an intervention targeted at group level reduces total buildings' consumption.

Second, there is growing interest in the interactions between behavioral and traditional policy instruments (Hagmann, Ho, & Loewenstein, 2019; Panzone, Ulph, Zizzo, Hilton, & Clear, 2018). This study explores the interplay between a behavioral intervention and a smart technology retrofit program, which took place before the energy-saving competition and involved a subset of highly consuming branches. Even if we cannot directly quantify their joint impact, our results suggest that the two programs may overlap, rather than complement each other. Both the behavioral and automation interventions prompt conservation outside working hours. Hence, combining these two types of intervention may fail to trigger positive synergies because they affect similar drivers of inefficiency.

The remainder of the paper is organized as follows. In Section 2.2 we provide a detailed description of the behavioral intervention. Section 2.3 discusses the data and results, while Section 2.4 concludes.

2.2 Intervention overview

2.2.1 Intervention and mechanisms of effects

The bank implemented a behavioral intervention to promote energy conservation among its employees, relying on external consultants specialized in nudges to design it. The core of the intervention was an energy-saving competition among its branches. Every month, the bank published the energy-saving ranking on the program webpage in three versions: a podium with the first three ranked, a list with the first ten, and a list with all the branches. The ranking was computed internally by the firm, considering the year-to-date savings compared to the consumption in the two previous years.[2] Due to billing constraints, rankings were published with two months of delay compared to the reference period. For each monthly ranking, employees of the top three branches received prizes in the form of eco-gadgets.[3] At the end of the intervention period, the three branches that saved the most were publicly awarded bigger prizes than monthly rewards (e.g., planting a tree with the certification of the winning branch).

To reinforce the energy-saving competition, additional materials were published on the program webpage and the company's newsletter on an ongoing basis. First, tips on conserving energy and reducing waste were provided, both through fliers and videos. As people are more

[2] The company used the following formula to compute the savings: $y_i = \frac{\sum_{i=1}^{12} \overline{x_i} - x_i}{\sum_{i=1}^{12} \overline{x_i}}$, where y_i is the energy savings from January 2019 to month i; $\overline{x_i}$ is the total electricity consumption from January to month i, averaged between the years 2017 and 2018; and x_i is the total electricity consumption from January to month i for the year 2019. As a check, we recalculated the savings and compared them with those computed by the firm. The two overlap, as shown in Figure A1.

[3] Each branch could receive the prize only once. Notably, if a firm that had already received the gadget was again ranked among the first three in another month, the prize would be given to the next highest-ranked firm that had not received it yet.

likely to comply with social norms that refer to a relevant reference group (Goldstein, Cialdini, & Griskevicius, 2008), videos were filmed in the bank buildings. They told the stories of employees seeking to conserve energy to improve their position in the monthly ranking. Second, employees were tasked with missions, also posted on the program webpage. Such missions mostly had engagement rather than conservation purposes. Some examples of these are the best picture showing how to save energy at home or the best suggestion for reducing waste in the branch. For each mission, the company selected a winner, who was rewarded with an eco-gadget. The different contents were posted simultaneously to enhance the program's visibility (e.g., the monthly ranking plus a video on how to reduce lighting consumption).

Let us conceptualize the mechanisms whereby the behavioral intervention may prompt employees' conservation efforts. We focus on non-pecuniary drivers because the material rewards for the winning branches are too small to justify behavioral change. A first possible mechanism is that by simply implementing the intervention, the company signals the injunctive norm of energy conservation at work. This could increase the "moral cost" of energy use (Allcott, 2011) for employees. The intervention may also prime employees to consider energy use for workplace behaviors (Carrico & Riemer, 2011). While these mechanisms characterize any campaign and are certainly at work in our context, the central element of the behavioral intervention is the energy-saving competition.

Extensive research shows that competitions and rankings affect behavior, both when they are privately or publicly conveyed and when they are decoupled from financial rewards (Cadsby, Song, Engle-Warnick, & Fang, 2019; Duffy & Kornienko, 2010; Tran & Zeckhauser, 2012). Private rankings motivate effort by appealing to competitive preferences (Charness & Rabin, 2002; Rustichini, 2008), or by yielding higher self-esteem (Kuhnen & Tymula, 2012) and self-image (Köszegi, 2006) when a person outperforms others. In our study, higher rankings mean more prosocial behavior. Hence, employees in high rankings may also draw "moral utility" (Levitt & List, 2007) from reducing the company's greenhouse gas emissions. Finally, the fact that rankings are publicly communicated adds another driver of behavioral change. Namely, conservation behavior becomes visible to others, thereby ensuring a green reputation for employees saving the most (Delmas & Lessem, 2014; Griskevicius, Tybur, & Van den Bergh, 2010). Employees wishing to obtain a prosocial reputation provide additional effort to reduce energy use. In sum, we expect that both intrinsic motivation and reputation motivation (Bénabou & Tirole, 2006) motivate employees to conserve energy in order to increase the ranking of their branch in the energy-saving competition.

2.2.2 Implementation

The project ran from January to December 2019. A total of 553 branches were assigned to the energy-saving competition (henceforth, *behavioral group*). As control, we used 70 branches that were not directly involved in the contest and that instead received a technological renovation (henceforth, a*utomation group*). The retrofit program took place before (from 2016 to 2017) and consisted of the installation of a building energy management system (BEMS), an integrated software–hardware system that controls the indoor climatic conditions in buildings. Branches allocation to the interventions was not random. Those that received the technological renovation were selected to reduce the investment payback time: they had higher baseline electricity consumption and higher consumption outside peak working hours,[4] the latter being an indicator of energy waste.

We exploit the different timings of the interventions to assess the impact of the competition on branches' monthly electricity consumption. We use a DID approach from July 2017, after the completion of all the retrofitting interventions,[5] to December 2019, when the behavioral intervention ended. This setting allows us to have a more than one year pre-intervention period to assess whether the parallel trend assumption is realistic, which is required for a DID estimation (Angrist & Pischke, 2008). A priori, there are no theoretical explanations for this assumption not to hold: the two groups are composed of branches located in the Italian territory and issues of attrition, self-selection, and partial compliance (Levitt & List, 2009) are ruled out because the bank managers administered the project with a top-down approach; that is, they assigned the branches to either of the two interventions, with no possibility of opting out.

Among the assumptions required for a DID estimation, our setting may not completely satisfy the lack of spillovers between treated and non-treated subjects. The bank partially involved the non-treated employees in the behavioral intervention to maximize their engagement with the company's initiative and possibly the overall energy savings. The online materials were available to all branches, including those that received the technological renovation. Moreover, the ranking was extended to all branches three times during the competition. This notwithstanding, we believe that the estimation bias is limited in our setting. The non-treated group did not have direct contact with the treated units, and mere information disclosure is often not enough to prompt behavioral change (Madrian, 2014). This is especially true for infrequent information. For example, Carroll et al. (2014) find that the same feedback

[4] The selection of the branches to renovate was based on consumption in 2015.
[5] The installation actually ended in May 2017. We left one month free to prevent possible transition effects from affecting our empirical analysis.

significantly reduced energy consumption when provided monthly, but not when provided bimonthly. Finally, if even any bias occurred in the estimation, it is downward, leading to a conservative assessment of the behavioral intervention's impact.

2.3 Results

2.3.1 Data and descriptive statistics

Our dataset for the empirical analysis combines the bank's administrative data, including branches' characteristics, and electricity consumption data. Electricity consumption was measured monthly through the meter installed in each branch. We have access to monthly billing records at branch level from January 2015 to December 2019. However, as already explained in Section 2.2, we use only the readings after July 2017 to assess the impact of the behavioral intervention. Before that date, branches in the automation group were under renovation (we estimate the retrofit effect in Section 2.3.4). Monthly billing records are divided by time of use (TOU). In Italy, TOUs correspond to the following hours:

- F1: from Monday to Friday, from 8.00 a.m. to 7 p.m., excluding national holidays;
- F2: from Monday to Friday, from 7.00 a.m. to 8.00 a.m. and from 7 p.m. to 11 p.m., and on Saturday, from 7 a.m. to 11 p.m., excluding national holidays;
- F3: from Monday to Saturday, from 11 p.m. to 7.00 a.m., and on Sundays and national holidays.

Distinct drivers contribute to energy consumption in different TOUs. The standard work schedule of the bank's branches is from 8.25 a.m. to 4.55 p.m. Hence, F1 represents peak working hours and captures consumption from both employees' activities and buildings. F2 represents energy use outside the main work schedule, partly due to human activities as some branches are open on Saturdays and some employees may work overtime, but mostly due to the passive consumption of buildings. F3 corresponds to outside working hours, and consumption here results only from buildings' passive consumption. We derive the total consumption of each branch by summing up the consumption in the three TOUs.

The initial sample size is 553 for the behavioral group and 70 for the automation group.[6] We drop two branches from the automation group because their meter is not uniquely identified. We also drop 39 branches from the behavioral group because their meter is likewise not uniquely identified or because they are excluded from the monthly rankings due to the lack

[6] The bank has a higher number of branches than those considered in the study. To be eligible to one of these two groups, the branch should not be an office, should have an uniquely identified meter and should not be assigned to receiving other retrofit interventions in the next years.

of historical data to compute their savings. We further exclude the branches that have less than two successful readings per year so that the sample composition is not excessively unbalanced across years. As non-successful readings, we consider those that are estimated, those non-positive or very close to zero, or those inconsistent across TOUs (i.e., very low in one while very high in another). We identify them as readings that are 95 percent lower or higher than the branch's mean energy consumption. Such values are likely due to temporary closing of branches or to data errors, which we cannot control for given the available data. The final sample size is 570 branches, 503 for the behavioral group and 67 for the automation group.

Table 2.1 reports sample descriptive statistics. As branches are not randomly assigned to the two programs, they have different characteristics. Consistent with the retrofit intervention's targeting criteria, the branches in the automation group are larger in terms of number of employees and surface than those in the behavioral group. These branches are also older than those involved in the energy-saving competition. However, this factor unlikely increases the difference between the two groups, because the renovation improved the energy performance of the branches in the automation group. The behavioral group branches are more likely to be located in the South and islands and less in the North than the automation group branches. As branches exposed to the behavioral intervention are smaller, they also use less energy than those receiving the renovation. Total baseline consumption, computed as the average pre-treatment monthly consumption in the year preceding the launch of the energy-saving competition (2018), is around 2,700 and 3,900 kWh for the two groups, respectively. In both conditions, more than half of the total energy consumption is generated during peak working hours (F1). The use of DID specification with fixed effects in the empirical analysis should control for group differences and prevent them from affecting the results.

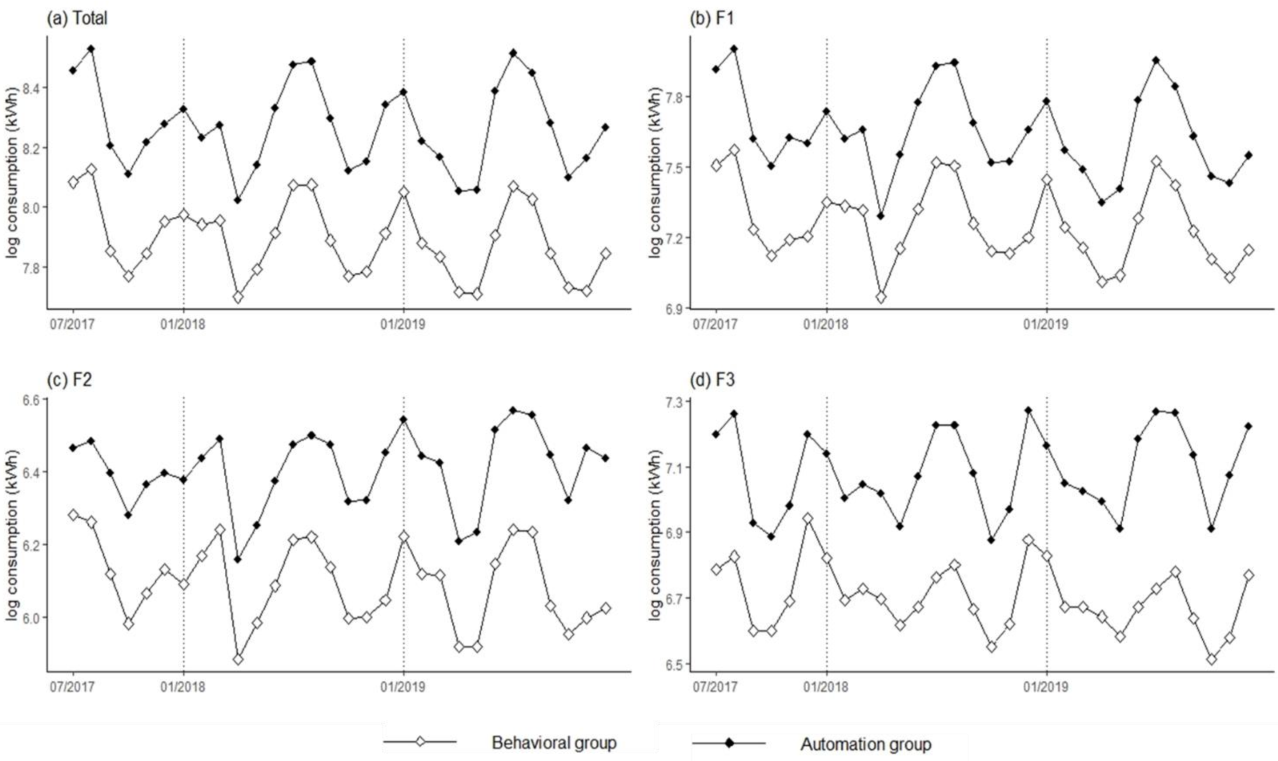
Table 2.1. Descriptive statistics

	Behavioral	Automation
N. of branches	503	67
Panel A: Controls		
Average number of employees	5.485	9.627
	(3.151)	(5.113)
Average surface (m2)	312.41	534.53
	(352.43)	(270.44)
Average opening year	2006	1991
	(15.6)	(22.7)
Electric air conditioning (%)	58.8	50.7
Area: Center (%)	9.15	6.0
Area: North (%)	40.6	79.1
Area: South and islands (%)	50.3	14.9
Pre-treat usage: TOT	2710	3921
	(1448)	(1884)
Pre-treat usage: F1	1447	2146
	(936)	(1243)
Pre-treat usage: F2	443	594
	(238)	(282)
Pre-treat usage: F3	820	1180
	(423)	(514)
Panel B: Outcomes		
Post-treat usage: TOT	2610	3872
	(1419)	(1894)
Post-treat usage: F1	1381	2031
	(894)	(1189)
Post-treat usage: F2	437	622
	(244)	(292)
Post-treat usage: F3	793	1219
	(428)	(574)

Note: The average number of employees is computed considering the number of employees in December 2018. Pre-treat usage is calculated as average monthly electricity consumption in 2018 (in kWh). Post-treat usage is calculated as average monthly electricity consumption in 2019 (in kWh). Standard deviations in parentheses when applicable.

