Reducing consumption of electricity: A field experiment in Monaco with boosts and goal setting

Nathalie Lazaric, Mira Toumi

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Nathalie LAZARIC, and Mira TOUMI**[1]*

Abstract

We investigate the complementarity among different treatments which involved "boosts" (provision of information) and "goals" (ambitious or modest goals) by means of a field experiment conducted in the Principality of Monaco between December 2018 and May 2019. We collected data from 77 households in four groups: ambitious electricity reduction goal combined with information (Treatment 1), modest electricity reduction goal combined with information (Treatment 2), only information (Treatment 3), and a control group (CG). Treatments 1 and 2 increased the chances of reduced electricity consumption. We show that a modest, more realistic electricity saving goal when combined with a "boost" generates better electricity conservation performance (T2). We explore the link between behavioral strategies and the household's concern for the environment in the context of the new ecological paradigm (NEP). Our results show that treatments T1 and T2 are efficient for reducing electricity consumption only in households with high levels of environmental concern; those whose level of concern about the environment is low will not respond to any of the behavioral interventions. We provide some recommendations for the implementation of behavioral tools and "boosts".

Keywords: Boost, nudges, goal setting, electricity consumption, field experiment, environmental profile.

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1. Introduction

Behavioral tools have attracted the attention of policy makers by providing concrete mechanisms and allowing actions in a range of fields: health, waste, energy preservation, nutrition among others (Hertwig and Ryall, 2020). The myriad examples around the world of use of nudges show their inherent attractiveness. It has been shown that certain behavioral tools such as nudges, boosts, and goals can promote green behaviors. Among these behavioral tools, boosts seem to have good potential by empowering individuals to rid themselves of biased judgments. For policy makers, agency is an important issue (i.e. how to influence changes at the individual level, in which context, and for what reasons). These ethical issues should not be neglected in deciding about appropriate tools. The adoption of greener behaviors is hampered by material, technological, financial, psychological and other dimensions. These biases mean that traditional approaches such as awareness campaigns and technological innovations proposed by standard economists may fail to generate lasting change. Behavioral economics may provide robust tools to help to reduce energy use, conserve water, and tackle nutrition, and health issues to accelerate the ecological transition; however, their implementation requires certain conditions.

Indeed, changing individual behavior towards reducing consumption of electricity takes much time and effort and is affected by problems such as potential inertia, individual agency, and motivation. These problems are linked to an overemphasis on energy efficient equipment policies rather than behavioral actions which improve individual level abilities (Maréchal and Holzemer, 2015; Buckley, 2020). Additionally, electricity is an invisible commodity which contributes to lack of awareness about its daily consumption (Hargreaves et al., 2013). European households are poorly informed about their electricity use and may lack knowledge about how to act on this issue (Belaïd and Joumni, 2020; Buckley, 2020).

Among the non-monetary tools that have been applied in the context of electricity consumption, nudges have become increasingly popular for correcting certain behavioral cognitive biases (Buckley, 2020; Schubert, 2017). In a recent meta-analysis of monetary and non-monetary interventions for households, Buckley (2020) shows that they can result in an overall reduction in electrical energy consumption of between 1.87% and 3.91%. When she compared differences among behavioral tools, Buckley found that monetary tools did not have a significant effect whereas non-monetary tools such as “information on households own consumption delivered via paper bills, online or in real-time and personalized advice are found to be most effective at lowering residential electricity consumption" (Buckley, 2020: 12).

Nudges which have been identified as promising for reducing electricity consumption (Charlier et al., 2020) suffer from several ethical problems (Schubert, 2017; Bradt, 2019; Hertwig and Ryall, 2020). They can alter citizens' behaviors by harnessing their cognitive biases but may not generate robust and durable behavioral changes. They are also highly context dependent (Schubert, 2017; Allcott and Rogers, 2014).

Boosts are seen as different from nudges (Schubert, 2017) and "self-nudges" (Reijula and Hertwig, 2020) and are attracting the attention of policy makers and practitioners (DellaValle and Sareen, 2020). Boosts allow citizens to improve their skills (Herwig, 2017). While proponents of nudges consider that human beings are prisoners of their automatic systems of cognition (Kahneman, 2011), proponents of boosts assume that individual competences can be enhanced and that individuals can overcome their biases through training (Hertwig and Ryall, 2020; Bradt, 2019). Thus, although boosts have attracted less attention than nudges, they represent an interesting line of enquiry in the context of behavioral tools to improve households' knowledge about electricity consumption.

