Can social information programs be more effective? The role of environmental identity for energy conservation★

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Abstract

Social information programs are widely used to nudge behavioural change. Their effectiveness strongly depends on household and individual traits. The existing evidence in economics and psychology points to the role of environmental values and identity in determining pro-environmental behavior and the impact of social information. In a large field experiment on household energy conservation, we combine electricity metering and survey data to test whether the impact of a social information program can be strengthened by leveraging environmental values and identity. We experimentally augment social information messages with an environmental self-identity prime. The self-identity prime does not strengthen the effectiveness of a social information program on average. Nonetheless, we find suggestive evidence that priming environmental self-identity can be effective if targeted to specific sub-groups.

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1. Introduction

Social information programs are widely used by policymakers to nudge behavioural change. Their popularity is attributable, at least in part, to existing evidence on their ability to influence behaviour in a variety of settings, from energy and water consumption (Allcott et al., 2011; Allcott and Rogers, 2014; Ayres et al., 2013; Brent et al., 2015; Ferraro and Price, 2013; Ferraro et al., 2011; Ferraro and Miranda, 2013; Jaime Torres and Carlsson, 2018), contributions to charitable causes (Frey and Meier, 2004; Shang and Croson, 2009), voting (Gerber and Rogers, 2009) and financial decisions (Beshears et al., 2015). While this literature has been ubiquitous in showing that social comparisons work, there is still uncertainty about why this is the case, and on sources of heterogeneity in their impact. One prominent explanation is that messages conveying information on others' conduct draw individuals' attention to a target behaviour and increase the moral cost of deviating from it (Schultz et al., 2007; Allcott, 2011).

A large literature in psychology discusses the influence of individual values on the impact of interventions fostering socially desirable conduct (Schwartz, 1992; Ghesla et al., 2019; Steg et al., 2015). According to this perspective, policy measures are contextual factors, which make certain values more salient (Steg, 2016). Salient values, in turn, are given larger weight in decision-making. In particular, evidence shows that values affect behavior by activating specific dimensions of an individual's self-identity, and argue that the desire to be consistent with one's salient identity is a strong motivator of value-compliant behavior (van der Werff et al., 2013b, 2014b).[1]

[1]This echoes an established tradition in economics, which sees identity as an important driver of behaviour (Akerlof and Kranton, 2000). Throughout the paper, we adhere to prominent definitions of values

In this paper we examine how identity affects the impact of social information interventions on a larger scale than the one typical of studies in psychology; on a behavioral outcome requiring prolonged effort; and through an experimental approach. First, we conduct exploratory analysis to test two hypotheses of identity theory. We investigate whether the impact of social information is higher, the stronger the personal values attached to the target behaviour by the individual. We also examine whether such effect occurs by making the corresponding dimension of self-identity salient, and whether it weakens over time, consistent with a salience-inducing mechanism. Second, drawing from the findings of this exploratory analysis and pre-existing evidence, we test whether directly manipulating the salience of individuals' value-congruent self-identity can strengthen the influence of a social information program on the desired behaviour, and explore sources of heterogeneity in this effect.

Like other studies in the social information literature, we address these questions in the context of household energy conservation.[2] The social information program that we study is a large scale randomized intervention, providing customers of a European utility with information on how their energy use compares to that of their neighbors (Allcott, 2011; Allcott and Rogers, 2014). Such information is included in a Home Energy Report,

and identity from psychology. Values are antecedents of preferences, intentions, and behaviour and represent guiding principles in everyone's life (Schwartz, 1992). Self-identity is instead defined as the extent to which one sees oneself as a type of person who acts according to certain principles (van der Werff et al., 2013b, 2014b).

[2] We focus on this setting for several reasons. First, energy conservation is important: it is a cornerstone of energy legislation around the world, and it can provide both private benefits in terms of reduced expenditures, as well as public benefits in terms of improved environmental quality and energy security. Second, energy conservation is a prime setting for social information research: a number of studies document the effectiveness of peer comparison programs in curbing energy use (see Gillingham et al. 2018 and Delmas et al. 2013a for comprehensive reviews). Third, it offers good data on actual, rather than self-reported, behavioural outcomes, namely monthly energy metered data.

distributed to customers via email (eHER). We experimentally manipulate self-identity by augmenting the standard eHER with an environmental self-identity prime. The prime, which was pre-tested online, draws from the literature on environmental self-identity by making past pro-environmental actions salient. To explore potential sources of heterogeneous impacts of these messages, we combine administrative data on consumption with survey data on a sub-sample of 4835 customers. This is similar to Byrne et al. (2018), which investigates the heterogeneous response to an energy conservation program from survey data on a sub-sample of almost 1200 program recipients and control households.

Our results paint a more nuanced role for values and identity than the one offered by pre-existing evidence. First, our exploratory analysis of sources of heterogeneity in the impact of the eHER reveals that environmental values are not conducive to energy reduction in response to an energy conservation nudge by themselves. We find, however, suggestive evidence that high environmental values increase the energy savings among program recipients with high baseline energy use. Second, we confirm that the eHER affects environmental self-identity by increasing its salience, as this effect is short-lived. Third, leveraging environmental values by making environmental self-identity more salient within the eHER does not increase the effectiveness of social information on average.[3] When we explore potential sources of heterogeneity in the impact of the self-identity prime, we find weak evidence that targeting a specific group of utility customers– users with high baseline energy consumption who behaved pro-environmentally in the past – can lead to energy savings.

Our study makes four main contributions to the literature. First, we contribute to the

[3]This analysis was pre-specified.

psychological literature on values and identity (Schwartz, 1992; Dunlap and Grieneeks, 1983; Groot and Steg, 2008; Steg et al., 2014b), by showing how to leverage values through the content of communication in a novel field setting, and discussing the limitations of this strategy. While extensive, the existing literature mainly relies on correlational evidence or on mediation analysis to establish causality (Nordlund and Garvill, 2016; Steg et al., 2005, 2012; Stern et al., 1995; Thøgersen and Ölander, 2002; van der Werff et al., 2013a). The few existing experimental studies adopting the same self-identity prime that we use mainly examine outcomes measured through self-reports (Cornelissen et al., 2008; van der Werff et al., 2014b,a), or that require little or no effort or cost (Cornelissen et al., 2008). Our online pre-test falls within this class of studies, and yields similarly strong results on the ability of self-identity primes to foster pro-environmental behaviour. In contrast, our field experiment reveals that the effect of priming is null overall, and weakly statistically significant only within specific groups of users when the outcome requires sustained behavioural change.

Second, the nature of our identity prime also allows us to speak to the open question on whether past moral deeds prompt behavioural consistency – thus generating positive spillovers (Susewind and Hoelzl, 2014; van der Werff et al., 2014a; Truelove et al., 2014)– or rather provide moral credits that can lead to compensatory actions -i.e. negative spillovers (Sachdeva et al., 2009; Truelove et al., 2014; Jordan et al., 2011; Tiefenbeck et al., 2013; Mazar and Zhong, 2010). To the best of our knowledge, our study provides the first evidence, albeit weak, of positive spillover effects from priming past behaviour on real world costly actions, among those individuals who acted pro-environmentally in the past.

Third, our results on how the eHER's impact on identity varies over time are consistent with evidence from Allcott and Rogers (2014) using daily energy use data, thus identifying a potential mechanism behind the temporal pattern of social information programmes' effect.

Fourth, our study is one of the first to investigate the impact of a social information program in a European country, namely Italy. The existing literature is almost exclusively based on US samples.[4] We only weakly echo in our setting the seminal results from Costa and Kahn (2013), which analyze heterogeneity with respect to political preference and revealed preference measures of environmental ideology.[5] We also confirm the presence of boomerang effects: social information results in higher energy use among customers with low baseline consumption (Byrne et al., 2018; Bhanot, 2017), in spite of the other program features aimed at preventing such boomerang effects (Schultz et al., 2007).

These findings have implications for the design and targeting of social information programs. In particular, we discuss the need for caution when deriving policy implications from controlled laboratory studies, however well designed. As for targeting, we propose ways to exploit identity priming through targeting to specific sub-groups. The increasing customization and digitalization of communication from energy utilities, together with the low marginal cost of these forms of communication, make targeting even small and specific, but responsive, groups of customers potentially cost-effective and policy relevant.

The remainder of the paper is organized as follows. Section 2 provides details of the design and data of the randomized controlled trial. Section 3 presents the empirical

[4]To the best of our knowledge, the only notable exception is Andor et al. (2020) in the German context.

[5]A similar revealed preference approach to elicit environmentalism is found in Kahn (2007), while others use survey-based approaches (Clark et al., 2003; Kotchen and Moore, 2007).

strategy and results in detail. Section 4 discusses the implications of our findings.

2. Design and data

2.1. Social information program

We evaluate one of the first social information programs implemented in the Italian energy retail market. The program is an example of Italian energy utilities' efforts to diversify their offers, complement energy provision with other services and digitalize their customers, in preparation of the market liberalization planned for 2022 and of the introduction of second generation smart meters, with the ability to provide real-time feedback on energy use directly to customers.

The program, launched in July 2016, targets roughly 500'000 existing customers from the pool of the utility's power or dual fuel customers at that time. To be eligible for the program, households must have a valid name and email address as of June 2016, live in single-family homes, have at least one year of valid pre-experiment energy consumption data, and satisfy some additional technical conditions.[6] Moreover, each eligible customer needs to have a sufficient number of neighbors, defined as fellow utility customers living in similar homes within a 10 km distance, to construct the neighbor comparison. A total of 459,653 eligible customers were initially included in the experimental sample, of which 413,653 and 45,860 were randomly assigned to the treatment and control groups, respectively.[7] The actual start date of the program differs for different customers. Namely,

[6] In particular, eligible customers need to have no negative electricity meter reads, at least one meter read in the previous three months, no significant gaps nor extreme peaks in usage history, and exactly one account per customer per location.

[7] Randomization was implemented by the utility through an algorithm (minmax t-statistic), which con-

customers can be divided among those who received their first communication in July 2016 (43%), October 2016 (34%) and December 2016 (23%).

The main goal of the program is to increase customers' loyalty, digitalization and engagement, whereas energy efficiency goals are secondary.[8] The intervention is similar to the ones by Opower, already described and evaluated by several papers (Allcott et al., 2011; Allcott and Rogers, 2014; Costa and Kahn, 2013).[9] It consists primarily of the eHER, which customers in the treatment group receive by email every two months.[10] The eHER features a static neighbour comparison, whereby one's own previous month consumption is compared with that of 100 similar homes nearby and of the 20 most efficient ones. In addition, the eHER contains normative feedback based on the recipient's efficiency: customers receive three, two or one thumbs-up, depending on how their consumption compares to that of the average neighbour or of efficient neighbors.[11]

By clicking on the email, customers are directed to their personal page on the utility's website, where they can consult their past bills and energy saving tips, and see a dynamic neighbour comparison in addition to the static one, among other features. The web portal

ducts 1000 randomizations and selects the most balanced draw, along baseline consumption and geographic location (Bruhn and McKenzie, 2009). The utility made the decision to keep the control group small, relatively to the treatment group, for business-related considerations.

[8]The fact that our partner utility serves customers spread all over the national territory; that its mission does not include environmental targets; and that the social information program analyzed in this paper is a digital engagement rather than a energy conservation one, are likely to reduce concerns of site selection bias as presented in Allcott (2015).

[9]Relative to similar programs conducted in the US and aimed at increasing energy efficiency, the one we analyze does not employ paper HER and does not include energy saving tips in the eHER. These design features are consistent with the program's purpose to direct program recipients to the online portal, but may reduce its effectiveness to curb energy use. However, recent evidence (Henry et al., 2019) has shown that eHER can deliver 2.9% energy savings, consistent with mail communication.

[10]Half of treated customers receive the eHER in even months, and the other half in odd months.

[11]The design of the normative feedback is different from the one more traditionally used, which includes emoticons with different expressions, possibly including negative ones.

is available to all customers, regardless of being in the treatment or control group, as long as they are registered to the website. As such, the experimental design relies on an encouragement design.

The administrative data on the program consist in historical electricity consumption data from July 2015 to March 2018. We compute average daily consumption in a month from the total monthly energy use. We exclude from the analysis customers with missing consumption over the entire period. For customers assigned to the program, we also know when they received each eHER and whether they were assigned to receive the treatment or control message in the self-identity marketing module test, conducted in November 2017 and described in the following sub-section.

2.2. The self-identity prime

In order to leverage the influence of environmental values on energy conservation, we augment the eHER with a message priming environmental self-identity. This design choice is inspired by theory and evidence in psychology on the correlation between environmental values, identity and pro-environmental behavior (van der Werff et al., 2013b). This correlation is also suggested, despite weakly, by our exploratory analysis on the impact of the eHER, as discussed below.

The eHER contains a section, normally at the bottom of the report, dedicated to season-specific messages or messages aimed at drawing customers' attention to specific features of the program suite, such as the energy-saving tips. In November and December 2017, we augmented the eHER by including a treatment or control message in this section. In particular, customers were randomized to receive one of the following messages:[12]

- Self-identity prime: *"How do you save energy at home? Do you switch off the light when you leave a room? Do you use efficient light-bulbs? Do you wash your clothes at low temperatures? You are helping the environment. Find other ways to save".*

- Control: *"How can you save energy in your house? When it comes to saving energy, every small action matters. Find ways to save".*

Figure 1 shows examples of the self-identity prime and control eHER.

