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Heterogeneity of social information programs: the role of identity and values

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Heterogeneity of social information programs: the role of identity and values[☆]

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Abstract

Social information programs are increasingly used to nudge behavioral change, but still relatively little is known about sources of heterogeneity in their impact. This paper examines whether individual values are associated with heterogeneous responses to social information. Using data from a large field experiment on household energy conservation, we combine electricity metering and survey data to study how environmental values affect the impact of the program. We then leverage the role of values by augmenting social information messages with an environmental self-identity prime. Results show that values are important drivers of heterogeneity. Moreover, enhancing social information by making environmental self-identity more salient boosts the social information impact, but only among individuals who acted pro-environmentally in the past.

Keywords: Energy consumption, Environmental Identity, Social norms, RCT
JEL classification: D91, Q49

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1. Introduction

Social information programs are increasingly used by policy makers to nudge behavioral change. Their popularity is attributable at least in part to existing evidence on their ability to influence behavior in a variety of settings, from energy and water consumption (Allcott et al., 2011; Ayres et al., 2013; Ferraro and Price, 2013; Ferraro et al., 2011; Ferraro and Miranda, 2013; Brent et al., 2015), contributions to charitable causes (Frey and Meier, 2004; Shang and Croson, 2009), voting (Gerber and Rogers, 2009) and financial decisions (Beshears et al., 2015). Despite growing interest in social comparison research, several open questions remain.

In particular, relatively little is known about the sources of heterogeneity in the effect of social information programs. Behavioral interventions are known to generate a wide range of responses. However, only a few studies explore differential responses to social information, based on baseline behavior (List et al., 2017; Bhanot, 2017; Ferraro and Miranda, 2013; Allcott, 2011; Ferraro and Price, 2013), political preferences (Costa and Kahn, 2013) or beliefs on the behavior targeted by the intervention (Byrne et al., 2018). All these studies find significant differences in the impact of social information depending on individual traits, and thus highlight the importance of research investigating how and why social information encourages behavior change.

This paper builds on this recent literature to examine the role played by one novel source of heterogeneity: individual values. Values are antecedents of preferences, intentions, and behavior and represent guiding principles in everyone's life (Schwartz, 1992). Values determine behavior and therefore represent a crucial source of heterogeneity in response. However, despite their important role in guiding behavior, the differential response to social information with respect to values has rarely been studied.

Because of heterogeneity, targeting the characteristics of program recipients becomes an important policy objective. An optimal targeting ensures that the effect of an information program is maximized. In this paper we wish to understand not only how social information can be effectively targeted, but also how social information programs can be designed to maximize their influence on behavior. Namely, if values matter, communication itself can be designed so as to strengthen their influence on the desired behavioral change. To this purpose, we exploit the correlation between values, which are considered as stable traits, and identity, which is the label used to describe yourself (van der Werff et al., 2014b). Given that identity can be made more salient through messages, we test whether adding an identity prime to social information makes values more effective.

Like other studies in the social information literature, we evaluate a program providing energy utility customers with information on their energy use, relative to that of their neighbors (Allcott, 2011; Allcott and Rogers, 2014). Such information is included in a Home Energy Report, which is distributed to customers via email (eHER). While associated with private savings, energy conservation also generates positive externalities in terms of environmental quality and climate change. We therefore study the role of environmental values in shaping response to the program. We also augment the message sent by the utility with an environmental self-identity prime. van der Werff et al. (2013) define environmental self-identity as the extent to which one sees oneself as a type of person who acts environmentally-friendly. Past environmental behavior is a driver of environmental self-identity, which in turn is related to future environmental behavior, such as energy conservation (van der Werff et al., 2014b). Drawing from this literature, we manipulate the contents of the home energy report in order to make past pro-environmental actions salient.

The analysis of the field experiment combines data from a randomized program on a large pool of customers from a European electricity utility, with survey data collected from a sub-sample of the program recipients and control group. Administrative data detail whether a person receives the social information, the frequency and type of information feedback, customers' engagement with it and energy consumption. Survey data include measures of environmental values, environmental self-identity and other household characteristics.

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.

2013 for comprehensive reviews), and the first papers looking at sources of heterogeneity in their impact also focus on this setting. It is thus interesting to assess the influence of values within this broader literature.[1] Third, it offers good data on actual, rather than self-reported, behavioral outcomes, namely monthly energy use.

This paper has two main findings. First, we provide evidence of heterogeneity in the impact of social information with respect to values. Environmental values are positively correlated with curtailment in energy use among program recipients. In particular, individuals with strong environmental values and high baseline energy consumption reduce consumption significantly more than other customers as a result of the intervention. We confirm in our setting 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).

Second, we address the role of values and how to leverage them in the context of household energy conservation. We find that augmenting social information with a message that makes environmental self-identity more salient boosts its impact, but only among individuals who effectively behaved pro-environmentally in the past. This is possibly due to the nature of the identity prime, which prompts people to remember past pro-environmental actions.

Our study makes three main contributions to the literature. First, as already mentioned above, we add to a small and recent literature on the heterogeneous effects of social information. The majority of existing papers mainly consider baseline behaviour as the unique source of heteroegenity (Allcott, 2011; List et al., 2017; Bhanot, 2017; Ferraro and Miranda, 2013; Ferraro and Price, 2013). On the contrary, Costa and Kahn (2013) analyse heterogeneity with respect to political preference and Byrne et al. (2018) with respect to beliefs on pre-treatment energy use. Similarly to what we do in our paper, Byrne et al. (2018) retrieve this information from a baseline survey. With respect to other studies, we examine a source of heterogeneity rooted in individuals' preferences, and that can be inter-

[1] This literature is almost exclusively based on US samples. Our study, to the best of our knowledge, is one of the first to investigate the impact of a social information program in a European country, namely Italy.

preted as a mechanism underlying other behaviors found to be associated with differences in program impacts, such as information acquisition and political affiliation. Our study thus fills a gap in the literature by investigating a fundamental mechanism underlying the impact of social information programs.

Second, even if values are deeply stable, we show how to leverage them through the content of communication. In doing so, we contribute to the psychological literature on values and identity (Schwartz, 1992; Dunlap and Grieneeks, 1983; Groot and Steg, 2008; Steg et al., 2014a). Previous studies that adopt the same self-identity prime mainly rely on 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). Moreover, an open question in psychology is whether past moral deeds are more likely to incentivize behavioral 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). Our study provides the first evidence, to the best of our knowledge, on the sign of spillover effects from priming past behavior on real world costly actions and a large sample.

Third, in the experiment we combine different nudges, by augmenting the standard social information message with the self-identity prime. While behavioral nudges are increasingly studied and adopted as policy tools, little is known about the combined effect of different interventions. As these tools become more popular, individuals are likely to be exposed to multiple behavioral policies, so this novel feature is timely. Our evidence indicates that the predicted effect of a nudge in a natural setting may be over-estimated if it is based on evidence from controlled experiments where the nudge is administered in isolation.

The remainder of the paper is organized as follows. Section 2 provides details of setting and design of the RCT. Section 3 discusses the RCT data and results in detail. Section 4 concludes.

2. Setting and Design

2.1. Setting

Once a monopoly, the Italian energy retail market was liberalized in 1999. The liberalization process has been slow, with over 60 per cent of domestic customers still buying their electricity at the conditions set by the public authority for energy as of 2017 (Arera, 2018). The market will be completely liberalized in 2019, when everyone has to purchase electricity from the free market. Another major change in the market consists in the replacement, started in 2018, of first generation smart meters, transmitting monthly data on energy use, with second generation ones, which will be able to provide real-time feedback on energy use directly to customers.