Another behavioral tool which has been used in the context of reducing electricity consumption is goal setting. Andor and Fels (2018) consider that a goal can become a concrete point of reference whose accomplishment will increase extrinsic forms of motivation. Goals combined with advice have received little research attention and are "a promising avenue for further research" (Anders and Fels, 2018: 186).

Given the limitations of nudges (Rebonato, 2012) and the unexplored potential of boosts combined or not with goals, we decided to investigate the relevance of these latter in the case of Monaco, a sovereign city-state located on the French Riviera in Western Europe. Monaco is interesting for at least two reasons. First, local government is keen to achieve an energy transition, and second, there are no empirical studies on this geographical area. In 2018 we implemented a field experiment designed to tackle the issue of reducing electricity consumption and measuring the effects on citizens' electricity consumption of boosts and goals.

We collected data from 77 households in four groups: ambitious electricity reduction goal combined with boosts (T1), modest electricity reduction goal combined with boosts (T2), only boosts (T3), and a control group with no goals and no boosts (CG). Our empirical findings show that the T1 and T2 groups reduced their electricity use which suggests that goals – especially realistic goals - combined with a boost produce better outcomes in terms of behavioral change.

The paper is organized as follows. Section 2 reviews the literature on behavioral tools related to electricity consumption. Section 3 describes the design of the experiment and the protocol, and section 4 presents the data analysis. Section 5 examines the sample and the data, and section 6 presents the results. Section 7 discusses our findings and some limitations of our study and whether it could be replicated in other contexts. Section 8 concludes the paper and provides some recommendations for policy.

2. Behavioral tools and electricity consumption: a short review

Policy makers are often inspired by behavioral science in their policy design and policy adaptations to different contexts (Schleyer, 2017; DellaValle and Sareen, 2020). According to Dolan et al. (2012), the most effective interventions for persuading individuals to adopt green behaviors are those which aim to change contexts and mindsets which suggests that nudges, goals, and boosts might be effective behavioral interventions. However, ethical assumptions and sources of inspiration for these behavioral tools differ. These divergences are explained and discussed below.

2.1. Nudges and boosts –are they similar or different?

According to Grüne-Yanoff and Hertwig (2016), the provision of information can affect behavioral interventions depending on the stage at which and the form in which the information is provided[2]. Nudges intervene by changing the context and architecture of the decision-making process and consider individuals' cognitive biases and exploit them in the absence of any individual motivation (Thaler and Sunstein, 2008). Nudges are defined as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid" (Thaler and Sustein, 2008: 6). In an energy

[2] The authors propose a set of policy intervention categories based on an analogy with mechanisms and decision making. These categories include existence of i) a decision making environment which includes an amount of available information and the decision context, ii) a set of search and selection rules which provide a set of information which the decision maker can use and choose among, and iii) a set of available options with different properties.

context, nudges have proven promising in terms of promoting green behaviors (Allcott, 2014; Charlier et al., 2020). Moreover, compared to traditional monetary tools such as taxes, nudges are relatively effective depending on the household's environmental sensitivity profile (My and Ouvrard, 2019).

Boosts differ in that they aim not to influence behavior but to create the conditions for learning. They do not change the choice architecture, but they foster individual competence to overcome rather than exploit cognitive biases (Schubert, 2017; Hertwig, 2017): "The common denominator behind boost policies is the goal of empowering people by expanding (boosting) their competences and thus helping them to reach their objectives (without making undue assumptions about what those objectives are)" (Grüne-Yanoff and Hertwig, 2016: 156). In other words, while nudges exploit the individual's unconscious and push them towards the "right" decision, boosts foster people's competence to make a conscious choice and exercise agency. Boosts aim to train individuals through the provision of relevant information, and thus, to empower them to become their own choice architects (Grüne-Yanoff and Hertwig, 2016; Hertwig and Grüne-Yanoff, 2017).

Bradt (2019) describes nudges and boosts as different in terms of their sources of inspiration and their implementation. Nudges consider prior heuristics at the individual level and assume cognitive bias as a matter of fact and act to try to overcome them; boosts are aimed at improving existing skill levels and changing certain individual heuristics and cognitive biases. Thus, boosts enter the cognitive black box to improve the level of existing skills and target the repertoire of individual heuristics directly and not just the environment.