The self-identity prime reminds individuals of past environmental actions. Following van der Werff et al. (2014b,a), it lists a set of easy actions, so that many customers would answer affirmatively to the questions in the message. This is motivated by theories of individual identity being history-dependent on one's own behaviour (Bénabou and Tirole, 2011), which are echoed by theory and evidence from psychology focusing on the environmental domain: the more often individuals acted pro-environmentally in the past, the more likely they are to perceive themselves as environmental-friendly persons. Therefore, making people's past pro-environmental actions salient can strengthen their environmental self-identity and, it is argued, make them more likely to act pro-environmentally in the future. However, two alternative arguments suggest a different impact of this form of priming. First, it can generate a moral credit (Sachdeva et al., 2009), which can lead to compensatory reasoning and actions. Second, emphasizing the environmental dimension of energy efficiency can backfire because of the possible political polarization surrounding environmental issues (Gromet et al., 2013).

[12]The randomization of customers to treatment and control messages was performed by the partner utility, following the same randomization routine described above.

To assess the impact of the prime based on past environmental actions, compare it to that of other primes inspired by the literature, and select the most effective message to be implemented in the field, we ran an online experiment with almost 1,000 participants. The pre-test included 4 treatments leveraging different mechanisms, which could motivate pro-environmental behaviour by making environmental identity salient. The experimental outcomes were an incentivized pro-environmental decision, namely a donation to an environmental charity, and stated intention to save energy, consistent with the goal of making the pre-test informative for the field study. Besides, we included a manipulation check in the experiment to verify that the prime actually activated environmental self-identity. All the details about the online experiment and its results are presented in Appendix A. We selected the prime that was the most effective in both boosting environmental self-identity and intention to save energy and encouraging subsequent costly pro-environmental behaviour.

2.3. Survey

We collected data from a sub-sample of program participants through an online survey conducted between April and June 2017.[13] The survey includes questions both on environmental values, which we assume to be stable and unaffected by the program, to inform the analysis on their impact on program effects; and on environmental identity, to test whether the program can influence it. The assumption of no treatment effects on values is consistent with a vast literature that reports that environmental values are stable in everyone's

[13]This means that we did not conduct the survey at baseline. Since we could only conduct one survey wave, we opted to do it after the program's start to collect information on behavioural outcomes beside energy use and inform the additional intervention we would include in the eHER.

life (van der Werff et al., 2013b). Moreover, we test it through balance tests between the control and the treatment group.

We measure environmental values by asking how important the protection of the environment and the preservation of nature are for the respondent (Steg et al., 2014a). The higher the score, the more important the value. We classify a customer as having high environmental values if her score is above the median one. We evaluate environmental self-identity through a question asking if acting pro-environmentally is an important part of oneself. Answers are expressed on a scale from 1 (disagree) to 7 (agree) (van der Werff et al., 2013b). Score values are then standardized for the analysis.

Beside these questions on energy use and the environment, the survey collects socio-economic information, such as gender, age and education of the respondent; ownership status of the house where the respondent lives and for which energy consumption is collected; and how long he or she has been living there.

To build the survey sample, we drew contacts from a list of 155,691 program participants who had given the utility informed consent to be contacted by third parties. We sent them an invitation to participate and a link to the online survey. Of those who accepted to take the survey, we screened out individuals not involved in household consumption and investment decisions. Survey completion was incentivized with a shopping voucher. With a response rate of about 3%, the final sample amounts to 4,385 customers, 3,595 from the treatment, and 790 from the social information program's control group.[14] 3,090 treated subjects were still with the utility as of November 2017, and thus participated in our test

[14] We kept the proportion between treatment and control households in the survey equal to that of the RCT sample.

on the role of environmental self-identity. Of them, 1,551 were allocated to the environmental identity treatment, and 1,539 to the control message. Figure 2 shows the sample flow diagram.

Three important potential issues are originating from the combination of survey and program data. These are attrition, sample selection bias and limited statistical power. Due to attrition, we lose 13.8% of the sample (571 respondents, 505 treated and 66 control) between July 2016 and March 2018. Attrition may be problematic for identification if it is correlated with the treatment status. However, as pointed out in Appendix B, attrition does not appear to be differential between treatment and control customers and does not have a systematic time trend. Moreover, we perform robustness checks in the analysis to control for attrition.

As for sample selection bias, we tried to ensure that the survey sample was representative of the larger population of program recipients along several characteristics, from age and gender of the contract holder, to area of residence and yearly baseline energy consumption. The effort to make the survey as representative as possible guarantees that the program's heterogeneous effects and information collected through the survey can be generalized to the full sample of program customers.

Finally, statistical power is a critical parameter in experimental research. Low power may cause incorrect inference as it increases the risk of false negatives and false positives, where non-existent effects are detected. A study may be underpowered both because the sample size is small. Because the underlying effect sizes are relatively small (Ioannidis, 2005). The present study is likely to suffer from both sources of low power. First, the sample of customers used in the analysis is only a subset of the full sample of program recipients, and the small relative size of the control group places further limitations on power. Second, low electricity usage may contribute to a limited effect of social comparison in the European context, compared to the US context. Therefore, when discussing our findings we report the ex-post Minimum Detectable Effect (MDE), i.e. that is, the effect that would have been detectable with 80% power at the 5% significance level ex post.[15] This allows us to assess whether issues related to low statistical power affect our results. We follow Haushofer and Shapiro (2016) and report MDE only for non significant parameters. This intuitive metrics allows us to distinguish between cases where treatment effects cannot be ruled out with confidence, from precisely estimated null results. This approach also facilitates comparisons with similar studies.

3. Results

This section discusses the results from the field experiment. After presenting summary statistics and balance tests, we examine the influence of environmental values on the impact of the eHER; the effect of the eHER on environmental self-identity; and the impact of the eHER augmented with the self-identity prime.

It is important at this stage to clearly distinguish between pre-specified and exploratory analysis. The Pre-Analysis Plan (PAP) for this study pre-specifies only the impact evaluation of our original treatment, i.e., the environmental self-identity prime, and its heterogeneous effects by baseline consumption and values.[16] The PAP also discusses the first set

[15] We thank an anonymous reviewer for this suggestion. Ex-post MDE are computed as SE(β)*2.8.

[16] The PAP is registered in the AEA RCT Registry, under trial number AEARCTR-0002699. It specified a large set of potential sources of heterogeneity that could affect the impact of the environmental prime on consumption. Given the decision to focus on this paper's values and identities, we do not report the results for the different sub-groups specified. The implementation of the extensive analyses contained in the Pre-Analysis

of exploratory analysis presented here, focusing on the heterogeneity in the impact of the standard eHER by environmental values: the suggestive evidence on this relationship represented a motivating factor for our experimental test of self-identity priming. The second piece of not pre-specified analysis, presented here, focuses on the heterogeneous effects of the prime depending on past environmental behavior.

3.1. Data and descriptive statistics

The dataset for our empirical analysis results from the combination of the survey and the administrative data we received from the utility, described in the previous section. When testing balance, we consider both the sample of customers who participated in the survey in May 2017, and the subset of those who were still customers of our partner utility at the time of the self-identity prime test in November. Moreover, we test whether the self-identity prime treatment is balanced across program participants. Finally, given that the empirical analysis explores heterogeneous treatment effects, we check for balance within the sub-groups identified by the heterogeneity analysis.

Table 1 presents balance tests for the entire sample of survey respondents, along with summary statistics of variables used in the empirical analysis as controls (Panel A) and outcomes (Panel B). We test the difference of means between treatment and control groups, and provide evidence that most variables are balanced, except for area of residence. Treated households are significantly less likely to live in the North and more likely to live in the South and Islands than control households.[17] Table 1, Columns 4 to 6, shows that a similar

Plan is available at: https://drive.google.com/file/d/1qYQJszDWicyYcbIgJXmlaUINPlhK-_jD/view?usp=sharing.

[17]Unbalanced covariates between treatment and control households are mainly due to the small size of the survey sample, and particularly of the control sub-sample. In order to achieve the targeted survey sample

pattern holds if we consider the November 2017 sub-sample. In Table 2 we test for balance of the self-identity prime treatment. The two sub-groups appear balanced along most dimensions, except for primary education, South and Islands location and house ownership. Finally, Tables C.1 and C.2 in the Appendix report the difference of means between treatment and control in the different sub-groups examined as part of our analysis of heterogeneous treatment effects, and its significance. The tables reveal that balance holds also for the sub-samples.[18] Any concern on the influence of imbalances between treated and control users on the results should be alleviated by the use of individual fixed-effects in the empirical analysis.

Overall, baseline energy consumption, computed as the average pre-treatment daily consumption for each month in the year preceding the launch of the program (July 2015-June 2016) is about 6.5 kWh.[19] We classify about 34% of customers as having high environmental values. Crucially, values do not significantly differ by treatment status, confirming the assumption on their stability that underlies our identification strategy. Our respondents are predominantly male, over 50, home owners, a high school or university degree, and Northern Italy.

size, we were faced with the option to either maintain balance on observable characteristics, but increase the data collection efforts targeted to the control group; or slightly relax the balance requirements on observables. We chose the latter option. This choice aimed not to introduce unbalances between treated and controls along unobservable characteristics, such as those associated with response to monetary incentives or repeated invitations to participate in the survey.

[18]Out of 104 tests performed in each table, less than 10% reveal some imbalances which do not appear systematic across covariates and sub-groups.

[19]As reference, consider that the sample of American households in Allcott and Rogers (2014) consumes on average 30.3 KWh per day. The lower level of consumption in Italy can be explained, among other things, by the fact that electricity is rarely used for heating.

3.2. Program impact on energy use and the role of environmental values

Our investigation of the role of environmental values and identity in affecting the impact of social information starts with the analysis of the heterogeneous treatment effects of the standard eHER. Specifically, we estimate the intention to treat effect of the eHER on consumption and its heterogeneity. This analysis is conducted on the sample of 4,385 customers who completed the survey, for the time period ranging from July 2015 to March 2018, and relies on the following specification:

$$y_{it} = \beta_1 DD_{it} + h_t + g_i + \varepsilon_{it} \tag{1}$$

where y_{it} is the average daily consumption in the month t. DD_{it} is the treatment indicator and is equal to one for treated customers after they receive the first communication, and zero otherwise. This specification, which is similar to the one adopted in Bertrand et al. (2004), is driven by the staggered start date of the intervention. As mentioned above, different customers received their first communication at different points in time. The regression also includes month-by-year fixed effects, h_t, and household fixed effects g_i. Standard errors are clustered at the level of household, to allow for the presence of within household correlation over time in the error term (Bertrand et al., 2004).

As in Allcott (2011) and Allcott and Rogers (2014), we keep in the sample the households who opted out of the program, even if they do not receive reports anymore, in order to prevent self-selection issues from affecting the results. Thus, we interpret the treatment as "receiving reports or opting out", and are likely to underestimate the effect of the program on the group of customers initially assigned to receive the eHER.[20]

Table 3 reports the marginal effect of receiving the eHER compared to the control group (Column 1), obtained from estimating Equation (1), along with the ex-post MDE (Column 2). The program's average treatment effect is -0.06 KWh/day, corresponding to a 0.9% reduction in usage. The coefficient is not statistically significant. In a companion paper, we conduct an impact evaluation of the same program using the whole sample of customers and find average savings from the program of 0.6% (with respect to pre-treatment usage), significant at 5% confidence level (Bonan et al., 2020). This is similar to the impact of the other European program provided in Andor et al. (2020). These programs' limited impact is compatible with lower electricity usage and the consequent smaller scope for energy conservation in Europe, relative to the US. The MDE in Column (2) is 0.11 kWh/day. Given an average daily consumption of 6.5 kWh, this corresponds to 1.7% reduction in daily energy use, which is within the range of impact estimates of similar programs available at the time.[21] This means that, ex-ante, our sample size was adequate to detect effect sizes in the order of magnitude of those found by evaluations we had access to at the time. Full regression results are presented in Table C.3 in the Appendix.

The effect estimated through Equation (1) depends on the average response of different types of customers, and may mask important differences between them. Therefore, we assess the heterogeneous effects of the program by estimating the following equation:

[20]More details on the sub-sample who opted out from the program and its characteristics can be found in Appendix B.

[21]The effect range in Allcott (2011) is 1.4-3.3%, while in Allcott and Rogers (2014) is 0.5-3.3%.

$$y_{it} = \beta_1 DD_{it} + \sum_{a=1}^{A} \beta_a DD_{it} * X_i + h_t + g_i + \varepsilon_{it} \quad (2)$$

where X_i is a matrix of dummy variables that capture relevant sources of heterogeneity. The first that we examine is pre-treatment energy consumption. We include this dimension of heterogeneity, because the cost of conservation is likely to be higher for low-usage households, who have little room for further improvements. This evidence is confirmed in Byrne et al. (2018), List et al. (2017) and Allcott (2011) for electricity and Ferraro and Price (2013), Bhanot (2017) and Ferraro and Miranda (2013) for water consumption, where high intensity users are more responsive than low ones to the program. Therefore, the null average treatment effect could simply mask important differences in reactions between high and low-usage households.

To estimate Equation (2), we interact the *DD* variable with dummy variables equal to one for the different quartiles of consumption in the year preceding the launch of the program (July 2015-June 2016). Table 3 reports the marginal treatments effects of receiving the eHER for the different sub-groups of households, computed as linear combinations of the parameters displayed in Column 2 of Table C.3. Households in the bottom quartile of energy use increases consumption by 0.187 kWh as a reaction to the eHER, and this is a statistically significant response at 1% level. The effect is generally not statistically significant for households in the middle of the consumption distribution, while it turns negative and statistically significant at 1% level for high energy users. Households in the top quartile significantly reduce daily consumption by 0.458 kWh after receiving the treatment. The MDEs for the non-significant parameters are in line with the existing literature on social information program applying large administrative samples (Allcott, 2011). They suggest that the program has no differential effect on middle users. Similar results are obtained if we interact the DD variable with a continuous measure of baseline energy usage (Column 3 of Table C.3). As in Byrne et al. (2018) and Bhanot (2017), these findings provide some evidence of a boomerang effect, whereby the eHER induces low-usage households to significantly increase consumption (Schultz et al., 2007). The injunctive norm, which conveys social approval within the eHER through a thumbs-up image, cannot counterbalance the boomerang effect in this sample of customers.