Figure 2.1 graphically illustrates the monthly energy consumption divided by TOU and program assignment. The months from July 2017 to December 2018 represent the pre-intervention period as the energy-saving competition was launched in January 2019 and was ongoing until December 2019. A first graphical inspection of the data supports the parallel trend assumption required for our DID specification, with the two groups following the same trend and seasonality in the pre-consumption period. The (generally) small effect of behavioral interventions makes it difficult to visually detect changes in energy use after the competition launch.

Figure 2.1. Electricity consumption per TOU and group from mid-2017 to 2019



Log monthly electricity consumption for the behavioral and automation group. Vertical dotted lines represent the beginnings of the years. The behavioral intervention was launched in January 2019.

2.3.2 Empirical analysis and results

2.3.2.1 Impact on energy use

We test the effect of the behavioral intervention on electricity consumption. To this aim, we estimate the following specification on the full sample for the period ranging from July 2017 to December 2019:

(1) $y_{it} = \beta_0 + \beta_1 * T_i * post_t + t_{pt} + \alpha_i + \lambda_t + \varepsilon_{it}$

where y_{it} is the monthly electricity consumption of branch i in period t; as we assess treatment effect on the different time of use (TOU), y_{it} denotes the total energy consumption, and the consumption subdivided in F1 (peak working hours, weekdays from 8 a.m. to 7 p.m.), F2 (low working hours, weekdays from 7 to 8 a.m. and from 7 to 11 p.m., and Saturday from 7 a.m. to 11 p.m.), F3 (non-working hours, weekdays and Saturday from 11 p.m. to 7 a.m., Sunday and holidays).

T_i is the indicator for the behavioral intervention and is equal to one for the branches assigned to the program and zero otherwise. $post_t$ is the post-treatment dummy and takes the value zero before January 2019 and one for all the periods thereafter. The regression also includes the monthly temperature of the main Italian provinces where branches are located, t_{pt},[7] and branch and month-by-year fixed effects, respectively denoted as α_i and λ_t. We allow for arbitrary within-branch correlation by clustering the standard errors at the branch level (Bertrand, Duflo, & Mullainathan, 2004).

Results are reported in Table 2.2. The behavioral intervention's effect on total monthly electricity consumption is negative, but it is not statistically significant (Column 1). Such effect, equal to 2.5 percent, is at the lower end of the effect of behavioral programs in the residential sector (Buckley, 2020; Delmas et al., 2013). Different mechanisms can explain this outcome. First, the program may have failed to engage the employees. However, survey and engagement data suggest that this is not a likely explanation (see Section 2.3.3 for further discussion). Second, the possible spillover to non-treated branches may reduce our estimate of the behavioral intervention's effect. Yet, we believe that the spillover is not strong enough to fully explain the lack of significance. We therefore rule out this explanation, or at least that it is the only one. Most likely, the characteristics of energy conservation in the workplace cause the small effect observed in this study.

Despite the behavioral intervention's insignificant effect on total consumption, we find it generates significant savings outside the main working hours. The effect is negative and significant for both F2 (Column 3) and F3 (Column 4), resulting in 7 and 6 percent savings, respectively. This value is quite high compared to the average effect of behavioral interventions and shows how non-price interventions can help firms reducing inefficiencies outside the work schedule. That energy savings are concentrated when employees are not at work is also found by Orland et al. (2014), in the context of a serious game intervention in the workplace. Going beyond a certain amount of energy savings is indeed difficult when people

[7] The temperature data are retrieved from the archives of the National Oceanic and Atmospheric Administration (source: https://www.ncdc.noaa.gov/, accessed 1 July 2020).

need to perform energy-consuming activities (Buchanan et al., 2015). Moreover, even in the housing sector, where people have a financial incentive to reduce their energy consumption, people are reluctant to sacrifice their comfort to conserve energy (Buchanan, Russo, & Anderson, 2014).

Table 2.2. Impact of the behavioral intervention on electricity usage

	(1) TOT	(2) F1	(3) F2	(4) F3
DID	-0.025	0.011	-0.075***	-0.067**
	(0.018)	(0.019)	(0.023)	(0.025)
N. branches	570	570	570	570
Observations	16,501	16,501	16,501	16,501

Regression of log monthly electricity consumption on treatment indicator. All the models include branch and time fixed effects and temperature of the province. *DID* is the difference-in-difference estimator for the behavioral intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the peak working hours, *F2* during the low working hours, and *F3* during the non-working hours. Standard errors clustered at the branch level reported in parentheses. *p < .05, **p < .01, ***p < .001.

2.3.2.2 Robustness checks

We test for sensitivity to our DID specification by varying the outcome, panel length, and sample used to estimate Equation (1). First, Column 1 to 4 of Table B1 show similar results if we estimate the regression in levels rather than logs. The only difference is that F1 turns out to be positively statistically significant, probably due to the presence of outliers in the untransformed dependent variable. Second, we restrict the analysis to the years 2018 and 2019 so that the lengths of the pre- and post-intervention periods are the same, and we replicate the results in Table 2.2 (Column 5 to 8). For the same period, we also estimate treatment effects on yearly rather than monthly energy consumption as this is another way to eliminate the serial correlation in the data (Bertrand et al., 2004). Results in Column 9 to 12 show that the significance levels are the same as in the main specification. Third, the behavioral intervention's impact is similar when we keep all the real meter readings in the database (Column 13 to 16). The higher noise in the data causes larger point estimates and standard errors than in the main specification, making the impact on F3 only marginally significant (p < .10).

Finally, we test whether our main specification is robust to an in-time placebo test. To this aim, we eliminate year 2019, during which the behavioral intervention was ongoing, and we check if our specification detects as significant a fictitious treatment starting in January 2018.

Table B2 shows that our specification does not detect significant treatment effects when no intervention occurred. Hence, we rule out the possibility that the pre-existing differences between the two groups cause our main results.

2.3.2.3 Heterogeneous program effects

We assess heterogeneous effects of the behavioral intervention according to the different branches' characteristics (i.e., pre-treatment energy consumption, heating type and size) by adding to Equation 1 interactions between treatment and post-intervention dummies with the relevant variable. We report in Table 2.3 the results for total electricity consumption. Results for the other TOUs, which are similar to those for total consumption, are reported in Table C1.

The first source of heterogeneity that we examine is the pre-treatment energy consumption. We include it because a higher initial energy consumption generally means a higher "slack" in resource usage (Tiefenbeck et al., 2018). Accordingly, households that have high pre-consumption levels are more responsive to non-pecuniary interventions (Allcott, 2011; Bonan et al., 2019; Byrne et al., 2018; List et al., 2017). However, evidence of whether this also applies in the workplace is scattered as previous studies do not investigate this dimension (Brown et al., 2013; Charlier et al., 2021; Handgraaf et al., 2013; Ornaghi et al., 2018). We thus estimate Equation 1, interacting intervention and post-intervention dummies with a continuous measure of consumption in the year preceding the implementation of the energy-saving competition (January-December 2018). The sign of the interaction goes in the expected direction, but it is not statistically significant (Column 1).

Although this is surprising, one mechanism may explain why we fail to reproduce this result. In the residential sector, non-pecuniary interventions prompt energy efficiency investments (Brandon et al., 2017). Heterogeneity in pre-consumption levels is partly explained by the fact that low energy users have already adopted energy efficiency measures and are less likely to do so again in response to the intervention. In contrast, employees cannot invest in building renovations to conserve energy; they can only change their behavior to reduce their consumption. This constraint probably causes the high-consuming branches to respond to the behavioral intervention to the same extent as the low-consuming branches do.

Next, we investigate heterogeneous effects based on other observable branch characteristics: heating type (gas vs. electricity) and size, in terms of number of employees and surface. These characteristics influence energy consumption and may indirectly affect interventions' impacts because they contribute to the pre-consumption levels. However, they may also have a direct impact, which we isolate through our fixed effects specification. That is, we assess how a specific characteristic interacts with the behavioral intervention net of all the other branch characteristics.

We expect the behavioral intervention to be more effective for the branches with electric heating. There, the employees have more energy-saving opportunities because they can optimize not only their use of appliances and lighting, but also heating settings. In contrast with our expectations, Column 2 shows a non-significant interaction. On the other hand, the behavioral intervention coefficient becomes statistically significant for branches without electric heating, showing that employees change their use of appliances and lighting but not of heating. The lack of interaction outside working hours (Table C1) also suggests that the employees do not optimize the climatic conditions (e.g., closing the windows and reducing indoor temperature) when leaving the office. This is consistent with findings from the residential sector that tenants who do not pay their bills are significantly less likely to change heating settings at night (Gillingham, Harding, & Rapson, 2012).

Table 2.3. Heterogeneous effect of the behavioral intervention

	(1) TOT	(2) TOT	(3) TOT	(4) TOT
DID	0.308	-0.040*	-0.024	-0.002
	(0.390)	(0.018)	(0.048)	(0.037)
DID x pre-treat	-0.042			
	(0.047)			
DID x heating		0.028		
		(0.035)		
DID x employees			0.001	
			(0.004)	
DID x surface				-0.001
				(0.001)
N. branches	570	570	570	570
Observations	16,501	16,501	16,501	16,501

Regression of log monthly total electricity consumption on treatment indicator. All models include branch and time fixed effects, temperature of the province and the post-treatment indicator interacted with the heterogeneity variables. DID is the difference-in-difference estimator for the behavioral intervention. Pre-treat is a continuous variable for average consumption before the launch of the competition (2018). Heating is a dummy equal to 1 if the branch has electric heating, 0 otherwise. Employees is a continuous variable for the number of employees in December 2018. Surface is a continuous variable for the squared meters. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

Finally, social norms and group dynamics within the workplace significantly influence employees' energy-saving behaviors (Staddon et al., 2016). Engineering studies also show that the effects of social influence programs depend on the characteristics of the network (Jain, Gulbinas, Taylor, & Culligan, 2013; Peschiera & Taylor, 2012). Smaller groups generate stronger peer effects (Boucher, Bramoullé, Djebbari, & Fortin, 2012). These, in turn, trigger conservation behaviors (Wolske, Gillingham, & Schultz, 2020). Moreover, feedback is more effective when it is possible to monitor how energy is related to individual behavior (Grønhøj & Thøgersen, 2011), which is easier to do in smaller groups. Accordingly, we expect the behavioral intervention to have a higher impact on smaller rather than larger branches. However, Column 3 and 4 show no interaction between the behavioral intervention and the branch size, for the number of employees and the surface, respectively.[8] Smaller branches are therefore not more responsive to the energy-saving competition. While surprising, this result is in line with the fact that the rate of contributions to public goods (X. M. Zhang & Zhu, 2011) and the rate of peer sanctions (Carpenter, 2007) do not depend on the group size. Survey data also suggest another explanation: other employees' engagement with the program does not affect individuals' engagement with it (see Section 2.3.3 for further details). Hence, peer effects may not have occurred regardless of the branch size.

2.3.3 Engagement with the behavioral intervention

This section analyzes employees' engagement with the behavioral intervention using survey data and the statistics of the interaction with the program webpage. The goal is to complement the quantitative analysis by exploring how and to what extent employees interacted with the initiative.

The survey, conducted at the end of the behavioral intervention (February-March 2020), was designed in collaboration with the managers of the program. The bank administered it to a subsample of its employees on the occasion of a broader questionnaire on corporate social responsibility. Overall, 1,152 employees participated in the survey. Respondents are predominantly male (61.1%), with ages ranging from 18 to more than 50, and with 43.8% of them working in branches and the rest in offices. In accordance with the company's privacy policy, responses were collected anonymously from all branches, with no possibility of linking the response to the branch where it came from. We therefore cannot discern whether

[8] Results do not change if we interact the treatment and post-treatment dummies with dummies for branches' size (i.e., equal to one if the branch has more employees than the median and if the branch has larger surface than the median, for heterogeneity in number of employees and surface, respectively).

respondents work in a branch belonging to the behavioral or the automation group. We can isolate whether they work in offices, which are not directly involved in the energy-saving competition.

Concerning the interaction with the program webpage, we have information on the number of accesses made to the platform. The data also illustrate the number and types of content posted online every month, and how many times each of them was viewed. As for the survey, we cannot distinguish whether the access was made by an employee from a behavioral group branch. Although our data are not suitable for estimating any treatment effect, we believe that they still provide insights into which parts of the behavioral intervention were more appreciated and what motivated employees to participate in the competition.

Survey results reveal that the initiative was known and welcomed by the employees. Overall, 74.7% of the respondents are aware of the behavioral intervention. Of these, most accessed the program's informative materials sometimes over the year (53.7%) or at least once per month (35.2%). Only 5.3% of the respondents declare that they had never accessed the platform. These figures are consistent with the data of engagement with the online platform. The platform was visited 31,444 times during the intervention. Considering that the total number of employees in the branches belonging to the behavioral group is 2,825,[9] the average number of accesses per targeted employee is 11.1 per year or 0.9 per month. Even if this is an overestimation as it also includes the visits from non-targeted employees, it shows a good level of engagement with the intervention. The core of the program, i.e., the ranking, was published 11 times over the course of the intervention (the June and July rankings were combined due to the summer break).

The survey also reveals that employees had a positive attitude toward the intervention, with 87% considering it useful, 58% considering it interesting, 84% agreeing that it prompts good behavior, and 86% saying that it gives tips on how to save energy. Most respondents also state that the intervention changed their behavior, with 77% applying some conservation tips in the workplace and 72% doing so at home. This last figure highlights the possibility of creating a positive spillover (Maki et al., 2019): prompting good behaviors in the workplace may also improve energy-saving practices at home.

We then focus on which parts of the behavioral intervention the employees perceived as more engaging. As in Senbel et al. (2014), participants were asked to indicate the three most important drivers of participation in the program. Table 2.4, Panel A summarizes the answers of respondents working in branches and aware of the project (N = 368). Overall, the most

[9] Sum of the employees working in the branches belonging to the behavioral group in December 2018.

relevant driver of engagement is the concern for environmental issues (96.7%), followed by the willingness to save energy more than the other branches do (18.5%). Peer pressure (i.e., colleagues and bosses' interest in the initiative) is not cited as an important driver of participation. This outcome may explain the absence of interaction between the number of employees and the behavioral intervention in our heterogeneity analysis. We expected smaller branches to react more to the intervention as smaller groups usually trigger more decisive social influence. However, survey data suggest that peer pressure did not happen in general. By targeting the branches rather than the smaller and more homogeneous units within them, the company may have failed to trigger this important dynamic.