More precisely, in a nudge view, heuristics are considered stable. This is based on Kahneman who distinguishes between system 1 "which operates automatically and quickly, with little or no effort and no sense of voluntary control" (Kahneman, 2011: 20) and is "not really educable" (Kahneman, 2011: 41), and system 2 which is slow, deliberate, conscious, controlled by the mental process and rational thinking. In contrast, the boost view inspired by the Fast and Frugal Heuristics program (Gigerenzer et al., 1999) considers that individuals are equipped with various sets of competences and have the option to choose among heuristics and select the most appropriate for his or her goals (Grüne-Yanoff et al., 2018: 249). Boosts and nudges have different ontological visions. In a nudge view, someone indicates the "proper" way to act in a particular context, while boosts deliver the tools required to act to solve the issue.

Boosts also differ from feedback and simple provision of information. Some feedback enables learning. It has been shown that learning-by-observing is based on feedback from use of household appliances (Kendel et al., 2017) over a prolonged period (more than 6 months) which allows the information to be absorbed and used to improve individual skills. Boosts aim to enable learning through continuous provision of information. Thus, the difference between feedback and boosts is based on the difference between information and knowledge. Feedback provides additional information and may enhance the conditions required for learning. Boosts increase individual learning and change individual heuristics but may require some investment to enable the learning. In addition, the content of the information provided by a boost is richer and more customized compared to the information contained in feedbacks.

2.2. Boosts and nudges: which tool can be chosen and implemented?

Nudges act to change behavior in the short term (Charlier et al., 2020) whereas boosts require some investment in training and need a long-term perspective to observe concrete results. Boosts give customized and recurrent advice which change individual heuristics and provide the ability to learn. A required condition for using boosts as a behavioral tool, is motivated participants. If motivation is low and the situation is very complex, for instance in some cases of risks in the insurance sector, nudges may appear more useful and easier to implement. As Bradt (2019) states, in principle, there are no good or bad behavioral tools but rather instruments that are more appropriate in some situations and some contexts. For instance, a policy maker should start with nudges and then implement boosts. Once boosts are implemented nudges are no longer either necessary or useful. Policy makers must choose between what can be done and what can be achieved based on the initial local conditions.

The choice among behavioral tools should be driven also by welfare, education concerns, and the policy framework. It has been acknowledged that:

> despite the widespread appeal of nudging, there are some limits. For instance, it is hard to imagine how without empowering people one could offer lasting and robust remedies to the problem bias, intentional; misinformation and micro-targeting present they face by today’s media consumers […] Equipping citizens to make judgment of information quality independently and competently is -despite the manipulation efforts- is indispensable to maintaining democratic forms of government. (Hertwig and Ryall, 2020: 1410)

Issues of democratic participation and learning may be more responsive to boosts to tackle misinformation among citizens about climate change (see van der Linden et al., 2017, for a longer discussion). Boosts are part of the capabilities approach in the sense of Sen (1999) since they consider humans as "intrinsically capable of acquiring greater abilities as they access degrees of freedom to act" (Della Valle and Sareen, 2020: 101). Democratic participation in the ecological transition can mean that boosts may provide the tools to empower actors who can influence economic and social change. This debate goes beyond tools and should be driven by policy, the local context, and the available resources. Boosts are more effortful and complex to implement than nudges. Thus, policy maker should remember that people are prone to making errors and suffering from cognitive biases. Devoting attention to learning is a prerequisite for promoting collective action to achieve an ecological transition and to allow citizens to participate in this shift. This issue is discussed in Banerjee and Duflo (2009) who argue that field experiments need to be co-designed by policy makers and researchers. Also, the results of field experiments must be assessed before considering replication or generalization.

2.3. Setting appropriate goals

Interventions that involve goals lead to efforts which persist over time (Locke and Latham, 2006). Goal setting promotes additional effort and commitment to achieve the goal (McCalley and Midden, 2002).