In anticipation of these changes, utilities have been engaged on two fronts. On one hand, they have been striving to diversify their offers and complement energy provision with other services, in an effort to attract new customers and retain existing ones. On the other hand, they have been trying to digitalize their customers, so as to be able to deliver smart services to them at lower cost. One such service is the provision of information to customers on their energy consumption. We partner with a large energy and gas utility to evaluate one of the first social information programs implemented in the Italian energy retail market.

2.2. Social information program

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. Eligible customers are randomly allocated to treatment and control groups through a randomization algorithm (minmax t-statistic) which conducts 1000 randomizations and selects the most balanced draw, along baseline consumption and geographic location (Bruhn and McKenzie, 2009). 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 to two years of valid pre-experiment energy consumption data, and satisfy some additional technical conditions.[2]

[2] 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

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.

The main goal of the program is to increase loyalty, digitalization and engagement of customers, whereas energy efficiency goals are secondary.[3] 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).[4] It consists primarily of the Home Energy Report, which customers in the treatment group receive by email (eHER) every two months.[5] The eHER features a static neighbor comparison, whereby one's own previous month consumption is compared with that of 100 similar homes nearby and of the 20 most efficient similar homes nearby. Besides information on neighbors' behavior and on how their own compares with it, i.e. the descriptive norms, the eHER contains normative feedback based on the recipients' efficiency. Customers receive three, two or one thumb up, depending on how their consumption compares to that of the top 20 neighbors or of the average neighbor.[6]

By clicking on the email, customers are directed to their personal page on the utility's website, where they can consult their past bills, see a dynamic neighbor comparison, as well as the static one, and energy saving tips, among other features. The web portal is available to all customers, regardless of being in the treatment or control group, as long as

per customer per location.

[3]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).

[4]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.

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

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

they are registered to the website. As such, the experimental design relies on an encouragement design.

In order to evaluate the role of environmental values on response to the eHER, and to identify a way to leverage and strengthen their effect, we augmented the eHER with a message priming environmental self-identity.

This design choice is motivated by two considerations. First, data from the survey, that we conducted with a sub-sample of utility customers, confirm the strong correlation between environmental values and environmental identity, also found in studies in psychology (van der Werff et al., 2013). Second, survey data also reveal the strong positive relationship between environmental values and identity on one hand, and pro-environmental behavior, including energy consumption and response to the eHER, on the other. We will describe the survey and discuss these results in detail below. Here it suffices to say that we wanted to test whether priming environmental self-identity could make the eHER more or less effective, given its positive correlation with stable traits – values- that guide pro-environmental behavior.

The eHER contains a section labeled the "marketing module". The marketing module is a space, 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 the marketing module. In particular, customers were randomized to receive one of the following messages:[7]

- 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.

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

The self-identity prime reminds individuals of past environmental actions. Theory and evidence from psychology explains the impact of the prime on environmental self-identity (van der Werff et al., 2014b): 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, it can also generate a moral credit (Sachdeva et al., 2009), which can lead to compensatory reasoning and actions. Here we follow van der Werff et al. (2014b,a), and select the set of easy actions listed for the self-identity prime above, as most customers would answer affirmatively to the questions in the message.

The treatment message was informed by the results of an online experiment that we ran to test the effectiveness of different identity primes. The selected one was the most effective in that context, in terms of both boosting environmental self-identity, intention to save energy as well as encouraging subsequent pro-environmental behavior. The online experiment involved almost 1,000 participants and included an incentivized pro-environmental decision (donation to an environmental charity). We tested 4 treatments leveraging different mechanisms, which could motivate pro-environmental behavior by making environmental identity salient. We further used the online experiment to perform a manipulation check on the prime, in order to verify that the prime actually activates the specific mental concept that it intends to address.

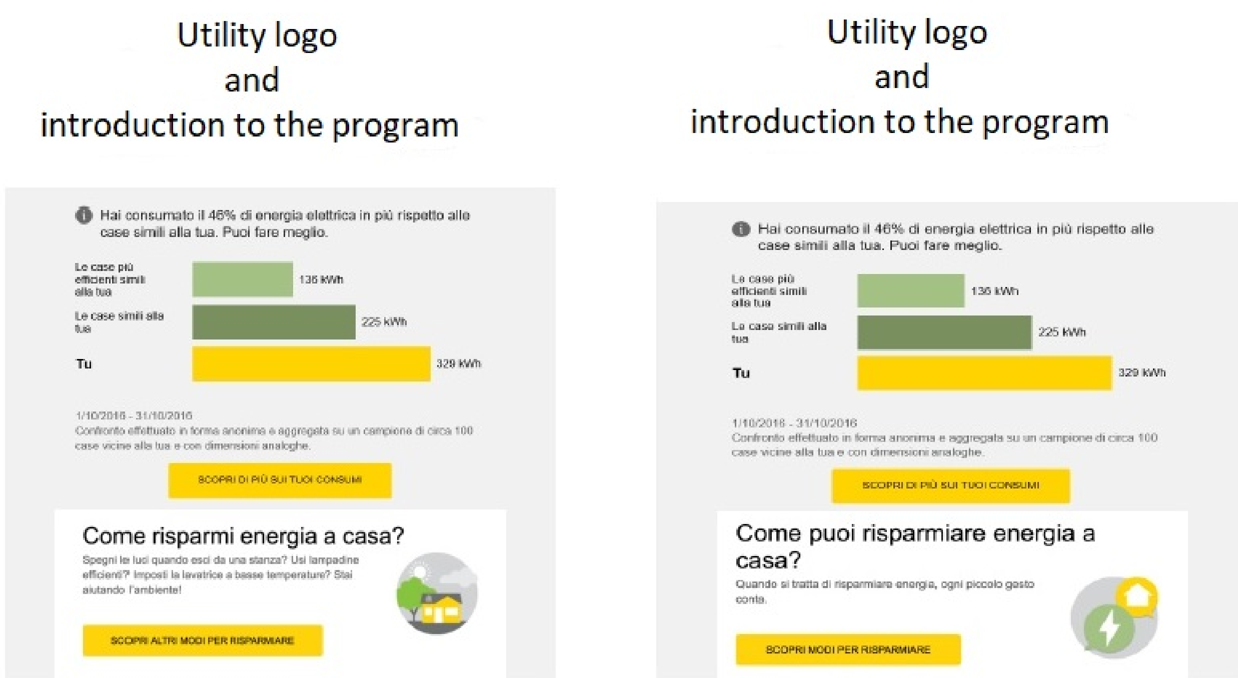

Figure 1: Samples of eHER sent on November 2017 containing environmental prime (left) and control message (right) in the marketing module area.

All the details about the online experiment and its results are presented in the appendix B.

2.3. *Survey*

We collected data from a sub-sample of program participants through an online survey conducted between April and June 2017. We did not conduct the survey at baseline. We collected data 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 it can be influenced by the program. The assumption of no treatment effects on values is consistent with a vast literature that reports that environmental values are stable in everyone's life (van der Werff et al., 2013). 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., 2014b). 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., 2013). 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 per cent, the final sample amounts to 4,385 customers, 3,595 from the treatment and 790 from the control group of the social information program.

Among treated subjects still with the utility as of November 2017, 3,090 were assigned to receive the eHER in November 2017 and thus participated in our test 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.

Two important potential issues originating from combining the survey and the program data for the analysis are attrition and sample selection bias. We lost 571 respondents (505 treated and 66 control) to attrition between May and November. Attrition may be problematic for identification if it is correlated with the treatment status. However, as pointed out in appendix A, 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.