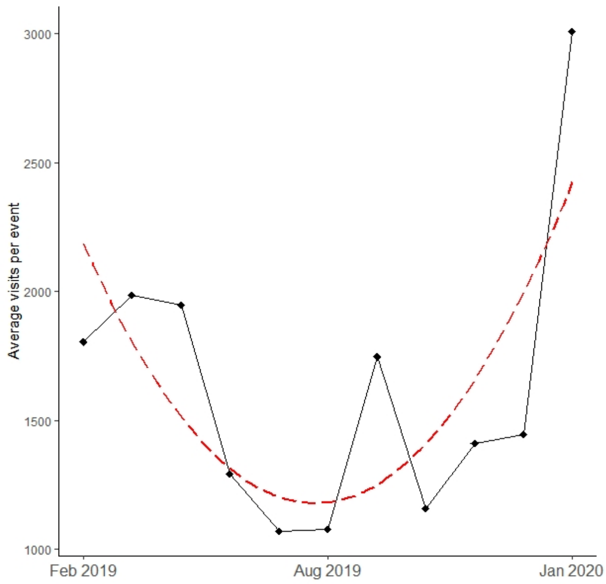
Table 2.4. Survey results

Panel (A): Which are the main drivers that made you participate in the initiative?	%
Concern for environmental issues	0.967
Willingness to save more energy than the other branches	0.185
My colleagues' interest in the initiative	0.049
My bosses' interest in the initiative	0.043
Presence of incentives and prizes	0.038
Panel (B): Which contents have you accessed?	%
News on the program platform	0.660
Informative materials	0.497
Monthly rankings	0.402
Missions	0.144
Videos with tips	0.136
None	0.046

Employees' engagement with the different parts of the initiative corresponds to the reported drivers of participation. Survey responses illustrate that news and informative materials were the most accessed contents, followed by the monthly rankings (Table 2.4, Panel B). Missions and videos were less relevant. Engagement data with the program webpage partially support survey answers. The intervention's main page was accessed 8,100 times, that of the monthly rankings 8,582 times, and that of missions 4,505 times. Videos with conservation tips were seen 4,524 times, and the rules of the game and the informative materials were seen 2,248 and 1,530 times, respectively. Taken together, survey and engagement data show that the additional incentives (i.e., missions, videos, and prizes) engaged employees less than the competition did. However, one main difference emerges between survey and interaction data. The former indicates that news was accessed more times than the rankings whereas the latter shows the opposite. This contrast is consistent with the fact that people tend to underestimate the effect of social influence on their behavior (Nolan, Schultz, Cialdini, Goldstein, & Griskevicius, 2008).

Finally, we use interaction data to monitor the employees' engagement over time. The number of contents posted varied by month because the company alternated news, missions, and videos. As a standardized proxy of engagement, we use the average number of views per content posted in that month. Figure 2.2 shows the engagement with the program from January 2019 to January 2020. The relation between time and engagement follows a U shape: it starts high and reaches its minimum during the summer break. It then increases again and achieves a peak at the end of the intervention. This shape is probably explained by the fact that the initial enthusiasm subsided over time but was ultimately rekindled by the final ranking.

Figure 2.2. Monthly average number of visits to the program webpage



Average number of views per content posted per month. The data from June and July 2019 were pooled together because only one ranking was published for the savings of these two months. The dashed line represents the fitted quadratic curve.

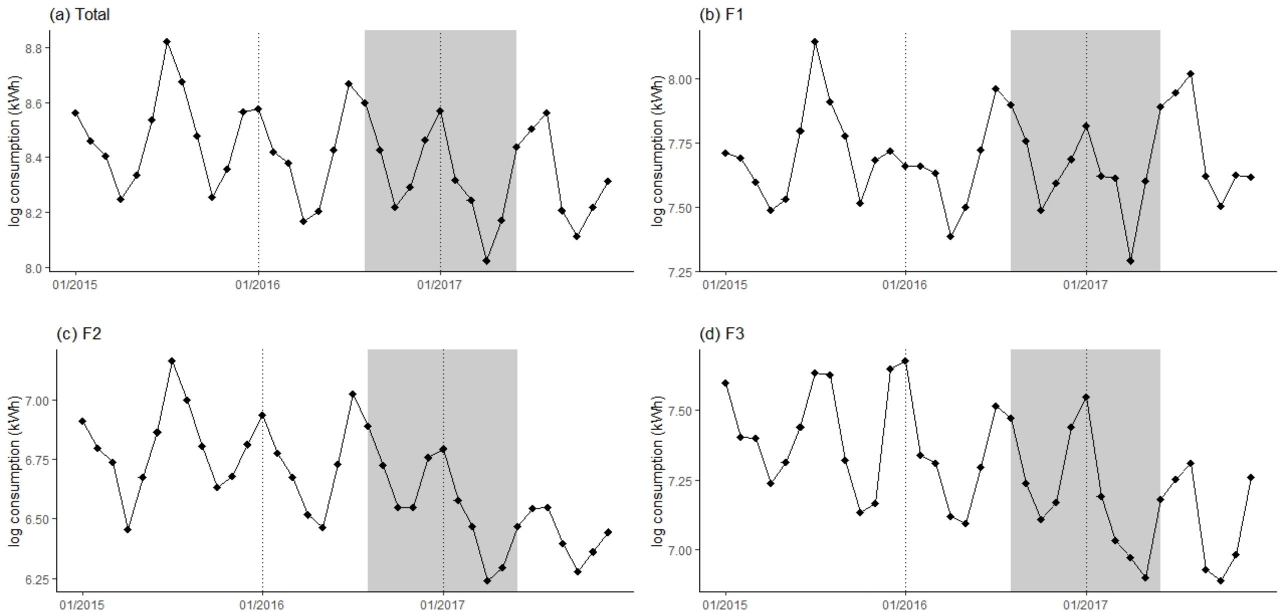
2.3.4 The retrofit program

We now assess the impact of the technological intervention, which consisted of a building energy management system (BEMS) implemented in the 67 branches belonging to the automation group. Each branch received the renovation on a date within the period from August 2016 to May 2017. The impact of the retrofit is clearly visible in Figure 2.3. During the installation period (grey area), energy consumption gradually reduces in all TOUs, especially outside the main working hours (Panel (c) and (d)), and remains low after the installation is completed. We empirically estimate the effect of BEMS using the following staggered DID specification from 2015 to 2017:

(2) $y_{it} = \beta_2 + \beta_3 * post_{it} + t_{pt} + \alpha_i + \lambda_t + \varepsilon_{it}$

where all the terms are the same as those in Equation (1), except that the analysis includes only the branches in the automation group[10] and that the variable for the post-intervention period, $post_{it}$, is branch-specific and takes the value zero before the retrofit month and one for all the periods thereafter.

Figure 2.3. Electricity consumption of the automation group per TOU from 2015 to 2017



Log monthly electricity consumption for the branches in the automation group. Vertical dotted lines represent the beginnings of the years. Gray area represents the BEMS installation period.

Results are reported in Table 2.5. We estimate that the technological renovation curbs total monthly consumption by 18 percent (Column 1). This amount is in line with the other BEMS implementations, which achieve average energy savings of 16-17 percent (Lee & Cheng, 2016). The reduction in consumption is statistically significant in all TOUs, but its magnitude

[10] We attempted to perform a DID similar to that used to assess the energy-saving competition, using the behavioral group as a control. However, the specification fails the placebo test for the parallel trend in the pre-intervention period. Before the BEMS installation, branches in the automation group had very high baseline energy consumption, poor energy performance due to the old buildings and possibly problems in buildings' parametrization, which may have caused the differences in trend.

varies across them: it is around 9 percent during the main work schedule (Column 2) and reaches a maximum in F2 of 28 percent in the evenings (Column 3).

Although we cannot directly compare the effects of the behavioral and technological interventions, our setting allows us to make two points. First, the retrofit's high effect size shows the efficacy of the smart management of buildings, in comparison to the energy-saving competition. From a behavioral perspective, the effectiveness of automation is explained by people's tendency to stick to the status quo (Kahneman, Knetsch, & Thaler, 1991), which makes them accept the indoor conditions they are provided with (Brown et al., 2013). This type of intervention is particularly suitable in the workplace, where market failures reduce employees' willingness to make an effort to save energy and responsiveness to behavioral interventions. Needless to say, technological retrofits are much more expensive than behavioral campaigns. Second, the retrofit, like the energy-saving competition, has a stronger effect outside the main work schedule. The two interventions act upon similar inefficiency sources, such as the appliances and lights left switched on overnight. Therefore, they may overlap rather than reinforce each other if they are implemented together.

Table 2.5. Impact of the retrofit on electricity usage

	(1) TOT	(2) F1	(3) F2	(4) F3
DID	-0.193^{***}	-0.095^{*}	-0.329^{***}	-0.281^{***}
	(0.047)	(0.047)	(0.064)	(0.069)
N. branches	67	67	67	67
Observations	2,275	2,275	2,275	2,275

Regression of log monthly electricity consumption on treatment indicator. All models include branch and time fixed effects and temperature of the province. *DID* is the staggered difference-in-difference estimator for the retrofit. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the peak working hours, *F2* during the low working hours, and *F3* during the non-working hours. Standard errors clustered at the branch level reported in parentheses. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

2.4 Conclusion

This study assesses the impact of a large-scale behavioral intervention implemented by an Italian bank to reduce energy consumption. The intervention consists of an energy-saving competition among the branches aimed at triggering employees' conservation efforts. Starting in January 2019, the program lasted one year and involved more than 500 branches. Employees participated in and engaged with the intervention, generating significant savings outside the main work schedule (by around 7 percent). However, this effect is not strong enough to significantly affect total electricity consumption.

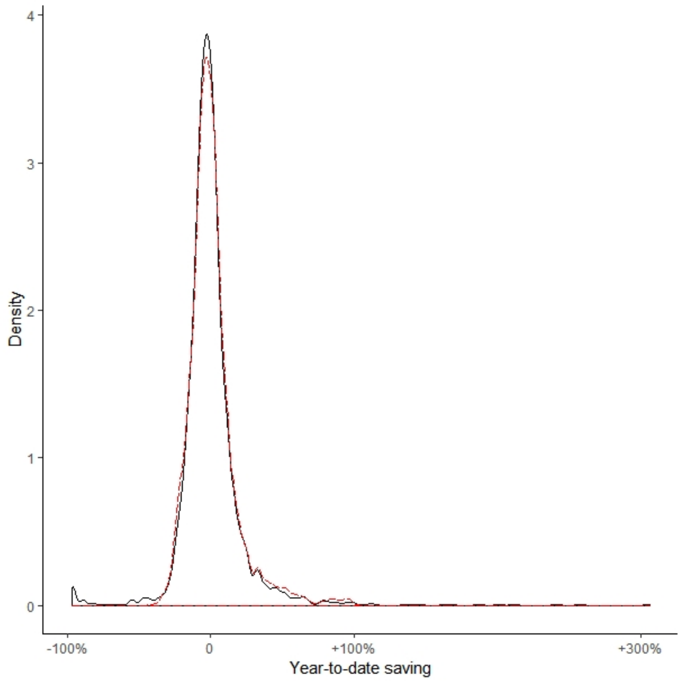
We also study the effect of a retrofit program automating building energy management. The intervention was applied to a subsample of branches with high baseline energy consumption from 2016 to 2017. Branches receiving this intervention reduced their energy consumption by 18 percent. The highest share of savings is registered outside working hours, reaching more than 25 percent.

This study has policy implications. Our results question the applicability of behavioral policies in the workplace or at least underscore how the context shapes their effectiveness. An intervention targeting overall buildings' consumption does not seem effective. Timely and behavior-specific feedback may be more suitable as it highlights the link between employees' efforts and energy savings. Finally, both the behavioral and technological interventions mostly reduce energy waste outside working hours. Hence, even when energy-efficiency programs have different natures, they may overlap if they address the same drivers of energy waste.

Appendix

Appendix A. Saving calculation of monthly ranking

Figure A1. Calculation of the saving by the company (black line) and by the authors (red line)



Appendix B. Robustness checks

Table B1. Impact of the behavioral intervention on electricity usage, robustness checks

	(1) TOT	(2) F1	(3) F2	(4) F3	(5) TOT	(6) F1	(7) F2	(8) F3	(9) TOT	(10) F1	(11) F2	(12) F3	(13) TOT	(14) F1	(15) F2	(16) F3
DID	-40.14	70.89*	-38.67**	-72.37*	-0.024	0.003	-0.065**	-0.057*	-51.07	51.64	-36.02**	-66.69*	-0.034	-0.022	-0.114**	-0.072
	(49.20)	(28.35)	(12.28)	(28.49)	(0.017)	(0.017)	(0.023)	(0.025)	(50.49)	(27.552)	(13.91)	(30.01)	(0.040)	(0.045)	(0.043)	(0.043)
N	570	570	570	570	570	570	570	570	570	570	570	570	570	584	584	584
Obs	16,501	16,501	16,501	16,501	13,253	13,253	13,253	13,253	1,140	1,140	1,140	1,140	17,182	17,182	17,182	17,182

Column 1 to 4: Regression of monthly electricity consumption on treatment indicator. Column 5 to 8: Regression of log monthly electricity consumption on treatment indicator, excluding year 2017. Column 9 to 12: Regression of yearly electricity consumption on treatment indicator, excluding year 2017. Column 13 to 16: Regression of log monthly electricity consumption on treatment indicator, including all real meters. All models include branch and time fixed effects and temperature of the province (temperature is not included in Column 9 to 12). *DID* is the difference-in-difference estimator for the behavioral intervention. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the peak working hours, *F2* during the low working hours, and *F3* during the non-working hours. Standard errors clustered at the branch level reported in parentheses. *N* represents the number of branches, *Obs* the number of observations. *p < .05, ** p < .01, ***p < .001

Table B2. Placebo test for the main specification

	(1) TOT	(2) F1	(3) F2	(4) F3
DID	-0.003	0.024	-0.032	-0.029
	(0.013)	(0.013)	(0.020)	(0.021)
N. branches	570	570	570	570
Observations	9,871	9,871	9,871	9,871

Regression of log monthly electricity consumption on treatment indicator, excluding year 2019. All models include branch and time fixed effects and temperature of the province. *DID* is the difference-in-difference estimator for the fictious behavioral intervention, which is 0 before January 2018 and 1 after. *TOT* denotes the total electricity consumption, *F1* the electricity consumption during the peak working hours, *F2* during the low working hours, and *F3* during the non-working hours. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

Appendix C. Heterogeneous effect of the behavioral intervention

Table C1. Heterogeneous effect of the behavioral intervention, all TOUs

	(1)	(2)	(3)	(4)	(5)	(6)	(10)	(11)	(12)	(13)	(14)	(15)
	F1	F2	F3	F1	F2	F3	F1	F2	F3	F1	F2	F3
DID	0.227	-0.083	0.266	0.015	-0.093***	-0.095**	0.035	-0.078	-0.078	0.053	-0.079	-0.049
	(0.348)	(0.365)	(0.527)	(0.021)	(0.028)	(0.030)	(0.049)	(0.056)	(0.063)	(0.038)	(0.043)	(0.048)
DID x pre-treat	-0.029	-0.001	-0.051									
	(0.045)	(0.057)	(0.076)									
DID x heating				-0.005	0.034	0.051						
				(0.037)	(0.045)	(0.049)						
DID x employees							-0.001	0.002	0.003			
							(0.004)	(0.006)	(0.006)			
DID x surface										-0.001	0.001	-0.001
										(0.001)	(0.001)	(0.001)
N. branches	570	570	570	570	570	570	570	570	570	570	570	570
Observations	16,501	16,501	16,501	16,501	16,501	16,501	16,501	16,501	16,501	16,501	16,501	16,501

Regression of log monthly electricity consumption on treatment indicator. All models include branch and time fixed effects, temperature of the province and the post-treatment indicator interacted with the heterogeneity variables. DID is the difference-in-difference estimator for the behavioral intervention. Pre-treat is a continuous variable for average consumption before the launch of the competition (2018). Heating is a dummy equal to 1 if the branch has electric heating, 0 otherwise. Employees is a continuous variable for the number of employees in December 2018. Surface is a continuous variable for the squared meters. F1 denotes the electricity consumption during the peak working hours, F2 during the low working hours, and F3 during the non-working hours. Standard errors clustered at the branch level reported in parentheses. *p < .05, ** p < .01, ***p < .001.

