Nudges: complements or substitutes of traditional energy policy instruments?

Abstract

Though nudges are gaining attention as complements to traditional policies, evidence of the interplay between these two policy instruments is lacking. Here, we discuss and evaluate how combinations of traditional tools and nudges may affect individuals' attitude towards energy consumption. Through an online experiment (N=566), we assess the impact of an energy policy mix which combines a traditional instrument (tax rebate) and a nudge (goal setting and feedback). We introduce an innovative incentive-compatible task: participants are asked to optimize their energy consumption on a virtual washing machine. Our findings do not show evidence of positive synergies between the traditional and the behavioral tools. Specifically, adding the economic incentive to the nudge neither strengthens the effect of the latter nor increases its medium-term impact. Our results suggest that a policy mix characterized by multiple stimuli can overwhelm individuals and eventually backfire.

Keywords: economic experiment, energy consumption, market-based policy, motivation crowding, nudge, policy mix

1 Introduction

Energy sector plays a strategic role in meeting worldwide sustainability goals, with its 35 percent contribution to global greenhouse gas emissions (Pachauri et al., 2014), energy sector plays a strategic role in meeting worldwide sustainability goals. The transition towards low-carbon solutions requires profound changes in the production and consumption of energy (Bridge, Bouzarovski, Bradshaw, & Eyre, 2013), and is therefore inherently complex (Rogge, Kern, & Howlett, 2017). Policy makers are required to implement a thorough set of interventions harmoniously orchestrated in policy mixes to overcome the many obstacles and achieve important changes (Fischer & Preonas, 2010; Rogge & Reichardt, 2016). To date, this process has primarily involved addressing energy sectors' market failures (Gillingham, Newell, & Palmer, 2009; Jaffe, Newell, &

Stavins, 2005; Rosenow, Fawcett, Eyre, & Oikonomou, 2016), through policy mixes which combine market-based instruments, such as subsidies and carbon trading schemes, and regulatory measures, like legally enforceable codes and standards (Jacobsson & Lauber, 2006; Johnstone, Haščič, & Popp, 2010; Lehmann, 2012; Sorrell & Sijm, 2012).

Demand-side interventions included in this type of policy mixes assume that individuals behave according to the rational actor model, and deliberately set their energy consumption in response to financial incentives or to information disclosure. However, evidence shows that real-world individuals often process information in a way that systematically differs from standard utility maximization predictions (Brekke & Johansson-Stenman, 2008; Brown & Hagen, 2010; Frederiks, Stenner, & Hobman, 2015; Wilson & Dowlatabadi, 2007), causing traditional policy interventions to be sometimes weakly effective (Gsottbauer & van den Bergh, 2011; Ito, 2014; Jaffe & Stavins, 1994; Stern et al., 1986). As a response, a new category of policy instruments has been introduced, the so-called nudges (or behavioral interventions), which 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). Given the different underlying assumptions between behavioral and traditional interventions, nudges are considered as valuable complements of traditional policy instruments and are therefore expected to support them when jointly implemented (Bahn-Walkowiak & Wilts, 2017; Benartzi et al., 2017; Dietz, Gardner, Gilligan, Stern, & Vandenbergh, 2009; Ferraro & Price, 2013; Goldin & Lawson, 2016; Rosenow et al., 2016; Rosenow, Kern, & Rogge, 2017).

Unfortunately, scientific evidence about the interplay between traditional policy instruments and nudges is still quite scattered. Existing evidence on behavioral-traditional interventions focuses only on specific instrument mix (Bettinger, Terry Long, Oreopoulos, & Sanbonmatsu, 2012; Chapman, Li, Colby, & Yoon, 2010; Goldin & Lawson, 2016; List, Metcalfe, Price, & Rundhammer, 2017; Mizobuchi & Takeuchi, 2013; Pellerano, Price, Puller, & Sánchez, 2017), and therefore does not draw general conclusions on the interplay between them. By contrast, studies taking a broader view have so far failed to consider nudges' specificities, treating interventions that mostly resemble nudges as a homogeneous policy class, which influences behavior alike (Bahn-Walkowiak & Wilts, 2017; Rosenow et al., 2016, 2017). We argue here for a unifying approach, able to explain and predict under which conditions nudges will actually reinforce traditional policy instruments. The term nudge encompasses a heterogeneous set of interventions; benefits from their combination with traditional instruments are therefore contingent on the type of intervention considered. Failing to assuming a realistic approach to behavioral interventions can lead to combinations of overlapping tools, thereby missing policy mixes' target of combining consistent and supporting policy instruments.

Investigating the interplay between nudges and traditional policy tools is important also for another reason. Nudges are growing in popularity as strategies to promote socially-relevant outcomes (Allcott, 2011; Araña & León, 2013; Ferraro & Price, 2013; Goldstein, Cialdini, & Griskevicius, 2008); when a new nudge is implemented it is added to an existing mix of policies which will certainly affect its effectiveness (Boonekamp, 2006; Howlett & Rayner, 2013), leaving little possibility to evaluate the instrument individually. As a consequence, considering whether the new instrument will reinforce or mitigate the effects of pre-existing policies increases the chance to achieve its intended outcome.

Our contribution to the literature is twofold. On the one hand, we provide a comprehensive framework to clarify the conditions under which positive or negative synergies might be expected. On the other hand, we collect evidence on a novel combination of traditional (rebate) and behavioral (goal setting and feedback) instruments, by using an online experiment in which subjects are asked to optimize their energy consumption. More specifically, we develop an innovative incentive-compatible task capturing the essential incentive structure of real energy behaviors. We compared the effect of policies by randomly assigning participants to either one policy instrument, or to their combination, or to a control condition. Our results show mitigating, rather than supporting effects between the two set of tools. This finding challenges the prevailing idea that nudges are under any condition valuable complements to traditional policy tools and suggests to consider their combinations with a case-by-case perspective.

The remainder of the paper is organized as follows: Section 2 discusses the general framework and reports our hypotheses. Section 3 details the methodology. Section 4 analyzes and reports the results. Section 5 discusses the main findings and concludes.

2 The role of nudges in traditional energy policy mixes

A broad and diverse class of interventions goes under the label "nudge", targeting different behavioral biases and entailing different levels of deliberation from the target subject (Thaler & Sunstein, 2008). We argue that when nudges interact with traditional policy tools, such heterogeneity needs to be considered, both in terms of underlying mechanisms promoting behavioral change and of nudges' function inside the policy bundle. On the basis of a critical review of existing literature, we propose two ways whereby nudges can be combined with traditional tools[1]. First, they can support market-based instruments by making them more easily accessible to individuals. Second, the two tools can be combined to simultaneously appeal to different sources of motivation, with the nudge targeting intrinsic or cognitive motives and the market-based instruments targeting economic ones.

In this section, we detail the two types of combinations and their expected interactions; we reinforce our discussion with available empirical evidence[2].

2.1 Nudges to streamline market-based policies' accessibility

A first combination of market-based and behavioral policy instruments can be designed so that the former is the pivotal incentive mechanism. Nudges have here an ancillary role to convey the economic incentive. Hence, this policy mix still leverages on the economic incentive to prompt behavioral change and the design is integrated with behavioral insights to increase its effectiveness.

Despite their behavioral change potential, market-based policies are often less effective than theoretical predictions (Gillingham et al., 2009; Ito, 2014). This is firstly caused by the presence of individuals who do not perform cost-benefit analyses in the process of choosing a specific option and are therefore insensitive to changes in the economic structure of energy alternatives (Chetty, Friedman, Leth-Petersen, Nielsen, & Olsen, 2014). Second, accessing the benefits conveyed by market-based policies can require noticeable effort to individuals, for instance in terms of searching governments' aid programs, or of completing the paperwork to apply for it (Klöckner, Sopha, Matthies, & Bjørnstad, 2013; Wilson & Dowlatabadi, 2007). Investing time and cognitive effort to select an energy virtuous option will provide private economic return in the future. Nevertheless, when individuals have present-biased preferences (Loewenstein & Prelec, 1992; Thaler, 1981) the search costs may loom larger than future benefits and this may represent a relevant barrier against market-based policy effectiveness.