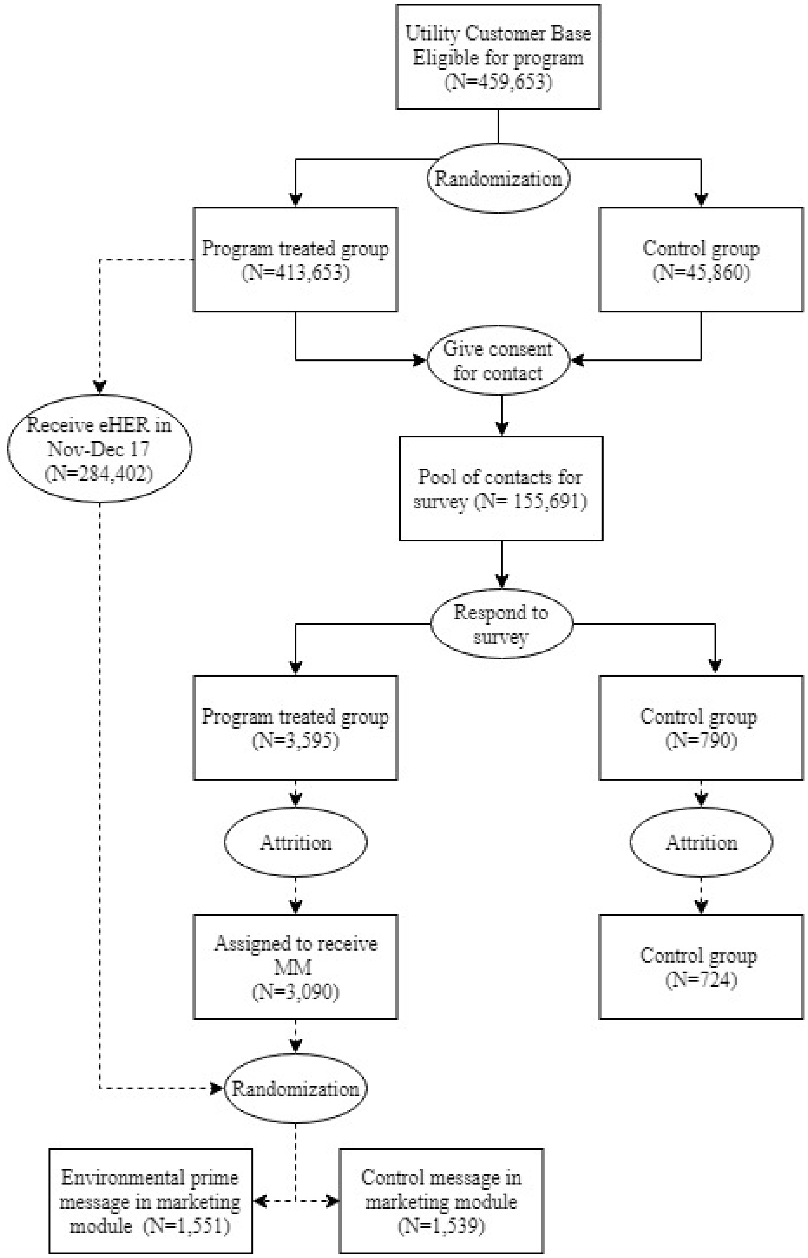

Figure 2: Sample flow diagram

The effort in making the survey as representative as possible guarantees that the heterogeneous effects of the program along with information collected through the survey can be generalized to the full sample of program customers.

3. Results

This section discusses the results from the field experiment. We first describe the dataset used in the analysis. We then discuss in details the impact of the program and of the self-identity prime test.

3.1. Data and descriptive statistics

The dataset for our empirical analysis results from the combination of the survey data, described in Section 2.3, and the administrative data we received from the utility. We discuss these data in more detail here. We have access to 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. We observe variation in the start date of the program for the different customers. Namely, customers can be divided among those who received their first communication in July 2016 (43%), October 2016 (34%) and December 2016 (23%).

When we check for balance, we need to consider the entire sample of customers who participated in our survey in May 2017, and the subset of those who were still customers of our partner utility at the time of the marketing module test in November. Moreover, we need to show whether the self-identity prime treatment is balanced across program participants in November 2017.

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. 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 kWh.[8] We classify about 34 per cent of customers as having high environmental values. Crucially, values do not significantly differ by treatment status, confirming our assumption on their stability and providing foundations for our identification strategy. Our respondents are predominantly male, over 50, home owners, with a high school or university degree, and from Northern Italy. Treated households are significantly less likely to live in the North and more likely to live in the South and Islands than control households. Table 1, Columns (4) to (6), shows that a similar pattern holds if we consider the November 2017 sub-sample. In Columns (1) to (3) of 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. The use of individual fixed-effects in the empirical analysis should prevent these imbalances from affecting the results.

[8] As a contextual factor, consider that the sample of American households in Allcott and Rogers (2014) consumes on average 30.3 KWh per day. In Italy, consumption is much lower, also because electricity is rarely used for heating.

Table 1: The program, summary statistics and sample balance

	(1) Program	(2) Control	(3) Difference	(4) Assigned to receive MM	(5) Control	(6) Difference
N. of observations	3595	790		3090	724	
Panel A: Controls						
Average pre-treat usage	6.289	6.455	-0.167	6.299	6.521	-0.222
Env. values above median	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 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.

3.2. *Empirical analysis and results*

3.2.1. *Program impact*

The first objective of the analysis is the impact evaluation of the eHER program. To meet this objective, we estimate the intention to treat effect of the eHER on consumption. The empirical analysis is conducted on a sub-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 over the billing period in the month t. DD 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. As in Allcott (2011) and Allcott and Rogers (2014), the treatment can be interpreted as "receiving reports or opting out". This is because some households can choose to opt out of the program. We keep these customers in the sample for the analysis, even if they do not receive reports anymore, to maintain the balance between treatment and control group. By doing that, we are likely to underestimate the effect of the program on the group of customers initially assigned to receive the eHER.[9]

[9] More details on the sub-sample who opted out from the program and its characteristics can be found in appendix A.

Table 2: Environmental prime in the marketing module, 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
Env. values above median	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 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.

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).

In Column (1) of Table 3, we present the results from estimating Equation (1). The average treatment effect is negative but it is not statistically significant. The point estimate is -0.060. Two motivations can explain the null effect of the treatment. First, it could be related to low power of the experimental analysis. The sample of customers used in the analysis is a subset of the full sample of program recipients.[10] Second, the estimated effect of Table 3 depends on the average response of different types of customers, but we know from previous research that the effect of similar programs varies not only over time but also across customers.

As a further layer of analysis, it would be interesting to assess which activities represent the source of energy savings, whether investments in efficient appliances or day-to-day change in behavior. However, with the available data, we are not able to give support to any of the two hypotheses. For example, using the survey data, we find that treated customers are as likely as customers in the control group to purchase efficient lightbulbs. However, there might be many types of energy efficient investments that we did not measure through the survey, that underlie these changes in energy use.

3.2.2. Heterogeneous effects of the program

A second objective of the analysis is to assess the heterogeneous effects of the program along two dimensions: pre-treatment energy consumption and baseline environmental values. This analysis aims to answer the question on which customers' characteristics make them more likely to respond to the eHER communication.[11]

The first source of heterogeneity that we examine is pre-treatment energy consumption. The cost for conservation is higher for low-usage households, because they are likely to

[10] In Bonan et al. (2018), the authors conduct an impact evaluation of the program using the whole sample of customers and find a point estimate of -0.045, significant at 5% confidence level.