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CHAPTER 3

A behavioral model for in-home displays usage in social housing districts

with Nives DellaValle (Eurac Reserach)[1,2]

Abstract

In-home displays providing real-time feedback have been widely used to reduce households' energy consumption. However, their effectiveness in vulnerable contexts has been largely overlooked. We develop a theoretical model on tenants' decision to use them. On the one hand, their usage yields a reduction in energy bills and CO2 emissions. On the other hand, their usage requires effort. We also include the impact of two cognitive biases, present bias and locus of control, proposing that the higher their severity, the more the equilibrium choice leans toward the non-usage alternative. Their consideration is particularly important in this setting. Scarcity affects the cognitive process in a way that may undermine the impact of policies that require beneficiaries' active behavioral change. Through a theoretical discussion, our work contributes to informing the design of policies aimed at tackling energy poverty.

Keywords: Energy poverty; Energy saving; Real-time feedback; Cognitive biases

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[2] *Author contributions:* VF conceived the study, led the development of the theoretical framework and the manuscript writing. NDV conceived the study, contributed to the development of the theoretical framework and to manuscript writing.

In the European Union, more than 50 million households suffer from energy poverty, making it one of the most challenging priorities of the European Commission.[3] In particular, energy poverty is a condition in which individuals cannot access the essential services of lighting, powering standard appliances, and adequate warming and cooling (Thomson, Bouzarovski, & Snell, 2017). Amongst other factors, the inability to keep one's house warm and cold is caused by the scarce energy performance of the dwellings (Ugarte et al., 2016). This is especially true for low-income households, who are less likely to have the resources to invest in efficiency renovations (Schleich, 2019). The European Commission has therefore identified in energy efficiency improvements a key policy lever to tackle energy poverty.[4] Improving the energy performance of buildings not only enhances the quality of life of vulnerable households (Jenkins, 2010), but also contributes to the EU climate-related goals (Charlier, Risch, & Salmon, 2018).

However, the built environment constitutes only part of a household energy consumption, and how tenants use it also represents a significant share (Guerra-Santin & Itard, 2010). As an example, behavioral factors explain between 30% and 50% of the variance of overall heating and cooling consumption (Mansouri, Newborough, & Probert, 1996; Sonderegger, 1978; Steemers & Yun, 2009). Hence, the effectiveness of technological interventions depends on the behavior of individuals who daily interface with them (Gillingham & Palmery, 2014). Ignoring the human dimension reduces the likelihood of achieving significant energy savings (Allcott, Mullainathan, & Taubinsky, 2014), which is usually referred to as the energy-efficiency gap (Dietz, 2010; Jaffe & Stavins, 1994) and rebound effects (Belaïd, Bakaloglou, & Roubaud, 2018; Milne & Boardman, 2000; Nässén & Holmberg, 2009). These behavioral factors weigh even more among vulnerable households, who usually display low socioeconomic status and have limited access to essential resources (DellaValle, 2019). Moreover, such a resource scarcity affects the cognitive process (Shah, Shafir, & Mullainathan, 2015) in a way that makes occupant behavior the "fourth driver of fuel poverty" (Kearns, Whitley, & Curl, 2019).

Acknowledging the interconnections between the built environment and tenants' behavior, SINFONIA[5] combines technological and behavioral policy levers to address energy poverty.

[3] https://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union/clean-energy-all-europeans%20
[4] https://ec.europa.eu/energy/en/topics/energy-efficiency/targets-directive-and-rules/energy-efficiency-directive
[5] SINFONIA is one of the pioneer projects promoting the retrofitting of social housing in Italy. Thanks to funding from the Seventh Framework Program of the European Union for Research, researchers from the Institute for Renewable Energy of the European Academy of Bolzano (Eurac Research), in collaboration with the Municipality of Bolzano/Bozen, supported by experts from IDM Südtirol - South Tyrol, the Institute for Social Building IPES, Alperia and Agenzia CasaClima, are transforming some

In the pilot case of Bolzano, coordinated by the Institute of Renewable Energy-Eurac Research, retrofitting interventions have been implemented to enhance the energy performance of social housing buildings (see DellaValle, et al. (2018) for further details). In addition to other activities that engage tenants in learning how to manage the renovated infrastructure, in-home displays (IHDs) are installed in the dwellings of tenants who gave the consent.[6] The IHDs provide real-time feedback on indoor parameters and energy consumption. Notably, every time a parameter overcomes an optimal threshold, the IHD sends out a pop-up specifying the problem and providing tips on how to solve it. The tenant can solve the pop-up by clicking on the relevant button.

This study focuses on the behavioral process underlying tenants' usage of IHDs. Our study contributes to energy poverty and IHDs research in two ways. First, we capitalize on the SINFONIA project, being this one of the first attempts to use real-time feedback in a setting characterized by low socioeconomic status (Šć, Warnier, & Nurminen, 2017), to advance the understanding of whether interventions that require active users' engagement can tackle energy poverty. Considering how the context shapes behavior not only makes policy making more informed, but also increases the likelihood to achieve projects' goals (Westskog, Winther, & Sæle, 2015).

Second, we model the decision to use the IHDs by accounting for the role of cognitive biases. Previous studies on IHDs mainly focused on their environmental and economic benefits and their technological features as sources of engagement (e.g., Pyrko (2011), Van Dam et al. (2010) and Westskog et al. (2015)). However, cognitive limitations affect the cost-benefit considerations of using energy-efficient technology (Spandagos & Ng, 2018), especially among vulnerable households (Mills & Schleich, 2012). While it is true that IHDs embed a huge potential to bring economic and environmental benefits (Fischer, 2008), such a potential can be undermined by, among others, behavioral factors. By combining these dimensions, our theoretical framework provides a set of testable implications on how cognitive biases affect the usage of energy-efficient technologies. More specifically, we theoretically show that with cognitive biases the perceived costs (benefits) of IHDs increase (reduce), thereby requiring that tenants derive higher economic and moral utility from IHDs for using them, relative to the situation with "rational" IHDs users.

areas of Bolzano/Bozen. At the core of this transformation is the renovation of a number of social housing districts, through the introduction of several technologies. These interventions aim to improve the quality of life at home, increasing energy saving and comfort for those who live there. For additional details see: http://www.sinfonia-smartcities.eu/en/project

[6] http://www.sinfonia-smartcities.eu/en/blog/post/behaviour-change-how-to-increase-the-impact-of-energy-efficient-renovation-projects

The remainder of the paper proceeds as follows. In Section 3.2 we review the relevant literature. Section 3.3 sets up the theoretical model and hypotheses. Conclusions and implications of our work are drawn in Section 3.4.

3.1 Cognitive biases and in-home displays

For decades policy makers have relied on the assumption that individual behavior complies with rational choice theory (Von Neumann & Morgenstern, 1944). However, extensive experimental and empirical evidence has shown that individuals systematically deviate from the assumptions of this theory (Camerer, Loewenstein, & Rabin, 2004). In particular, to perform rational calculations under limited cognitive capacity (Simon, 1955), individuals employ heuristics (Tversky & Kahneman, 1974). However, these may often lead to systematic errors (e.g., cognitive biases).

Among the most prominent deviations from rational choice theory, other-regarding preferences certainly have received the greatest attention in the experimental literature. In particular, studies on the topic have confronted the classical assumption that individuals display strictly selfish preferences (i.e., individuals only care about their own wellbeing) with the evidence that they also care about the wellbeing of others and the society as a whole. These other-regarding concerns are especially relevant in the context of energy consumption, and this is well-acknowledged in the related literature (Frederiks, Stenner, & Hobman, 2015a). Indeed, being the climate the most prominent public good (Brekke & Johansson-Stenman, 2008), the decision to conserve energy is also explained by a motivation to contribute to others' wellbeing (Bénabou & Tirole, 2006; Farrow, Grolleau, & Ibanez, 2017). In our study, we account for these preferences.

Another deviation from rational decision-making is the tendency to place attention on objectives that are close in time and disregard those that are distant (also called *present bias*). Such a tendency results in decisions that are guided by a preference for options that provide immediate benefits, even when other alternatives would provide higher benefits in the future (Loewenstein & Prelec, 1992). In the context of energy consumption, the economic (Harding & Hsiaw, 2014) and environmental (Brekke & Johansson-Stenman, 2008) consequences associated with the effort required to consume less energy are delayed. Therefore, the decision to use energy efficiently can be seen as an intertemporal decision and may be affected by present bias (Harding & Hsiaw, 2014).

While present bias has been extensively studied in the context of energy efficiency (Newell & Siikamki, 2015), to the best of our knowledge, this is the first that investigates how it explains the engagement with IHDs. As for the decision to consume less energy, also using IHDs can be seen as an intertemporal choice associated with immediate cost and delayed benefit. Regarding the cost, it has two main components. The former refers to the opportunity cost of time to interact with the monitor, understand its feedback, and apply it to daily behavior (Sintov & Schultz, 2017). The latter is caused by the reduced comfort associated with lower energy consumption (Pierce, Schiano, & Paulos, 2010). In contrast, the benefits of IHDs are delayed and made salient only at the end of the billing period. Hence, those who assign higher values (namely, are more present biased) to the immediate costs of using IHDs than to their delayed benefits, might be less willing to use them.

At the same time, IHDs are likely to reduce the negative consequences associated with present bias, by making salient the energy consumed and the associated outcomes (Hargreaves, Nye, & Burgess, 2010). For this and other reasons, it is thus crucial to better understand the interplay between present bias and IHDs usage. And this is particularly true for social housing contexts. As the surrounding social and economic backgrounds generally influence intertemporal decisions (Watts, Duncan, & Quan, 2018), also energy-related behaviors may be affected by living in conditions of resource scarcity (DellaValle, 2019).

Finally, in this study, we account for the role of *locus of control*, which is "a generalized attitude, belief, or expectancy regarding the nature of the causal relationship between one's own behavior and its consequences" (Rotter, 1966:2). Locus of control represents the extent to which individuals perceive outcomes in their life as caused by their actions (Rotter, 1966). Specifically, locus of control is internal if one feels control over outcomes, and external if one perceives that outcomes are caused by factors beyond her control. Having an internal locus of control relates to the belief that there is a higher return in doing an activity (Caliendo, Cobb-Clark, & Uhlendorff, 2015), and to higher persistence in trying to achieve a goal (Ng, Sorensen, & Eby, 2006). In the context of IHDs, behavioral change may be thwarted by perceived action potential (Frederiks, Stenner, & Hobman, 2015b).

This psychological concept has only recently been introduced in the economic literature to explain human behavior. However, attitudes affect the link between preferences and behavior, and cannot be disregarded while investigating the heterogeneity behind IHDs engagement (Buchanan, Russo, & Anderson, 2015). With this study, we introduce locus of control as a driver of engagement with IHDs. This question is particularly interesting for vulnerable contexts, in which individuals are more likely to display a more external locus of control (Sheehy-skeffington & Rea, 2017). In particular, if occupants with a more external locus of control do not feel in control over their energy consumption, they may perceive that using IHDs will not generate significant energy saving. This, in turn, may undermine the perceived economic and environmental benefits of using IHDs and the motivation to use them. Moreover, it is likely that an external locus of control also predicts low persistence in interacting with the IHD and reacting to its feedback. On the other hand, however, IHDs embeds the potential to empower consumers to take action with respect to lowering their energy consumption (Grønhøj & Thøgersen, 2011). Hence, it may also be the case that IHDs help overcome the behavioral consequences of an external locus of control.

3.2 Theoretical framework

We formalize a simple theoretical framework for tenants' usage of IHDs. Engagement with IHDs is essential because, alone, this technology does not conserve energy. Rather, it provides information that tenants need to process and implement in order to decrease their energy consumption (Buchanan, Russo, & Anderson, 2014). Hence, without engagement and interaction with IHDs, energy saving is not achievable (Matsukawa, 2004; Nunes, Pereira, Quintal, & Bergés, 2011). Our model provides testable hypotheses on the extent to which cognitive biases affect tenants' usage of the energy-efficient technology.

3.2.1 Tenants' utility

We assume that interaction with IHDs generates energy saving compared to the baseline of no intervention. Under no IHDs, individuals consume energy e_0. We assume that $e_0 * p_e \leq y$, where p_e is the price of energy and y is income. Namely, individuals can afford the energy costs they faced under no intervention. [7] Individuals can choose to interact with IHDs to reduce their consumption. Their decision variable is the level of interaction with IHDs, x. x is a continuous variable; $x \in [0; 1]$, so that $x = 0$ means no interaction, and $x = 1$ full interaction. In practical terms, this variable represents whether a tenant interacts with the IHD and solves the pop-ups. One means that the tenant solves a problem every time a new one arises, and zero that the tenant never touches the screen.

An interaction with IHDs equal to x leads to an energy consumption of $e(x)$; $e' < 0$ and $e'' > 0$, so that more interaction leads to lower consumption, with diminishing return. Diminishing return is consistent with previous literature showing that over usage, IHDs do not offer new information any longer (Buchanan et al., 2015). If $x = 0$, $e(x) = e_0$; if $x = 1$, $e(x) = e_{min} <$

[7] We consider the situation where tenants of social housing have full responsibility of their energy bills, as this is the case in Bolzano. However, in other social housing districts, tenants might not be charged with any energy bill, or only up to a certain amount. It would be possible to adapt the model considering these variations, for instance by eliminating the economic incentive as in Myers & Souza (2020) or by modeling the economic utility as a step function.

e_0, which represents the technically minimum possible level of final energy consumption achievable through behavioral change;[8] $e(x) \leq e_0$ because we assume that interacting with IHDs generates energy saving, equal to: $\Delta e = e_0 - e(x)$.

Energy savings have two main effects on individuals' utility. On the one hand, savings generate economic and moral utility because they reduce the energy bills and CO2 emissions associated with one's consumption. On the other hand, they generate disutility, for instance, in terms of opportunity cost of time to use the IHD and of lower social comfort of reducing energy consumption.