In an energy use context, goals whether imposed by a third party or chosen by the individual can have a positive effect on energy use (Dolan et al., 2010). However, the ambitiousness of the goal matters. Abrahamse et al. (2005) and Wood and Newborough (2007) show that more ambitious compared to modest goals lead to higher energy savings. However, a goal perceived as unrealistic reduces individual motivation. For example, Harding and Hsiaw (2014) show that goals need to be realistic: too modest goals require little effort for their achievement. However, if the goal is considered unrealistic, the individual will make no efforts to try to achieve it. Harding and Hsiaw (2014) studied a group of individuals residing in Northern Illinois in the United States where the citizens chose their energy consumption goals. A goal of reducing consumption by 15%, achieved better results (11% reduction) than very low or unrealistically high goals. In their frame, goals greater than 0% but less than 15% were considered "realistic" whereas 15%-50% goals were considered "over -optimistic" (Harding and Hsiaw, 2014). Who sets the goal is also important and Abrahamse et al. (2005: 266) argue that although the "goal can be set by households themselves or by some external entity … research suggests that there is no difference in energy savings between the two".

Our methodological design involves a goal imposed by an external entity. This ensures a better balance among our diverse groups since volunteers are more likely to choose a realistic goal. Also, this allows investigation of the effect of a promising new behavioral tool a "boost" combined with a goal as discussed above, with possible more lasting behavior change rather than short-term behavior changes (Hertwig and Grüne-Yanoff, 2017). Following Buckley (2020), we combine goal setting with boosts, and observe the impact of boosts as explained in more detail below.

3. Experimental design

3.1. Field experiment method and recruitment of participants

The field experiment was conducted in the Principality of Monaco over the six-month period December 2018 to May 2019 (see figure 1). This is a unique setting. First, a large proportion of its population are financially well endowed and live in apartments in tower blocks that were built mostly in the 1970s. Second, average electricity consumption per inhabitant in Monaco tends to be below the average for its neighbor France. However, this is due mostly to Monaco's residents spending only part of the year in Monaco rather than because they are more careful about their energy consumption which makes comparison difficult. Third, 90% of Monaco's electrical energy is supplied by France and includes a high percentage of renewable electricity (75% for Monaco compared to only 20% for the whole of France). This promotes more careful use of energy and more attention to the environment[3]. Fourth, its government is involved in a retrofitting program to reduce greenhouses gas emissions from buildings and ensure that all new buildings conform to environmental standards.

We conducted the field experiment with the support of the main local energy provider (SMEG) based on a clear division of tasks to build trust and provide transparency for volunteers about the scientific objectives of our protocol. A letter of invitation was sent out by the local provider

[3] The 2017 *White Book on the Energy Transition in the Principality of Monaco* describes the aim of reducing greenhouse gas emissions by 80% (compared to 1990 levels) by 2050, and achieving carbon neutrality in the long run.

and the scientific team to 5,000 households[4] across the Principality to ensure inclusion of a diverse range of buildings including social housing, and a range of citizens from employees to professionals to ensure a representative sample. Consultation with SMEG ensured that the sample included different types of dwellings with different heating systems (not just based on electricity) and dwellings that were not part of the current retrofitting program. Agreement to participate was by freepost surface mail response or by email. Eligibility was based on two criteria: access to the Internet, and not being involved in the insulation program running during the period of the experiment.

We received a total of 127 positive responses. The participants were asked to complete a questionnaire[5] at two fixed points in time: prior to the treatment, and six months after the experiment. The *ex-ante* questionnaire asked about the household's socio demographics, ecological concerns and commitment, electricity use, heating system, and curtailment behaviors. The *ex-post* questionnaire was aimed at capturing changes to household socio demographics, household composition, and energy use and obtain feedback on the experiment. The timeline is depicted in figure 1.