[11] Consistent with our initial intentions, the Pre-Analysis Plan specified a large set of potential sources of heterogeneity to be tested in the analysis. However, the decision to focus on environmental values in this paper implies that we only tested for heterogeneous treatment effects along the dimensions discussed in this sub-section.

have implemented saving actions in the past, and thus have smaller room for improving their efficiency. Moreover, doing so would probably require more costly investments, if low cost ones have already been implemented. This evidence is confirmed in Byrne et al. (2018); List et al. (2017); Allcott (2011) for electricity and Ferraro and Price (2013); Bhanot (2017); Ferraro and Miranda (2013) for water consumption, where high intensity users are more responsive than low ones to the program. The null average treatment effect presented in Table 3, Column (1) could, therefore, simply mask important differences in reactions between high and low-usage families.

To test this hypothesis we estimate Equation (1), allowing for some heterogeneous effects. In particular, we interact the *DD* variable with a continuous measure for consumption in the year preceding the launch of the program (July 2015-June 2016). Column (2) of Table 3 reports the coefficient of this interaction variable, which is negative and statistically significant. The higher the baseline consumption, the greater the energy curbing effect of the eHER. We also create a dummy equal to one for households with baseline energy usage above the median and interact it with the *DD* variable. Column (3) presents the estimation results.

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

	(1)	(2)	(3)	(4)	(5)
	Daily electricity usage, KWh/day				
DD	-0.060	0.382***	0.118***	-0.069	0.310***
	(0.039)	(0.063)	(0.040)	(0.043)	(0.077)
DD*Pre-treat usage		-0.069***			-0.058***
		(0.009)			(0.012)
DD*Above median pre-treat usage			-0.366***		
			(0.045)		
DD * Above median env. values				0.019	0.221**
				(0.046)	(0.107)
DD*Pre-treat usage*Above median env. values					-0.035*
					(0.018)
Constant	7.912***	7.912***	7.912***	7.920***	7.919***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
Observations	136,359	136,359	136,359	135,478	135,478
R-squared	0.082	0.084	0.083	0.082	0.085
Number of customers	4,385	4,385	4,385	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 the period July 2015- June 2016. All specifications include customer fixed effects and month by year fixed effects.

Consistent with the previous findings, households in the upper percentile respond to the eHER by curbing consumption. The conditional average treatment effect for households in the top 50 per cent of the baseline usage distribution is negative and statistically significant. Among these households, treatment reduces daily consumption by 0.25 kWh. The average daily consumption is 10.87 kWh for households above median baseline consumption. The estimated conditional average treatment effect suggests that high usage households reduce daily consumption by 2.3 per cent, which is in line with the findings reported in Byrne et al. (2018); List et al. (2017); Allcott (2011). Conversely, families in the bottom percentiles increase consumption, as indicated by the positive and statistically significant coefficient of the variable *DD*. As in Byrne et al. (2018); Bhanot (2017), these findings provide some evidence of a boomerang effect, whereby the eHER induces low-usage households to significantly increase usage (Schultz et al., 2007). The injunctive norm, which conveys social approval within the eHER through a thumb up image, is not able to counterbalance this boomerang effect in this sample of customers.

As a second dimension of heterogeneity, we want to test if the response to peer comparison depends on one's environmental values. Do individuals, who endorse high environmental values, respond more strongly to the treatment? Or does the opposite occur? On the one hand, curbing energy is harder if one already made large efforts in reducing energy consumption. This is likely the case for individuals who hold high environmental values. On the other hand, the information delivered through the eHER is effective when it resonates with people's central values (Steg et al., 2015). Social information can thus be more effective among those who strongly care about the environment, if it makes them more inclined to act on their 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 interact the *DD* variable with a dummy for above median environmental values. Note 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 coefficient of this interaction is reported in Column (4) of Table 3 and is statistically not significant. This indicates that people who endorse high environmental values display a response to the treatment similar to that of people with low environmental values. The opposing influence of the two mechanisms described above can justify the absence of an effect, on average. Moreover, in order to observe any treatment effect, there needs to be both the willingness and the possibility of reducing energy use. We therefore expect households with high environmental values and high baseline consumption to be the most reactive to the information contained in the eHER. We thus examine the interaction between baseline consumption and environmental values. We interact the variable *DD* with average pre-treatment energy consumption and high environmental values.

We find that the coefficient of the double interaction is negative and statistically significant. The estimated parameter is reported in Column (5) of Table 3. We also plot the treatment effect computed for the different values of pre-treatment consumption and for people with high (red line) and low (black line) environmental values, along with 95% confidence intervals, in Figure 3. Treatment effects are positive for low levels of baseline consumption and turn negative after daily pre-treatment consumption reaches 6 kWh, for both high and low environmental values. After this point, the response to peer comparison is much steeper for people with high environmental values than for people with low environmental values. For instance, a person with baseline daily consumption of 10 KWh, who belongs to the 9th decile of the distribution, reduces energy consumption by 0.40 and 0.27 kWh if she/he endorses high and low environmental values, respectively. This result suggests 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, for high pre-consumption, which allows larger margins of adjustment, high environmental values boost the effectiveness of peer comparison.

We perform different robustness checks to the main specification of Table 3. First, as in Allcott (2011) and Allcott and Rogers (2014), our treatment indicator identifies all customers who are sent the eHER, regardless of whether they open or not the reports. Since within our data we can distinguish customers who never opened the eHER, we can perform the analysis after excluding them from the sample. We are aware that this opens our results to concerns about endogeneity of engagement with the eHER. Nevertheless, we believe that showing the effect of the treatment on customers who actually engage with it is interesting, even if the random allocation of the treatment so defined is not guaranteed. Results are reported in Table C.1. As indicated in Columns (1) and (2), the significance of the coefficients remains unaltered, while the magnitude of the treatment effect is larger in this sub-sample. Second, we exclude possible outliers in the pre-treatment consumption variable, by replacing the values in the bottom 1 per cent and top 99 per cent with values just above/below (winsorizing). Results are in Columns (3) and (4) of Table C.1.