Tenants' utility is made of two components, an economic and a moral one. We model economic utility as $g(\Delta e * p_e; y)$, where: p_e is the price of energy and y is individuals' current income. As individuals who can afford their current expenses are less interested in interacting with IHDs to reduce their bills (Pyrko, 2011; Westskog et al., 2015), utility from economic savings is assumed to depend on current income. $\frac{\partial g}{\partial e} > 0$; $\frac{\partial^2 g}{\partial e^2} < 0$, so that utility is quasi linear in energy saving; $\frac{\partial g}{\partial y} > 0$ $\frac{\partial^2 g}{\partial y^2} < 0$, to capture the fact that sensitivity reduces with higher income.

We model moral utility as a moral subsidy, in which consumers receive moral utility μ for every unit of e not consumed (Allcott & Kessler, 2019): $M = \mu * (\Delta e)$. Individuals with higher μ perceive greater moral utility from saving energy, as energy conservation can be seen as a form of contribution to the common good, notably the environment. Therefore, they have a strong incentive to use IHDs to reduce their consumption. Finally, we model disutility as $f(\Delta e, \alpha)$, where α is a taste parameter. It considers both the negative utility generated by using IHDs and by reducing personal energy consumption. To represent that there is diminishing return to effort in the process of domestic energy conservation (Oikonomou, Becchis, Steg, & Russolillo, 2009), we assume that the marginal disutility is positively and weakly increasing in Δe (and therefore in x): $f' > 0, f'' \geq 0$.

3.2.2 Equilibrium choice without cognitive biases

Let $\theta = \{y, p_e, \alpha, \mu\}$ be the vector of factors that affect utility. The consumer maximizes:

(1) $\max_x U(\theta) = g(\Delta e * p_e; y) + \mu * (\Delta e) - f(\Delta e, \alpha)$

[8] We consider a setting where energy efficiency investments are exogenous. This generally applies to vulnerable contexts, in which households cannot afford this kind of investment, and can achieve energy saving mostly by changing their behavior (Dillahunt et al., 2009).

Consumers' equilibrium choice of x, denoted $x^*(\theta)$, is determined by the following first-order condition:

(2) $g'(\Delta e * p_e; y) * e'(x) + \mu * e'(x) = f'(\Delta e, \alpha) * e'(x)$

Simplifying, the equilibrium choice becomes:

(3) $g'(\Delta e * p_e; y) + \mu = f'(\Delta e, \alpha)$

Such that the economic plus the moral utility should equal the marginal disutility.

3.2.3 The role of locus of control and present bias

We extend the framework to consider how present bias and locus of control affect the usage of IHDs. Cognitive biases affect choice but not experienced utility (Allcott & Kessler, 2019).

Present bias. To consider the effect of present bias, the terms that affect utility with delay are discounted at rate $\beta * \delta$, where δ denotes the discount factor for exponential time-consistent impatience and β represents a preference for immediate gratification (Rabin & O'Donoghue, 2000). Energy is a good that yields immediate utility and delayed economic and environmental consequences (Harding & Hsiaw, 2014). Hence, in the present, individuals face discounted economic and moral utility associated with energy saving, of $\beta * \delta * g(\Delta e * p; y)$ and $\beta * \delta * \mu * (\Delta e)$, respectively. We make two simplifying assumptions: first, all aspects in any future period, viewed from today, are discounted at rate $\beta \leq 1$. Second, subjects discount economic and moral outcomes at the same rate (Hardisty & Weber, 2009). Disutility $f(\Delta e, \alpha)$ is not discounted as it is simultaneous to the decision to interact with IHDs.

Locus of control. We include locus of control by considering the relation between actual and perceived energy saved generated by IHDs usage. We assume that individuals do not know how their interaction with IHDs affects their energy consumption –namely, $e(x)$ is unknown. This assumption is realistic, as individuals are often unconscious of how to reduce their energy consumption or the effort required to do it (Mizobuchi & Takeuchi, 2013). Each individual has a subjective belief on this relation $\tilde{e}(x, loc)$, which depends on the degree of internalization of the locus of control *loc* (low *loc* corresponds to an internal locus of control, high *loc* to an external locus of control).

We assume that locus of control remains constant over time and, therefore, is not affected by IHDs. One may argue that by improving the knowledge on the functional relation between x and e, IHDs empower occupants and reduce the influence of locus of control. However, previous evidence shows that, despite affecting other outcomes, such as awareness about own and appliances' consumption, IHDs do not increase tenants' sense of personal control (Buchanan et al., 2014). Locus of control is indeed a dispositional trait, which is hardly affected by short-term interventions, and is independent from realistic behavior-outcome relation (Ajzen, 2002).

Similarly to Caliendo et al. (2015), we assume a multiplicative effect of locus of control: $\tilde{e}(x, loc) = e(\frac{x}{h(loc)})$, with $h'(loc) > 0$. In this way, for the same level of x, an individual with an external locus of control perceives a lower effect on energy consumption compared with a peer with a more internal one. In other words, the more external the locus of control, the higher the perceived level of interaction required to achieve a specific level of energy saving. Locus of control has an effect on the elements described above: $\tilde{e}(x, loc)$ substitutes $e(x)$ in the expression of Δe, that becomes: $\widetilde{\Delta e} = e(0) - \tilde{e}(x, loc)$. Economic and moral utilities therefore become $g(\widetilde{\Delta e} * p; y)$ and $M = \mu * (\widetilde{\Delta e})$, so that the more external the locus of control, the lower the perception of energy saving from a specific level of interaction x and the lower the resulting economic and moral utility. In the same way, a more external locus of control increases the perceived amount of interaction required to achieve a saving equal to x, affecting the disutility as follows: $f(\widetilde{\Delta e}, \alpha)$. Hence, a more external locus of control is likely to increase the perceived opportunity cost of time and effort of using IHDs. Taken together, these effects may result in lower HIDs usage.

3.2.4 Equilibrium choice with cognitive biases

Let $\theta = \{y, p_e, \alpha, \mu, \delta, \beta, loc\}$ be the new vector of factors that affect utility. The consumer maximizes:

(4) $\max_x U(\theta) = \beta * \delta * (g(\widetilde{\Delta e} * p_e; y) + \mu * (\widetilde{\Delta e})) - f(\widetilde{\Delta e}, \alpha)$

where $\widetilde{\Delta e} = e_0 - e(\frac{x}{h(loc)})$.

Consumers' equilibrium choice of x, denoted $x^*(\theta)$, is determined by the following first-order condition:

(5) $\beta * \delta * e'\left(\frac{x}{h(loc)}\right) * \left(\mu_e + g'\left(e_0 - e\left(\frac{x}{h(loc)}\right) * p_e; y\right)\right) = f'\left(e_0 - e\left(\frac{x}{h(loc)}\right), \alpha\right) * e'\left(\frac{x}{h(loc)}\right)$

Simplifying, the equilibrium choice becomes:

(6) $\beta * \delta * \left(\mu_e + g'\left(e_0 - e\left(\frac{x}{h(loc)}\right) * p_e; y\right)\right) = f'\left(e_0 - e\left(\frac{x}{h(loc)}\right), \alpha\right)$

Such that the economic and moral utility, discounted at rate $\beta * \delta$ and affected by the locus of control $h(loc)$, should equal the marginal disutility from x^*, in turn biased by $h(loc)$.

3.2.5 Hypotheses

From the equilibrium analyses reported in Sections 3.3.2 and 3.3.4, we draw the hypotheses on the effect of economic and moral utility. In particular, equilibrium choices show that the sum of economic and moral components has to be higher than the disutility for interaction to happen. Hence, we hypothesize the following:

Hypothesis 1: *The more stringent the budget constraint, the higher the usage of IHDs.*

Hypothesis 2: *The higher the moral tax associated with energy consumption, the higher the usage of IHDs.*

By comparing the two equilibrium choices, we draw the following hypotheses on the effect of cognitive biases:

Hypothesis 3: *The higher the focus on the present, the lower the usage of IHDs.*

Namely, myopia discounts the utility derived from events occurring in the future. Economic and moral utilities are discounted in Eq. (6) but not in Eq. (3). Consequently, a present biased person draws less utility from a level of interaction *x* compared with another who is time consistent.

Hypothesis 4: *The more external the locus of control, the lower the usage of IHDs.*

Notably, an external locus of control reduces the perceived amount of energy saved from a specific level of interaction *x*. Hence, for the same *x*, when the subject has an external locus of control, the utility in Eq. (3) is higher, and the disutility is lower, than in Eq. (6).

Hypothesis 5: *Tenants will use the IHDs if the perceived discounted economic and environmental utility achieved with a specific level of interaction, biased by the locus of control, is higher or equal than the perceived disutility associated with that amount of interaction.*

When we account for cognitive biases, tenants' motivation to use the IHDs needs to be higher than in the no-bias scenario. Indeed, the utility not only needs to overcome the effort required to interact with the IHDs, but also the distortion added by cognitive biases. The difference between the choices without and with biases augments in the severity of biasedness.

3.3 Discussion and conclusion

In this study, we proposed a theoretical framework providing a flexible tool to assess the effect of cognitive biases on IHDs usage in social housing districts and beyond. The next step of this study will consist in testing the hypotheses drawn from our model with field data from Bolzano social housing districts, where IHDs are currently under installation. We will combine data on IHDs usage with survey information on preferences and cognitive biases. We expect the validated model to provide insights on the role played by IHDs in the tackling of energy poverty, especially when tenants are required to be actively engaged. Meantime, our theoretical framework provides a starting point to better inform the design of future projects aimed at tackling energy poverty, since accounting for the effect of cognitive biases generally increases the chance to achieve policies' goals (Bertrand, Mullainathan, & Shafir, 2004).

Furthermore, our model can also be tested among high-income households. Evidence on IHDs' effectiveness is still mixed in this context (Buchanan et al., 2015), and cognitive biases may unveil an unobserved driver of (lack of) engagement. Moreover, the sources of interest in the IHDs and cognitive biases may have a different effect in high-income contexts (Dillahunt, Mankoff, Paulos, & Fussell, 2009; Westskog et al., 2015). As an example, the economic incentive is likely to weigh more for vulnerable consumers as, by reducing the energy costs, they will have more financial resources to access other necessary goods that they may not afford otherwise (Schaffrin & Reibling, 2015). On the other hand, high-income households may be more interested in the environmental (or social) return of IHDs (Kollmuss & Agyeman, 2002).

This study is by no means without limitations. At this stage, this work could be perceived as a theoretical exercise, given that the hypotheses, even if grounded on empirical evidence, need to be tested in the specific social housing context to draw policy implications. Such empirical exercise should also seek to quantify the extent to which cognitive biases reduce the savings achievable by IHDs. The magnitude would indicate whether technologies saving energy with or without human engagement are more suitable for a specific context. Second, we focused only on a specific cognitive bias and a psychological concept, whereas others, such as status quo bias, social influence and loss aversion, may also play an important role in this setting. These elements could be conveniently added to the model presented here. As an example, the effect of social influence on moral utility can be modeled as in Myers & Souza (2020). Finally, we model tenants' choices as time-invariant. The model would benefit from considering the time dimension and endogenous cognitive biases. In particular, future research may be worthwhile to investigate whether real-time feedback affects the perception of control over energy consumption. If IHDs empower consumers, their benefits exceed their short-term implementation and have broader implications for the fight against energy poverty.

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CHAPTER 4

Moral cleansing in the interpersonal and environmental domains

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Abstract

This study investigates the moral dynamics triggered by different types of immoral behaviors. We implement an incentivized online experiment (N=532) in which participants are randomly assigned to recall a time they harmed another person or the environment or a neutral event. They are then provided with the opportunity to engage in costly (donating) or costless (signing a petition) cleansing and to choose the beneficiary of the prosocial behavior. We find that having harmed another person triggers costly moral cleansing. Instead, when the victim is the environment, participants do not even display costless cleansing. Moreover, we observe a preference for restituting in the same domain as the transgression. Our results extend the understanding of moral cleansing and suggest some policy implications.

Keywords: Moral cleansing; Cognitive dissonance; Morality; Environment; Spillover; Online experiment

[1] *Author contributions:* VF conceived the study, led the collection and the analysis of the data and the writing of the manuscript. JT contributed to conception and the design of the study, to data analysis, to the writing of the manuscript, and was responsible for the funding.

4.1 Introduction

Despite people's willingness to be and to be perceived as honest and moral (Abeler, Nosenzo, & Raymond, 2019; Mazar, Amir, & Ariely, 2008), they often engage in immoral behaviors (e.g., Dong, Dulleck, & Torgler, 2012; Fischbacher & Föllmi-Heusi, 2013; Fisman & Miguel, 2007). Individuals hold an ideal moral self-image about themselves, which serves as a reference point against which they compare their current level of morality (Brekke, Kverndokk, & Nyborg, 2003). Failing to comply with this ideal standard entails psychological costs (Thielmann & Hilbig, 2019), commonly referred to as cognitive dissonance in social psychology (Festinger (1962); see Konow (2000) for an economic model of the theory). The amount of cognitive dissonance triggered by immoral deeds is subjective: it increases with the perceived importance of the transgressed behavior (Starzyk, Fabrigar, Soryal, & Fanning, 2009).

One way to solve this cognitive dissonance is moral cleansing. Namely, individuals behave more morally (or more prosocially) after a moral transgression so that the gap between their ideal and their actual moral self-image is (ideally) closed (Brañas-Garza, Bucheli, Paz Espinosa, & García-Muñoz, 2013; Ploner & Regner, 2013; Sachdeva, Iliev, & Medin, 2009). Indeed, both economic (e.g., Bénabou & Tirole, 2011; Gneezy, Imas, & Madarász, 2014; Schmitz, 2019) and psychological (e.g., Mazar & Zhong, 2010; Miller & Effron, 2010; Monin & Miller, 2001) studies show that individuals perceive moral decisions within the context of previous and future behaviors that help establish and maintain their moral self-image. As with the amount of experienced cognitive dissonance, increasing the moral magnitude of a transgression increases moral cleansing (Jordan, Mullen, & Murnighan, 2011). As a result, people experience cognitive dissonance and solve it through moral cleansing only when they commit immoral acts that are central to their moral self-image.

This study adds to the moral cleansing literature in two ways. First, we compare moral cleansing across two domains of morality: one relating to interpersonal behavior and the other to environmental conservation. As outlined above, several studies have investigated individual drivers of cleansing for the same type of immoral behavior. However, there is little evidence on the comparison of moral dynamics across different domains. Based on past research, we argue that differences in moral cleansing between moral domains depend on how much these domains are, in general, embedded in people's moral identity. Specifically, we investigate whether the cognitive dissonance from harming nature is different from that of violating interpersonal rules of morality. We selected these domains because there is an ongoing debate around the morality of environmental issues. Many posit that environmental issues are moral problems (Feinberg & Willer, 2013; Jia, Soucie, Alisat, Curtin, & Pratt, 2017; Nyborg, Howarth, & Brekke, 2006), while some argue that they activate the human moral judgment system differently from interpersonal moral dilemmas (e.g., Gardiner, 2006; Markowitz & Shariff, 2012; Weber, 2006). To the best of our knowledge, this is one of the first studies that contributes to this debate with empirical evidence.