Within this framework, nudges can be implemented to reduce search and information costs of accessing the market-based intervention. To the best of our knowledge, no policy mixes of this kind exist in the energy domain. However, a recent literature review by Benartzi et al. (2017) reports preliminary successful cases in other domains. In the field of education, college attendance was significantly increased by streamlining the application process for financial aid system, achieved with the provision of personal assistance (Bettinger et al., 2012). A similar successful example draws from the health domain, where defaulting individuals in free vaccination appointments significantly increased vaccination rate (Chapman et al., 2010). Accordingly, this way of combining traditional and behavioral interventions seems a viable option in the hands of policymakers to promote more sustainable energy consumption patterns. As an example, governments can default households in a subsidized energy plan from renewable sources, or increase the demand for energy efficient appliances by providing personal assistance to access investment capital.

A final argument in support of this mix of behavioral and traditional instruments relates to the possible benefits on public perception of nudges. Their acceptability is indeed conditional to their objective, and to the way they act upon individuals' behaviors (Schubert, 2017). As an example, green defaults seek to improve societal, more than individual, welfare and impact behavior with little awareness, thereby resulting in mixed public acceptability (Hagman, Andersson, Västfjäll, & Tinghög, 2015; Reisch & Sunstein, 2016). If green nudges are implemented to promote both community's and individual's goals, their perceived legitimacy may ultimately increase. This can be achieved by integrating them in energy policy mixes, where low CO2 options promoted by nudges are made economically convenient for the individual through market-based interventions, such as subsidies and feed-in tariffs.

2.2 Nudges to complement economic incentive of market-based policies

A second option for energy policy mixes involving behavioral and economic instruments lies in integrating the economic incentive with other motivational appeals, such as moral and social motives. In fact, since reducing personal CO2 emissions means contributing to a public good (Brekke & Johansson-Stenman, 2008), this decision is underlain by social and moral arguments that go beyond mere self-interest (Andreoni, 1990;

Fischbacher, Gächter, & Fehr, 2001; Nyborg, Howarth, & Brekke, 2006). In this respect, behavioral and traditional policies can be combined as stand-alone instruments, where the former targets social or moral motives, and the latter the economic incentive.

To date, there is no consensus on the outcome of this way of conceiving policy mixes. A first shortcoming in the literature is the limited evidence available, which does not allow to assess the kind of interplay more likely to arise. As an example, List et al. (2017) show that adding a financial reward to a social comparison increases energy saving. However, in their study they do not compare the effect of the mix with that of the economic intervention alone, making impossible to conclude that positive synergies arise in their setting. Mizobuchi & Takeuchi (2013) have indeed observed that the marginal gain from adding a comparative feedback to a reward is not significant[3].

In addition, it is unclear why one type of synergies should be predominant with respect to the other. Existing literature accounts for the generation of both reinforcing and overlapping interplay. On the one hand, insomuch as behavioral and traditional interventions influence decision-making through different channels, they are expected to result in mutually supporting synergies (Bahn-Walkowiak & Wilts, 2017; Larrick, Weber, Ungemach, Johnson, & Camilleri, 2017; Rosenow et al., 2016, 2017). Consistently 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).

On the other hand, behavioral sciences suggest that some aspects of human cognition may actually hinder the creation of the expected benefits. First, according to motivation crowding-out hypothesis, providing an external reward in exchange for a socially-desirable behavior may erode the moral and social arguments involved in the decision-making process (Ariely, Bracha, & Meier, 2009; D'Adda, 2011; Frey & Jegen, 2001; Pellerano et al., 2017). As a consequence, in the attempt to combine policies appealing to different sources of motivation, the economic incentive of the market-based policy may undermine, rather than support, non-economic sources of motivation. Second, evidence demonstrates that humans feature limited cognitive resources (Jacoby, 1984; Malhotra, 1984), which make them struggle when provided with too much information. While using nudges to streamline traditional policies' accessibility circumvents this problem, the same may not be true when using them to complement the economic incentive. If the policy mix seeks to increase the salience of multiple sources of motivation, it may cognitively overload subjects, inducing them to disregard the message (Iyengar & Lepper, 2000), or to focus only on part of it (Shr, Ready, Orland, & Echols, 2019), resulting in substitution effects.

2.3 The current study

Through an online experiment, we aim to provide new evidence on the interaction between behavioral and market-based policies. Specifically, we combine two tools that already proved their effectiveness but that have not yet being tested in combination: *rebate, as a market-based intervention* (Datta & Filippini, 2016; Datta & Gulati, 2014), and *goal setting and feedback, as a nudge* (Abrahamse, Steg, Vlek, & Rothengatter, 2007; Loock & Staake, 2013; McCalley & Midden, 2002)[4].

Regarding the rebate, it encourages virtuous behavior through a financial incentive, namely providing an energy saving target to residential and business customers and giving an economic prize for its achievement. According to standard economic reasoning, individuals react to monetary incentives because they value their material pay-off, and are therefore motivated to conserve energy to increase it (Alberini, Gans, & Velez-Lopez, 2011; Halvorsen & Larsen, 2001; Vaage, 2000). This argument leads to our first hypothesis.

Hypothesis 1: Rebate motivates participants to achieve the energy saving target.

Goal setting affects decision-making by harnessing cognitive biases in human decision-making (Harding & Hsiaw, 2014; Koszegi & Rabin, 2006). It entails the provision of an energy saving goal, without any material incentive to achieve it. The lack of a material reward would make this intervention ineffective for *homo economicus*; however, it has been shown that individuals react to non-binding goals because they exhibit reference-dependent preferences and loss aversion (Kahneman & Tversky, 1979; Koszegi & Rabin, 2006). By acting as a reference point, the goal divides the space of outcomes into gains and losses, respectively when the goal is achieved and when not. If the comparison between one’s performance and the goal is favorable (negative), the individual will perceive a gain (loss) and will derive (lose) some utility. Goal setting is usually more effective when the goal is self-set by the subject (Andor & Fels, 2018), and when it is integrated with a feedback (Abrahamse, Steg, Vlek, & Rothengatter, 2005). Letting subjects self-set their own targets increases goals' motivational power by enhancing internal commitment (Bénabou & Tirole, 2004), and by reflecting personal expectations on future outcomes (Hsiaw, 2013; Koszegi & Rabin, 2006). Feedback increases intervention's effectiveness as it reveals how one is performing compared to the goal and allows to adjust effort and performance accordingly (Locke & Latham, 2002). Hence, we hypothesize the following.

Hypothesis 2: Goal setting and feedback motivate participants to achieve the energy saving target.

As far as the interaction between the two instruments is concerned, pre-existing evidence is mixed. Our null hypothesis is formulated in line with the prevailing view on policy mixes, which assumes that combinations of tools targeting different motivational sources will achieve positive synergies (see Section 2.2). The policy mix tested in this study simultaneously conveys economic and cognitive appeals, through the rebate and the nudge respectively. On the basis of this reasoning, we formulate our last hypothesis as follows.

Hypothesis 3: The combination of the two policy instruments leads to greater goal achievement than the overall effect of each instrument individually adopted. Namely, there is marginal gain in combining the interventions with respect to individual policies implementation.

3 Methodology

To test our hypotheses, we conducted an online experiment on the online platform Prolific. We developed an innovative task that captures main features of real-world everyday energy decisions. In this regard, our work is novel: earlier attempts to reproduce energy behaviors in a virtual setting were missing some key elements, such as incentive-compatibility (McCalley, de Vries, & Midden, 2011; McCalley & Midden, 2002), environmental externalities (Casal, DellaValle, Mittone, & Soraperra, 2017; Martín et al., 2016), or the personal return associated with energy saving (Lange, Steinke, & Dewitte, 2018). Our task captures and incentivizes the essential elements of actual energy behaviors, represented by a trade-off between private and societal benefits on one side and personal disutility on the other. Including these design features yields results that capture participants' actual preferences in terms of energy practices. In the meanwhile, the virtual setting allows to investigate the mechanism underlying the observed interplay between the two policy instruments.