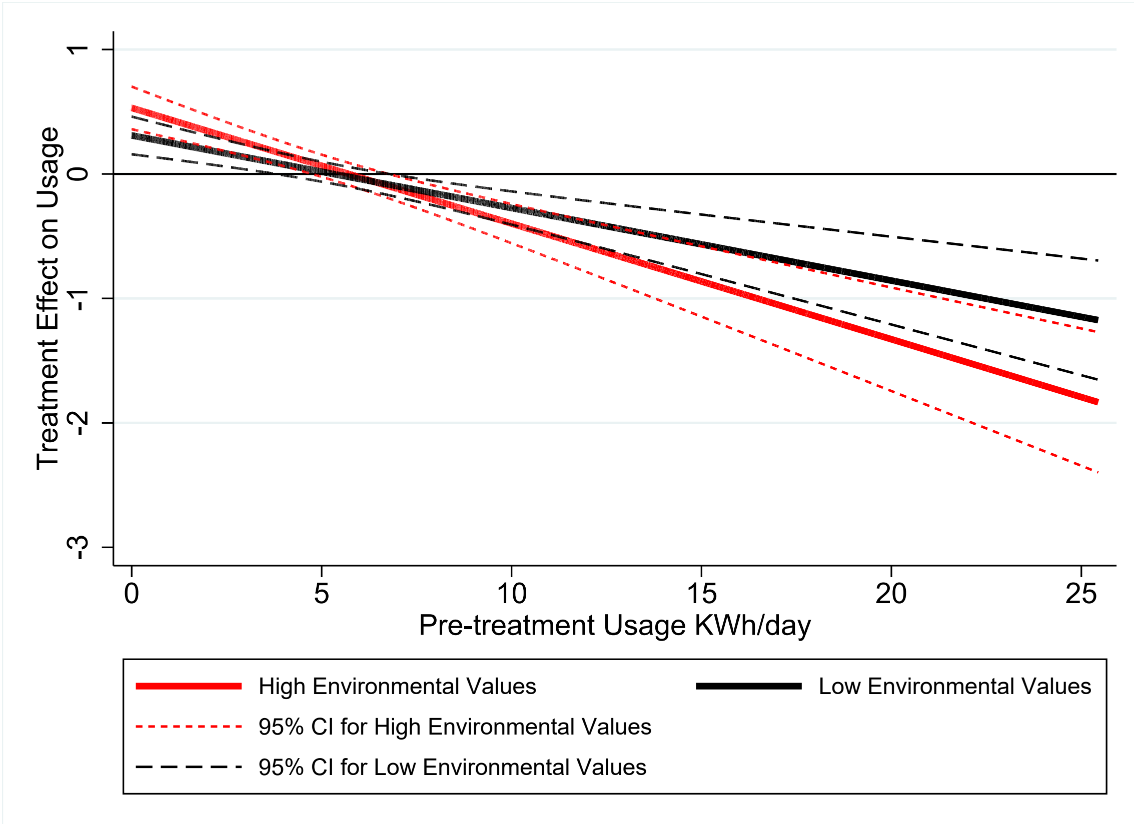

Figure 3: Heterogeneous effects of the program on electrcity usage, by pre-treatment usage and environmental values

The coefficient of the triple interaction reduces slightly in magnitude, but it is still statistically significant at conventional levels. 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. Given that we do not observe differential attrition between treated and control customers, as pointed out in appendix A, excluding customers who leave the utility does not affect the results, which are qualitatively similar to the ones shown in Table 3, as shown in Columns (5) and (6).

3.2.3. A possible mechanism

Why do environmental values amplify the impact of social information in the context of energy use? Our hypothesis is that the information contained in the eHER makes people focus on the consequences, in terms of energy use, of their own actions. This is similar to Allcott (2011), who suggests that some of the reports' effects act through drawing attention to or increasing the moral cost of energy use. This hypothesis produces two main testable implications. First, if the eHER affects behavior through this mechanism, its effectiveness should be higher among individuals with strong environmental values: the higher their environmental values, the stronger the connection individuals make between energy use and the environment. Second, if the eHER works by increasing attention to the moral cost of energy use, then this salience-inducing effect should vary, namely weaken, over time.

This sub-section tests these two implications. We test if the communication received through the eHER makes environmental considerations more salient, and examine sources of heterogeneity in this effect consistent with the two implications. We measure the salience of environmental considerations using data on environmental self-identity among treated and control customers. We focus on environmental self-identity because, contrary to values, which are stable traits, identity can be made more salient by contextual features. Moreover, environmental self-identity and values are positively correlated, as we will discuss below.

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

$$y_i = \beta_0 + \beta_1 Program_i + X_i + \varepsilon_i \tag{2}$$

where y is environmental self-identity, *Program* is the 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, lengths 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 add a dummy for environmental values above the median.

Results are presented in Table 4. The coefficient of the treatment variable is positive but not statistically significant, indicating that, on average, the treatment does not influence environmental self-identity. This result emerges in specifications without and with socio-demographic controls (Columns (1) and (2), respectively).

We test the first implication of our hypothesis - that the impact of the eHER should be stronger among individuals with stronger environmental values - by interacting the treatment variable with a dummy for above median environmental values. The coefficient of the interaction term is positive and statistically significant (Column (3)). While the eHER does not alter the environmental self-identity among those with low environmental values, it does increase it if customers care a lot about the environment. For instance, in a person with high values, the treatment increases environmental self-identity by 0.11 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 a decrease in daily consumption, in particular among those with high environmental values.

In order to test the second implication of our hypothesis, that the increased salience of environmental self-identity induced by the eHER is short-lived, 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 in which we measured her environmental self-identity. Moreover, 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. 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. Specifically, drawing from the forgetting curve hypothesis (Murre and Dros, 2015), we apply an exponential decay function to the number of days and multiply the treatment dummy variable by this function.

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*Above median env. values			0.123*	
			(0.074)	
Above median 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.

We find that the effect of this discounted treatment is positive and statistically significant, as reported in Column (4) of Table 4.[12] 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, but they backslide after a few weeks.

Table 4 shows additional findings. In particular, environmental values are an important predictor of environmental self-identity. Individuals with above median score of environmental values more likely think that acting pro-environmentally is an important part of who they are. 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). This relationship ensures that the influence of environmental self-identity on pro-environmental actions is not short-lived, and could explain the persistence of the effect of social information in the domain of energy conservation (Brandon et al., 2017). Finally, we find that the higher pre-treatment consumption is, the lower the importance of acting pro-environmentally is, although the coefficient is not statistically significant.

We conduct some robustness checks, whose results are presented in Table C.2 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.

3.2.4. The environmental identity prime

The evidence provided so far shows that, among customers with high pre-program energy use, high environmental values are associated with a stronger treatment effect. Second, among individuals with high environmental values, the treatment positively influences environmental self-identity. Given that we found that environmental values mat-

[12] 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, while 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).

ter, we now ask whether, by purposefully priming environmental self-identity within the eHER, we can strengthen the effect of values on the desired behavioral change. This is a more direct test of our 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 thus the moral cost of energy use higher.

We therefore evaluate the impact on consumption of augmenting the eHER with the environmental self-identity prime that 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 marketing module (November 2017-March 2018).

We denote by P_m^p an indicator variable for whether month m is in period p:

$$\begin{aligned} Y_{im} = \tau^1 Program_i \times P_m^1 + \tau^2 Program_i \times P_m^2 + \\ \alpha^1 Prime_i \times P_m^1 + \alpha^2 Prime_i \times P_m^2 + \\ h_m + g_i + \varepsilon_{itm} \end{aligned} \tag{3}$$

where $Program_i$ is equal to one for customers in the eHER program treatment group. $Prime_i$ is equal to one for treated customers also receiving the environmental self-identity prime in the marketing module. The first line identifies the main effect of receiving the eHER in the periods before (first term) and after (second term) the prime was sent. The second line identifies the treatment effect for the group of households receiving the eHER augmented with the environmental identity prime, in the post prime period (second term). It also contains a placebo test for the validity of the randomization of treatment (first term). 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 marketing module.

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_m and g_i are month-by-year and individual fixed effects, respectively. Standard errors are clustered at the level of household.

In Table 5 we present the effect of the prime while the whole set of results from estimating Equation 3 is in Table C.3. In Column (1), the coefficient attached to the variable $Prime * P2$ is not statistically significant and indicates that the prime is not able to exert a significant effect on energy conservation.[13] Drawing from the results in the previous sections, we test any heterogeneous effect of the standard program message and the prime message with respect to the same observed characteristics. First, we aim to confirm possible results obtained examining the heterogeneity on the basis of pre-treatment energy consumption. Results are reported in Column (2). We continue to find a non-statistically significant effect of the prime on energy conservation in period 2, as indicated by the coefficients of $Prime * P2$ and $Prime * P2 * Pre - treat\ usage$.