Second, we include the characteristics of moral cleansing acts in moral balancing. Different types of moral cleansing exist, varying in costliness, impact, and beneficiary of the behavior (West & Zhong, 2015). For example, a person who feels bad about using unfair tactics to get a promotion at work might apologize to the other candidate(s) (costless, low impact) or renounce the position and let another person have it (costly, high impact). Another approach to reducing the cognitive dissonance experienced could be doing another good deed, such as donating money to a charity (costly, high impact), which would be a cleansing effort directed toward a third party. To date, why one cleansing strategy is preferred over another remains unclear (West & Zhong, 2015). A better understanding of when people use which cleansing strategy is needed to assess the potential of inducing cognitive dissonance as a means of fostering prosocial behavior (Gamma, Mai, & Loock, 2018; Thorman, Whitmarsh, & Demski, 2020). Inducing cognitive dissonance may be justified if it makes people engage in high-impact prosocial behaviors to compensate for their previous immoral deeds. If only costless and low-impact cleansing is induced, this type of intervention is difficult to justify.

The remainder of the paper proceeds as follows. In Section 4.2 we review the relevant literature and develop hypotheses. Section 4.3 describes the experimental design. Results are presented in Section 4.4, and Section 4.5 concludes.

4.2 Background and hypotheses

4.2.1 Experienced cognitive dissonance and moral cleansing strategy

Similarly to the decision to behave prosocially (Bénabou & Tirole, 2006), we propose that individuals evaluate the costs and benefits of moral cleansing when deciding how to cleanse a transgression. Costs and benefits depend on the cleansing act. Costs can, for example, include the monetary cost of donating money and the opportunity cost of time spent volunteering. Benefits refer to the effective removal of the cognitive dissonance triggered by the transgression. As prosocial behaviors that entail high costs are strong signals of one's morality (Gneezy, Imas, Brown, Nelson, & Norton, 2012), we propose that the costlier the cleansing behavior, the higher its "cleansing potential". Individuals balance the costs and benefits of various cleansing options by considering the distance between their actual and desired level of morality. For example, if the transgression has little impact on a person's moral self-image, as it is not deemed important, a low-cost cleansing option may be sufficient to solve the dissonance.

It has been widely demonstrated that transgressing rules of interpersonal morality triggers cognitive dissonance (e.g., Matthey & Regner, 2011; Rabin, 1994; Spiekermann & Weiss, 2016); see Stone & Fernandez (2008) for a review of psychological studies). As a consequence, it also prompts moral cleansing (Brañas-Garza et al., 2013; Gneezy et al., 2014; Meub, Proeger, Schneider, & Bizer, 2016). Here we argue that the dissonance caused by an interpersonal moral transgression is typically so intense that it requires costly cleansing to re-establish one's moral self-image. This leads to our first hypothesis:

Hypothesis 1. Being mindful that one has transgressed rules of interpersonal morality increases one's propensity to engage in costly moral cleansing.

People tend to exploit grey areas to blur the difference between morality and immorality and escape the psychological discomfort of their acts (Celse, Max, Steinel, Soraperra, & Shalvi, 2019; Feiler, 2014). Although we expect individuals to also experience disutility after transgressing rules of environmental morality, the link between behavior and outcome is typically more blurred in these cases, compared with transgressions in the field of interpersonal morality. Maintaining a positive moral self-image while behaving selfishly is therefore easier in the environmental domain, and people may not necessarily experience cognitive dissonance when they engage in behaviors that are harmful to the environment. For example, the (little) evidence about individuals' need to cleanse after harming the environment is mixed. Some observed it (Gholamzadehmir, Sparks, & Farsides, 2019; Stikvoort, Lindahl, & Daw, 2016), whereas others did not (Ho, Taber, Poe, & Bento, 2016; Meijers, Noordewier, Verlegh, Zebregs, & Smit, 2018). The evidence on whether individuals avoid information about the environmental impact of their behaviors is also mixed (D'Adda, Gao, Golman, & Tavoni, 2018; Lind, Nyborg, & Pauls, 2019; Momsen & Ohndorf, 2019, 2020). Strategic information avoidance, whereby individuals remain willingly uninformed about the consequences of their behavior (Dana, Weber, & Kuang, 2007), is another way to avoid the cognitive dissonance resulting from self-interested behaviors (Nyborg, 2011; Spiekermann & Weiss, 2016). In summary, we expect that environmental misconduct triggers cognitive dissonance, but typically not enough to justify costly moral cleansing. Hence, we hypothesize that:

Hypothesis 2. Being mindful that one has transgressed rules of environmental morality increases one's propensity to engage in costless, but not in costly, moral cleansing.

Combining the evidence on the two domains, we expect that breaching rules of interpersonal morality generates more dissonance than breaching rules of environmental morality. Accordingly, the former is more likely to trigger costly cleansing behavior than the latter. This leads to our next hypothesis:

Hypothesis 3. Overall, the propensity to engage in costly moral cleansing is higher after transgressing rules of interpersonal morality than rules of environmental morality.

4.2.2 Correcting the wrong vs. affirming one's moral self-image

Moral cleansing strategies not only vary in costliness, but also regarding the beneficiary of the prosocial behavior (West & Zhong, 2015). Individuals can restore their moral self-image by correcting the wrong they did or by affirming their morality through acts that are (at least at first glance) unrelated to the transgression (Stone, Cooper, Wiegand, & Aronson, 1997). The former may be considered a direct strategy, as it removes the cause of the cognitive dissonance by correcting the inconsistent behavior and re-aligning it with one's ideal moral self-image. For example, inducing a feeling of hypocrisy by eliciting people's support for water conservation, and reminding them about their past transgression with regard to this goal prompted shorter showers (Dickerson, Thibodeau, Aronson, & Miller, 1992). Similarly, participants exposed to false feedback on their own racial prejudices resolved the dissonance by donating more to a black (vs. a white) panhandler (Dutton & Lake, 1973).

The latter, more indirect strategy is based on the idea that moral self-regulation is a dynamic process that includes past and future acts. It has been proposed that the gap between the actual and ideal moral self-image can be closed by affirming a virtuous but different aspect of the self (Steele, 1988). For example, participants who cheated to increase their profits in a deception game affirmed their moral self-image by donating more to a charity (Gneezy et al., 2014). Similarly, Jordan et al. (2011) found that making previous immoral acts salient triggers stronger prosocial intention (Study 2) and less cheating (Study 3). They interpret these outcomes in light of Self-Completion Theory (Wicklund & Gollwitzer, 1982), suggesting that generic moral behaviors can compensate for a previous immoral deed because they provide symbols of one's moral standing.

Both the above mentioned direct and indirect strategies for reducing cognitive dissonance are well documented in the cited literature. However, to the best of our knowledge, only Stone et al. (1997) investigated when which strategy is preferred. When both options were available, they found a preference for practicing the transgressed behavior over a good deed in an unrelated domain, even if the former was costlier. Their findings suggest that strategies aimed at directly rectifying the wrong and confronting the source of cognitive dissonance promise higher cleansing potential than self-affirmation strategies. Self-affirmation strategies may still solve, or at least reduce, the cognitive dissonance by boosting one's general moral self-image, but they are less effective in restoring the threat to one's moral self-image from a specific immoral act.

We extend the limited research on whether people prefer direct or indirect cognitive dissonance reduction strategies (Stone et al., 1997) by investigating cases that differ in the closeness of the link between the immoral and the cleansing act. Indeed, in Stone et al. (1997), the behavior proposed to solve the dissonance (purchase of condoms) was close to that used to trigger it (bad sexual habit). We investigate whether the preference for direct restitution holds when the two behaviors belong to the same domain of morality but do not tackle the same act or, in other words, whether breaching rules of interpersonal (environmental) morality directs the cleansing effort toward other human beings (environment). As it appears that direct dissonance solving strategies have higher cleansing potential, we expect to replicate the findings of Stone et al. (1997). This leads to our fourth hypothesis.

Hypothesis 4. Individuals generally prefer a moral cleansing strategy in the same ethical domain in which the transgression occurred.

4.3 Materials and methods

4.3.1 Participants and procedure

To test our hypotheses, we conduct an experiment on the online platform Prolific.[2] Previous studies with similar design features (Ding et al., 2016; Jordan et al., 2011) found an effect size of around d = 0.5–0.6. However, they had different dependent variables and applied only to the domain of interpersonal morality. Hence, we expect a smaller effect size. Using G*Power (Erdfelder, Faul, Buchner, & Lang, 2009), we calculate that at least 176 participants per condition are needed to detect an effect size of d = 0.3, with two-tailed α = .05 and a statistical power of 80%.

The experimental design proceeds as follows. First, we measure participants' moral and environmental identities. This stage also includes an attention check to prevent inattentive answers (i.e., to answer "strongly disagree" to one item). Then, participants are randomly

[2] This kind of platform offer reliable results for experimental research, as shown by replications of well-known experiments (Horton, Rand, & Zeckhauser, 2011; Palan & Schitter, 2018; Paolacci, Chandler, & Ipeirotis, 2010). It also allows for better external validity when compared to research conducted using student samples (Henrich, Heine, & Norenzayan, 2010).

assigned to one of three experimental conditions. The feeling of dissonance is triggered in two of these conditions by making participants recall either a misbehavior with consequences for other people or a misbehavior with consequences for the environment. Those assigned to the control group (the third condition) recall a neutral event. Participants are then provided with the opportunity to support a humanitarian or an environmental cause to serve as a possible cleansing strategy. They can do so by donating part of their bonus payment (costly cleansing) or by signing a corresponding petition (costless cleansing). They also have the option to go directly to the end of the study without supporting either of the causes. Participants are then debriefed and go to the end of the study.

The experiment took place in December 2019. Overall, 556 participants completed the study. We removed 18 participants who did not comply with the attention check. We also eliminated 6 participants who failed to comply with the experimental instruction of recalling past misbehavior (2 from the interpersonal recall, 4 from the environmental recall). Hence, our final sample size is 532 participants. Each participant was given £1 for participation. In addition, 10% of participants were randomly drawn to receive the payment bonus. We transferred the amount corresponding to the payment bonus minus the donation they reported in the survey to them. This was donated to support the selected campaign. We also sent the link of the selected campaign to those participants who were willing to sign the petition.

4.3.2 Treatments

Treatments are implemented with a three-level single factor (interpersonal morality, environmental morality, neutral) between-subjects design. In all three treatments, participants write about an event that happened in the past; the type of event varies according to the experimental conditions (Ding et al., 2016; Jordan et al., 2011; Mulder & Aquino, 2013; Zhong & Liljenquist, 2006). Participants in *interpersonal morality* recall a time they harmed another person, those in e*nvironmental morality* a time they harmed the environment, and those in the control group a neutral event. Instructions for the *interpersonal* recall and the control conditions are taken from (Barkan, Ayal, Gino, & Ariely, 2012); the *environmental* recall is framed to ensure consistency across experimental conditions (see Appendix A for full experimental recalls).

4.3.3 Environmental and moral self-identity

We measure interpersonal moral and environmental self-identities as control variables. Psychological studies show that the centrality of these constructs in individuals' self-concept predicts engagement in moral (e.g., Aquino, Freeman, Reed, Lim, & Felps, 2009) and environmental (e.g., Whitmarsh & O'Neill, 2010) decisions as well as in balancing moral dynamics (e.g., Mulder & Aquino, 2013). Our items are adapted from the internalization subscale of the moral identity measure (Aquino & Reed, 2002), as described below.

Consistent with Panzone et al. (2018), we measure environmental self-identity including only "environmentally responsible" as personal trait from the moral identity scale. The included items are: (1) "Being environmentally responsible is an important part of who I am." (2) "I view myself as an environmentally responsible person." (3) "Being environmentally responsible is not really important to me (reversed)." (4) "I strongly aspire to be environmentally responsible." Cronbach's alpha for a scale based on all four items is acceptable (.81), but if the third item is left out, it is improved (.83). Hence, we use items 1, 2, and 4 to measure environmental self-identity in the following analysis.

To make the measurement of environmental and moral self-identities more similar, we measured interpersonal moral self-identity only with regard to the personal characteristic "helpful" from the moral identity scale. The included items are: (1) "Being helpful is an important part of who I am." (2) "I view myself as a helpful person." (3) "Being helpful is not really important to me (reversed)." (4) "I strongly desire to be helpful." Again, Cronbach's alpha for a scale based on all four items is acceptable (.74), but if the third item is left out, it is considerably improved (.81). Hence, we use items 1, 2, and 4 to measure moral self-identity in the remaining of the analysis.

Responses were given on a 9-point Likert scale from 1 = "Totally disagree" to 9 = "Totally agree." We include additional items to mask the relevant measures,[3] and we randomize the order of presentation of the questions to avoid order effects bias.

4.3.4 Dependent variable: amount and type of moral cleansing

Our dependent variable consists of how much and which type of prosocial behavior participants displayed after being exposed to one of our three manipulations. After the experimental manipulations, participants were provided with different cleansing options. Cognitive dissonance research finds that people tend to prefer the first coping strategy they are offered (Gosling, Denizeau, & Oberlé, 2006). To avoid the order of the presentation of alternatives influencing the selection of the cleansing strategy, we displayed the different cleansing options together, and we randomized the order of presentation of the two

[3] Specifically, we measured creative and intelligent identities. As we introduced these items for design purposes, they are excluded from the main analysis. However, results do not change if we include them.

campaigns. Moreover, to measure the preference for a specific cleansing strategy, participants could choose only one of them (Stone et al., 1997).

We included four cleansing options that varied in two dimensions: the costliness (and presumably the cleansing potential; see Section 4.3.5) of the behavior and the beneficiary. Participants were offered the opportunity to support either the *Fight inequality beat poverty*[4] *campaign* or the *Stop plastic choking our oceans campaign.*[5] We selected these campaigns from renowned international organizations (Oxfam and WWF respectively), aiming for one that addressed a humanitarian cause and one that addressed an environmental one. If participants wanted to support one of these campaigns, they could do so by donating part of the payment bonus or by signing the corresponding petition. Those willing to donate indicated the amount, ranging from £0.10 to £10, they would donate if they were the winner of the bonus and to which campaign.

The interpretation of the dependent variable goes as follows. Participants exposed to our manipulations engaged in costly cleansing if they donated more than the control group and in costless cleansing if they signed the petition more often than the control group. Reaching the end of the study without doing either meant no cleansing. Finally, if participants supported the campaign in the same domain of morality as the recalled transgression, they engaged in direct restitution (e.g., those assigned to the *interpersonal morality* condition support the humanitarian campaign), whereas if they supported the campaign in the other domain, they engaged in self-affirmation (e.g., those assigned to the *interpersonal morality* condition support the environmental campaign).