In this section, we describe our task and the experimental procedure in detail.

3.1 Task design

3.1.1 Description

Using oTree (Chen, Schonger, & Wickens, 2016), we created a task that simulates washing machine usage in a virtual setting. The virtual control panel of the washing machine included three parameters, namely, *temperature, program* and, *duration,* that participants could set by pressing on a specific button (Figure 1, left). At every round, participants were provided with a washing load, characterized by two parameters: material and level of dirt. We included 5 materials (A, B, C, D, E) and 2 levels of dirt (low, high), for a total of 10 combinations. Order of presentation of washing loads was randomized across participants. The washing machine was supplied with manual instructions (Figure 1, right), which reported how to use the panel and how to optimize energy consumption depending on load characteristics.

FIGURE 1 APPROXIMATE HERE

The baseline consumption of the washing machine was a function of the temperature required for the washing load of the specific round. To increase realism, the baseline consumption was comparable with the one of a washing machine purchased after year 2000 for a 6 kg load, according to the following formula: $consumption\ (kWh) = 0.0254 * temperature_i - 0.3786$ (Milani, Camarda, & Savoldi, 2015). At every round, we recorded participants' percentage of energy saving s_{ij} (i: participant, j: round), which was derived from the combination of parameters selected (Table 1 reports a summary of the options and the corresponding saving). At the last round, we computed the final percentage of saving for participant i as mean value of all rounds: $s_i(\%) = \sum_{j=1}^{10} s_{ij}$.

TABLE 1 APPROXIMATE HERE

3.1.2 Energy-related elements

To ensure incentive-compatibility and to increase realism, we included some additional elements to the design, which are summarized in Table 2. In the real world, curtailing energy consumption ensures two types of benefits: private economic return from lower energy cost and positive externality on the environment. We reproduced the economic return with a variable payment proportional to participants' final saving (see Section 3.2 for details). Then, to recreate the positive externality of energy conservation, we introduced a donation to

WWF[5] increasing in participant's saving, according to the following scheme: s_i between 5% and 10% led to a donation of £ 0.10, s_i between 10% and 20% of £ 0.20, s_i higher than 20% of £ 0.50. In this way, despite taking place in a simulated setting, behavior in our task has real consequences on the environment. We finally added to the design the disutility that individuals face when reducing their own energy consumption. In the context of actual energy behaviors, it relates to the search costs of acquiring new information and to the effort to apply it to daily practices (Oikonomou, Becchis, Steg, & Russolillo, 2009). We reproduced this personal cost with the effort of reading and implementing manual instructions: the higher the energy saving associated with a specific combination of parameters, the higher the effort to implement it. As an example, setting the correct temperature and the standard program yielded to a saving of 5%, whereas the correct temperature, the optimized program, and the duration, to a saving of 30%.

TABLE 2 APPROXIMATE HERE

3.2 Experimental procedure

The experiment was launched on the online platform Prolific Academy in September 2018. 574 participants completed the task. Each participant received £ 1.5 as a fixed participation payment and an additional bonus between £ 0 and £ 1.4, according to the following schema:

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

where a represents fixed participation fee. The term $b * \gamma * s_i$ represents the variable bonus payment: s_i is a continuous variable that represents *participant* i's final percentage of saving. b is the maximum variable payment from energy saving, equal to £ 1; γ is a multiplicative factor that serves to normalize the payment considering saving's range of variation, between 0 and 25; $\gamma = \frac{100}{25}$, so that variable payment is £ 0 if $s_i = 0$, and £ 1 if $s_i = 25$; the term $c * prize_i * \delta_i$ represents the economic prize for achieving the energy saving goal: c corresponds to the monetary prize received in exchange for goal achievement, equal to £ 0.4. $prize_i$ is a dummy for the presence of the economic prize in the experimental condition (1 = yes) (see Section 3.3); δ_i is a dummy that represents whether *participant i* achieves energy saving target g_i (1 = $\delta_i \geq g_i$).

All participants performed the same task. First, each participant received written instructions about the experiment and the usage of the control panel. To ensure understanding, they had to answer correctly to a comprehension check to proceed to the task; next, subjects were given 2 washing trials to familiarize with the control panel. Before proceeding to the 10 payoff-relevant washing rounds, participants were randomly assigned to one treatment. The experiment ended with a measure of cognitive function, in the form of cognitive reflection test (CRT) (Frederick, 2005) and of SAT test preparation, and with a questionnaire about environmental values, with three items taken from the Value Inventory Scale (Davidov, Schmidt, & Schwartz, 2008). Collecting these measures allows us to control for individual cognitive endowment and to gather information about the cognitive effort associated with our task. Specifically, a positive correlation between measures of cognitive function and participants' performance will provide support to the assumption that our task involves cognitive effort. The same argument applies to environmental values and the positive externality associated with energy saving in our task[6].

3.3 Treatments

Treatments were implemented with a 2x2 between-subject design and varied the type of incentive (Table 4 reports a summary of our experimental conditions):

Nudge: Goal setting and feedback. Participants were required to set their own energy saving goal g_i for the 10 rounds. Participants were provided with feedback at every round, reporting the comparison of their performance against their goal.

Market-based intervention: Rebate. Participants were provided with an energy saving target g_i for the 10 rounds. They received an economic prize of £ 0.4 in case of target achievement. In order to ensure that experimental conditions did not differ under goal distribution perspective, in *Market-based intervention* we assigned goals drawing from those in *Nudge* and *Policy mix* conditions. More precisely, we first launched *Nudge* and *Policy mix*; then, we randomly drew values from goals self-set by participants in *Nudge* and *Policy mix* and assigned them to participants in the *Market-based intervention* condition. Figure 2 reports goal distribution per goal's nature and shows that there are no significant differences between endogenous and exogenous goals.

FIGURE 2 APPROXIMATE HERE

Policy mix: Goal setting, feedback, and rebate. Participants were required to set their personal goal g_i, and they were provided with feedback at every round. After setting their own goal they were informed that in case of goal achievement, they would receive an economic prize of £ 0.4.

Control. Participants went through the task without goal assignment and without additional economic incentives.

TABLE 3 APPROXIMATE HERE

3.4 Analysis

To test our hypotheses on policies, we perform a regression analysis on participants' performance in all rounds. We consider two experimental outcomes: *goal achievement and energy saving*. Goal achievement is a dummy equal to 1 if the saving of participant *i* for round *j* is higher or equal to the goal ($1 = s_{ij} \geq g_i$); energy saving represents the saving achieved by participant i for round j (s_{ij}). Our main focus is on goal achievement; the reason is that our treatments are designed to maximize the percentage of goals attained rather than energy saving *per se*. The impact on energy saving is indeed mediated by the goal that participants have to achieve: rewarding participants if they achieve 5% of saving leads to lower conservation effort compared to a goal equal of 25%. Treatment effects are therefore expected to be weaker on energy saving than on goal achievement. However, to increase findings' robustness to an alternative specification of the dependent variable and to the comparison with the control group we propose the estimation also on energy saving.

To assess treatment effects we estimated the following mixed models with random intercept at individual level (Moffatt, 2015):

$$y_{ij} = \beta_0 + \sum \beta_i * treat_i + \beta_3 * env_i + \beta_4 * cogn_i + \beta_5 * round + \beta_6 * X_i + u_i + \varepsilon_{ij} \quad (2)$$

$$y_{ij} = \beta_0 + \sum \beta_i * treat_i + \beta_3 * env_i + \beta_4 * cogn_i + \beta_5 * round + \sum \beta_i * treat_i * round + \beta_8 * X_i + u_i + \varepsilon_{ij} \quad (3)$$

where y_{ij} denotes each of the two characterization of the dependent variable. Given the nature of our dependent variables, we estimated a generalized linear mixed model on goal achievement and a linear mixed model on energy saving. $treat_i$ is a dummy for the random exposure to each of our treatments. We included two variables related to real energy saving behavior, i.e., env_i, which represents participant *i*'s environmental values, coded as average respond to the three related questions, and $cogn_i$, which stands for participant *i*'s cognitive function, and sums up the number of correct question on the math test and on CRT. These variables provide us with a guidance about the involvement of cognitive effort and environmental values in the task. $round$ represents a continuous variable for washing cycles. 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}.