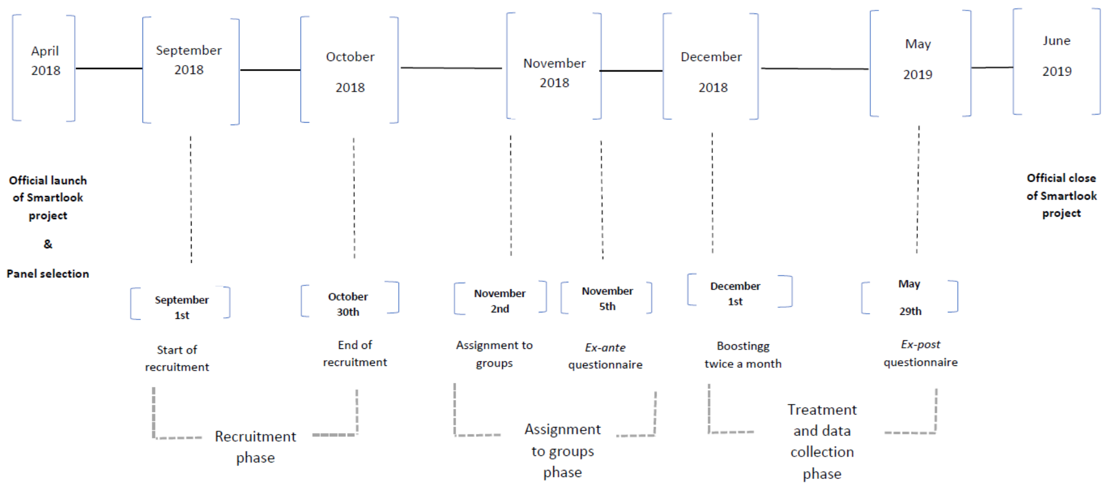

Figure 1: Timeline and main phases of the Smartlook field experiment

3.2. Treatments and groups

Conditional on replying to the ex-*ante* questionnaire, participants were randomly assigned to one of the experimental treatments or to the control group. Methodologically, the sampling

[4] The Principality of Monaco included 38,300 inhabitants in 2018 (source: Monaco en chiffres, IMSEE, 2019). The letter is provided in appendix 1-a; appendix 1-b describes the location in the Principality of Monaco.
[5] Available in French, English and Italian.

strategy relied on households who volunteered to participate which is similar to other opt-in methods and is described by Harrison and List (2004) as a "framed field experiment". This indicates that volunteer-based experiments do not preclude random assignment of participants to different groups (see also Gandhi et al., 2016 and Karlin et al., 2015 on random assignment in electricity related field experiments).

Participants in the three treatment groups were informed that they would receive twice-monthly emails containing instructions with a reminder of their electricity use reduction goal (if assigned to a group with a goal), and a set of boosts[6]. The emails sent to the control group informed them only that they were part of an experiment aimed at gathering information on Monegasque households' energy transition. The households in the control group responded to both the *ex-ante* and *ex-post* questionnaires but had no goals and did not receive boosts. However, to establish transparency and trust as recommended by Vassileva et al., (2013) and discussed in Kendel et al., (2017) all four groups were told that they would receive a summary of our empirical findings.

Despite declared willingness to participate in the experiment, the final sample included only 77 households that fulfilled the criteria of responding to the ex-ante questionnaire and being permanent inhabitants during the period of the field experiment. 89 of the original 127 volunteers completed the ex-ante questionnaire but this included 12 households not resident in Monaco throughout the period of the experiment.

Table 1: Sample allocation and treatments

Treatments	Label	Ex-ante quest	Goal setting	Boosts	Ex-post quest	N	Observation Period
T 1	Boost & ambitious goal	+	+	+	+	16	28 weeks
T 2	Boost & modest goal	+	+	+	+	17	28 weeks
T 3	Boost only	+	-	+	+	21	28 weeks
CG	Control group	+	-	-	+	23	28 weeks
Total						77	28 weeks

[6] Boosts were formulated by the project team building on ADEME (the French Environment and Energy Management Agency) statistics and information from other environmental associations. The information provided to participants consisted of an explanation of the problems related to electricity consumption and some practical advice about how to reduce it. The boosts were aimed at increasing participants' knowledge and skills. The boosts were in line with time of year (Christmas time, the beginning of spring). Boosts were sent by email and were aimed at increasing the volunteers' knowledge and learning (see appendices 2, 3-a and 3-b for details and examples).

Table 1 presents the grouping of participants and the treatments:

- Treatment 1 (n=16): volunteers set an ambitious electricity consumption reduction goal compared to the previous six months usage (25%) and received boosts on electricity saving.
- Treatment 2 (n =17): volunteers set a modest (15%) electricity consumption reduction goal compared to the previous six months usage, and a set of boosts.
- Treatment 3 (n= 21): volunteers who received only boosts (advice) about how to reduce their electricity consumption.
- Control Group (=23): the control group of volunteers who received neither a goal nor boosts.

4. Data analysis

4.1. Dependent variable: household consumption of electricity

Quarterly data on electricity consumption in kWh were provided to each volunteer household by the local provider. These data allowed us to build our dependent variable i.e. average household electricity consumption per month in kWh. We measured the dependent variable at two points in time: pre-treatment period (6 months), and intervention period (6 months)[7]. This allowed us to estimate the change in household electricity consumption in the treatment groups linked to the treatment and/or variables such as environmental concern (explanatory variables).