Second, we also tested heterogeneous treatment effects of the identity prime with respect environmental values. We do not find any significant difference in energy use between high and low values individuals. This result contributes to a recent literature suggesting that whether past moral deeds lead to behavioral consistency or to moral licensing depends on how important behavior 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 but 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 exerts no effect on electricity consumption, we consider an additional dimension of heterogeneity. The effectiveness as a self-identity prime of reminding people of past pro-environmental actions is likely to depend on their actual past pro-environmental conduct.

[13] We can only estimate ITT effects, because, while we are able to measure if any report has been opened in a specific month, we do not know which report.

Table 5: Impact of the environmental prime on electricity usage, main and heterogeneous effects

	(1)	(2)	(3)
	Daily electricity usage, KWh/day		
Prime*P2	0.110	-0.078	-0.301
	(0.081)	(0.204)	(0.301)
Prime*P2*Pre-treat cons		0.029	0.075
		(0.036)	(0.050)
Prime*P2*High pro-env behavior			0.576
			(0.396)
Prime*P2*Pre-treat cons*High pro-env behavior			-0.124*
			(0.070)
Constant	7.921***	7.920***	7.919***
	(0.071)	(0.070)	(0.070)
Observations	121,638	121,638	121,638
R-squared	0.083	0.087	0.088
Number of customers	3,814	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.

The prime could have no effect or even backfire if administered to people who hardly engaged in pro-environmental behaviors (van der Werff et al., 2014b). We thus study the heterogeneity of treatment effects based on prior adoption of pro-environmental behavior, measured at the time of the survey.[14] In particular in the survey we asked respondents how often they completely switch off electronic devices, such as TVs or computers and use this variable to measure past pro-environmental behavior. Answers vary from one (never) to five (always). We compute a dummy variable equal to one for answers ranging from 4 to 5. We use this dummy variable as a proxy for actual pro-environmental behavior. According to this variable, 43 per cent 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. Results are presented in Column (3). Interestingly, the coefficient of the variable $Prime * P2 * Pre - treat\ usage * High\ pro - env\ behav$ is negative and statistically significant, with a point estimate of -0.124. This result suggests that the prime has a boosting effect on top of the effect of the eHER, among high usage individuals if they behaved pro-environmentally in the past.

We plot in Figure 4 the conditional average treatment effect of receiving the eHER coupled with the prime (red line) versus receiving the eHER without the prime (black line) for individuals who behaved pro-environmentally. The figure indicates that, conditional on effective targeting, priming environmental self-identity through recalling past pro-environmental actions, can boost the effect of the eHER on energy conservation.[15]

[14] We acknowledge that this dimension of heterogeneity did not feature in the pre-analysis plan.

[15] Consider that more than 50 percent of the households' pre-treatment consumption is bounded between 5 and 10 KWh/day. These values correspond to the area where the CI of the red line lies below the zero axis.

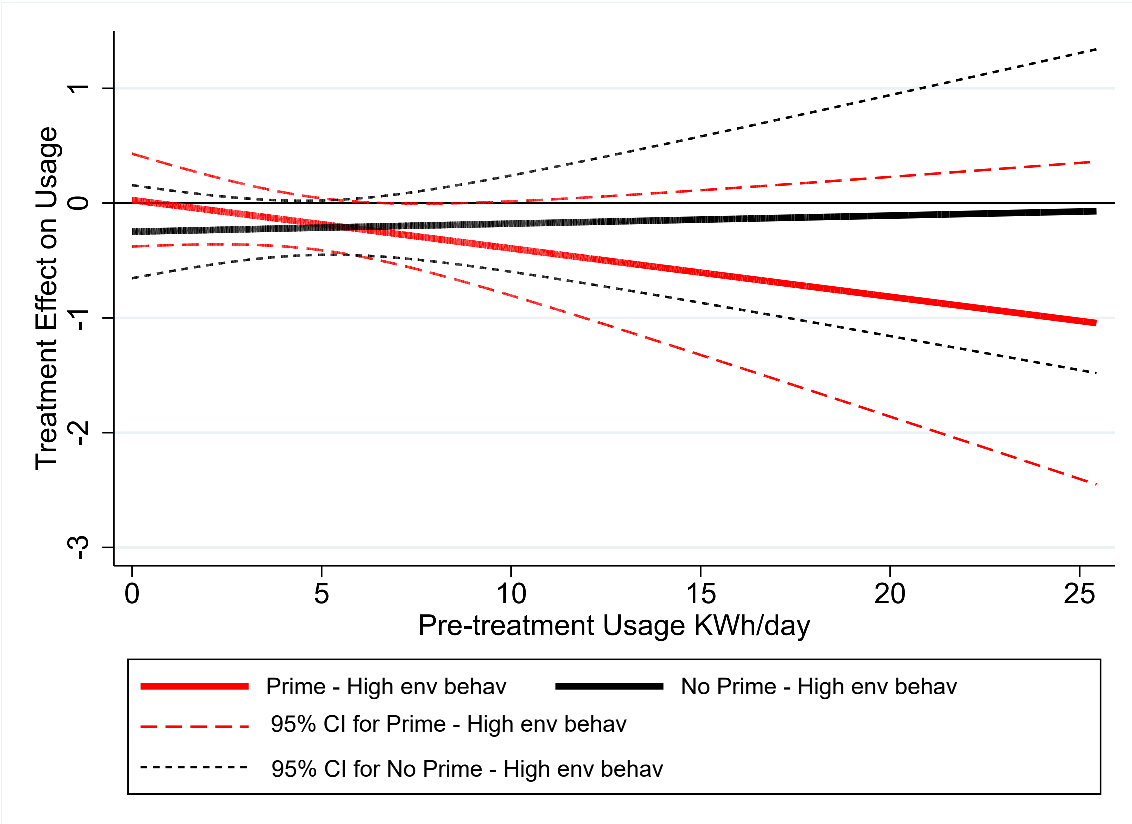

Figure 4: Heterogeneous effects of the environmental prime on electricity usage, by pre-treatment usage and pro-environmental behavior

The figure also indicates that the prime is able to counteract the boomerang effect of the standard eHER. 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. The graph indicates that the prime backfires if it is addressed to people who hardly engage in pro-environmental behaviors. This result further highlights how important effective targeting of information treatments is.[16]

Table C.3 reports the full set of coefficients from estimating Equation 3. The coefficient of the variable $Program * P1$ in Column (1) is -0.073 and indicates that, on average, the eHER has a curbing 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 (3), in agreement with the findings of Table 3 where we allow the effects to vary depending on pre-treatment usage, the coefficients of the variable $Pogram * P1 * Pre-treat\ usage$ are negative and statistically significant, with a point estimates of -0.092 and -0.094. The coefficients confirm the curbing effect of the eHER for high usage individuals. Finally, the placebo test on the validity of the randomization is confirmed by the non statistically significant coefficients of the variables $Prime * P1$ and $Prime * P1 * Pre - treat\ usage$ in all specifications. Individuals randomly selected to receive the prime should not behave differently from individuals receiving the control message in the pre-prime period 1.

[16]The impact of the prime in the field, when embedded within the eHER, differs from the impact of the same prime when administered in isolation, in the context of the online experiment that motivated its adoption. Namely, the online experiment results show a positive and statistically significant effect of the prime on pro-environmental behavior, which can be observed for the sample as a whole (see Table C.6).