The model reported in Eq. (2) allows to estimated overall treatment effect, the one in Eq. (3) to examine the dynamic effect of manipulations on participants' behavior.

4 Results

4.1 Sample characteristics

Due to our experimental design, we launched experimental sessions in different waves. We first launched *Nudge* and *Policy mix*. Unfortunately, while running this session we had a problem with the database, and some participants could not finish the task. They are therefore not included in the analysis. We launched a second session for *Nudge* and *Policy mix* to complete data collection. Of our sample of 574, we eliminated two participants who could complete the task during the problem with the database but reported slow processing time. Results do not change if they are included in the analysis. We also excluded from the analysis 6 participants who had missing socio-demographic characteristics. Our final sample is of 566 participants.

Table 4 reports participants' characteristics. Participants' gender and age are unbalanced across the experimental conditions, with lower share of male in *Market-based intervention* and *Control* and younger population in *Policy mix*. To avoid that these variables affect experimental results, we control for them in our analysis. Importantly, environmental values and cognitive function, the relevant participants' characteristics for our study, are balanced across the four experimental conditions.

TABLE 4 APPROXIMATE HERE

4.2 *Treatment effects*

4.2.1 *Goal achievement*

To investigate our hypotheses about incentives, we estimated Eq. (2) and Eq. (3) on goal achievement in all rounds. Results are reported in Table 5. We first focus on overall treatment effects; then we discuss dynamic effects on participants' behavior.

We find support of our hypotheses about the effect of individual policies. In line with Hypothesis 1 and 2, treatments motivated participants to achieve their energy saving target, with 51% of goal achieved in *Market-based intervention* condition, and 42% in *Nudge* (Figure 3). To test if combining incentives achieves positive synergies, we focus on the coefficient of *Policy mix* of Eq. (2). Even if not significantly, policy mix effect is lower than that of the traditional intervention. With respect to *Nudge*, *Policy mix* achieves higher goal achievement, but non-significant. As the combination of the two instruments achieves an effect that is in magnitude included between that of single policies, rather than higher, our findings contravene positive synergies assumption. Hypothesis 3 is therefore non supported.

FIGURE 3 APPROXIMATE HERE

Even if overall treatment effects do not differ across experimental conditions, they exhibit substantial differences with respect to dynamics. Model 2 in Table 5 reports significant positive interaction between *Traditional intervention* and round (*Round*) which is not present in *Nudge* and *Policy mix (*Round x Nudge and Round x Mix). These results find support in Figure 3, where *Market-based intervention* shows an increasing pattern, whereas the other experimental conditions do not exhibit a clear trend. These findings suggest that *Policy mix* affects behaviors as *Nudge* does, with no added value from the economic incentive.

TABLE 5 APPROXIMATE HERE

4.2.2 *Energy saving*

Next, to increase the robustness of our findings we investigated our hypotheses on a different specification of the dependent variable, and we estimated Eq. (2) and Eq. (3) on overall energy saving. As expected, energy saving is influenced by goals ($B = .298$, $p < .001$), and because goal distribution spans between 0% and 25% in all the experimental conditions (Figure 2), treatment effect is weakened when evaluating its impact on final saving.

Table 6 shows that treatment effect on energy saving is analogous to that on goal achievement. Experimental conditions do not significantly differ with respect to overall energy saving. However, coefficients of treatment dummies give an indication of their relative impact. The coefficient of *Policy mix* in Model 1 of Table 6 is lower than that of *Nudge* and *Market-based intervention*. Focusing on dynamic treatment effects, Model 2 of Table 6 shows that energy saving increases over rounds for participants assigned to control condition and to *Market-based intervention*, but this effect is cancelled out in *Nudge* and *Policy mix*. Results on energy saving are therefore in line with the lack of positive synergies observed on goal achievement.

TABLE 6 APPROXIMATE HERE

5 Potential mechanisms

To shed further light on the drivers of the lack of positive synergies, we perform a few additional analyses. More precisely, we focus on the constitutive elements of *Policy mix* and *Market-based intervention* that affect our results. Section 5.1 discusses the effect of the economic incentive; we then examine nudge's impact, respectively focusing on goal setting in Section 5.2 and on feedback in Section 5.3.

5.1 Motivation crowding-out

We analyze whether appealing to economic motivation has a negative effect on intrinsic motivation to improve energy performance –namely, whether motivation crowding-out is the main driver of our result. If this was the case, we would expect a lower impact of individual environmental attitudes on performance in the experimental conditions involving an extrinsic monetary incentive. We therefore examine whether *Market-based intervention* and *Policy mix* negatively affect intrinsic motivations, by re-estimating the model reported in Eq. (2) and including interactions between treatments and pre-existing environmental values[7].

Results of the estimates are reported in Table 8, keeping distinct goal achievement (Model 1) and energy saving (Model 2). No significant interaction is observed between treatments and environmental values, suggesting that the extrinsic incentives do not undermine participants' intrinsic motivation. We therefore tend to exclude that motivation crowding-out is the likely explanation for the lack of positive synergies observed in our study. This finding is aligned with earlier work on behavioral-traditional mixes (Mizobuchi & Takeuchi, 2013), where no motivation crowding-out is observed when jointly implementing social comparison and economic incentive.

TABLE 7 APPROXIMATE HERE

5.2 *Nature of goal setting*

We investigated whether the nature of goal setting affects participants' performance. Specifically, we explore the hypothesis that self-set goals mirror expectations on future outcomes and thus they should have higher motivational power than randomly assigned goals. This should foster positive synergies in policy interventions[8]. We test whether goals were formulated according to rational considerations by regressing self-set goals on relevant participants' characteristics[9].

Table 7 reports regression results. It shows a significant positive effect of environmental values and of cognitive function on formulation of goals. Participants therefore set their goals considering both their willingness to contribute to the common cause and to their capability to reduce their energy consumption. This result reinforces the idea that, by better matching targets' characteristics, self-set goals should have greater motivational power than externally-imposed targets as those of traditional market-based programs. However, in our setting this did not translate into greater effect than randomly assigned goals. We therefore exclude that better assigned goals in *Nudge* and *Policy mix* were the driver of our results.

TABLE 8 APPROXIMATE HERE

5.3 *Feedback*

In this section we discuss how feedback impacted participants' behavior. Feedback allows participants to learn about the environment and about the matching between their skills and the task. Thus, we expect that feedback provision would improve participants' performance. However, our findings reveal a puzzling outcome: as reported in Section 4.1 and 4.2, only those participants who did not receive any feedback improved their performance over rounds. We further unpack this result to investigate whether these differences emerge as the experiment progresses. At this aim, we re-estimate Eq. (3) by substituting the continuous variable round with a dummy variable *Second half*, equal to 1 when $round > 5$ and equal to 0 otherwise.

Table 9 summarizes the regression results. A lower performance among participants exposed to feedback is observed only in the second part of the task, where those assigned to *Traditional intervention* and to *Control* improve their performance whereas those exposed to *Nudge* and *Policy mix* did not. Lack of staying effect from behavioral interventions is not unique in our case (Buchanan, Russo, & Anderson, 2015; Ferraro & Price, 2013; Gneezy & List, 2006; Landry, Lange, List, Price, & Rupp, 2010). With this respect, a relevant contribution is from Ito et al. (2018), who directly compared the effect of moral suasion with that of economic incentive in the context of residential electricity consumption. They found significant differences in the staying effect of these programs: the impact of non-pecuniary intervention diminishes with repeated exposure, whereas that of the economic incentive remained stable and significant over time.

Surprisingly, in our setting the combination of behavioral-traditional tools does not show the positive medium-term impact of pecuniary interventions, but rather, the waning effect of nudges. This suggests that augmenting the nudge with the economic incentive failed to generate the expected benefits. We interpret this result in light of limited cognitive resources notion (Jacoby, 1984; Malhotra, 1984), and specifically, with the finding that 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). Exposing participants to both behavioral and traditional interventions procedure seemingly reduced the attention they paid to the economic incentive, consequently reducing its impact and hindering the creation of positive synergies.