[7] The collaboration with the SMEG gave us access to data on the electricity consumption of a sample of permanent residents over a 12 month period . To avoid the sample including temporary residents, SMEG identified households who were resident in the 6 months before the start of the experiment. To adjust and correct for potential effects of season, we included variables for weather and average consumption of electricity in Monaco. Average electricity consumption per treatment in kWh over the 6 months before and during the experiment including 95% confidence values is provided in appendices 4-a and 4-b. We observed that the consumption of the treatment groups differed statistically from that of the control group. We observed also that in June, July, and August (before the experimental intervention) average consumption did not differ statistically among T1, T3, and the CG. During the first 3 months of the experiment, December, January, and February we observed different average consumption; at the 95% confidence level average consumption was higher in the CG compared to the T1, T2, and T3 groups (see appendix 4-c).

4.2. Explanatory variables: environmental concern, environmental commitment, curtailment behaviors, dwelling

Our explanatory variables include environmental values and commitment, participant's socio-demographic characteristics, dwelling type (i.e., owned or rented), and energy practices in line with Belaïd and Joumni (2020).

The presence of altruistic and/or biospheric values (see Stern and Dietz 1994) i.e., the weight given to outcomes affecting other individuals, and broader environmental concerns are considered among the principles guiding lifestyle (Schwartz 1992) and explain the likelihood of engaging in a range of environmentally relevant behaviors (Baum and Gross 2017). Most work on individual environmental values uses survey data and measures based on self-reported behavior, behavioral intentions, or other expressions of concern for the environment. We used Dunlap et al.'s (2000) NEP or New Ecological Paradigm scale which is used widely in psychology and shows high internal reliability and provides good results allowing control for and prediction of pro-environmental behavior (Davis et al., 2009).

We measure environmental commitment based on membership of an environmental association. Stern (2000: 409) defines environmental citizenship as including "petitioning on environmental issues and contributing to environmental organizations". It follows that environmental citizenship is captured by the activation of feelings of personal obligation to act and actions related to an association.

We include a set of virtuous behaviors related to energy practices i.e., curtailment behaviors affecting energy consumption (e.g., turning off the heating system when not in the house, not using the prewash program on the washing machine, etc.)[8] to measure energy behaviors (as discussed in the GEB or General Ecological Behavior scale). The GEB includes 40 questions (Kaiser 1998) about energy behavior. We selected five items related to energy behaviors from Kaiser and Biel (2000) to describe energy behaviors as explained by Kaiser et al. (2003)[9]**.**

4.3. Difference-In-Differences method

To estimate the causal relationships between the treatments and the levels of electricity consumption, we compare the performance of the treated and non-treated household groups

[8] For more detail see Nauges and Wheeler (2017).

[9] Appendix 5 provides details of items selected to define energy behavior.

before and after the field experiment. The three treatment groups received three different treatments: (T1) ambitious goal setting and boost; (T2) modest goal setting and boost, and (T3) only boost. Following Angrist and Pischke (2008), we employ difference-in-differences (DID) estimations to control for household characteristics and we clustered standard errors to households. The DID method allows us to control for observed and unobserved time invariant characteristics and time-varying factors common to all groups which might be correlated to the treatments. Our counterfactual is the variation in the control group's electricity consumption i.e., the amount of electricity that would have been consumed without the treatment[10].

To estimate the treatments effect, we rely on the following DID estimation equation (Eq. (1))

$$
\begin{aligned}
Y_{it} = \quad & \beta_0 + \beta_1 T1_i + \beta_2\ time_{post_{it}} + \beta_3 \left(time_{post_{it}} * T1_{it}\right) \\
& + \beta_4 T2_i + \beta_5 \left(time_{post_{it}} * T2_{it}\right) + \beta_6 T3_i + \beta_7 \left(time_{post_{it}} * T3_{it}\right) \\
& + (individual\ \ s\ characteristics)' \beta_8 + (dwelling\ characteristics)' \beta_9 \\
& + \beta_{10}\ weather\ temperature + \varepsilon_{it}
\end{aligned}
$$

where i and t refer to the household i treated with treatment T. We observe households in two periods, before the treatment *(t=0)* and after the treatment (*t=1*).

Y_{it} the dependent variable of interest is average monthly electricity consumption by household i at time t. β_0 is the constant term and is the electricity consumption of the control group in the reference period June to November 2018.