The core of our heterogeneity analysis lies in the test of how the response to peer comparison depends on one's environmental values. Do individuals, who endorse high environmental values, respond more strongly to the treatment? On one hand, we argued that the information delivered through the eHER is effective when it resonates with people's central values (Steg et al., 2015). Thus, social information should be more effective among those who care about the environment, if it makes them more inclined to act on their values and if it increases the moral cost of deviating from a target behaviour, such as energy conservation. On the other hand, curbing energy consumption is harder if one already made large efforts to do so, which may be the case for individuals holding high environmental values. The sign of the effect of values is thus an empirical question.

To compute the heterogeneous treatment effect with respect to environmental values, we estimate Equation (2) by interacting the *DD* variable with a dummy for above median environmental values, labelled "high environmental values".[22] We find that, compared to

[22] Recall that this analysis relies on the assumption that environmental values, which we measure through the survey we conduct after the start of the program, are not influenced by the treatment. As already mentioned, this assumption is confirmed both by the psychological literature and by balance tests reported in Table 1.

the control group, the treatment effect is not statistically significant neither for the subsample of consumers who endorse high environmental values nor for customers with low environmental values (Table 3). The respective ex-post MDEs are between 1.8 and 2.1% of the outcome mean and, once again, suggest that estimates are relatively precise. No significant differential effect between these two group arises, as confirmed by interaction coefficient in Column 4 of Table C.3. On average, the opposing influence of the two mechanisms described above can justify the absence of an effect.

It is also possible that both the willingness and the possibility of reducing energy use are necessary for treatment effects to occur. We therefore test whether households with high environmental values and high baseline consumption are the most reactive to the information contained in the eHER. Namely, we interact the variable *DD* with average pre-treatment energy consumption and high environmental values. We employ both a continuous measure and dummies for quartiles of baseline energy use. Column 5 of Table C.3 report the regression results using a continuous measure of energy consumption. The point estimate of the triple interaction is -0.035 and is significant at 10% level.

To ease interpretation, Figure 3 plots how the treatment effect varies for different values of pre-treatment consumption and for high (red line) versus low (black line) environmental values, along with 95% confidence intervals. The figure indicates that treatment effects are positive for low levels of baseline consumption and turn negative as consumption increases, for both high and low environmental values. The turning point is in correspondence to daily pre-treatment consumption of 6 kWh. After this point, the response to peer comparison is much steeper for people with high environmental values than for people with low environmental values. Only the marginal effects for the bottom and top quartiles of the pre-treatment consumption distribution are significantly different from zero.

Similarly, Table 3 reports that a person who belongs to the top quartile of the distribution, reduces energy consumption by 0.38 and 0.62 kWh if she endorses low and high environmental values, respectively. The corresponding regression results are in Column 6 of Table C.3. These results suggest that, when baseline consumption is low, it is hard to further reduce it, no matter if the person receiving the eHER holds high or low environmental values. On the contrary, when baseline consumption is high and the scope for reductions, high environmental values boost the effectiveness of peer comparison.[23]

The exploratory heterogeneity analysis offers suggestive evidence that the treatment is effective on a specific sub-group of users. To assess this result's policy relevance, we must ask how empirically and conceptually relevant this group is. Columns 4 and 5 of Table 3 indicate the number of households falling in the different sub-groups. The number of consumers in the top quartile of the consumption distribution who endorse high environmental values amounts to 343 consumers, corresponding to roughly 8% of the sample.[24] This is not a trivial sub-group, but it is arguably small enough that the cost-effectiveness of targeting it is likely to depend on the marginal cost of communication.

One can also question whether the coexistence of high consumption and high environmental values is an idiosyncratic feature of our sample, unlikely to occur in other settings. We think that this is not the case, for a number of reasons. First, we measure environmental values at the individual level, while consumption is determined at the household

[23]The F-test on the joint significance of the coefficients of the interactions of DD with environmental values and consumption from Column 5 and 6 of Table C.3 are 2.15, p-value=0.12, and 2.87, p-value=0.022, respectively.

[24]The share of high usage - high values customers in the treatment and control is similar.

level: recent studies show how externalities at the household level severely limit individual household members' conservation efforts, leading to inefficiencies and to the limited impact of conservation messages (Jack et al., 2018). Second, empirical evidence shows that misperceptions of own energy usage are widespread (Allcott, 2016; Gillingham et al., 2009; Gillingham and Palmer, 2014). Specifically, in a survey with a sample of utility customers, only 25% were found to hold correct beliefs on their own level of energy consumption. More than 38% of respondents under-estimated it (Byrne et al., 2018). Importantly, it is precisely on these subjects that a social information message, similar to the one we study, was most effective.[25]

We thus believe that it is possible that an individual with high environmental values underestimates her household's energy consumption, and is revealed actually to consume more than the average user. Thanks to their high environmental values, these individuals are particularly reactive to the information contained in the eHER. Their reaction is nearly double compared to consumers who do not endorse high environmental values, as indicated by Table 3.[26] The highly exploratory nature of this analysis, together with the marginal statistical significance of the results (significant at the 10% level) suggest

[25]We also look at the characteristics of customers with high usage – high values, in terms of observable covariates presented in Table 1. We find that customers in this group are significantly older and with house tenure greater than five years. No significant differences arise in terms of gender, education, house ownership and geographical location, compared to the remaining sample.

[26]We perform different robustness checks to the main specification of Table C.3. Results are reported in Table C.4. First, since within our data we can distinguish customers who never opened the eHER, we can perform the analysis after excluding them from the sample (Columns 1 and 2). While this opens our results to concerns about endogeneity of engagement with the eHER, we believe that showing the effect of the treatment on customers who actually engage with it is interesting. Second, we exclude possible outliers in the pre-treatment consumption variable, by replacing the values in the bottom 1% and top 99% with values just above/below (Columns 3 and 4). Finally, we repeat the exercise on the sample of customers who remain with the utility and for whom we have energy use data for the entire study period (Columns (5) and (6)). Results are robust to the different specifications.

interpreting these results with caution. In addition, the larger point to be made from our analysis is that environmental values, by themselves, are not conducive to energy reduction in response to an energy conservation nudge.

3.3. Program impact on environmental self-identity

Next, we test whether the social information message affects consumption by increasing the salience of energy conservation and the moral cost of energy use, thus making users' environmental self-identity more prominent upon receipt of the eHER. A salience-inducing mechanism should imply a time-varying effect of the eHER on self-identity, namely one that weakens over time. It varies with the source of environmental self-identity, i.e., values.

We start by estimating the following equation, to assess the average impact of the eHER on environmental self-identity:

$$y_i = \beta_0 + \beta_1 Program_i + \boldsymbol{\gamma X_i} + \varepsilon_i \tag{3}$$

where y is environmental self-identity, *Program* is a dummy variable equal to one for customers assigned to the treatment group and zero for those in the control group and X is a matrix of household time-invariant characteristics collected through the survey. Namely, we add controls for baseline consumption, gender and age of the respondent, dummy variables for education, ownership status of the house where the respondent lives, length of stay in the current residence, and geographical dummies for the area of residence. Finally, given that environmental values are an important driver of environmental self-identity, we include a dummy for high environmental values.

Results are presented in Table 4. The treatment variable's coefficient is positive but not statistically significant, indicating that, on average, the treatment does not influence environmental self-identity. This result emerges in specifications with and without socio-demographic controls (Columns 1 and 2, respectively). Environmental values are an important predictor of environmental self-identity. The strong positive correlation between values and self-identity indicates that self-identity has a stable core, as suggested in van der Werff et al. (2014b), and provides the foundation for the priming intervention analysed in the next sub-section. Pre-treatment consumption is instead negatively correlated with the reported importance of acting pro-environmentally, although not significantly so.

Next, we test whether the eHER increases self-identity more among recipients with high environmental values, consistent with self-identity theories and with our results on the heterogeneous impact of the eHER. The interaction term's coefficient between treatment and high environmental values is positive and statistically significant at 10% level (Column 3). While the eHER does not alter environmental self-identity among customers with low environmental values, it does increase it if they care about the environment. Specifically, in a person with high values, the program increases environmental self-identity by 0.12 standard deviation. This result seems to suggest that environmental self-identity can be prompted through the information delivered in eHER. It also indicates that environmental identity can represent a channel, through which the eHER leads to lower consumption among users with high environmental values.

In order to more specifically test that the effect we observe is consistent with a salience-inducing mechanism, we exploit the difference among survey respondents between the date of the survey and the date when they received the previous eHER. The effect of the treatment on identity should be stronger, the shorter the interval between the moment when a consumer received the eHER and the moment when we measured her environmental self-identity. We therefore discount the treatment dummy by the number of days between the receipt of the last report prior to the survey and the survey. In particular, we believe that the decay in salience should follow a non-linear pattern, steeper at the beginning, due to a decline of memory retention in time: drawing from the forgetting curve hypothesis (Murre and Dros, 2015), we thus apply an exponential decay function to the number of days and multiply the treatment dummy variable by this function.

We find that this discounted treatment's effect is positive and statistically significant at 1% level, as reported in Column 4 of Table 4.[27] Environmental identity is significantly higher among treated customers who recently received the eHER. These results are in line with the time-varying effects of the HER reported in Allcott and Rogers (2014). Using high frequency data, the authors find that consumers immediately react to the report by reducing energy use. Still, they backslide after a few weeks.[28]

Our findings are consistent with models of environmental self-identity as grounded in environmental values', but also as more easily affected by contextual factors than values, which are stable traits. These results thus justify the priming treatment that we evaluate next.

[27]The sample size is reduced to 3,965 observations due to missing values in the date of receipt of the last eHER before the survey. The loss of observations occurs only in the treated group and involves people with older age and lower house tenure. At the same time, no systematic difference arises in terms of education, gender, geographical location and house ownership between the treated sample in Columns 2 and 3 as compared to the one in Column 4.

[28]We conduct a series of robustness checks, whose results are presented in Table C.5 in Appendix C. We remove from the sample customers who never opened the eHER (Columns 1 and 2) or did not open it before the survey was completed (Columns 3 and 4); and address potential outliers in the pre-treatment consumption variable (Columns 5 and 6). Results are robust to these alterations.

3.4. The environmental identity prime

The analyses conducted so far were explorative and aimed at informing which dimension of heterogeneity could be exploited in the design of the prime. This evidence suggests stronger treatment effects among customers with high pre-program energy use and high environmental values; and that, among individuals with high environmental values, the treatment positively influences environmental self-identity.

We now evaluate whether, by purposefully priming environmental self-identity within the eHER, we can strengthen the effect of values on the desired behavioural change. This is a more direct test of the hypothesis that the eHER works by increasing the moral cost of energy use, especially among customers who care about the environment. By priming environmental self-identity within the eHER, we should make environmental considerations more salient and increase the moral cost of energy use.

As pre-specified in a Pre-Analysis Plan, we evaluate the impact on consumption of the eHER augmented with the environmental self-identity prime, which we included in the November-December 2017 report, relative to the standard report and to the control. Following Allcott and Rogers (2014), we consider three periods. Period 0 is the pre-treatment period (July 2015-June 2016), period 1 is the period during which program participants receive the standard eHER (July 2016-October 2017), period 2 is the post-prime period following the delivery of the eHER augmented by the environmental prime (November 2017-March 2018).

We estimate:

$$Y_{it} = \tau^1 DD1_{it} + \tau^2 DD2_{it} + \alpha^1 PP1_{it} + \alpha^2 PP2_{it} + h_t + g_i + \varepsilon_{it} \tag{4}$$

where $DD1_{it}$ and $DD2_{it}$ are equal to one if customer i is assigned to the eHER program and month t is in period 1 and 2, respectively, and zero otherwise. $PP1_{it}$ and $PP2_{it}$ are equal to one for treated customers who are assigned to receive the environmental self-identity prime and month t is in period 1 and 2, respectively, and zero otherwise. τ^1 and τ^2 identify the main effect of receiving the standard eHER in the periods before (first term) and after (second term) the prime was sent, respectively, compared to the control group. The third element constitutes a placebo test for the validity of the randomization of treatment: the coefficient α^1 indicates any differential effect of receiving the eHER in the periods before the prime was sent between the two groups assigned to receiving the treatment and the control message in the augmented eHER. The fourth coefficient, α^2, identifies the treatment effect for the group of households receiving the eHER augmented with the environmental identity prime, in the post prime period, compared to households that receive only the eHER with the control message. The treatment effect of receiving the prime compared to the control group is therefore given by the sum of τ^2 and α^2. This specification allows us to confirm the main findings of the impact evaluation of the eHER in period 1 and to detect any effect of the environmental self-identity prime in period 2. h_t and g_i are month-by-year and individual fixed effects, respectively. Standard errors are clustered at the level of household.

The marginal effect of receiving the self-identity prime compared to the control group ($\tau^2 + \alpha^2$), obtained from estimating Equation 4, is reported in Column 1 of Table 5. Households receiving the prime reduces consumption by 0.05KWh, compared to the control group, but this response is not statistically significant.[29] The size of the corresponding

[29]We can only estimate ITT effects, because, while we are able to measure if any report has been opened

MDE is around 5%. It is larger than those in Table 3 and generally larger than the effects reported in the social information literature, except for few cases (Andor et al., 2020; Farrow et al., 2017; Delmas et al., 2013b). For example Delmas et al. (2013b), in their meta-analysis, report that information based energy conservation experiments led to an average 7.4% energy saving. Table C.6 in the Appendix presents the whole set of results. The coefficient of the variable $PP2$ is not statistically significant and indicates that the prime does not significantly affect energy conservation compared to the control message.