TABLE 9 APPROXIMATE HERE

6 Conclusion

Providing both theoretical and experimental insights, this study contributes to the emerging literature on the interplay between traditional policies and nudges. We propose a novel classification of how the two tools can be combined based on their characteristics and their relative function when they are jointly implemented. Next, through an online experiment, we investigate whether positive or negative synergies arise when a tax rebate, a goal setting and feedback are jointly implemented to promote energy conservation.

Our findings indicate that combining the two instruments does not strengthen the effect of single policies. We therefore reject the hypothesis of positive synergies between the policy instruments implemented in this study. The examination of medium-run policies' impact enables to pinpoint the mechanisms underlying our results. Indeed, when implemented alone, the market-based intervention and the nudge significantly differ in terms of dynamic impact on participants' behavior: while the economic incentive effect has a sustained effect over rounds, that of nudge wanes in the second part of the task. Interestingly, we observe that the mix exhibits the same decline as the nudge. This suggests that the nudge "cognitively crowds-out" the economic motivation: by diverting participants' attention from the economic incentive, the behavioral intervention reduces its impact and hampers the creation of the expected benefits.

Overall, our study suggests that behavioral and traditional interventions may or may not generate positive synergies, depending on how and which tools are combined. However, our work presents some limitations. First, our study was performed in a virtual setting. Although we carefully designed our experiment to represent energy behaviors, external validity considerations call for caution. Additionally, the experimental setting leaves little room for cost-effective analysis. Nevertheless, one key feature of nudges is their high return per money invested; future empirical work is needed to investigate how traditional-behavioral mixes perform under a cost-adjusted perspective and not only in terms of absolute impact. Finally, we examined some drivers of the lack of positive synergies, but we only inferred them from our results. Further research may be worthwhile to formally test them and to investigate the possibility to achieve reinforcing effects by increasing the salience of the economic incentive.

Notes

[1] In terms of traditional tools, we limit our analysis to market-based interventions, namely regulations that encourage behavior through market signals. We exclude regulatory measures that forbid or impose specific choice alternatives, and therefore restrict the opportunity set without affecting subjects' preferences.

[2] Energy behaviors included in our analysis refer to any end-user action leading to a reduction in CO_2 emissions from energy consumption. This can be accomplished with subjects' adoption of greener technologies, as well as with a change in their way to use the same capital stock. It is beyond the scope of our study to differentiate

within the category of energy behaviors. See Barr et al. 2005 and Oikonomou et al. 2009 for clarifications on differences between end-user energy behaviors.

[3] Another contribution is from Petersen, Shunturov, Janda, Platt, & Weinberger (2007), who investigate the joint effect of social comparison feedback, economic incentive and educational campaign on energy conservation in a student dormitory. However, their design does not allow to disentangle the effect of individual policies and the marginal gain from combining them.

[4] Note that it beyond the scope of this paper to compare the effect of non-pecuniary and pecuniary interventions. For experimental evidence on the topic see (Delaney & Jacobson, 2016).

[5] The beneficiary environmental organization was selected with the aim of maximizing its appeal to a wide audience: WWF is internationally well known and is widely perceived as politically neutral (Cracknell, Miller, & Williams, 2013; Pharoah, 2017).

[6] Results reported below (see Table 5 and Table 6) indeed provide support to the assumption that the task involves cognitive effort and that it relates to individual environmental values.

[7] Results are robust also if we pool together the two treatments conveying an economic incentive to increase statistical power.

[8] Note that in our setting goals are bounded by the experimental design. We therefore do not consider the situation where participants set for themselves overly-optimistic and non-attainable goals. For related literature, see (Harding & Hsiaw, 2014) and Loock & Staake (2013).

[9] We excluded those assigned to *Market-based intervention* as they were randomly assigned to goals. For them, no relation is observed between characteristics and goal level.

References

Abrahamse, W., Steg, L., Vlek, C., & Rothengatter, T. (2005). A review of intervention studies aimed at household energy conservation. *Journal of Environmental Psychology*, *25*(3), 273–291. https://doi.org/10.1016/j.jenvp.2005.08.002

Abrahamse, W., Steg, L., Vlek, C., & Rothengatter, T. (2007). The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents. *Journal of Environmental Psychology*, *27*(4), 265–276. https://doi.org/10.1016/j.jenvp.2007.08.002

Alberini, A., Gans, W., & Velez-Lopez, D. (2011). Residential consumption of gas and electricity in the U.S.: The role of prices and income. *Energy Economics*, *33*(5), 870–881. https://doi.org/10.1016/j.eneco.2011.01.015

Allcott, H. (2011). Social norms and energy conservation. *Journal of Public Economics*, *95*(9–10), 1082–1095. https://doi.org/10.1016/j.jpubeco.2011.03.003

Andor, M. A., & Fels, K. M. (2018). Behavioral Economics and Energy Conservation – A Systematic Review of Non-price Interventions and Their Causal Effects. *Ecological Economics*, *148*(November 2017), 178–210. https://doi.org/10.1016/j.ecolecon.2018.01.018

Andreoni, J. (1990). Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving. *The Economic Journal*, *100*(401), 464-477.

Araña, J. E., & León, C. J. (2013). Can Defaults Save the Climate? Evidence from a Field Experiment on Carbon Offsetting Programs. *Environmental and Resource Economics*, *54*(4), 613–626. https://doi.org/10.1007/s10640-012-9615-x

Ariely, D., Bracha, A., & Meier, S. (2009). Doing Good or Doing Well? Image Motivation and Monetary Incentives in Behaving Prosocially. *American Economic Review*. https://doi.org/10.1257/aer.99.1.544

Bahn-Walkowiak, B., & Wilts, H. (2017). The institutional dimension of resource efficiency in a multi-level governance system—Implications for policy mix design. *Energy Research and Social Science*, *33*, 163–172. https://doi.org/10.1016/j.erss.2017.09.021

Barr, S., Gilg, A. W., & Ford, N. (2005). The household energy gap: Examining the divide between habitual- and purchase-related conservation behaviours. *Energy Policy*, *33*(11), 1425–1444. https://doi.org/10.1016/j.enpol.2003.12.016

Bénabou, R., & Tirole, J. (2004). Willpower and personal rules. *Journal of Political Economy*, *112*(4), 848–

886. https://doi.org/10.1177/1045389X15592482

Benartzi, S., Beshears, J., Milkman, K. L., Sunstein, C. R., Thaler, R. H., Shankar, M., … Galing, S. (2017). Should Governments Invest More in Nudging? *Psychological Science*, *28*(8), 1041–1055. https://doi.org/10.1177/0956797617702501

Bettinger, E. P., Terry Long, B., Oreopoulos, P., & Sanbonmatsu, L. (2012). Information in College Decisions: Results From the H&R Block and FAFSA Experiment. *The Quarterly Journal of Economics*, *127*(3), 1205–1242. https://doi.org/10.1093/qje/qjs017.Advance

Boonekamp, P. G. M. (2006). Actual interaction effects between policy measures for energy efficiency-A qualitative matrix method and quantitative simulation results for households. *Energy*, *31*(14), 2512–2537. https://doi.org/10.1016/j.energy.2006.01.004

Brekke, K. A., & Johansson-Stenman, O. (2008). The behavioural economics of climate change. *Oxford Review of Economic Policy*, *24*(2), 280–297. https://doi.org/10.1093/oxrep/grn012

Bridge, G., Bouzarovski, S., Bradshaw, M., & Eyre, N. (2013). Geographies of energy transition: Space, place and the low-carbon economy. *Energy Policy*. https://doi.org/10.1016/j.enpol.2012.10.066

Brown, G., & Hagen, D. A. (2010). Behavioral Economics and the Environment. *Environmental and Resource Economics*, *46*(2), 139–146. https://doi.org/10.1007/s10640-010-9357-6