The dummies ($T1_i$ $T2_i$ $T3_i$) equal 1 if the household received the corresponding treatment (treatment 1, treatment 2, or treatment 3) and zero otherwise. Therefore β_1 (β_4 and β_6) capture the differences among the households included in the $T1$ ($T2$ and $T3$) group and the households in the control group before the treatments.

$time_{post_{it}}$ is a time dummy which takes the value 0 before the treatment and 1 after treatment is introduced. Therefore, β_2 captures the change in households' electricity consumption in the absence of treatments.

[10] We checked the parallel trend assumption i.e. that before the experiment the treated and non-treated groups were characterized by parallel trends; in our case, this means that the control group's average electricity consumption was similar to the consumption in the treatment groups (T1, T2, T3) before the treatment. We tested this assumption formally using the fully flexible model for parallel paths proposed by Mora and Reggio (2017); our sample met this identifying assumption. Results available on request. All the variables included are described in appendix 6.

The coefficients of the interaction terms $time_{post_{it}} * T1_{it}$ $(time_{post_{it}} * T2_{it} and\ time_{post_{it}} * T3_{it})$ measure the causal effect on electricity consumption of treatment 1, treatment 2, and treatment 3 i.e. the effect of an ambitious goal and boosts, a modest goal and boosts, and only boosts.

The full set of controls for the observable characteristics includes two vectors. The vector *Individual characteristics* includes variables describing the respondent's environmental habits and some individual data such as age, profession, NEP scale score, GEB items and environmental commitment. The total number of people in the household (adults and children) is a non-neutral variable and is related to the family's everyday habits (Gram-Hanssen, 2014). The generational impact of age has also been shown to be important (Chancel, 2014).

Dwelling characteristics includes variables for number of people in the household, dwelling surface area, and type of heating system. Following Gram-Hanssen (2014), we use household size rather than electricity consumption per square meter as an explanatory variable for electricity consumption.

Since we are estimating electricity consumption during a period of time which involves a change of season (winter to spring) it is important to consider outside temperature changes. Kavousian et al. (2013) show the importance of outside temperatures for explaining residential electricity use; therefore, we include in our model the variable *weather temperature* as a control[11]. ε_{it} is a random, unobserved term which contains the errors due to omitted covariates.

5. Data and sample characteristics

Table 2 presents the characteristics of the sample that completed the *ex-ante and ex-post* questionnaires and are permanent residents.

[11] The variable weather temperature corresponds to the average monthly temperature in the Principality and proxies for exogenous climatic conditions in our estimation. Appendix 4-a shows the evolution of the weather during the period of analysis i.e., June 2018 to May 2019. The square of weather temperature is used in the econometric estimation. The average temperature decreases during the winter (October to January) and explains the significant effect on electricity consumption observed in the regression analysis.

Table 2: Sample description (N=77)

Variables	Mean	Std. Dev.	Min	Max
Men	0.594	0.491	0	1
Age (45-55 years old)	0.300	0.459	-	-
Monegasque nationality	0.501	0.500	0	1
French nationality	0.125	0.330	0	1
Italian nationality	0.224	0.417	0	1
Owner	0.434	0.495	0	1
Single	0.332	0.471	0	1
Married	0.667	0.471	0	1
Post-secondary diploma	0.168	0.374	0	1
License (secondary diploma)	0.135	0.341	0	1
Master / Engineer	0.360	0.480	0	1
Employee	0.263	0.440	0	1
Higher intellectual profession~~s~~	0.151	0.358	0	1
Retired	0.310	0.463	0	1
Surface (area) (m²)	102.010	46.402	30	250
No. of inhabitants (persons)	2.227	1.110	0	5
High NEP	0.51	0.50	0	1
Belonging to a green NGO	0.095	0.29	0	1
Individual heating system	0.574	0.494	0	1
Previous participation in an experiment	0.088	0.284	0	1
Individual electric heating system	0.419	0.493	0	1
Prewash	3.945	1.747	0	5
Full load in washing machine	4.297	1.159	0	5
Turn off heating at night	2.364	2.252	0	5
Turn on heating to avoid wearing thick clothing	1.391	1.584	0	5
Reduce heating if absent for more than 4 hours	2.932	2.178	0	5
Turn off lights in unoccupied rooms	4.608	0.8194	0	5
Average electricity consumption (kWh)	318.461	196.073	2.89	1659.60

Socio demographic and household characteristics. In terms of gender and age distribution, men are slightly overrepresented (60%) in our sample. On average, respondents were aged between 46 and 55 years (30%) similar to the Monegasque average age (46.6 years). Our sample is composed of citizens who are working (70%), 26.3% as employees and 15.1% professionals. The average number of people per dwelling is 2.2 which is line with the average for the whole Principality[12], and 43% of participants own their dwelling.