The prime's null effect is in sharp contrast with the impact of the same prime in our online pre-test: there, we obtain a positive and statistically significant effect of the prime on pro-environmental behaviour, which can be observed for the sample as a whole (see Table C.9).

Next, we test the heterogeneous effect of the standard program message and the prime-augmented message with respect to the same pre-specified characteristics that we examined above. We therefore estimate the following Equation:

$$\begin{aligned} Y_{it} = \tau^1 DD1_{it} + \sum_{a=1}^{A} \tau_a^1 DD1_{it} * X_i + \tau^2 DD2_{it} + \sum_{a=1}^{A} \tau_a^2 DD2_{it} * X_i \\ +\alpha^1 PP1_{it} + \sum_{a=1}^{A} \alpha_a^1 PP1_{it} * X_i + \alpha^2 PP2_{it} + \sum_{a=1}^{A} \alpha_a^2 PP2_{it} * X_i \\ +h_t + g_i + \varepsilon_{it} \end{aligned} \tag{5}$$

As before, X_i is a matrix of variables that capture the dimension of heterogeneity of interest.

in a specific month, we do not know which report.

First, we focus on pre-treatment energy consumption, to confirm existing results on its relevance as a source of heterogeneous treatment effects. Results are reported in Column 2 of Table C.6. Compared to the eHER, we continue to find a statistically insignificant effect of the prime on energy conservation in period 2, as indicated by the coefficients of $PP2$ and $PP2 * Pre - treat\ usage$. Second, we test heterogeneous treatment effects of the identity prime with respect to environmental values.[30] We do not find any significant difference in energy use between high and low values individuals (Column 3) and the effect on customers with high values is also not significant compared to the control group (Table 5). This insignificant response to the prime is also confirmed in a triple interaction with environmental values and pre-treatment consumption.[31] This result contributes to a recent literature suggesting that whether past moral deeds lead to behavioural consistency or to moral licensing depends on how important behaviour is to one's moral self (Miller and Effron, 2010; Thøgersen, 2004; Thøgersen and Crompton, 2009). According to these studies, priming environmental self-identity works only for those who care about the environment to begin with. We find no support for this hypothesis in our data.

To understand why the prime message does not affect electricity consumption, we use our survey data to explore an additional dimension of heterogeneity, which should more directly affect the response to the specific prime that we use. Namely, we test whether the effectiveness of reminding people of past pro-environmental actions depends on how

[30] As already mentioned, the Pre-Analysis Plan specified a large set of potential sources of heterogeneity that could affect the impact of the environmental prime on consumption. To offset the increased potential for false positives that arise because we analyse the effect of the treatment across multiple subgroups, in the populated PAP, we report the sharpened two-stage q-values proposed by Benjamini et al. (2006) and discussed in Anderson (2008).

[31] Results are not shown but are available upon request.

they actually behaved (van der Werff et al., 2014b). We thus study the heterogeneity of treatment effects based on prior pro-environmental behaviours, measured at the time of the survey. In particular, in the survey we ask respondents how often they completely switch off electronic devices, such as TVs or computers, and use this variable to measure past pro-environmental behaviour. Answers vary from one (never) to five (always). We compute a dummy variable equal to one for answers ranging from 4 to 5 and use it as a proxy for actual pro-environmental behaviour. According to this variable, 43% of the sample respondents acted pro-environmentally in the past. We then interact the treatment indicators with pre-treatment energy consumption and with this dummy variable. We acknowledge that this dimension of heterogeneity did not feature in the PAP.

Results are presented in Column 4 of Table C.6. The coefficient of the variable $PP2 * Pre - treat\ usage * High\ pro - env\ behav$ is negative and statistically significant at the 10% level, with a point estimate of -0.124. This result weakly suggests that the prime strengthens the effect of the eHER among high usage individuals who behaved pro-environmentally in the past.[32]

Two graphical representations of these results help in making their implications clearer. First, we plot in Figure 4 the conditional average treatment effect of receiving the eHER coupled with the prime (red line) compared to the control group, along with the conditional average treatment effect of receiving the eHER without the prime (black line) compared to the control group, for individuals who behaved pro-environmentally. The figure indicates that, conditional on effective targeting, priming environmental self-identity through

[32]We acknowledge that the coefficient turns not statistically significance if we compute the sharpened two-stage q-values to address multiple hypotheses testing (q-value=0.535).

recalling past pro-environmental actions can boost the effect of the eHER on energy conservation. The figure also indicates that the prime is able to counteract the boomerang effect of the standard eHER. Second, in Figure 5 we plot the conditional average treatment effect of receiving the prime-augmented eHER for individuals who behaved (red line) or did not behave (blue line) pro-environmentally in the past compared to the control group. The graph indicates that the prime backfires if it is addressed to people who hardly engage in pro-environmental behaviours.

We also estimate a specification using a triple interaction between pro-environmental behaviour and dummy variables for quartiles of pre-treatment consumption. Results are in Column 5 of Table C.6, while Table 5 computes the marginal treatment effects of receiving the eHER augmented with the prime compared to the control group, in the different subgroups of customers. Households targeted by the prime generally do not respond by increasing consumption: consistent with Figure 4, no boomerang effect occurred. Moreover, the linear combination of estimated parameters for high-usage households who acted pro-environmentally in the past, yielding the treatment effect of the prime for this sub-group compared to the control group, is -0.462 and is statistically significant.[33] As a consequence of the reduced size of the different sub-samples considered, the MDEs become larger and range between 6 and 9% of the outcome mean. Although these may appear as relatively large effects for the European context, pointing to under-powered results, their size is still consistent with Byrne et al. (2018), the only work that, to the best of our knowledge, analyzes the heterogeneous effects of an information treatment combining administrative data

[33] The F-test on the joint significance of the coefficients of the heterogeneous effects of $DD2$ and $PP2$ with respect to pro-environmental behaviour and consumption from Column 4 is 3.43, from Column 5 is 1.81 and both reject the hypothesis that these effects are jointly equal to zero.

on energy usage with survey measures.[34]

As discussed above concerning environmental values, we do not believe the coexistence of high household consumption and individual self-reported conservation efforts to be an idiosyncratic feature of our sample: there might be imperfect information on household members' energy usage, the respondent's efforts to conserve energy may not be shared by other family members, or there may be a misperception on the impact of energy saving actions (Jack et al., 2018). Moreover, this sub-group is arguably empirically relevant, representing almost 9% of the sample.

Table C.6 reports the other coefficients from estimating Equation 5. The coefficient of the variable $DD1$ in Column 1 is -0.073, significant at 10% level, and indicates that, on average, the eHER has a negative effect on energy consumption in the pre-prime Period 1. On the contrary the coefficients of the other variables are not statistically significant. In Columns 2 and 4, the coefficients of the variable $DD1 * Pre - treat\ usage$ is negative and statistically significant at 1% level, with a point estimates of -0.092 and -0.094. These results confirm the effect of the eHER on high-usage individuals. Finally, the placebo test on the validity of the randomization is confirmed by the non statistically significant coefficients of the variables $PP1$ and $PP1 * Pre - treat\ usage$ in all specifications. As expected, individuals randomly selected to receive the prime did not behave differently from individuals receiving the control message in the pre-prime period 1.[35]

[34] Their MDEs for the dimensions of heterogeneity of interest range between 2.6 and 15%.

[35] We perform a series of robustness checks. First, in Column 1 of Table C.7, we deal with possible outliers by winsorizing the pre-treatment consumption variable. The triple interaction coefficient turns not-statistically significant, but the point estimate is in line with the main specification. Second, we use different definitions of the indicator of prior pro-environmental behaviour. We make the classification of prior pro-environmental conduct more restrictive, by defining it as always switching off electric appliances not in use. The dummy variable is set equal to one only for answers equal to 5. 22% of individuals are now classified as

4. Discussion

We present evidence from the evaluation of a social information program on energy consumption. We combine metered energy usage and survey data to test whether social information can be made more effective, by leveraging its impact on the moral cost of deviation from the target behaviour. We find that program recipients with strong environmental values are not overall more responsive to the intervention. Further exploring the heterogeneity of treatment effects shows weak evidence that the eHER reduces consumption more among a specific sub-group of users, i.e. those with high environmental values, who also have high pre-program energy use.

We then exploit the link between values and environmental identity and find that environmental identity is more prominent upon receipt of the eHER. This effect is short-lived, consistent with a mechanism relying on salience. We thus test whether priming self-identity can make the eHER more effective. In the field, we augment the standard social information message with a prime used in psychology to increase environmental self-identity. We find that, on average, our prime does not further reduce energy use with respect to the standard report, but its impact can be improved by means of effective targeting. We provide suggestive evidence that the prime succeeds in reducing energy use among high energy users who acted pro-environmentally in the past.

Our results suggest a much smaller role for environmental values and identity in fos-

having behaved pro-environmentally. We present the empirical findings in Column 2. The point estimate of the coefficient of the triple interaction $PP2 * Pre-treat\ usage * High\ pro-env\ behav$ is now 0.17 (significant at 5% level) which is about 40% larger than the estimate presented in Table C.6. This finding indicates that, by restricting the definition of people who behave pro-environmentally, we find stronger effects of the prime on energy conservation.

tering pro-environmental behavior than the one proposed by much of the psychological literature. The impact of values and identity on the effectiveness of social information is null overall, and marginally statistically significant only for specific groups of users. This is in contrast with existing evidence in psychology and the results of our own pre-test of the environmental identity prime, where the impact of priming is statistically significant overall.

We consider a few potential explanations for the discrepancy between the results of the field and the online experiments, which, in our opinion, represent important caveats for those wishing to draw policy lessons from laboratory or online experiment, and point to relevant directions for future research.[36] First, while the online pre-test evaluated the impact of the identity prime in isolation, the field experiment embedded it within the eHER, which prominently features another energy conservation nudge. Given that exposure to multiple behavioral intervention is increasingly likely as these policy tools gain popularity, it is important to systematically assess how their impact varies as they are combined, and be cautious in generalizing lessons on their effectiveness from abstract laboratory results. Research on the combined impact of different nudges is still scant.

Second, the online and field experiments differ in the timing and duration of the behavioral outcomes with respect to the exposure to the prime. The outcome in the online pre-test was observed immediately after the prime and required simple actions (donation to a charity and expression of an intention to save energy). The outcome in the field experiment (energy consumption) instead entailed sustained effort along multiple dimensions,

[36] Of course we acknowledge that the online pre-test and the field experiment differ along various other dimensions, which could also affect the results.

from switching off lights to unplugging devices, etc. Research on the different mental processes involved in immediate reactions and sustained behavioral responses suggest a different role for identity in these two realms (Kahneman, 2011). Indeed, our own analysis of the salience-inducing effect of the eHER indicates that it is short-lived. Existing evidence, both from the energy conservation and from other domains, confirms the temporary nature of the effects of behavioral interventions (Gneezy and List, 2006; Allcott, 2016). Evaluating systematically how the impact of social information and identity priming vary with the nature and the duration of a task is an interesting avenue for further research.[37]

Our study has implications for policy design and targeting. The heterogeneity in program effects suggests that effective targeting of social information can maximize its impact on desired behaviour, which can be further enhanced thanks to synergies with other well-targeted behavioural interventions. However, it also shows that heterogeneity makes it hard to devise broad-spectrum behavioural tools. While targeting on the basis of certain traits, such as energy consumption, appears straightforward, screening individuals on the basis of their environmental values or pro-environmental behavior is more challenging. Our results suggest a potential strategy, which could serve the joint purpose of identifying individuals with high environmental values and building the foundations for effective identity priming: promoting initiatives with strong environmental contents, such as commercial offers on green energy or petitions for environmental causes. By signing up to these initiatives, individuals would both signal their environmental values, and build a stock of prior environmental actions that could be subsequently made salient within identity primes

[37] We are grateful to an anonymous reviewer for highlighting this point.

similar to the one we adopt.

More broadly, our study speaks to the debate on the cost-effectiveness of eHER programs. Traditional programs are not estimated to be cost-effective in most industrialized countries with relatively low electricity consumption levels and carbon intensities of electricity generation (Andor et al., 2020). These estimates are based on the assumption that HER are printed and delivered by post, with an estimated marginal cost of USD 1 per report. In the program evaluated here, the reports are delivered by email with substantial implications for cost-effectiveness considerations. Existing evidence demonstrates that electronic HER are at least as effective as physical reports, and therefore more cost-effective, given their lower marginal cost (Henry et al., 2019). The growing trend towards digitalization and customization of customer services by utilities raises the possibility that eHER represent an effective policy tool to foster energy efficiency among highly responsive subgroups. On the other hand, our results unambiguously confirm that the cost-effectiveness of traditional social information program is likely to be restricted to high energy usage countries (and users).

From a methodological point of view, our study, similarly to Byrne et al. (2018), attempts to empirically explore the heterogeneous impact of energy conservation interventions on the basis of personal traits that are hard to observe through administrative or large scale survey data. This poses important challenges. As these personal traits can typically only be measured directly through ad-hoc surveys, the resulting empirical analysis will likely rely on smaller samples and be characterized by more limited statistical power, relative to large-scale evaluations based exclusively on administrative data. In spite of these limitations, we believe that these exercises have real value, in that they represent an effective strategy to identify potential sources of heterogeneity in the effect of interventions. Their findings can suggest where to focus efforts for larger-scale follow-up replications.