Buchanan, K., Russo, R., & Anderson, B. (2015). The question of energy reduction: The problem(s) with feedback. *Energy Policy*, *77*, 89–96. https://doi.org/10.1016/j.enpol.2014.12.008

Casal, S., DellaValle, N., Mittone, L., & Soraperra, I. (2017). Feedback and efficient behavior. *PLoSOne*, *12*(4), e0175738. https://doi.org/10.1007/s11947-009-0181-3

Chapman, G. B., Li, M., Colby, H., & Yoon, H. (2010). Opting in vs opting out of influenza vaccination. *JAMA - Journal of the American Medical Association*. https://doi.org/10.1001/jama.2010.892

Chen, D. L., Schonger, M., & Wickens, C. (2016). oTree-An open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, *9*, 88–97. https://doi.org/10.1016/j.jbef.2015.12.001

Chetty, R., Friedman, J. N., Leth-Petersen, S., Nielsen, T. H., & Olsen, T. (2014). Active vs. Passive decisions and crowd-out in retirement savings accounts: Evidence from Denmark. *Quarterly Journal of Economics*, *129*(3), 1141–01219. https://doi.org/10.1093/qje/qju013

Cracknell, J., Miller, F., & Williams, H. (2013). *Passionate Collaboration? Taking the pulse of the UK environmental sector*. Retrieved from http://www.greenfunders.org/wp-content/uploads/Passionate-Collaboration-Full-Report.pdf

D'Adda, G. (2011). Motivation crowding in environmental protection: Evidence from an artefactual field experiment. *Ecological Economics*, *70*(11), 2083–2097. https://doi.org/10.1016/j.ecolecon.2011.06.006

Datta, S., & Filippini, M. (2016). Analysing the impact of ENERGY STAR rebate policies in the US. *Energy Efficiency*, *9*(3), 677–698. https://doi.org/10.1007/s12053-015-9386-7

Datta, S., & Gulati, S. (2014). Utility rebates for ENERGY STAR appliances: Are they effective? *Journal of Environmental Economics and Management*, *68*(3), 480–506. https://doi.org/10.1016/j.jeem.2014.09.003

Davidov, E., Schmidt, P., & Schwartz, S. H. (2008). Bringing values back in: The adequacy of the European social survey to measure values in 20 countries. *Public Opinion Quarterly*, *72*(3), 420–445. https://doi.org/10.1093/poq/nfn035

Delaney, J., & Jacobson, S. (2016). Payments or Persuasion: Common Pool Resource Management with Price and Non-price Measures. *Environmental and Resource Economics*, *65*(4), 747–772. https://doi.org/10.1007/s10640-015-9923-z

Dietz, T., Gardner, G. T., Gilligan, J., Stern, P. C., & Vandenbergh, M. P. (2009). Household actions can provide a behavioral wedge to rapidly reduce US carbon emissions. *Proceedings of the National Academy of Sciences*, *106*(44), 18452–18456. https://doi.org/10.1073/pnas.0908738106

Ferraro, P. J., & Miranda, J. J. (2013). Heterogeneous treatment effects and mechanisms in information-based environmental policies: Evidence from a large-scale field experiment. *Resource and Energy Economics*, *35*(3), 356–379. https://doi.org/10.1016/j.reseneeco.2013.04.001

Ferraro, P. J., & Price, M. K. (2013). Using nonpecuniary strategies to influence behavior: Evidence from a large-scale field experiment. *Review of Economics and Statistics*, *95*(1), 64–73. https://doi.org/10.1162/REST_a_00344

Fischbacher, U., Gächter, S., & Fehr, E. (2001). Are People Conditionally Cooperative ? Evidence from a Public Goods Experiment. *Economics Letters*, *71*(3), 397–404. https://doi.org/10.2139/ssrn.203288

Fischer, C., & Preonas, L. (2010). Combining Policies for Renewable Energy: Is the Whole Less Than the Sum of Its Parts? *International Review of Environmental and Resource Economics*, *4*(1), 51–92. https://doi.org/10.1561/101.00000030

Frederick, S. (2005). Cognitive Reflection and Decision Making. *Journal of Economic Perspectives*, *19*(4), 25–42. https://doi.org/10.1257/089533005775196732

Frederiks, E. R., Stenner, K., & Hobman, E. V. (2015). Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. *Renewable and Sustainable Energy Reviews*, *41*, 1385–1394. https://doi.org/10.1016/j.rser.2014.09.026

Frey, B., & Jegen, R. (2001). Motivation crowding theory: a survey of empirical evidence. *Journal of Economic Surveys*. https://doi.org/10.1111/j.1467-629X.1980.tb00220.x

Gillingham, K., Newell, R. G., & Palmer, K. (2009). Energy Efficiency Economics and Policy. *Annual Review of Resource Economics*, *1*, 597–620. https://doi.org/10.1146/annurev.resource.102308.124234

Gneezy, U., & List, J. A. (2006). Putting behavioral economics to work: Testing for gift exchange in labor markets using field experiments. *Econometrica*. https://doi.org/10.1111/j.1468-0262.2006.00707.x

Goldin, J., & Lawson, N. (2016). Defaults, mandates, and taxes: Policy design with active and passive decision-makers. *American Law and Economics Review*, *18*(2), 438–462. https://doi.org/10.1093/aler/ahw007

Goldstein, N. J., Cialdini, R. B., & Griskevicius, V. (2008). A Room with a Viewpoint: Using Social Norms to Motivate Environmental Conservation in Hotels. *Journal of Consumer Research*, *35*(3), 472–482. https://doi.org/10.1086/586910

Gsottbauer, E., & van den Bergh, J. C. J. M. (2011). Environmental Policy Theory Given Bounded Rationality and Other-regarding Preferences. *Environmental and Resource Economics*, *49*(2), 263–304. https://doi.org/10.1007/s10640-010-9433-y

Hagman, W., Andersson, D., Västfjäll, D., & Tinghög, G. (2015). Public Views on Policies Involving Nudges. *Review of Philosophy and Psychology*. https://doi.org/10.1007/s13164-015-0263-2

Halvorsen, B., & Larsen, B. M. (2001). The flexibility of household electricity demand over time. *Resource and Energy Economics*, *23*(1), 1–18. https://doi.org/10.1016/S0928-7655(00)00035-X

Harding, M., & Hsiaw, A. (2014). Goal setting and energy conservation. *Journal of Economic Behavior & Organization*, *107*, 209–227. https://doi.org/https://doi.org/10.1016/j.jebo.2014.04.012

Howlett, M., & Rayner, J. (2013). Patching vs Packaging in Policy Formulation: Assessing Policy Portfolio Design. *Politics and Governance*, *1*(2), 170–182. https://doi.org/10.12924/pag2013.01020170

Hsiaw, A. (2013). Goal-setting and self-control. *Journal of Economic Theory*, *148*(2), 601–626. https://doi.org/10.1016/j.jet.2012.08.001

Ito, K. (2014). Do Consumers Respond To Marginal or Average Price ? Evidence from Nonlinear Electricity Pricing. *American Economic Review*, *104*(2), 537–563. https://doi.org/http://dx.doi.org/10.1257/aer.104.2.537

Ito, K., Ida, T., & Tanaka, M. (2018). The Persistence of Moral Suasion and Economic Incentives: Field Experimental Evidence from Energy Demand. *American Economic Journal: Economic Policy*, *10*(1), 240–267. https://doi.org/DOI: 10.1257/pol.20160093

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology*, *79*(6), 995–1006. https://doi.org/10.1037/0022-3514.79.6.995

Jacobsson, S., & Lauber, V. (2006). The politics and policy of energy system transformation - Explaining the German diffusion of renewable energy technology. *Energy Policy*, *34*(3), 256–276. https://doi.org/10.1016/j.enpol.2004.08.029

Jacoby, J. (1984). Perspectives on Information Overload. *Journal of Consumer Research*, *10*(March), 432–435.