4.3.5 Pilot study

Before the main study, we ran a pilot study on Prolific with a different sample (N=149) for two reasons. First, the pilot was used to select cleansing strategies for the main study that varied in costs and benefits, as expressed in Section 4.2.1, assuming that costlier behaviors more strongly signal one's moral image and therefore have stronger cleansing potential. Second, we assessed whether being exposed to the *interpersonal morality* or *environmental morality* treatment increased the mental accessibility of the domain of the recalled transgression. This was to control whether a preference for making restitution in the same domain (Hypothesis 4) could be caused by a saliency effect, rather than by its higher

[4] https://oxfamapps.org.uk/inequality/ accessed on 11/14/2019.
[5] https://wwf.panda.org/get_involved/campaign_with_us/plastics_campaign_page/ accessed on 11/14/2019.

perceived cleansing potential (Stone et al., 1997). Detailed materials and results are available in Appendix B.

Concerning the cleansing strategies, the pilot study revealed that donating money makes people feel better and requires more effort than signing a petition. This is consistent with the assumption that donating money represents a costly but effective strategy to restore one's moral self-image. Signing a petition is a cheaper and weaker strategy to solve cognitive dissonance.

Next, the pilot study revealed that our manipulations do not significantly affect the mental accessibility of the two domains of morality. Participants in the pilot study were randomly assigned to either the *interpersonal morality* or *environmental morality* manipulation, and then performed a word completion task where they converted word fragments into meaningful words (Zhong & Liljenquist, 2006). The fragments could be completed as social-related, environment-related, or neutral words. Following Zhong & Liljenquist (2006), we assume that the domain's mental accessibility is reflected in the number of fragments completed with words belonging to it. We found that the number of social- or environment-related words recalled does not differ across experimental conditions (Table B.1), indicating that the interpersonal (environmental) domain is *not* more accessible for participants assigned to the *interpersonal* (*environmental*) *morality* treatment. Hence, we can rule out that a saliency effect drives the results of the main experiment.

4.4 Results

4.4.1 Descriptive statistics

Participants' socio-demographic characteristics and responses per experimental condition are reported in Table 4.1. The percentage of males is 36.9%, but varies across experimental conditions, from 29.5% in the *interpersonal morality* condition to 42.2% in the control group. The average age is 35.6 years, and 48.9% of participants have an undergraduate degree as highest educational level. On average, participants display stronger interpersonal moral than environmental self-identity ($M = 7.27$ vs. 6.21 on a 9-point scale, $p < .001$). This is not surprising (de Groot & Steg, 2008). Environmental self-identity is unbalanced across experimental conditions, being higher in the *interpersonal morality* condition and lower in the control group, apparently mirroring how women generally care more than men about environmental issues (Hirsh, 2010). To avoid participant characteristics affecting experimental results, we control for them throughout our analysis.

Overall, 53% of participants donate and 16.5% sign the petition. Hence, in our setting, the favorite channel to support an online cause is via donation. The average donation is £2.43, which is in line with the average transfer in dictator games (Engel, 2011). There is a general preference for the *Stop plastic choking our ocean* campaign over *Fight inequality beat poverty*, with 44.5% choosing the former and 24.9% the latter. This difference mirrors current growing concerns about environmental issues.

Table 4.1. Participants' characteristics and responses per experimental condition

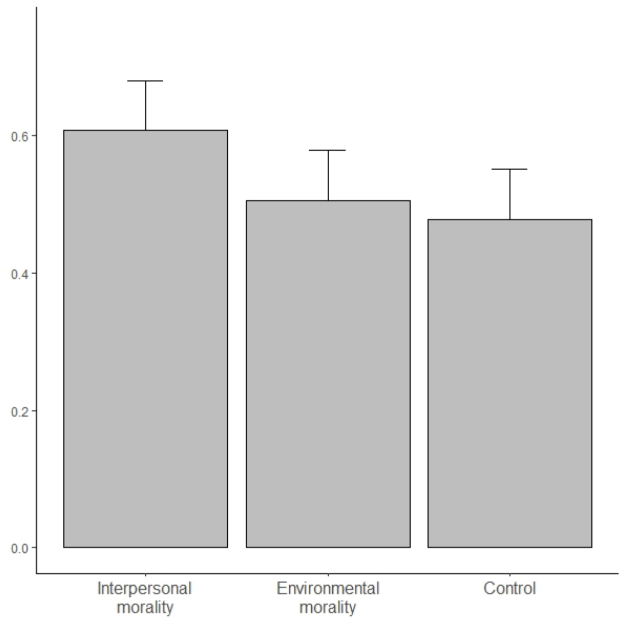
	Interpersonal	Environmental	Control	Total
N	176	176	180	532
Male (%)	0.29[a]	0.39[ab]	0.42[b]	0.37
Average age	35.3	35.2	36.6	35.6
	(12.6)	(12.1)	(14.5)	(13.11)
Undergraduate (%)	0.47	0.48	0.51	0.49
Interpersonal moral identity	7.31	7.24	7.26	7.27
	1.47	1.54	1.41	1.47
Environmental identity	6.57[a]	6.11[b]	5.94[b]	6.21
	1.69	1.71	1.84	1.77
Donating (%)	60.8[a]	50.6[ab]	47.8[b]	53.0
Signing petition (%)	13.0	16.0	21.0	17.0
Average donation (£)	2.94[a]	2.11[b]	2.25[ab]	2.43
	(3.10)	(2.71)	(2.95)	(2.94)
Humanitarian campaign (%)	0.31[a]	0.19[b]	0.24[ab]	0.25
Environmental campaign (%)	0.42	0.47	0.44	0.44

Note: Interpersonal denotes the *interpersonal morality* treatment, Environmental denotes the *environmental morality* treatment. Standard deviations in parentheses. Different superscript letters in a row mean that differences between groups are statistically significant at the 0.05 level, based on Scheffe's multiple comparison test.

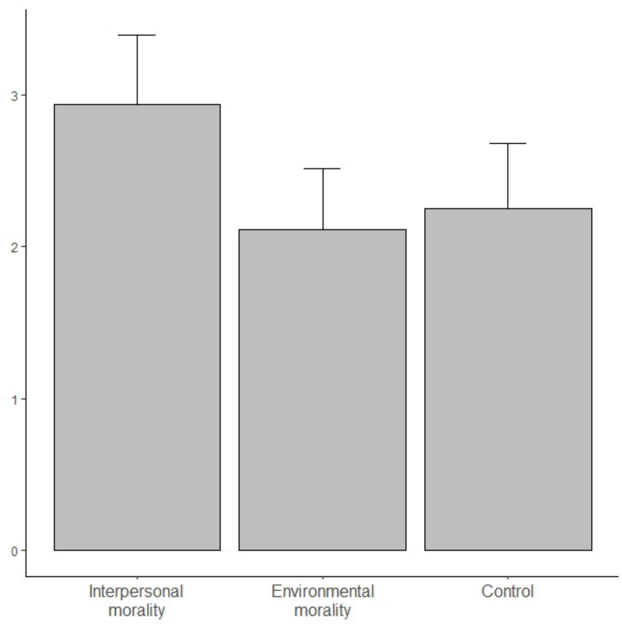
The results reported in Table 4.1 provide preliminary support for our hypotheses about costly cleansing. Both the percentage of participants donating and the average donation differ among the three experimental conditions, with higher values in the *interpersonal morality* treatment. More precisely, 60.8%, 50.6%, and 47.8% of participants donate, leading to an average donation of £2.94, £2.11, and £2.25 in the *interpersonal morality*, *environmental morality*, and control conditions, respectively. These findings are further illustrated in Figure 4.1. The share of participants signing the petition does not differ significantly across conditions.

Figure 4.1 Donating per experimental condition

A. Percentage of participants donating



B. Average donations



Error bars represent 95% confidence intervals.

We also find partial support for the direct restitution hypothesis in Table 4.1. Recalling the harm done to another person increases support for the humanitarian campaign: 31.2% of participants assigned to the *interpersonal morality* treatment support the *Fight inequality beat poverty* campaign, whereas only 19.3% and 24.4% support this campaign in the *environmental morality* and control groups. Directional support is also found with regard to the environmental campaign, but here the differences across experimental conditions are not significant.

4.4.2 Treatment effect on the type and amount of moral cleansing

We investigate how the psychological discomfort created by recalling past transgressions affects the cleansing strategy by comparing the amount and type of cleansing across the three experimental conditions. First, we assess treatment effects on the probability of engaging in costly cleansing (i.e., donating). Second, we assess whether those who are not motivated to engage in costly cleansing still engage in costless cleansing (i.e., signing a petition). To study the latter, we include only participants who do not donate and compare the probability of signing the petition vs. going directly to the end of the study. Since these analyses involve binary outcome variables, we use logistic regression. Finally, we assess treatment effects on average donation using a left-censored Tobit. As some participant characteristics are unbalanced across conditions, we control for them in all regression analyses. Table 4.2 reports experimental results.

Consistent with our hypothesis that behaviors harmful to other people trigger a need for effective (which usually means costly) cleansing (Hypothesis 1), Table 4.2 shows that significantly more participants donate in the *interpersonal morality* condition than in the control group (Column 1, $p = .033$). We also observe a higher average donation in this condition (Column 3, $p = .043$). The costless cleansing option is not used to solve the cognitive dissonance caused by the interpersonal transgression recall, as shown by the significant lower number of participants in the *interpersonal morality* signing the petition than those in the control group (Column 2). Hence, empirical evidence confirms our first hypothesis. Even in the presence of costless cleansing options, people prefer to engage in costly prosocial behavior to more strongly signal their morality (Gneezy et al., 2012) and solve the cognitive dissonance stemming from an interpersonal misbehavior.

Next, we investigate whether harming the environment generates costless moral cleansing (Hypothesis 2). Table 4.2, Column 2 shows that participants in the *environmental morality* condition are *not* more likely to sign a petition than those in the control group. Hence, our hypothesis that recalling past environmentally harmful behavior triggers costless cleansing is not supported. We also find no effect on donation: the environmental transgression recall prompts the same number of donors and average donation as in the control group. It appears that, in our setting, making people mindful of their past environmentally harmful acts does not generate a need to compensate with more prosocial behavior.

Table 4.2. Treatment effect on the decision to donate, to sign the petition, and on average donation

	(1) Donating (Costly cleansing)	(2) Signing (Costless cleansing)	(3) Average donation
Interpersonal	0.469*	-0.746*	1.121*
	(0.220)	(0.368)	(0.554)
Environmental	0.099	-0.481	-0.055
	(0.215)	(0.333)	(0.556)
Interpersonal moral identity	0.134	0.033	0.337
	(0.094)	(0.145)	(0.243)
Environmental identity	0.210*	0.619***	0.715**
	(0.095)	(0.164)	(0.241)
Constant	-0.069	0.669	-0.234
	(0.366)	(0.628)	(0.926)
N	532	250	532

Note: Logistic regression (Column 1 and 2). Left-censored Tobit (Column 3). Interpersonal denotes the *interpersonal morality* treatment, Environmental denotes the *environmental morality* treatment. Baseline condition: control group. All the specifications include demographic controls. Interpersonal moral and environmental identity measures are standardized. Standard errors in parentheses. § p < .10, * p < .05, ** p < .01, *** p < .001

Taken together, these results are in line with the proposition that breaching rules of interpersonal morality generates more cognitive dissonance than breaching rules of environmental morality. As a formal test of this claim, we compare the cleansing strategies between the interpersonal transgression and the environmental transgression recalls. The difference between the *interpersonal morality* and *environmental morality* coefficients in Table 4.2 is assessed using F-tests. The probability of donating differs between the two conditions in the expected direction, but the difference is not significant at the 5% level (Column 1, p = .094). However, the average donation is significantly higher in the *interpersonal morality* than in *environmental morality* condition (Column 3, p = .033). Hence, we find empirical support for the hypothesis that personal environmental damage triggers less cognitive dissonance relative to wrongdoing toward another person.

Finally, participants' identities also play a role. In line with previous literature, environmental self-identity significantly increases the inclination to donate (Column 1, p = .027) and sign the petition (Column 2, p > .001) and also the amount donated (Column 3, p = .003). Surprisingly, interpersonal moral self-identity does not influence any of these dependent variables. This might be because we measured only one aspect of moral identity to make the measurement of interpersonal moral and environmental self-identities similar, reducing the multi-dimensional moral identity concept (Aquino & Reed, 2002) to only one trait (*helpfulness*). Other traits might be more important for the cleansing behaviors included in this study.

4.4.3 Treatment effect on the beneficiary of moral cleansing

We test the hypothesis that individuals prefer to restitute in the domain where the transgression occurred, instead of an unrelated domain (Hypothesis 4), by comparing which campaign is selected by participants assigned to the different experimental conditions. Logistic regressions are used, where the dependent variable is equal to 1 for the humanitarian campaign and 0 for the environmental campaign. Hence, we estimate treatment effects on which campaign is selected by those supporting one of those campaigns. We also investigate the differences in who is the beneficiary of donation and petition-signing behaviors, restricting the analysis to those who engage in the specific cleansing act. Participants' characteristics are used as control variables in all the specifications. Results are reported in Table 4.3.

Table 4.3 show that the treatments influence the selection of the campaign in the expected direction. Participants in the *interpersonal morality* condition are more likely to choose the humanitarian campaign (reflected in the positive sign for interpersonal in Column 1). Those in the *environmental morality* condition are more likely to choose the environmental campaign (reflected in the negative sign for environmental). A separate F-test shows that the difference between the two coefficients is highly significant ($p = .007$). Consistent with earlier findings (de Groot & Steg, 2008), a stronger interpersonal moral self-identity increases the likelihood of supporting the humanitarian rather than the environmental campaign (Column 1, $p = .003$), and a stronger environmental self-identity increases the likelihood of supporting the environmental rather than the humanitarian campaign (column 1; $p < .001$).

Table 4.3 Treatment effect on the campaign selected

	(1) Humanitarian campaign	(2) Donation for humanitarian	(3) Petition for humanitarian
Interpersonal	0.453§	0.534§	0.267
	(0.272)	(0.315)	(0.625)
Environmental	-0.315	-0.052	-1.727*
	(0.289)	(0.330)	(0.757)
Interpersonal moral identity	0.409**	0.443**	0.411
	(0.138)	(0.158)	(0.312)
Environmental identity	-0.503***	-0.445**	-0.827**
	(0.126)	(0.140)	(0.317)
Constant	-0.146	-0.454	1.637
	(0.458)	(0.511)	(1.207)
N	369	282	87

Note: Logistic regression. Interpersonal denotes the *interpersonal morality* treatment, Environmental denotes the *environmental morality* treatment. Baseline condition: control group. All analyses include demographic controls. Interpersonal moral and environmental identity measures are standardized. Standard errors in parentheses. § p < .10, * p < .05, ** p < .01, *** p < .001

Next, Table 4.3, Column 2, shows that the recall of interpersonal and environmental transgressions also affects the selection of the beneficiary of donation (among those who donate) in the expected direction. The weaker effect of the environmental treatment on donations and the smaller sample size make the difference between the two recalls significant only at the 6% level (F-test, p = .061). The effects of interpersonal moral and environmental self-identities on the selection of beneficiaries for a donation are the same as before: the former increases the likelihood of donating for the humanitarian cause (p = .005) and the latter for the environmental cause (p = .002).