5. Figures and tables

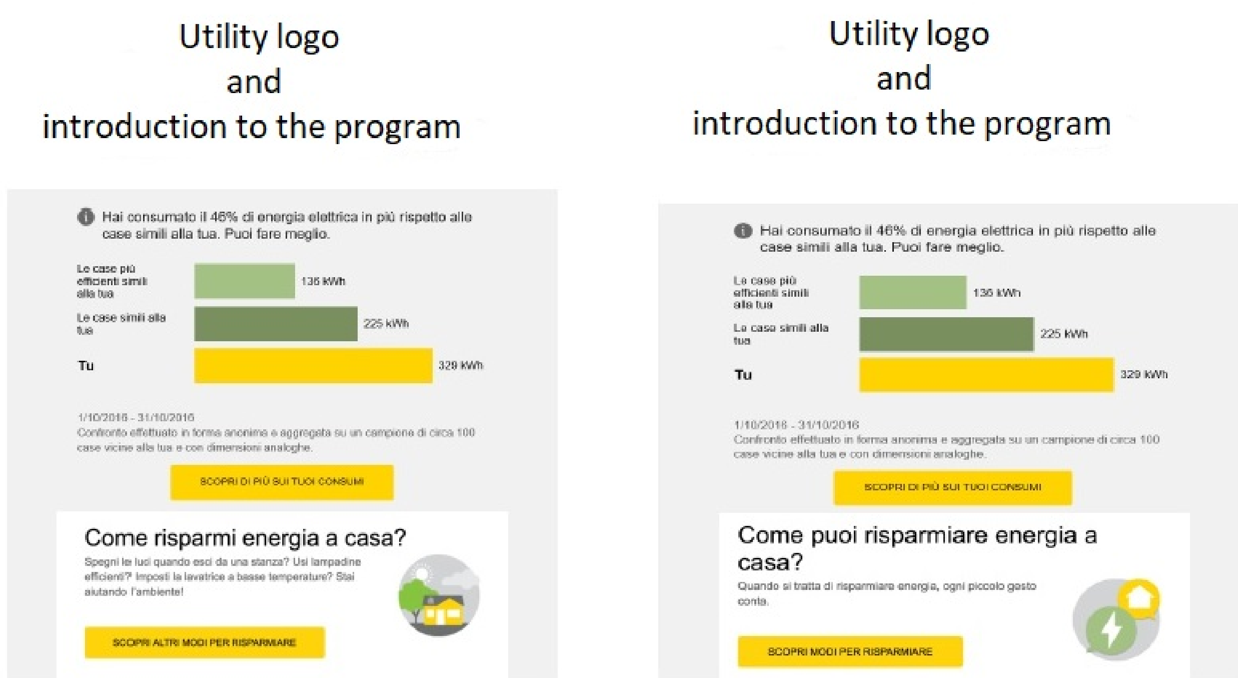

Figure 1: Samples of eHER sent on November 2017 containing environmental prime (left) and control message (right) in the bottom area.

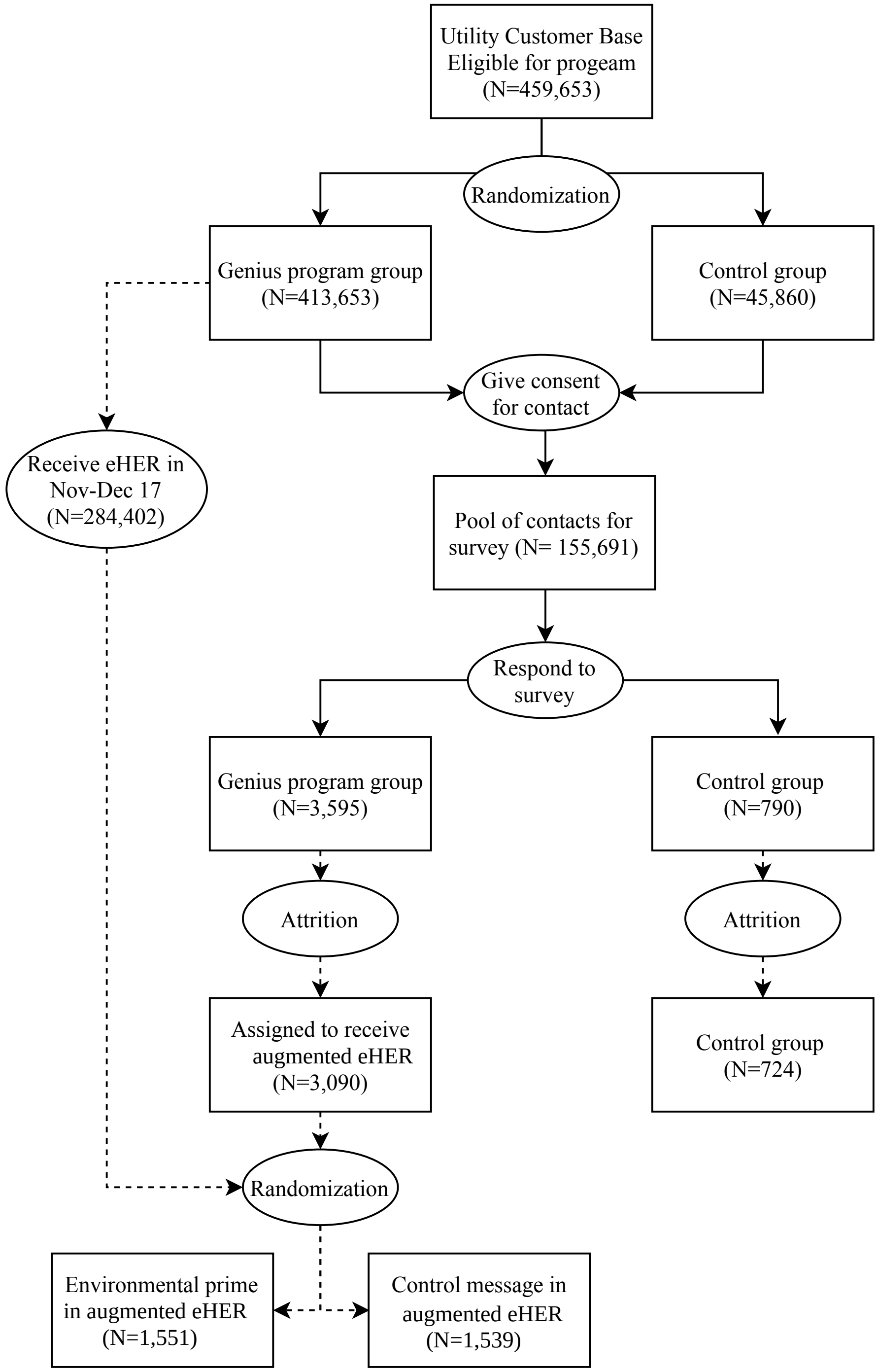

Figure 2: Sample flow diagram

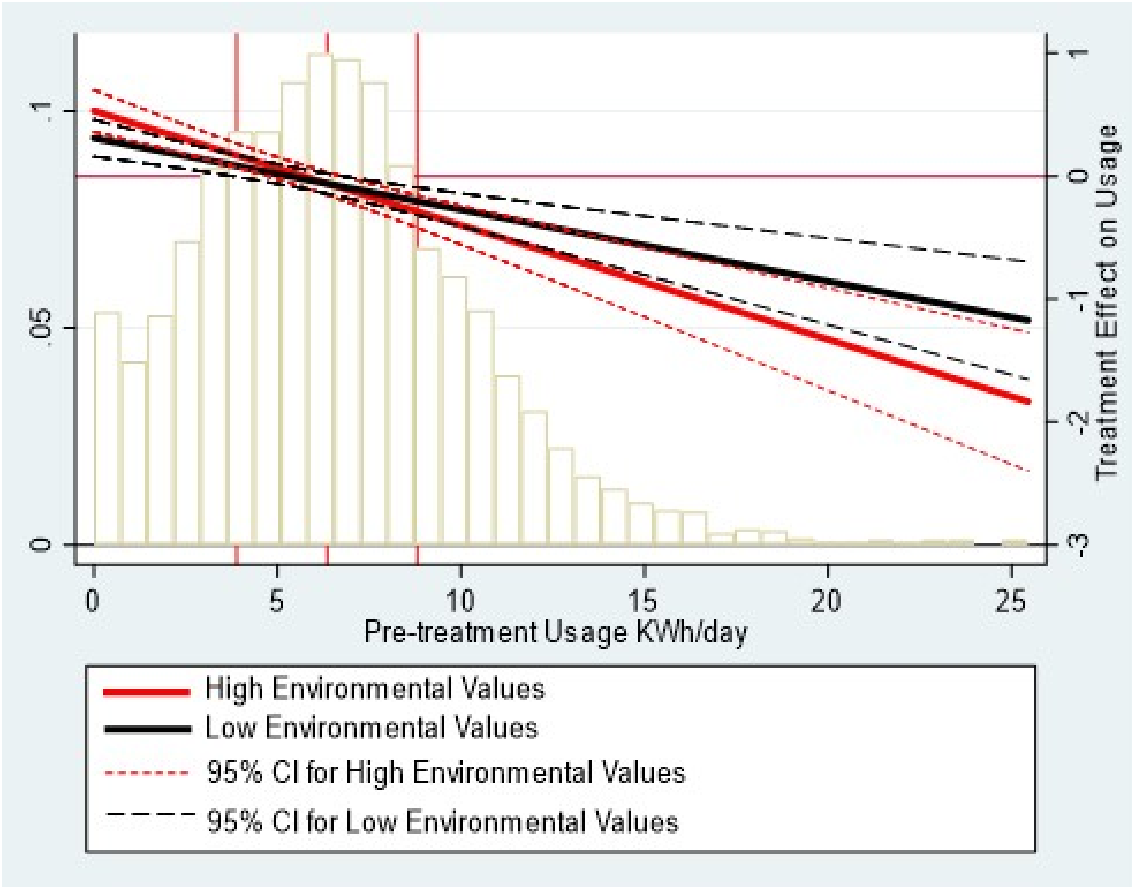

Figure 3: Heterogeneous effects of the environmental prime on electricity usage, by pre-treatment usage and environmental values. The vertical axis on the left is for the histogram of pre treatment usage. The vertical axis on the right indicates the magnitude of the treatment effect. The vertical red bars indicate the first, second and third quartile of pre treatment usage.

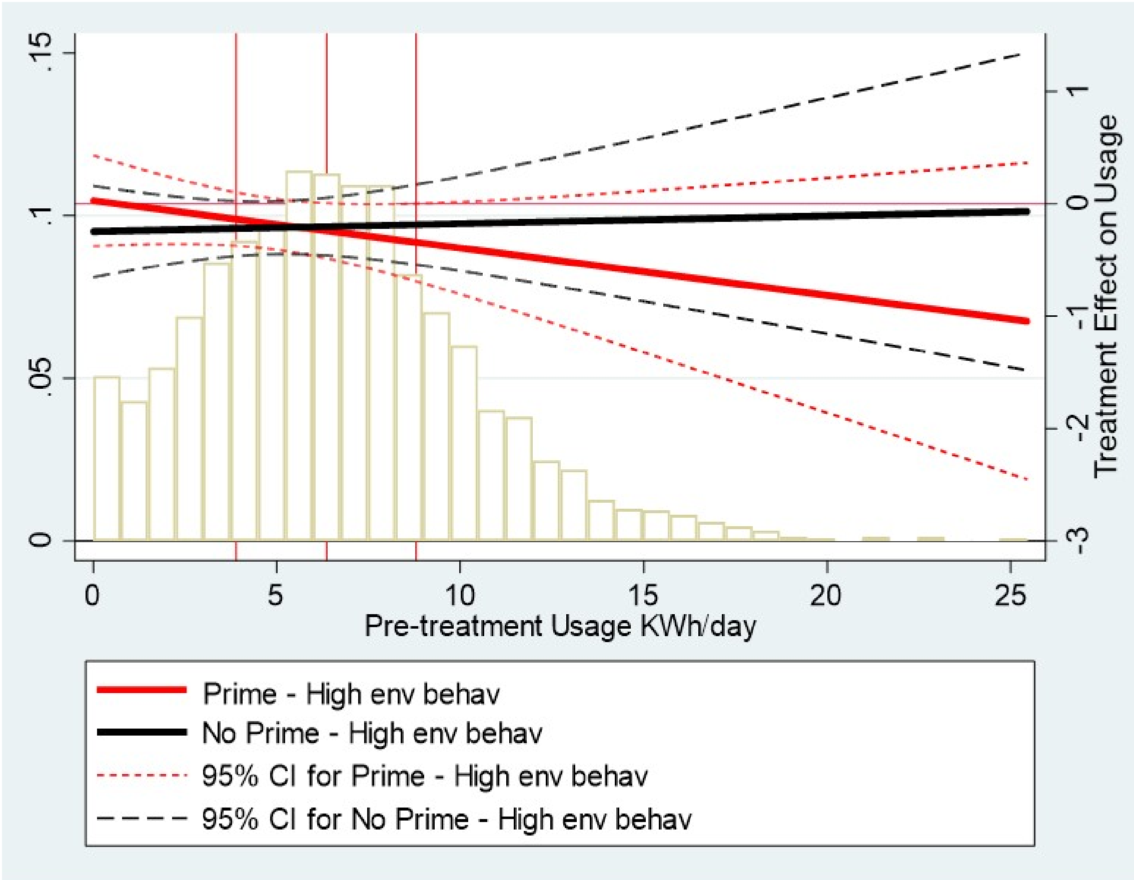

Figure 4: Heterogeneous effects of the environmental prime on electricity usage, by pre-treatment usage and pro-environmental behavior. The vertical axis on the left is for the histogram of pre treatment usage. The vertical axis on the right indicates the magnitude of the treatment effect. The vertical red bars indicate the first, second and third quartile of pre treatment usage.