Jaffe, A. B., Newell, R. G., & Stavins, R. N. (2005). A tale of two market failures: Technology and environmental policy. *Ecological Economics*. https://doi.org/10.1016/j.ecolecon.2004.12.027

Jaffe, A. B., & Stavins, R. N. (1994). The energy-efficiency gap What does it mean? *Energy Policy*, *22*(10), 804–810. https://doi.org/10.1016/0301-4215(94)90138-4

Johnstone, N., Haščič, I., & Popp, D. (2010). Renewable energy policies and technological innovation: Evidence based on patent counts. *Environmental and Resource Economics*. https://doi.org/10.1007/s10640-009-9309-1

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

Klöckner, C. A., Sopha, B. M., Matthies, E., & Bjørnstad, E. (2013). Energy efficiency in Norwegian households - identifying motivators and barriers with a focus group approach. *International Journal of Environment and Sustainable Development*, *12*(4), 396. https://doi.org/10.1504/ijesd.2013.056348

Koszegi, B., & Rabin, M. (2006). A Model of Reference-Dependent Preferences. *Quarterly Journal of Economics*, *121*(4), 1133–1165. https://doi.org/https://doi.org/10.1093/qje/121.4.1133

Landry, C. E., Lange, A., List, J. A., Price, M. K., & Rupp, N. G. (2010). Is a donor in hand better than two in the bush? Evidence from a natural field experiment. *American Economic Review*. https://doi.org/10.1257/aer.100.3.958

Lange, F., Steinke, A., & Dewitte, S. (2018). The Pro-Environmental Behavior Task: A laboratory measure of actual pro-environmental behavior. *Journal of Environmental Psychology*, *56*, 46–54. https://doi.org/10.1016/j.jenvp.2018.02.007

Larrick, R. P., Weber, E. U., Ungemach, C., Johnson, E. J., & Camilleri, A. R. (2017). Translated Attributes as Choice Architecture: Aligning Objectives and Choices Through Decision Signposts. *Management Science*, (March 2019). https://doi.org/10.1287/mnsc.2016.2703

Lehmann, P. (2012). Justifying a policy mix for pollution control: A review of economic literature. *Journal of Economic Surveys*. https://doi.org/10.1111/j.1467-6419.2010.00628.x

List, J. A., Metcalfe, R. D., Price, M. K., & Rundhammer, F. (2017). Harnessing Policy Complementarities to Conserve Energy: Evidence from a Natural Field Experiment. *NBER Working Paper No. 23355*. https://doi.org/10.3386/w23355

Locke, E. A., & Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American Psychologist*, *57*(9), 705–717. https://doi.org/10.1037/0003-066X.57.9.705

Loewenstein, G., & Prelec, D. (1992). Anomalies in Intertemporal Choice: Evidence and an Interpretation. *The Quarterly Journal of Economics*, *107*(2), 573–597. https://doi.org/10.2307/2118482

Loock, C., & Staake, T. (2013). Motivating Energy-Efficient Behavior With Green is: an Investigation of Goal Setting and the Role of Defaults. *Mis Quarterly*, *37*(4), 1313–1332.

Malhotra, N. K. (1984). Reflections on the Information Overload Paradigm in Consumer Decision Making. *Journal of Consumer Research*, *10*(4), 436–440. https://doi.org/10.1086/208982

Mansur, E. T., & Olmstead, S. M. (2012). The value of scarce water: Measuring the inefficiency of municipal regulations. *Journal of Urban Economics*. https://doi.org/10.1016/j.jue.2011.11.003

Martín, N. G., Sabater-Grande, G., García-Gallego, A., Georgantzis, N., Barreda-Tarrazona, I., & Belenguer, E. (2016). Economic Experiments Used for the Evaluation of Building Users' Energy-Saving Behavior. In *Energy Performance of Buildings* (pp. 107–121). Springer, Cham. https://doi.org/10.1201/9781351071697

McCalley, L. T., de Vries, P. W., & Midden, C. J. H. (2011). Consumer response to product-integrated energy feedback: Behavior, goal level shifts, and energy conservation. *Environment and Behavior*, *43*(4), 525–545. https://doi.org/10.1177/0013916510371053

McCalley, L. T., & Midden, C. J. H. (2002). Energy conservation through product-integrated feedback: The roles of goal-setting and social orientation. *Journal of Economic Psychology*, *23*(5), 589–603.

https://doi.org/10.1016/S0167-4870(02)00119-8

Milani, A., Camarda, C., & Savoldi, L. (2015). A simplified model for the electrical energy consumption of washing machines. *Journal of Building Engineering*, *2*, 69–76. https://doi.org/10.1016/j.jobe.2015.04.007

Mizobuchi, K., & Takeuchi, K. (2013). The influences of financial and non-financial factors on energy-saving behaviour: A field experiment in Japan. *Energy Policy*, *63*, 775–787. https://doi.org/10.1016/j.enpol.2013.08.064

Moffatt, P. G. (2015). *Experimetrics: Econometrics for experimental economics*. Macmillan International Higher Education. https://doi.org/10.1007/978-1-4612-0669-9

Nyborg, K., Howarth, R. B., & Brekke, K. A. (2006). Green consumers and public policy: On socially contingent moral motivation. *Resource and Energy Economics*, *28*(4), 351–366. https://doi.org/10.1016/j.reseneeco.2006.03.001

Oikonomou, V., Becchis, F., Steg, L., & Russolillo, D. (2009). Energy saving and energy efficiency concepts for policy making. *Energy Policy*, *37*(11), 4787–4796. https://doi.org/10.1016/j.enpol.2009.06.035

Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., & Dubash, N. K. (2014). *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*. IPCC. https://doi.org/10.1017/CBO9781107415324

Pachur, T., Schulte-Mecklenbeck, M., Murphy, R. O., & Hertwig, R. (2018). Prospect theory reflects selective allocation of attention. *Journal of Experimental Psychology: General*, *147*(2), 147–169. https://doi.org/10.1037/xge0000406

Pellerano, J. A., Price, M. K., Puller, S. L., & Sánchez, G. E. (2017). Do Extrinsic Incentives Undermine Social Norms? Evidence from a Field Experiment in Energy Conservation. *Environmental and Resource Economics*, *67*(3), 413–428. https://doi.org/10.1007/s10640-016-0094-3

Petersen, J. E., Shunturov, V., Janda, K., Platt, G., & Weinberger, K. (2007). Dormitory residents reduce electricity consumption when exposed to real-time visual feedback and incentives. *International Journal of Sustainability in Higher Education*, *8*(1), 16–33. https://doi.org/10.1108/14676370710717562

Pharoah, C. (2017). *Top 100 Fundraising Charities Spotlight*.

Reisch, L. A., & Sunstein, C. R. (2016). Do Europeans Like Nudges? *Ssrn*, *11*(4), 310–325. https://doi.org/10.2139/ssrn.2739118

Rogge, K. S., Kern, F., & Howlett, M. (2017). Conceptual and empirical advances in analysing policy mixes for energy transitions. *Energy Research and Social Science*, *33*, 1–10. https://doi.org/10.1016/j.erss.2017.09.025

Rogge, K. S., & Reichardt, K. (2016). Policy mixes for sustainability transitions: An extended concept and framework for analysis. *Research Policy*, *45*(8), 1620–1635. https://doi.org/10.1016/j.respol.2016.04.004

Rosenow, J., Fawcett, T., Eyre, N., & Oikonomou, V. (2016). Energy efficiency and the policy mix. *Building Research and Information*, *44*(5–6), 562–574. https://doi.org/10.1080/09613218.2016.1138803

Rosenow, J., Kern, F., & Rogge, K. (2017). The need for comprehensive and well targeted instrument mixes to stimulate energy transitions: The case of energy efficiency policy. *Energy Research and Social Science*, *33*, 95–104. https://doi.org/10.1016/j.erss.2017.09.013

Schubert, C. (2017). Green nudges: Do they work? Are they ethical? *Ecological Economics*. https://doi.org/10.1021/acsinfecdis.7b00072

Shr, Y. H. (Jimmy), Ready, R., Orland, B., & Echols, S. (2019). How Do Visual Representations Influence Survey Responses? Evidence from a Choice Experiment on Landscape Attributes of Green Infrastructure. *Ecological Economics*, *156*(February 2018), 375–386. https://doi.org/10.1016/j.ecolecon.2018.10.015

Sorrell, S., & Sijm, J. (2012). Carbon Trading in the Policy Mix. *Oxford Review of Economic Policy*, *19*(3), 420–437. https://doi.org/10.1093/oxrep/19.3.420

Stern, P. C., Aronson, E., Darley, J. M., Hill, D. H., Hirst, E., Kempton, W., & Wilbanks, T. J. (1986). The effectiveness of incentives for residential energy conservation. *Evaluation Review*, *10*(2), 147–176.

https://doi.org/https://doi.org/10.1177/0193841X8601000201

Thaler, R. H. (1981). Some Empirical Evidence About Time Inconsistency. *Economics Letters*, *8*(3), 201–207. https://doi.org/10.1016/0165-1765(81)90067-7

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness.* (Yale University Press, Ed.). New Haven: Yale University Press.