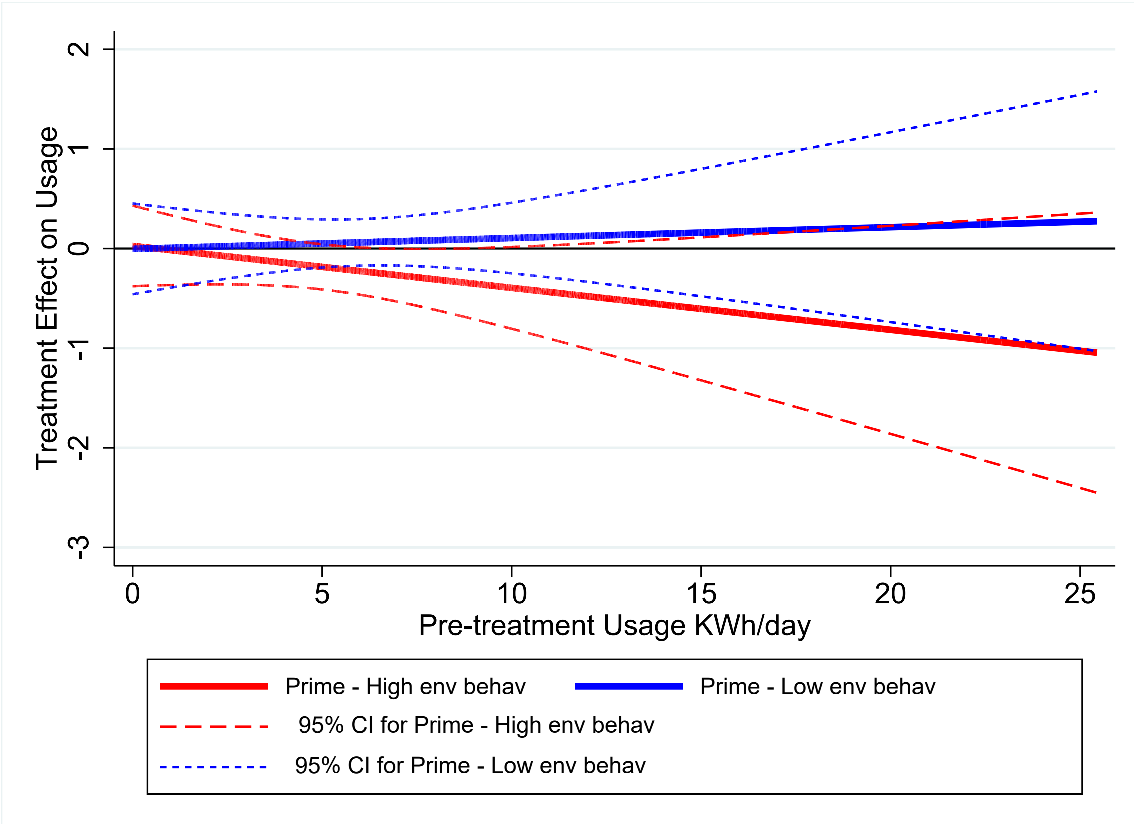

Figure 5: Heterogeneous effects of the environmental prime on electricity usage, by pre-treatment usage and pro-environmental behavior

We compute some robustness checks. First, we vary the length of the post-prime period 2. This exercise allows us to analyze the persistence of the effect of the environmental identity prime. In the main analysis, period 2 ranges from November 2017 to March 2018. In Column (1) of Table C.4, we include only observations in the November-December period. The coefficient of the triple interaction $Prime * P2 * Pre - treat\ usage * High\ pro - env\ behav$ reduces in magnitude and turns statistically non-significant. In Columns (2) and (3) we include observations in the November-January and November-February periods, respectively. The coefficients increase and are comparable in magnitude to the one reported in Table C.3, which is 0.12. Such a trend indicates that reducing consumption in response to the prime takes time. In Column (4) we deal with possible outliers by winsorizing the pre-treatment consumption variable. The coefficient turns not-statistically significant but the point estimate is in line with the main specification.

Finally we perform some robustness checks on the way we compute the pro-environmental behavior indicator. 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 equal to one only for answers equal to 5. Twenty two per cent of individuals are now classified as having behaved pro-environmentally. We present the empirical findings in Column (5) of Table C.4. The point estimate of the coefficient of the triple interaction $Prime * P2 * Pre - treat\ usage * High\ pro - env\ behav$ is now 0.17, which is about 40 per cent larger than the estimate presented in Table 5. This finding indicates that, by restricting the identification of people who behave pro-environmentally, we are able to strengthen the effect of the prime on energy conservation.

4. Conclusion

We present evidence from the evaluation of a social information program on energy consumption. In addition to assessing the overall impact of the program, we combine administrative and survey data to study sources of heterogeneity in the program's effect. In particular, the novel focus of the paper is on the role of environmental values. We find that program recipients with strong environmental values and high pre-program energy use are the most responsive to the intervention and reduce consumption.

Given that values, which we consider as stable traits, along with the psychological literature, are strongly correlated with environmental identity, which instead can be made more salient, we test whether priming self-identity can make the intervention 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 the prime succeeds in further reducing energy use, with respect to the standard report, but only among individuals who acted pro-environmentally in the past. This result is important in itself, since it sheds light on an unsettled debate about spillovers in pro-environmental behavior (Truelove et al., 2014; d'Adda et al., 2017). It also contributes to the debate on how to leverage moral deeds to induce further pre-social behavior.

Our study has implications for policy. The heterogeneity in program effects, and in particular the presence of boomerang effects among low energy users, suggests that effective targeting of social information can maximize its impact on desired behavior. It shows how multiple behavioral interventions can be combined to boost intervention effectiveness, but also that heterogeneity makes it hard to devise broad-spectrum behavioral tools. Finally, the role of values, which are stable personal traits formed early in life, in strengthening the effect of the treatment on energy efficiency and in curing boomerang effects, also points to the important function of education.

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Appendix

A. 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 A.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 A.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 3 and C.3 do not change when they are excluded since the beginning, as shown in Tables C.1 and C.4, 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 A.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 A.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: less than 5 years	-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