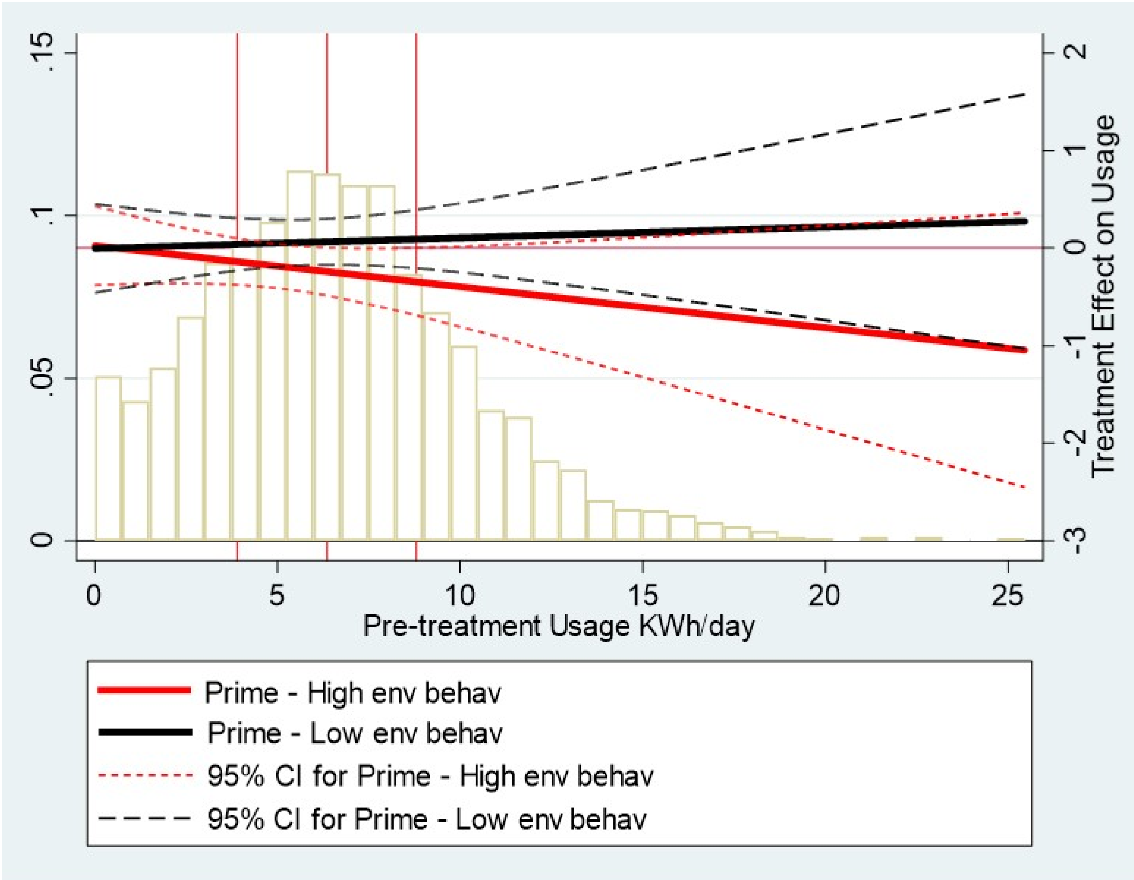

Figure 5: Heterogeneous effects of the environmental prime on electricity usage, by pre-treatment usage and pro-environmental behavior. The vertical axis on the left is for the histogram of pre treatment usage. The vertical axis on the right indicates the magnitude of the treatment effect. The vertical red bars indicate the first, second and third quartile of pre treatment usage.

Table 1: The program, summary statistics and sample balance

	(1) Program	(2) Control	(3) Difference	(4) Assigned to receive aug eHER	(5) Control	(6) Difference
N. of observations	3595	790		3090	724	
Panel A: Controls						
Average pre-treat usage	6.464	6.608	-0.144	6.479	6.670	-0.192
High environmental values	0.348	0.331	0.017	0.347	0.336	0.011
Female	0.314	0.292	0.022	0.316	0.296	0.020
Age	52.932	53.542	-0.610	53.115	53.709	-0.593
North	0.465	0.522	-0.057***	0.461	0.514	-0.053**
Center	0.290	0.289	0.002	0.292	0.297	-0.005
South and Islands	0.245	0.190	0.055***	0.247	0.189	0.058***
Schooling: primary	0.010	0.009	0.001	0.009	0.010	-0.001
Schooling: secondary	0.112	0.113	-0.000	0.113	0.116	-0.003
Schooling: high school	0.530	0.561	-0.031	0.526	0.554	-0.028
Schooling: undergraduate	0.298	0.280	0.019	0.301	0.285	0.016
Schooling: MA/PhD	0.050	0.038	0.012	0.051	0.036	0.016*
House owned	0.855	0.863	-0.008	0.864	0.870	-0.006
House tenure: less than 5 years	0.153	0.154	-0.001	0.148	0.151	-0.003
Panel B: Outcomes						
Average post-treat usage	6.389	6.606	-0.217	6.412	6.690	-0.277*
Environmental self-identiy, z-score	0.010	-0.034	0.044	0.029	-0.031	-0.062

Notes: Columns (3) and (6) report difference in means between groups and significance levels of a two-sided t-test (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Pre-treat usage is calculated as the average daily electricity consumption in a month, over the period July 2015- June 2016. Post treatment usage is calculated as the average daily electricity consumption in a month, over the period July 2016-March 2018

Table 2: Environmental prime in the augmented eHER, summary statistics and sample balance

	(1) Env. prime message	(2) Control message	(3) Difference
N. of observations	1551	1539	
Panel A: Controls			
Average pre-treat usage	6.503	6.453	0.050
High environmental values	0.344	0.351	-0.007
Female	0.320	0.311	0.009
Age	52.852	53.381	-0.529
North	0.466	0.455	0.010
Centre	0.302	0.283	0.019
South and Islands	0.233	0.262	-0.029*
Schooling: primary	0.005	0.012	-0.007**
Schooling: secondary	0.108	0.118	-0.011
Schooling: high school	0.532	0.520	0.011
Schooling: undergraduate	0.301	0.300	0.001
Schooling: MA/PhD	0.054	0.049	0.005
House owned	0.877	0.851	0.027**
House tenure: less than 5 years	0.153	0.143	0.010
High pro-environmental behavior	0.431	0.426	0.004
Panel B: Outcomes			
Average post-treat usage	6.463	6.361	0.102

Notes: The last Column reports difference in means between groups and significance levels of a two-sided t-test (*** p<0.01, ** p<0.05, * p<0.1). Pre-treat usage is calculated as the average daily electricity consumption in a month, over the period July 2015-June 2016. Post treatment usage is calculated as the average daily electricity consumption in a month, over the period July 2016-March 2018.

Table 3: Marginal effect of the program

	(1) Marginal effect compared to control	(2) MDE	(3) MDE as % mean pre-treat usage	(4) N. Control	(5) N. Program
Program	-0.06	0.108	0.017	790	3595
Q1 of Pre-treat usage	0.187***			192	894
Q2 of Pre-treat usage	0.050	0.132	0.020	182	909
Q3 of Pre-treat usage	-0.035	0.143	0.022	213	875
Q4 of Pre-treat usage	-0.458***			199	892
Low env value	-0.069	0.119	0.018	526	2327
High env value	-0.050	0.134	0.021	260	1243
Q1 of Pre-treat usage; low env value	0.177***			128	585
Q1 of Pre-treat usage; high env value	0.200***			64	309
Q2 of Pre-treat usage; low env value	0.051	0.154	0.024	123	558
Q2 of Pre-treat usage; high value	0.036	0.173	0.027	59	351
Q3 of Pre-treat usage; low env value	-0.113*			137	574
Q3 of Pre-treat usage; high env value	0.119	0.206	0.032	76	301
Q4 of Pre-treat usage; low env value	-0.384***			138	610
Q4 of Pre-treat usage; high env value	-0.619***			61	282

Notes: The marginal effects are computed from the coefficients reported in Table C.3 and refer to treated customers, i.e. enrolled in the program. *** p<0.01, ** p<0.05, * p<0.1 for the linear combinations of the parameters in the different sub-groups. The outcome is daily electricity usage, in KWh/day. The ex-post MDE is computed using the conventional 5% level of statistical significance and 80% power level.

Table 4: The impact of the program on environmental self-identity

	(1)	(2)	(3)	(4)
	Environmental self-identity index			Discounted for delay
Program	0.044	0.030	-0.011	0.148***
	(0.039)	(0.037)	(0.047)	(0.050)
Program*High env values			0.123*	
			(0.074)	
High env values		0.801***	0.699***	0.793***
		(0.026)	(0.069)	(0.028)
Pre-treat usage		-0.005	-0.005	-0.008*
		(0.004)	(0.004)	(0.005)
Constant	-0.034	-0.806***	-0.769***	-0.795***
	(0.035)	(0.229)	(0.232)	(0.230)
Observations	4,370	4,347	4,347	3,965
R-squared	0.000	0.167	0.168	0.169
Controls	No	Yes	Yes	Yes

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. OLS estimates. Controls include a dummy for female respondent, age, four dummies for different levels of education, two dummies for geographical location, dummies for house ownership and less than five years tenure.

Table 5: Marginal effect of prime

	(1) Marginal effect compared to control	(2) MDE	(3) MDE as % of mean pre-treat usage	(4) N. Control	(5) N. Control Message	(6) N. Prime
Prime	-0.052	0.310	0.048	724	1539	1551
Low env value	-0.071	0.331	0.051	478	993	1009
High env value	-0.029	0.370	0.057	242	536	529
Q1 of Pre-treat usage; Low pro env behav	0.118	0.516	0.079	83	177	175
Q1 of Pre-treat usage; High pro env behav	-0.013	0.378	0.058	85	210	201
Q2 of Pre-treat usage; Low pro env behav	-0.038	0.393	0.061	93	234	216
Q2 of Pre-treat usage; High pro env behav	-0.234	0.412	0.063	75	143	192
Q3 of Pre-treat usage; Low pro env behav	0.172	0.425	0.065	117	232	236
Q3 of Pre-treat usage; High pro env behav	-0.280	0.526	0.081	85	166	138
Q4 of Pre-treat usage; Low pro env behav	0.035	0.605	0.093	124	240	256
Q4 of Pre-treat usage; High pro env behav	-0.462*			62	137	137

Notes: The marginal effects are computed from the coefficients reported in Table C.6 and refer to customers assigned to receive the environmental prime. * $p<0.1$ for the linear combinations of the parameters in the different sub-groups. The outcome is daily electricity usage, in KWh/day. The ex-post MDE is computed using the conventional 5% level of statistical significance and 80% power level.

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Appendix

A. Online experiment

A.1. Set up

We complement the field experiment with an online one, conducted with a sample of 976 participants recruited on an online labor platform in September 2017. Since we wanted the online test to inform the self-identity prime in the field experiment, we chose Prolific Academic, a UK platform giving access to a primarily European sample of online workers.[38] Participants received a participation fee of 1 GBP, plus an additional 1 GBP bonus payment. The survey lasted about 5 minutes.

The online experiment serves two purposes. First, we test different ways to encourage pro-environmental behaviour and select the field experiment's best performing message. Second, we use the online experiment to perform a manipulation check on the prime. A concern that arises when designing a prime is whether it works through the proposed channel (Cohn and Maréchal, 2016). A manipulation check tests that the prime actually activates the specific mental concept that it intends to address. Therefore, through the online experiment we test if messages designed with the aim of activating environmental self-identity actually succeed in doing so, and which prime performs best along this dimension.

The experiment consists in a survey containing different versions of the prime. Immediately after the prime, we measure environmental self-identity and individual intentions to save energy, as outcome variables of the manipulation check. We randomize the order with which we ask the self-identity and intention questions after the prime. We use the same questions that we include in the field experiment survey to measure environmental self-identity. For individual intention to save energy, we ask the extent one intends to save energy on a scale from 1 (not at all) to 10 (very much). These variables represent an important element of the manipulation check, because they tell us whether the prime effectively activates environmental self-identity. We expect that participants primed with

[38] About 70 per cent of the Prolific sample is from European countries, the modal age of the sample population is between 20 and 30 years old, 45 per cent is employed full time, and more than 30 per cent has an undergraduate degree.

the treatments are more likely to perceive themselves as environmental-friendly persons or more willing to act pro-environmentally.

The survey also elicits an incentivized pro-environmental decision. We ask respondents whether they wish to donate part of their 1 GBP bonus payment to the European Alliance to Save Energy (EU-ASE), an environmental NGO advocating for energy efficiency at the European level. We use donations as our main proxy of the ability of the prime to foster pro-environmental behaviour.

We also collect information on gender, age, schooling and experience with the platform and elicit environmental values.

The design includes four treatment and one control messages. We randomly show one version of the prime message or a control message. Messages were randomized at the individual level through a random number generator. The treatment messages leverage different mechanisms that we believed could motivate pro-environmental behaviour by making environmental identity salient. The prime that we label as Identity is the one we employed in the field experiment. We already discussed the rationale for this treatment in Section 2.1 above. In the treatment we label as Values, we asked subjects to think if they care about the environment. Through the Experience treatment, we wanted subjects to remember a moment when they felt connected to nature. Finally, in the Disease treatment, we leveraged fear of energy use's health consequences as a motivator of energy conservation: previous research shows the effectiveness of this type of message in inducing energy saving behaviour in the field (Asensio and Delmas, 2015, 2016). Section A.3 reports the experimental instructions including the treatment and control messages.

A.2. Results

We first provide descriptive statistics and balance tests of treatment sub-groups along different dimensions in Table C.8. Groups are balanced across observable characteristics, as confirmed by the fact that we never reject the null hypothesis of joint significance of the coefficients attached to the treatment dummies, in regressions with observable characteristics as dependent variables.