Vaage, K. (2000). Heating technology and energy use: A discrete/continuous choice approach to Norwegian household energy demand. *Energy Economics*, *22*(6), 649–666. https://doi.org/10.1016/S0140-9883(00)00053-0

Wilson, C., & Dowlatabadi, H. (2007). Models of Decision Making and Residential Energy Use. *Annual Review of Environment and Resources*, *32*(1), 169–203. https://doi.org/10.1146/annurev.energy.32.053006.141137

List of figures

Figure 1. Simulated washing machine control panel (on the left) and manual instructions (on the right)

Figure 2. Distribution of energy saving goals per goal's nature

Note: dashed lines represent average goal level per goal's nature. Result of two samples Kolmogorov-Smirnov test confirms that the two samples belong to the same distribution (p= .968).

Figure 3. Percentage of goal achieved per round and per experimental condition

Note: dashed line represents mean goal achievement per experimental condition.

List of tables

Table 1. Available combinations of washing parameters and related energy saving

	Opt 1	**Opt 2**	**Opt 3**	**Opt 4**	**Opt 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

Table 2. Summary of the elements included in energy decisions, and their translation into real and our simulated settings

Feature	**Actual**	**Simulated**
Private economic return	Monetary saving in the energy bill	Variable bonus payment proportional to energy saving
Positive externality	Reduced CO2 emissions and reduced environmental damage	Donation to an environmental association increasing in participants' saving
Disutility	Opportunity cost of time and discomfort	Reading and implementing washing machine instructions; greater effort required for higher energy saving combinations

Table 3. Summary of features per treatment

	Nudge	**Market-based**	**Policy mix**	**Control**
Personal benefit	Yes	Yes	Yes	Yes
Environmental benefit	Yes	Yes	Yes	Yes
Goal	Endogenous	Exogenous	Endogenous	No goal
Feedback	Yes	No	Yes	No
Additional financial incentive	No	Yes	Yes	No

Table 4. Participants' socio-demographic characteristics per experimental condition

	Nudge	Market-based	Policy mix	Control	P-value[1]
N	132	142	147	145	

Male (%)	0.583	0.437	0.639	0.503	0.003
Age (years)	30.5	30.8	28.4	31.7	0.066
	(11.3)	(10.6)	(8.84)	(11.1)	
Graduate (%)	0.409	0.535	0.456	0.531	0.102
Env	4.980	4.920	4.960	4.910	0.575
	(0.828)	(0.790)	(0.750)	(0.775)	
Cogn	3.560	3.820	3.840	3.840	0.269
	(1.450)	(1.350)	(1.320)	(1.400)	

Note: Standard errors reported in parentheses. [1]Value from Kruskal-Wallis-test, a non-parametric test to investigate whether independent samples originate from the same population.

Table 5. Treatment effect on goal achievement

	Goal achievement (1)		Goal achievement (2)	
	β	SE	β	SE
Nudge	-0.205	(0.351)	0.317	(0.408)
Mix	-0.104	(0.342)	0.292	(0.397)
Env	0.242	(0.179)	0.243	(0.180)
Cogn	0.386***	(0.107)	0.388***	(0.107)
Round	0.022	(0.015)	0.080***	(0.027)
Round x Nudge			-0.095**	(0.038)
Round x Mix			-0.072**	(0.036)
Constant	-1.125	(1.158)	-1.453	(1.169)
Demographic controls	Yes		Yes	
Observations	4,210		4,210	
N Subject ID	421		421	
Akaike Inf. Crit.	4,104.283		4,100.928	

Note: Generalized Linear Mixed Model, random intercept at individual level. Baseline: *Market-based intervention.* Standard errors reported in parentheses. ***: p< .01, **: p< .05, *: p< .1.

Table 6. Treatment effect on energy saving

	Energy saving (1)		Energy saving (2)	
	β	SE	β	SE
Nudge	0.017	(0.011)	0.042^{***}	(0.012)
Market-based	0.015	(0.011)	0.018	(0.012)
Mix	0.014	(0.011)	0.040^{***}	(0.012)
Env	0.017^{***}	(0.005)	0.017^{***}	(0.005)
Cogn	0.026^{***}	(0.003)	0.026^{***}	(0.003)
Round	0.002^{***}	(0.0004)	0.005^{***}	(0.001)
Round x Nudge			-0.005^{***}	(0.001)
Round x Market-based			-0.0005	(0.001)
Round x Mix			-0.005^{***}	(0.001)
Constant	-0.002	(0.031)	-0.016	(0.031)
Demographic controls	Yes		Yes	
Observations	5,660		5,660	
N Subject ID	566		566	
Akaike Inf. Crit.	-11,097.230		-11,091.590	

Note: Linear Mixed Model, random intercept at individual level. Baseline: *Control*. Standard errors reported in parentheses. ***: p< .01, **: p< .05, *: p< .1.

Table 7. Motivation crowding-out on goal achievement and energy saving

	Goal achievement		Energy saving	
	β	SE	β	SE
Nudge	1.804	(2.171)	0.020	(0.067)
Mix	0.530	(2.199)	0.077	(0.069)
Market-based			0.048	(0.067)
Env	0.424	(0.310)	0.022^{**}	(0.010)

Cogn	0.392***	(0.107)	0.026***	(0.003)
Round	0.022	(0.015)	0.002***	(0.0004)
Env x Nudge	-0.405	(0.432)	-0.001	(0.013)
Env x Mix	-0.129	(0.439)	-0.013	(0.014)
Env x Market-based			-0.007	(0.013)
Constant	-2.075	(1.727)	-0.025	(0.051)
Demographic controls	Yes		Yes	
Observations	4,210		5,660	
N Subject ID	421		566	

Note: Generalized (left) and Linear (right) Mixed Model, random intercept at individual level. Standard errors reported in parentheses. ***: p< .01, **: p< .05, *: p< .1.

Table 8. Goal level per participants' characteristics

	Goal level	
	β	SE
Env	0.012**	(0.006)
Cogn	0.012***	(0.003)
Constant	0.062*	(0.035)
Demographic controls	Yes	
Observations	279	
R2	0.061	
Adjusted R2	0.044	
F statistic (df = 5; 273)	3.547***	

Note: Linear regression. Standard errors reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9. Dynamic treatment effects on goal achievement and on energy saving

	Goal achievement		Energy saving	
Nudge	0.262	(0.370)	0.034***	(0.011)
Market-based	0.166	(0.360)	0.028***	(0.011)
Trad			0.014	(0.011)
Env	0.244	(0.180)	0.017***	(0.005)
Cogn	0.390***	(0.107)	0.026***	(0.003)
Second half	0.595***	(0.158)	0.027***	(0.004)
Second x Nudge	-0.941***	(0.217)	-0.035***	(0.006)
Second x Mix	-0.547***	(0.210)	-0.029***	(0.006)
Second x Market-based			0.003	(0.006)
Constant	-1.316	(1.167)	-0.003	(0.031)
Demographic controls	Yes		Yes	
Observations	4,210		5,660	
N Subject ID	421		566	

Note: Generalized (left) and Linear (right) Mixed Model, random intercept at individual level. Standard errors reported in parentheses. ***: p< .01, **: p< .05, *: p< .1.