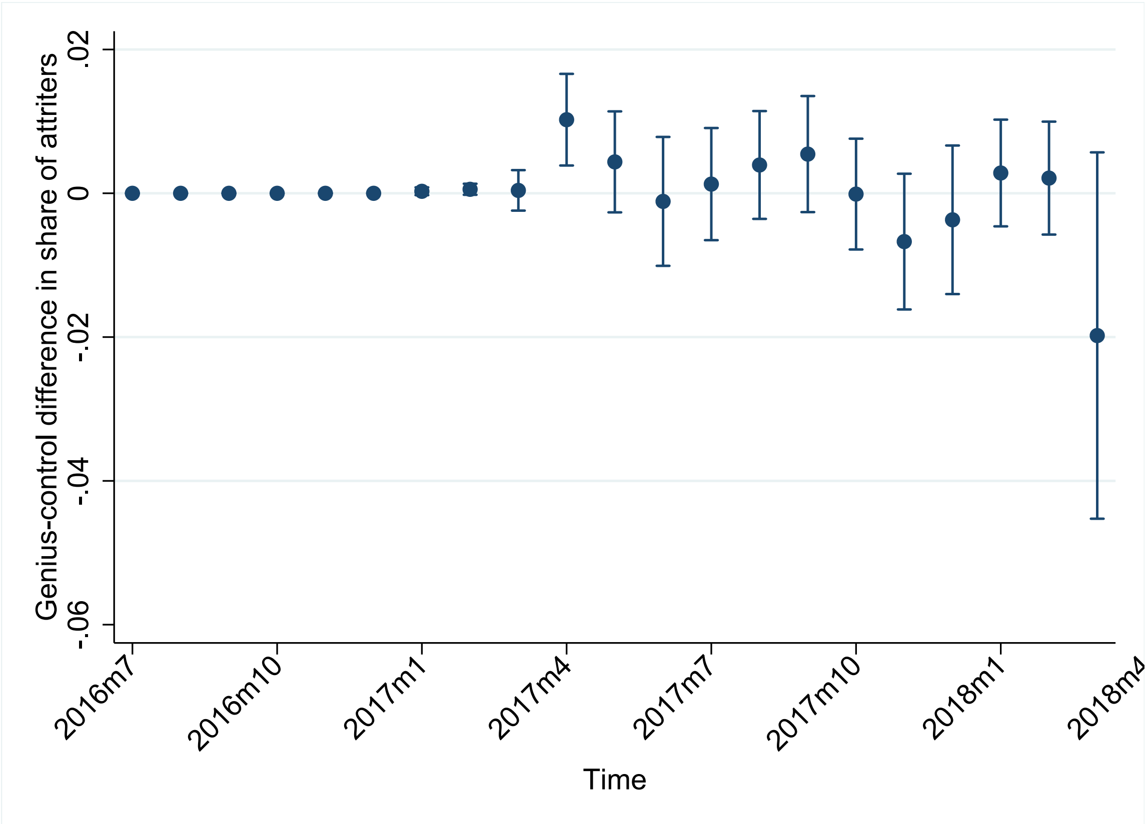

Figure A.1: Differential attrition over time

B. Online experiment

B.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.[17] 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 behavior, and select the best performing message for the field experiment. 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 the treatments are more likely to perceive themselves as environmental-friendly persons

[17] 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.

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 behavior.

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 behavior 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 2.2 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 the health consequences of energy use as a motivator of energy conservation: previous research shows the effectiveness of this type of message in inducing energy saving behavior in the field (Asensio and Delmas, 2015, 2016). Section B.3 reports the experimental instructions, including the treatment and control messages.

B.2. Results

We first provide descriptive statistics and balance tests of treatment sub-groups along different dimensions in Table C.5. 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.6 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).[18] 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 with about 5 per cent higher scores, on average and *ceteris paribus*. The identity prime over-performs not only with respect to the control message, but also to 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).

B.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".*

[18] 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' behavior 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.

C. Robustness checks

Table C.1: 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 * Above median env. values		0.245*		0.197*		0.242**
		(0.126)		(0.106)		(0.116)
DD * Pre-treat usage * Above median 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.2: 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*Above median env. values		0.127*		0.111		0.123*
		(0.076)		(0.076)		(0.074)
Above median 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.3: Impact of the environmental prime on electricity usage, main and heterogeneous effects

	(1)	(2)	(3)
	Daily electricity usage, KWh/day		
Program*P1	-0.073*	0.520***	0.569***
	(0.043)	(0.075)	(0.102)
Program*P1*Pre-treat usage		-0.092***	-0.094***
		(0.012)	(0.016)
Program*P1*High pro-env behav			-0.089
			(0.139)
Program*P1*Pre-treat usage*High pro-env behav			-0.000
			(0.024)
Program*P2	-0.163	0.054	0.298
	(0.114)	(0.176)	(0.234)
Program*P2*Pre-treat usage		-0.034	-0.064*
		(0.027)	(0.038)
Program*P2*High pro-env behav			-0.547*
			(0.280)
Program*P2*Pre-treat usage*High pro-env behav			0.071
			(0.051)
Prime*P1	0.033	-0.077	-0.207
	(0.044)	(0.104)	(0.148)
Prime*P1*Pre-treat usage		0.018	0.037
		(0.018)	(0.024)
Prime*P1*High pro-env behav			0.296
			(0.208)
Prime*P1*Pre-treat usage*High pro-env behav			-0.047
			(0.036)
Prime*P2	0.110	-0.078	-0.301
	(0.081)	(0.204)	(0.301)
Prime*P2*Pre-treat usage		0.029	0.075
		(0.036)	(0.050)
Prime*P2*High pro-env behav			0.576
			(0.396)
Prime*P2*Pre-treat usage*High pro-env behav			-0.124*
			(0.070)
Constant	7.921***	7.920***	7.919***
	(0.071)	(0.070)	(0.070)
Observations	121,638	121,638	121,638
R-squared	0.083	0.087	0.088
Number of customers	3,814	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.

Table C.4: Impact of the environmental prime on electricity usage, robustness checks

Dep Var: Daily electricity usage, KWh/day	(1) Until Dec 17	(2) Until Jan 18	(3) Until Feb 18	(4) Winsorized pre-treat usage	(5) Top pro-env behav
Program*P1	0.578***	0.576***	0.573***	0.575***	0.579***
	(0.104)	(0.103)	(0.102)	(0.102)	(0.084)
Program*P1*Pre-treat usage	-0.095***	-0.095***	-0.094***	-0.095***	-0.097***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.013)
Program*P1*High pro-env behav	-0.101	-0.098	-0.094	-0.093	-0.215
	(0.139)	(0.139)	(0.139)	(0.140)	(0.179)
Program*P1*Pre-treat usage*High pro-env behav	0.002	0.001	0.001	0.001	0.018
	(0.024)	(0.024)	(0.024)	(0.025)	(0.036)
Program*P2	0.075	0.137	0.206	0.223	0.272
	(0.246)	(0.247)	(0.243)	(0.228)	(0.197)
Program*P2*Pre-treat usage	-0.048	-0.053	-0.053	-0.053	-0.060**
	(0.037)	(0.037)	(0.039)	(0.038)	(0.030)
Program*P2*High pro-env behav	-0.378	-0.469*	-0.520*	-0.473*	-0.990***
	(0.275)	(0.278)	(0.287)	(0.277)	(0.308)
Program*P2*Pre-treat usage*High pro-env behav	0.050	0.062	0.067	0.060	0.144**
	(0.050)	(0.051)	(0.053)	(0.051)	(0.066)
Prime*P1	-0.221	-0.217	-0.212	-0.183	-0.159
	(0.149)	(0.149)	(0.149)	(0.144)	(0.120)
Prime*P1*Pre-treat usage	0.039*	0.039	0.038	0.034	0.031
	(0.024)	(0.024)	(0.024)	(0.023)	(0.020)
Prime*P1*High pro-env behav	0.308	0.304	0.302	0.286	0.338
	(0.206)	(0.207)	(0.207)	(0.205)	(0.251)
Prime*P1*Pre-treat usage*High pro-env behav	-0.050	-0.049	-0.048	-0.047	-0.059
	(0.036)	(0.036)	(0.036)	(0.036)	(0.049)
Prime*P2	-0.210	-0.229	-0.272	-0.192	-0.240
	(0.300)	(0.301)	(0.311)	(0.294)	(0.242)
Prime*P2*Pre-treat usage	0.070	0.070	0.073	0.059	0.058
	(0.050)	(0.050)	(0.052)	(0.050)	(0.041)
Prime*P2*High pro-env behav	0.452	0.509	0.531	0.506	0.844*
	(0.392)	(0.393)	(0.408)	(0.389)	(0.432)
Prime*P2*Pre-treat usage*High pro-env behav	-0.112	-0.117*	-0.118	-0.115	-0.172**
	(0.069)	(0.069)	(0.072)	(0.070)	(0.087)
Constant	7.917***	7.918***	7.919***	7.919***	7.919***
	(0.069)	(0.070)	(0.070)	(0.070)	(0.070)
Observations	110,531	114,281	117,984	121,638	121,638
R-squared	0.094	0.091	0.090	0.088	0.088
Number of customers	3,814	3,814	3,814	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 3. All specifications include customer fixed effects and month by year fixed effects.

Table C.5: 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
Environmental values above median	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.6: 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).