Turning to the main findings of the experiment, Table C.9 shows results from OLS regressions of our outcome variables – environmental self-identity, intentions to save energy, and donations to the environmental NGO- on treatment dummies and demographic controls (gender, age, schooling, experience with the platform and environmental values).[39] The identity prime has a positive and statistically significant effect on all outcomes compared to the control message. As for both environmental self-identity and intention to save energy, relative to subjects in the control condition, respondents in the identity priming treatment display about 5 per cent higher scores, on average and *ceteris paribus*. The identity prime over-performs with respect to the control message and the messages priming environmental values (p-value=0.022 and 0.0381, respectively) and inducing fear of the health consequences of energy use (p-value=0.068 and 0.0378, respectively). However, it cannot be distinguished from the effect of the environmental experience prime (p-value=0.316 and 0.536). Finally, participants reading the identity message donate 11 pence more (out of a £1 initial endowment), compared to the control group, i.e. about 74 per cent increase. The coefficient for identity is significantly different from the one attached to values (p-value=0.038), but not from the ones for experience and disease (p-value=0.21 and p-value=0.15, respectively).

A.3. Instructions

Messages tested:

1. Control: *"Change your energy consumption. Find ways to save energy today."*
2. Identity: *"Do you switch off the lights when you leave a room? Do you own efficient lightbulbs? Do you wash your clothes at low temperatures? By saving energy you contribute to environmental quality. Find ways to save energy today."*
3. Values. *"Do you care about the environment? By saving energy you contribute to environmental quality. Find ways to save energy today."*
4. Experience: *"Do you remember the last time you enjoyed nature? And what is your favourite tree? By saving energy you contribute to environmental quality. Find ways to save energy today"*.

[39]The loss of 6 observations due to missing values in some of the controls included in the regressions is uncorrelated to any particular treatment arm. Given that both identity and intentions are categorical variables, we also use ordered logistic regression models, while we take into account the censored nature of donation by using a Tobit model. Results, available upon request, are similar to the ones presented.

5. Disease: *"Do you know that diseases, such as childhood asthma and cancer are linked to exposure to outdoor air pollution, generated by energy use? By saving energy you contribute to environmental quality. Find ways to save energy today".*

Measure of Intention

Do you intend to save energy? Please report your answer on a scale from 1 (Not at all) to 10 (Very much).

Measure of self-identity

Please indicate to what extent you agree with the following statements on a scale ranging from 1 (Totally disagree) to 7 (Totally agree) *Acting pro-environmentally is an important part of who I am*

Donation

Since everyone has different ideas about supporting organisations dedicated to energy conservation, we are using this survey to understand individuals' behaviour in case they have the chance to choose whether or not to support one of them. The European Alliance to Save Energy (EU-ASE) is an organization devoted to promoting energy efficiency at the European level, through legal change and policy making.

Would you like to donate part of your participation bonus to EU-ASE? Please enter a donation between 0£ and 1£. We will make the donation on your behalf. The donation will be deducted from your bonus payment of 1£.

We will send you a receipt of the donation at the end of the study.

Please choose using the drop-down list below how much you would like to donate, between 0£ and £1.

B. Attrition, optout and missing data

The program experiences two types of attrition: customers may move to a different house or change the energy provider, however we are unable to distinguish between the two cases. In both circumstances, we stop observing consumption data after a certain date. To guarantee the internal validity of the analysis of the program, attrition needs not to be differential across treatment and control customers. In table B.1, Column (1), we report the results of a regression where a binary variable equal to one for customers dropping out of the sample after the launch of the program and zero otherwise is regressed on the treatment status and other customer controls. We find no evidence of differential attrition. We also check for the absence of a systematic time trend in attrition. Figure B.1 shows treatment-control differences in the share (and 95% confidence intervals) of attriters by month, since the launch of the program. The evidence suggests that attrition was unsystematic over treatment and time. Attriters after the launch of the program are included in the main analysis up to the date they drop out of the sample, however results in Tables C.3 and C.6 do not change when they are excluded since the beginning, as shown in Tables C.4 and C.7, respectively.

Customers assigned to the program may decide to opt-out from the program in order not to receive the eHER anymore, but still remain utility customers. This phenomenon regards 3.2 percent of the treatment group and is concentrated in the first six months since the launch of the program (56 percent of opt-out cases occur before February 2017), at the time the first eHER was sent. Column (2) of Table B.1 shows opt-out determinants for the treated sample. It turns out that slightly older people with higher pre-treatment consumption tend to opt out more frequently than the rest of the sample. Given the limited extent of the phenomenon and the small size of the significant coefficients, we do not believe that this might affect our main results of the analysis. However, one should keep in mind that customers who opted-out are maintained in the treatment sample and included in the whole analysis (their electricity consumption is still observable), in order to avoid generating sample imbalances. As such, opting out of the program dilutes the program's effect which would be eventually underestimated.

The missing data of two important survey variables is another source of concern. In particular, the variables for environmental values and environmental identity have 29 and 15 missing values, leading to a final non-missing sample size of 4,356 and 4,370, respectively. Columns (3) to (5) show that missing data in these variables, besides being limited in size, occur on a relatively unsystematic basis.

Table B.1: Attrition and missing values

	(1)	(2)	(3)	(4)	(5)
			Missinng value in		
	Attriter after Jul 16	Optout	Env values	Env self-identity	Env values or self-identity
Program	0.020		0.002	0.003*	0.004
	(0.013)		(0.003)	(0.002)	(0.003)
Female	-0.018	0.005	-0.000	0.003	0.001
	(0.011)	(0.007)	(0.003)	(0.002)	(0.003)
Age	-0.001***	0.001***	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Schooling: secondary	-0.092	0.032	-0.041	-0.042	-0.040
	(0.066)	(0.035)	(0.033)	(0.033)	(0.033)
Schooling: high school	-0.074	0.034	-0.038	-0.041	-0.035
	(0.065)	(0.034)	(0.033)	(0.033)	(0.033)
Schooling: undergraduate	-0.088	0.020	-0.038	-0.043	-0.037
	(0.066)	(0.034)	(0.033)	(0.033)	(0.033)
Schooling: MA/PhD	-0.110	0.013	-0.041	-0.035	-0.035
	(0.068)	(0.036)	(0.033)	(0.034)	(0.033)
North	0.019	-0.009	0.004	0.002	0.004
	(0.013)	(0.008)	(0.003)	(0.002)	(0.003)
Centre	-0.015	-0.006	0.003	0.001	0.004
	(0.014)	(0.009)	(0.003)	(0.002)	(0.003)
Pre-treat usage	-0.002	0.002**	-0.000	-0.000	-0.000
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)
House owned	-0.070***	-0.000	0.000	0.002	0.001
	(0.017)	(0.010)	(0.004)	(0.002)	(0.004)
House tenure	-0.004	0.006	0.009*	0.007**	0.012**
	(0.016)	(0.010)	(0.005)	(0.004)	(0.006)
Constant	0.335***	-0.065*	0.032	0.025	0.024
	(0.074)	(0.039)	(0.033)	(0.033)	(0.034)
Observations	4,385	3,595	4,385	4,385	4,385
R-squared	0.012	0.010	0.005	0.011	0.005
Mean Dependent Variable	0.138	0.0326	0.00661	0.00342	0.00821

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

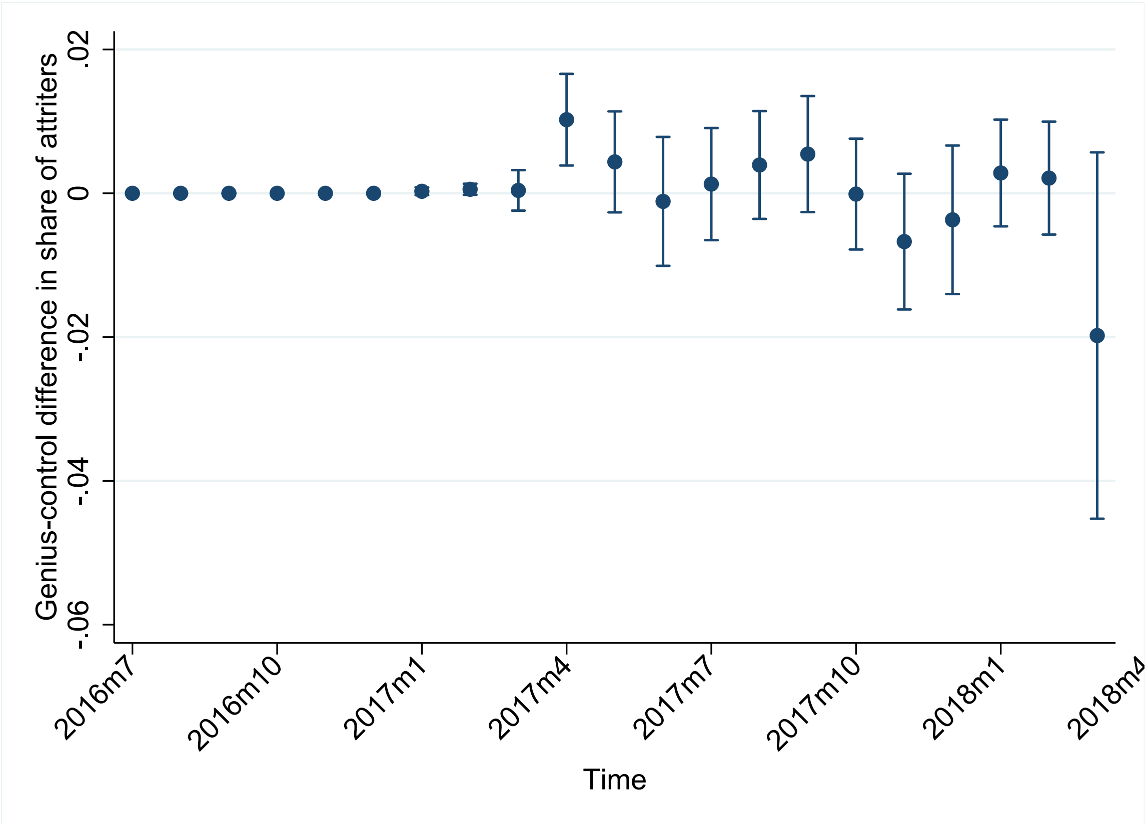

Figure B.1: Differential attrition over time

C. Additional tables

Table C.1: The program, sample balance for sub-groups

	Q1 use low values	Q1 use high values	Q2 use low values	Q2 use high values	Q3 use low values	Q3 use high values	Q4 use low values	Q4 use high values
	Difference: Program versus control							
Pre-treat usage	-0.042	-0.113	-0.094	-0.044	-0.017	-0.094	-0.045	0.012
Female	0.052	0.049	-0.003	0.045	0.033	0.098*	-0.079*	0.021
Age	-0.702	0.45	-0.471	-4.78**	-0.025	-1.536	0.528	-0.594
Primary S.	0.008	-0.016**	0.006	-0.017**	0.005	-0.007	-0.002	0.014
Secondary S.	0.047*	-0.018	-0.025	-0.007	-0.024	-0.022	0.001	0.066
High school	-0.048	-0.066	-0.023	0.098	-0.046	0.006	-0.029	-0.12
Undergraduate S.	-0.038	0.114*	0.043	-0.057	0.021	0.022	0.032	0.011
MA/PhD	0.031	-0.014	0	-0.017	0.043**	0.001	-0.002	0.03
North	-0.078	-0.043	-0.026	-0.053	-0.063	-0.005	-0.065	-0.125*
Centre	0.037	0.033	0.013	0.059	0.009	-0.073	-0.035	-0.033
South and Islands	0.041	0.01	0.013	-0.006	0.054	0.079	0.1**	0.157**
House owned	-0.048	0.019	0.034	0.016	-0.035	-0.028	0	0.032
House tenure	-0.019	-0.011	0.074**	-0.004	-0.047	0.024	-0.028	-0.012
Post-treatment usage	0.038	-0.246	-0.142	0.018	0.087	-0.086	-0.492	-0.274
Env self-identiy, stdz score	-0.067	-0.072	-0.174*	0.329***	0.005	0.205**	0.186*	-0.027

Notes: The table reports difference in means between program and control customers in the different sub-groups defined by the combination of pre-treatment electricity usage quartiles and environmental values (high vs low); subgroups' sample sizes are shown in Table 3; significance levels of a two-sided t-test are expressed as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C.2: Environmental prime in the augmented eHER, sample balance for sub-groups

	Q1 use low env b	Q1 use high env b	Q2 use low env b	Q2 use high env b	Q3 use low env b	Q3 use high env b	Q4 use low env b	Q4 use high env b
	Difference: Prime versus control							
Pre-treat usage	-0.001	-0.015	0.011	-0.096	-0.068	-0.042	-0.179	0.189
Female	0.089	-0.017	-0.023	0.105	-0.002	0.138**	-0.073	0.019
Age	-0.327	-0.167	-1.937	-1.587	-1.407	-1.957	-0.647	1.686
Primary S.	0	-0.019	-0.006	-0.013	0	0.003	0.008	-0.016
Secondary S.	0.003	0.034	0.005	-0.041	0.016	-0.12***	0.012	-0.012
High school	-0.141**	0.003	0.015	0.068	-0.047	-0.027	-0.018	-0.013
Undergraduate S.	0.088	-0.026	-0.017	0.027	0.002	0.084	-0.016	0.014
MA/PhD	0.05	0.008	0.003	-0.041	0.029	0.061**	0.014	0.028
North	-0.187***	0.027	-0.032	-0.04	0.008	-0.036	-0.009	-0.194**
Centre	0.12*	-0.095	0.094	0.017	-0.054	0.009	-0.106**	0.14**
South and Islands	0.067	0.067	-0.062	0.023	0.045	0.027	0.114***	0.054
House owned	-0.01	-0.02	0.064	0.036	-0.05	-0.008	0.014	0.072
House tenure	0.018	-0.021	0.032	0.073	0.012	-0.057	-0.022	-0.051
Post-treatment usage	0.019	0.026	-0.136	-0.074	0.143	-0.191	-0.433	-0.167
High env values	0.021	0.026	0.009	0.026	-0.019	-0.032	0.021	-0.019