Finally, in line with our Hypothesis 4, among those choosing to sign a petition, the interpersonal transgression recall increases the probability of choosing the petition for the humanitarian cause and the environmental transgression recall increases the probability of choosing the petition for the environmental cause (Column 3). The difference between the two conditions is statistically significant (F-test, p = .016). The likelihood of signing the petition for the environmental cause increases with environmental self-identity (p = .009), as expected. Similarly, the likelihood of signing the humanitarian petition increases with interpersonal moral self-identity, but due to the small sample size this effect is not statistically significant at the conventional level.

In summary, we find empirical support for Hypothesis 4. Recalling past behaviors that were harmful to other human beings generates more support for a humanitarian cause. This holds despite the rather weak link between the recalled immoral behavior and the cleansing behaviors. A symmetric relationship is found for the environmental cause, but with a weaker effect. Besides the experimental manipulation, pre-existing preferences—measured as interpersonal moral and environmental self-identities—also significantly affect the selection of the beneficiary of the moral cleansing effort.

4.5 Discussion and conclusions

The aim of this paper was to investigate how different types of immoral behavior trigger moral cleansing. We conducted an online experiment where participants were randomly assigned to recall a time they harmed another person or the environment or a neutral event. They were then provided with the opportunity to cleanse their guilty conscience by supporting a humanitarian or an environmental campaign, either by donating (costly cleansing) or by signing a petition (costless cleansing). We use the amount and type of cleansing as evidence of revealed situational preferences for cleansing strategies and the amount of cognitive dissonance from misbehaving in different domains. In addition, we investigate whether individuals prefer to give back in the same domain as the transgression or whether it is sufficient to engage in any good deed that will affirm a moral self-image. Furthermore, the study brings early evidence on the fact that individuals consider the costs and benefits of the available cleansing strategies before choosing which one to engage in.

We find that breaching rules of interpersonal morality triggers moral cleansing, both in terms of probability of donating and average donation. We extend on previous studies with the same result by showing that people prefer costly to costless cleansing after committing this kind of moral transgression. The underlying explanation is that people trade off the costs and benefits of cleansing. They choose costlier alternatives when they need stronger expressions of their morality to solve a more intense cognitive dissonance. The costliness of the chosen cleansing option is also an indicator of the size of the cognitive dissonance.

Consistent with existing evidence (Ho et al., 2016; Meijers et al., 2018), we find that no cleansing—not even costless—is triggered by behavior that has negative consequences for the environment. We also find that participants recalling an environmental misbehavior donate significantly less than those recalling an interpersonal misconduct. This supports the claim that environmental issues activate the human moral judgment system differently from other moral behaviors.

What is striking is the lack of even virtually costless cleansing acts after an environmental transgression. Based on earlier studies (D'Adda et al., 2018; Gholamzadehmir et al., 2019; Stikvoort et al., 2016; Stone & Fernandez, 2008), we expected that being made mindful of having caused harm to the environment would generate some cognitive dissonance. Perhaps not enough to motivate the engagement in costly prosocial behavior—and renounce part of the participation bonus to support a good cause—but enough to trigger cheap prosocial behavior and sign a petition. This is not the case in our setting, as we do not detect any difference in the amount of moral cleansing between the *environmental morality* condition and the control group.

Different mechanisms may explain the lack of moral cleansing following the environmental manipulation. First, the nature of environmental issues, being complex, global, and unintentional (Markowitz & Shariff, 2012), may have liberated selfish behavior without compromising participants' moral self-image. Second, our cleansing options may not have been sufficiently appealing to participants. However, the fact that environmental self-identity positively influenced both the donation to the environmental cause and the signing of the environmental petition makes this possibility less likely. Be that as it may, future research should attempt to further clarify the reasons for the lack of cleansing after recalling an environmental transgression.

Finally, we find support for the hypothesis that moral cleansing is not merely a strategy to reaffirm one's moral self-image. Rather, moral cleansing efforts are preferably directed toward correcting a person's wrongdoing. Doing so seems to ensure a more effective resolution of the cognitive dissonance triggered by a specific immoral act (Stone et al., 1997). We observe a general preference for supporting a humanitarian cause after being made mindful of interpersonal transgressions and supporting an environmental cause for breaching the norms of environmental conservation. At first glance, this effect could also be caused by another mechanism: recalling a transgression increases the mental accessibility of the particular domain (Stone et al., 1997). We rule out this explanation in the pilot study where we show that being made mindful of our interpersonal (environmental) moral transgressions does not increase the saliency of the social (natural) realm.

4.5.1 Limitations

Like all research, this study has limitations. First, despite our attempt to include different cleansing strategies in our setup, we could only include a limited set, making the generalizability of our results to settings including other cleansing options uncertain. For example, it is unclear what people would do if cleansing was triggered in the context of shopping: would they buy more expensive sustainable products or would they be satisfied with cheaper greenwashing goods? Field experiments would provide stronger evidence to inform policy makers on when and where the kind of intervention studied here is suitable to promote costly prosocial behaviors. Second, this is the first study to bring evidence that individuals consider the costs and benefits of cleansing strategies before engaging in them. Future research should investigate this trade-off as a continuum and estimate how much people are willing to pay to solve the dissonance of different kinds of immoral behaviors. Finally, we constrained the choice to two specific online campaigns, which may have biased participants' selection of one over the other. However, since participants were randomly assigned to the experimental conditions, we presume that the preference for the campaigns was equally distributed in the three conditions.

Appendix

Appendix A. Recalls for experimental conditions

Interpersonal morality "We all sometimes do and say things we regret. Please describe below one unethical thing you have done, one that made you feel guilt, regret or shame. Other people engaging in this type of introspective task frequently write about instances where they acted selfishly at the expense of someone else, took advantage of a situation and were dishonest, or an event in which they were untruthful or disloyal. Please use the following box to describe this situation in which you behaved unethically, describing what happened, how you felt, and which emotions you experienced"

Environmental morality "We all sometimes do and say things we regret. Please describe below one thing harmful to the environment you have done, one that made you feel guilt, regret or shame. Other people engaging in this type of introspective task frequently write about instances where they took a flight when alternative modes of transportation were available, disposed improperly a hazardous waste, or an event in which they wasted a lot of water or food. Please use the following box to describe this situation in which you harmed the environment, describing what happened, how you felt, and which emotions you experienced"

Control group "We all spend our time in different ways. Please think of how you spend your evenings and describe below a typical instance. Other people engaging in this type of introspective task frequently write about instances where they make dinner, watch TV, read a book, or spend time with friends. Please use the following box to describe how you spent the night, describing what happened, how you felt, and which emotions you experienced"

Appendix B. Pilot study

The pilot study consisted of two sessions. The first part was identical across the two sessions and collected information about cleansing behaviors with the following questions: "Please consider a social or an environmental cause of your own choice that you would like to support. Consider next which is the best way of doing so through online action. This is a hypothetical question, you will not be asked to perform any of the activities in practice.

Considering only online actions..

..to what extent would supporting the cause in the following ways make you feel good?

	Not at all				Very much
Donating money	(1)	(2)	(3)	(4)	(5)
Signing a petition	(1)	(2)	(3)	(4)	(5)

..to what extent would supporting the cause in the following ways require effort from you?

	Not at all				Very much
Donating money	(1)	(2)	(3)	(4)	(5)
Signing a petition	(1)	(2)	(3)	(4)	(5)

..to what extent would doing the following contribute to support the cause"

	Not at all				Very much
Donating money	(1)	(2)	(3)	(4)	(5)
Signing a petition	(1)	(2)	(3)	(4)	(5)

Results show that donating money makes people feel better ($M = 3.83$ vs. 3.57, $p = .046$) than signing a petition, and, at the same time, entails greater effort ($M = 3.31$ vs. 2.39, $p < .001$). We do not find any significant difference in the extent to which the two actions are perceived to contribute to support the cause ($M = 3.77$ vs. 3.74, $p > .10$).

The second part of the pilot study collected information about the mental accessibility of the domain of the recalled transgression, through a word completion task. The two sessions included different word fragments. Session 1 (N= 59) included nine words; three (i.e., P_ _R, O_ _ _ R, F_ _ _ _OW) could be completed as either social-related (i.e., peer, other, fellow) or unrelated words (e.g., pair, occur, follow); three (i.e., N_ _ _RAL, G _ _SS, T_ _E) could be completed as either environment-related (i.e., natural, grass, tree) or unrelated words (e.g., neutral, glass, time); the remaining three were neutral. With Session 2 (N= 90), we increased task sensitivity by replacing the least effective fragments (i.e., tree, peer and fellow) with new ones (i.e., waste, family and mother), and by adding four fragments (i.e., S_N, B_Y, C_ _ _D, HO_ _ E) that could be completed with either social-related (i.e., son, boy, child/crowd, house) or environmental-related (i.e., sun, bay, cloud, horse) words.

We sum the number of social-related and environmental-related words participants used to complete the word fragments to measure the mental accessibility of the two domains, and we test whether they differ across experimental conditions. Results are reported in Table B1; with Panel A, Panel B and Panel C, detailing Session 1, Session 2 and a pooled analysis of the two sessions, respectively. No significant difference is observed between the two experimental conditions, showing absence of saliency effect.

Table B1. Number of social-related and environmental-related recalled words per experimental condition

	Interpersonal morality	Environmental morality	Two-sided T-test, p-value
	Panel A: Session 1		
N	29	30	
Social words	0.52	0.43	0.63
Environmental words	1.14	1.4	0.19
	Panel B: Session 2		
N	43	47	
Social words	3.28	3.11	0.51
Environmental words	2.65	2.88	0.37
	Panel C: Pooled analysis		
N	72	77	
Social words	2.17	2.06	0.71
Environmental words	2.04	2.30	0.21

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Conclusion

This Doctoral thesis extends the understanding of when nudges promote environmental and energy conservation. Environmental problems represent one of the most difficult and urgent challenges that humanity has ever faced. Nudges can contribute to addressing them inasmuch as they influence people to make pro-environmental choices. Three empirical and one theoretical chapters investigate applications of nudges and identify situations where they are (or are not) suitable instruments for prompting pro-environmental behaviors.

In the first Chapter, we study the interplay between nudges and traditional policy instruments. In an incentivized online experiment, we expose participants to either a nudge, an economic incentive, a combination of the two, or a control condition, and we compare their performance. By performance, we mean the virtual energy saving achieved in our task, which tries to realistically reproduce actual conservation behavior. We do not find evidence of synergies. Rather, the two interventions combined do not affect behavior in a different way than the nudge alone, suggesting that the latter captures participants' attention and "cognitively" crowds out the financial incentive.

The second Chapter presents the application of a behavioral intervention—in the form of an energy-saving competition among a company's branches—to conserve energy in the workplace. Our difference-in-difference specification detects a reduction in branches' monthly electricity consumption, but this effect is significant only outside the main work schedule. The fact that we observe an impact smaller than in the residential sector suggests that the characteristics of the workplace undermine the impact of behavioral policies. Practitioners should consider the context in which a nudge is implemented to increase its effectiveness. Finally, our assessment of the impact of a previous retrofitting intervention, conducted on a subsample of highly consuming branches, shows a large effect, especially outside the main working schedule. This suggests that when implemented together with the nudge, they would overlap because they act upon the same drivers of inefficiencies.

In the third Chapter, we model the behavioral process underlying the usage of in-home displays that provide real-time feedback on households' energy consumption, including variables that generate utility (economic and moral) and disutility, and two cognitive biases (i.e., present bias and locus of control). We argue that the cost-benefit analysis is affected by cognitive biases, which push toward the non-usage equilibrium the more severe they are. This study contributes to the understanding of how cognitive biases affect the impact of nudges that require active behavioral change. Being in a vulnerable condition generally increases the severity of cognitive biases, making their role particularly relevant when the objective is fighting energy poverty.

The fourth Chapter empirically investigates whether environmental issues activate people's moral intuition. We conduct an incentivized online experiment in which, after recalling a time they harmed the environment or another person or a neutral event, participants have the opportunity to cleanse their wrongdoing with prosocial behavior. We find that those participants reminded of their interpersonal transgressions engage in costly moral cleansing, while those reminded of their environmental transgressions do not even display costless moral cleansing. These results represent, to the best of our knowledge, the first empirical proof that environmental problems activate the human's moral judgment system in a different way than other domains of morality. As a policy implication, the study shows that moral cleansing, which has sometimes been used to promote prosocial behavior, cannot be triggered when the initial bad deed has consequences for the environment.

While nudges have been praised for their wide applicability and low implementation costs, this thesis highlights some potential shortcomings in their application.

First, the results identify situations in which nudges are more likely to substitute, rather than complement, traditional policy instruments. This is of practical relevance because it shows unpredicted side effects of nudges, which may also negatively affect other policy instruments. Nudges are often proposed as complements to other policy instruments because they affect behaviors differently. However, this thesis stresses that this depends on how the two tools are combined and shows an instance where the two tools generate displacements (Chapter 1). On the other hand, there are other applications of nudges in which they are more likely to support traditional policy instruments, namely, when nudges are subordinated to traditional interventions. As an example, if the nudge makes the benefits of market-based interventions more readily available, or makes occupants use the retrofitted infrastructure efficiently (as in Chapter 3), synergies may arise. Future empirical work is needed to shed light on other combinations of behavioral and traditional instruments and synthesize the findings in a framework that allows us to predict when synergies or displacements arise.

Second, this thesis highlights the role of the context in which behavioral interventions are implemented. Most energy nudges are applied in the residential sector, on high-income households. Their potential in other settings has yet to be discovered. This work shows how two different contexts, for different reasons, may hinder their applicability. The context shapes the characteristics of energy behaviors and people's cognitive processes. The most suitable behavioral instrument must be identified by taking the context into account. For example, in the workplace, energy consumption results from all employees' behavior, making it hard to disentangle one's contribution to energy consumption and the saving resulting from one's behavioral change. In the workplace, a nudge that makes these aspects transparent is probably more effective than one that addresses aggregate outcomes (as in Chapter 2). With respect to using nudges in vulnerable contexts, practitioners should consider how this condition affects cognitive processes. As scarcity taxes cognitive resources, choice defaults are particularly suitable in reducing the mental load of accessing government aid programs. As all nudges are not equally valuable across situations, including the contextual characteristics in their selection increases the chance of achieving policy goals. Further research is needed to understand which behavioral interventions are most effective for each context, considering both policy goals and distributional consequences.

In sum, this Doctoral thesis evaluates the effectiveness of green nudges across various contexts and questions the perceived morality of environmental issues. The results emphasize the strong influence that the context exerts on behavioral interventions, stressing the need of identifying the most suitable tool for each situation. Finally, the thesis shows that people react less to environmental issues than to other moral issues, and this constitutes a major obstacle to foster environmental conservation.