Notes: The table reports difference in means between customers assigned to receive the environmental prime and control ones in the different subgroups defined by the combination of pre-treatment electricity usage quartiles and pro-environmental behaviour (high vs low); subgroups' sample sizes are shown in Table 5; significance levels of a two-sided t-test are expressed as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table C.3: Impact of the program on electricity usage, main and heterogeneous effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Daily electricity usage, KWh/day					
DD	-0.060	0.187***	0.382***	-0.069	0.310***	0.177***
	(0.039)	(0.047)	(0.063)	(0.043)	(0.077)	(0.054)
DD*Q2 Pre-treat usage		-0.137***				-0.126**
		(0.048)				(0.062)
DD*Q3 Pre-treat usage		-0.221***				-0.290***
		(0.052)				(0.066)
DD*Q4 Pre-treat usage		-0.644***				-0.561***
		(0.071)				(0.090)
DD*Pre-treat usage			-0.069***		-0.058***	
			(0.009)		(0.012)	
DD*High env values				0.019	0.221**	0.023
				(0.046)	(0.107)	(0.068)
DD*Pre-treat usage*High env values					-0.035*	
					(0.018)	
DD*Q2 Pre-treat usage*High env values						-0.038
						(0.096)
DD*Q3 Pre-treat usage*High env values						0.210**
						(0.107)
DD*Q4 Pre-treat usage*High env values						-0.258*
						(0.145)
Constant	7.912***	7.912***	7.912***	7.920***	7.919***	7.919***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
Observations	136,359	136,359	136,359	135,478	135,478	135,478
R-squared	0.082	0.084	0.084	0.082	0.085	0.085
Number of customers	4,385	4,385	4,385	4,356	4,356	4,356

Notes: Standard errors clustered at the customer level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Observations are months. Reference period for the analysis: July 2015- March 2018. Pre-treat usage is calculated as the average daily electricity usage in a month over July 2015-June 2016. The variable "High environmental values" is equal to one when above the median. All specifications include customer fixed effects and month by year fixed effects. The F-test on the joint significance of the coefficients of the interactions of DD with environmental values and pre-treatment usage in column (5) is is F(2, 4355) = 2.15 (p-value=0.12) and column (6) is F(4,4355) = 2.87 (p-value=0.022).

Table C.4: Impact of the program on electricity usage, main and heterogeneous effects, robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var: Daily electricity usage, KWh/day	Opened eHER		Winsorized pre-treat usage		Non-attriter	
DD	0.497***	0.415***	0.398***	0.333***	0.361***	0.280***
	(0.073)	(0.091)	(0.062)	(0.076)	(0.068)	(0.083)
DD*Pre-treat usage	-0.080***	-0.067***	-0.072***	-0.062***	-0.066***	-0.054***
	(0.011)	(0.014)	(0.009)	(0.012)	(0.010)	(0.013)
DD*High env values		0.245*		0.197*		0.242**
		(0.126)		(0.106)		(0.116)
DD*Pre-treat usage * High env values		-0.040*		-0.031*		-0.038*
		(0.021)		(0.018)		(0.020)
Constant	8.168***	8.174***	7.912***	7.919***	7.936***	7.940***
	(0.069)	(0.069)	(0.067)	(0.067)	(0.071)	(0.071)
Observations	125,872	125,051	136,359	135,478	120,883	120,129
R-squared	0.091	0.091	0.085	0.085	0.085	0.085
Number of customers	4,038	4,011	4,385	4,356	3,781	3,757

Notes: Standard errors clustered at the customer level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Observations are months. Reference period for the analysis: July 2015- March 2018. Pre-treat usage is calculated as the average daily electricity usage in a month, over the period July 2015-June 2016. All specifications include customer fixed effects and month by year fixed effects.

Table C.5: The impact of the program on environmental self-identity, robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var: Environmental self-identity index	Open eHER		Open eHER before survey		Trimmed pre-treat usage	
Program	0.023	-0.019	0.029	-0.008	0.030	-0.011
	(0.038)	(0.048)	(0.038)	(0.048)	(0.037)	(0.047)
Program*High env values		0.127*		0.111		0.123*
		(0.076)		(0.076)		(0.074)
High env values	0.800***	0.699***	0.783***	0.697***	0.801***	0.699***
	(0.029)	(0.069)	(0.030)	(0.069)	(0.026)	(0.069)
Pre-treat usage	-0.006	-0.006	-0.007	-0.007	-0.006	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Constant	-0.748***	-0.633***	-0.786***	-0.753***	-0.803***	-0.766***
	(0.231)	(0.230)	(0.245)	(0.248)	(0.229)	(0.232)
Observations	3,740	3,740	3,485	3,485	4,347	4,347
R-squared	0.165	0.165	0.160	0.160	0.167	0.168
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. OLS estimates. Controls include a dummy for female respondent, age, four dummies for different levels of education, two dummies for geographical location, dummies for house ownership and less than five years tenure.

Table C.6: Impact of the environmental prime on electricity usage, main and heterogeneous effects

	(1)	(2)	(3)	(4)	(5)
	Daily electricity usage, KWh/day				
DD1	-0.073*	0.520***	-0.060	0.569***	0.247***
	(0.043)	(0.075)	(0.051)	(0.102)	(0.074)
DD1*Pre-treat usage		-0.092***		-0.094***	
		(0.012)		(0.016)	
DD1*High env values			-0.046		
			(0.062)		
DD1*Pre-treat use*High pro-env beh				-0.000	
				(0.024)	
DD1*High pro-env behav				-0.089	-0.051
				(0.139)	(0.091)
DD1*Q2 Pre-treat usage					-0.097
					(0.094)
DD1*Q3 Pre-treat usage					-0.285***
					(0.094)
DD1*Q4 Pre-treat usage					-0.786***
					(0.130)
DD1*Q2 Pre-treat use*High pro-env beh					-0.034
					(0.131)
DD1*Q3 Pre-treat use*High pro-env beh					-0.081
					(0.139)
DD1*Q4 Pre-treat use*High pro-env beh					0.046
					(0.202)
DD2	-0.163	0.054	-0.173	0.298	-0.147
	(0.114)	(0.176)	(0.127)	(0.234)	(0.145)
DD2*Pre-treat usage		-0.034		-0.064*	
		(0.027)		(0.038)	
DD2*High env values			0.002		
			(0.118)		
DD2*Pre-treat use*High pro-env beh				0.071	
				(0.051)	
DD2*High pro-env behav				-0.547*	-0.044
				(0.280)	(0.155)
DD2*Q2 Pre-treat usage					0.235
					(0.149)
DD2*Q3 Pre-treat usage					0.141
					(0.168)
DD2*Q34 Pre-treat usage					-0.318
					(0.284)
DD2*Q2 Pre-treat use*High pro-env beh					-0.109
					(0.253)
DD2*Q3 Pre-treat use*High pro-env beh					-0.297
					(0.247)
DD2*Q4 Pre-treat use*High pro-env beh					0.309
					(0.393)

cont.

	(1)	(2)	(3)	(4)	(5)
PP1	0.033	-0.077	-0.008	-0.207	0.060
	(0.044)	(0.104)	(0.056)	(0.148)	(0.105)
PP1*Pre-treat usage		0.018		0.037	
		(0.018)		(0.024)	
PP1*High env values			0.121		
			(0.088)		
PP1*Pre-treat use*High pro-env beh				-0.047	
				(0.036)	
PP1*High pro-env behav				0.296	0.046
				(0.208)	(0.133)
PP1*Q2 Pre-treat usage					-0.161
					(0.137)
PP1*Q3 Pre-treat usage					0.012
					(0.143)
PP1*Q4 Pre-treat usage					0.097
					(0.183)
PP1*Q2 Pre-treat use*High pro-env beh					0.007
					(0.185)
PP1*Q3 Pre-treat use*High pro-env beh					-0.110
					(0.210)
PP1*Q4 Pre-treat use*High pro-env beh					-0.231
					(0.280)
PP2	0.110	-0.078	0.102	-0.301	0.265
	(0.081)	(0.204)	(0.106)	(0.301)	(0.190)
PP2*Pre-treat usage		0.029		0.075	
		(0.036)		(0.050)	
PP2*High env values			0.039		
			(0.162)		
PP2*Pre-treat use*High pro-env beh				-0.124*	
				(0.070)	
PP2*High pro-env behav				0.576	-0.088
				(0.396)	(0.240)
PP2*Q2 Pre-treat usage					-0.390
					(0.239)
PP2*Q3 Pre-treat usage					-0.087
					(0.258)
PP2*Q4 Pre-treat usage					0.235
					(0.377)

	cont.				
	(1)	(2)	(3)	(4)	(5)
PP2*Q2 Pre-treat use*High pro-env beh					0.044
					(0.346)
PP2*Q3 Pre-treat use*High pro-env beh					-0.023
					(0.366)
PP2*Q4 Pre-treat use*High pro-env beh					-0.675
					(0.530)
Constant	7.921***	7.920***	7.928***	7.919***	7.919***
	(0.071)	(0.070)	(0.071)	(0.070)	(0.070)
Observations	121,638	121,638	120,804	121,638	121,638
R-squared	0.083	0.087	0.084	0.088	0.087
Number of customers	3,814	3,814	3,787	3,814	3,814

Notes: Standard errors clustered at the customer level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Observations are months. Reference period for the analysis: July 2015- March 2018. Pre-treat consumption is calculated as the average daily electricity consumption in a month, over the period July 2015- June 2016. All specifications include customer fixed effects and month by year fixed effects. F-test on the joint significance of the coefficients of the heterogeneous effects of $DD2$ and $PP2$ with respect to pro-environmental behaviour and pre-treatment usage from Column (4) is F(4, 3813) = 3.43 (p-value=0.008) and Column (5) is F(8, 3813) = 1.81 (p-value=0.07).

Table C.7: Impact of the environmental prime on electricity usage, robustness checks

Dep Var: Daily electricity usage, KWh/day	(1) Winsorized pre-treat usage	(2) Top pro-environmental behaviour
DD1	0.575***	0.579***
	(0.102)	(0.084)
DD1*Pre-treat usage	-0.095***	-0.097***
	(0.016)	(0.013)
DD1*High pro-env behav	-0.093	-0.215
	(0.140)	(0.179)
DD1*Pre-treat usage*High pro-env behav	0.001	0.018
	(0.025)	(0.036)
DD2	0.223	0.272
	(0.228)	(0.197)
DD2*Pre-treat usage	-0.053	-0.060**
	(0.038)	(0.030)
DD2*High pro-env behav	-0.473*	-0.990***
	(0.277)	(0.308)
DD2*Pre-treat usage*High pro-env behav	0.060	0.144**
	(0.051)	(0.066)
PP1	-0.183	-0.159
	(0.144)	(0.120)
PP1*Pre-treat usage	0.034	0.031
	(0.023)	(0.020)
PP1*High pro-env behav	0.286	0.338
	(0.205)	(0.251)
PP1*Pre-treat usage*High pro-env behav	-0.047	-0.059
	(0.036)	(0.049)
PP2	-0.192	-0.240
	(0.294)	(0.242)
PP2*Pre-treat usage	0.059	0.058
	(0.050)	(0.041)
PP2*High pro-env behav	0.506	0.844*
	(0.389)	(0.432)
PP2*Pre-treat usage*High pro-env behav	-0.115	-0.172**
	(0.070)	(0.087)
Constant	7.919***	7.919***
	(0.070)	(0.070)
Observations	121,638	121,638
R-squared	0.088	0.088
Number of customers	3,814	3,814

Notes: Standard errors clustered at the customer level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Observations are months. Reference period for the analysis: July 2015- March 2018. Pre-treat consumption is calculated as the average daily electricity consumption in a month, over the period July 2015- June 2016. P1 and P2 refer to Period 1 and Period 2 described in equation 4. All specifications include customer fixed effects and month by year fixed effects.

Table C.8: Manipulation check, summary statistics and sample balance

	(1) Control	(2) Identity	(3) Values	(4) Experience	(5) Disease	(6) F-stat
N. of observations	196	195	196	196	193	
Panel A: Controls						
Female	0.617	0.667	0.587	0.592	0.596	0.92
Age	35.418	34.703	34.107	35.490	34.399	0.63
High education	0.544	0.621	0.619	0.526	0.576	1.478
Some experience with PA	0.531	0.564	0.582	0.610	0.544	1.48
High environmental values	0.566	0.471	0.459	0.520	0.476	1.54
Panel B: Outcomes						
Env self-identity index (1-7)	4.836	4.974	4.673	4.933	4.699	1.56
Intention to save energy (1-10)	7.730	8.010	7.582	7.872	7.684	1.59
Donantion (pence)	14.490	24.718	17.755	20.306	19.793	2.75**

Note: The last Column reports the F-stat test for the joint significance of the treatment coefficients in a regression where the observable characteristics are the dependent variables.

Table C.9: Manipulation check, regression

	(1) Env self-identity index	(2) Intention to save energy	(3) Donation
Identity	0.265**	0.411**	10.751***
	(0.128)	(0.172)	(3.169)
Values	-0.003	0.021	3.977
	(0.127)	(0.168)	(2.862)
Experience	0.185	0.236	6.565**
	(0.129)	(0.172)	(2.932)
Disease	-0.005	0.099	5.939**
	(0.129)	(0.168)	(2.962)
Constant	3.388***	6.058***	17.435***
	(0.188)	(0.271)	(4.358)
Observations	970	970	970
R-squared	0.300	0.197	0.040
Controls	Yes	Yes	Yes

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All models are estimated with OLS. Controls include a dummy for female respondent, age, dummy for high education (BA or higher), some experience with the work platform (dummy), environmental values above the median (dummy).