[12] The *Monaco en chiffres /Monaco in figures* (2019) report shows that there are 37.8% single person households, 32.3% two-person households, and 14.6 % of households that include three (or more)individuals.

Household's environmental concerns. We use the short version of the NEP scale (Davis et al., 2009; Schleyer-Lindenmann et al., 2016) to create a proxy variable for NEP score (M=1.78, Sd=0.82. Med = 23). Volunteers with an average NEP score below the median are considered less concerned about and less sensitive to environmental issues (Low NEP); volunteers with an average NEP score above the median are considered the most sensitive to environmental issues (High NEP)[13]. The dummy variable High NEP/Low NEP allows us to investigate the potential correlation between environmental concern and environmental behavior which Davis et al. (2009) assume. Our sample includes some low NEP profiles (49%) and a significant

proportion of high NEP profiles (51%).

Table 3: Environmental concern profiles

	Treatment				
NEP Profile	Boost & ambitious goal (T1)	Boost & modest goal (T2)	Boost only (T3)	Control group (CG)	Total
High NEP	44%	67%	45%	52%	51%
Low NEP	56%	33%	55%	48%	49%
Total	100%	100%	100%	100%	100%

Energy behaviors.

The volunteers responded to five items on energy behavior from the GEB scale (Kaiser and Biel 2000)[14]. We added a question about membership of an environmental NGO[15]. 64% of the sample reported collecting laundry to make enough for a full washing machine load, and 65% said they did not use the pre-wash program. 57% of dwellings had an individual heating system and 42% were on a shared system. Half (49%) of our sample had electric heating systems. 52% used eco-efficient light bulbs, and 32.93% used standard light bulbs, and 76.02% said they turned off lights in unoccupied rooms. 10% of participants were members of a green NGO.

[13] Internal consistency for the NEP scale is shown by a coefficient alpha of 0.87, suggesting relatively high internal consistency of the items. A reliability coefficient of 0.70 or higher is considered acceptable. The reliability coefficient corresponds to the usual results for this type of scale for instance, alpha= 0.75 in Davis et al. (2011).

[14] Our choice to use only 5 items from the GEB scale was to increase the chances that respondents would complete the questionnaire. Respondents were asked to indicate their level of agreement with each of the items as: "never", "seldom", "sometimes", "often", "always". The responses were scored from 1 to 5 from never to always (see appendix 5).

[15] Are you currently a member of an NGO working on sustainable development or environmental protection? (Q36).

6. Results

6.1. Evolution of electrical consumption across treatments

Table 4: Electricity consumption statistics before and during the field experiment

Treatment	Average energy consumption per household during the pre-treatment period (a)	Average energy consumption per household during the treatment period (b)	Difference (%) (c)	Diff-in-Diff (%) (d)	Pvalue (e)
Boost & ambitious goal (T1)	329.22 kWh	369.11 kWh	12%	-19%	0.0778 *
Boost & modest goal (T2)	236.34 kWh	252.47 kWh	7%	-24%	0.0177 **
Boost only (T3)	295.00 kWh	343.49 kWh	16%	-15 %	0.1237
Control (CG)	314.96 kWh	412.67 kWh	**31%**	-	-
Average of the panel	296.71 kWh	352.82 kWh	18.91 %		

Note: Column (a) is average electricity consumption by treatment in kWh during the 6 months before the start of the experiment, June 2018 to November 2018. Column (b) is average electricity consumption by treatment during the 6 months of the experiment December 2018 to May 2019. Column (c) is based on treatment and shows the difference in average energy consumption between the two periods i.e., during the experiment period minus the average consumption in the 6 months before the experiment in percentage. Column (d) shows the percentage variation (between the periods and with respect to the control group) in the percentage of variation in the control group (CG). Column (e) presents the results of a t-test of the difference between the average consumptions of the treated groups compared to the control group.

Table 4 presents the descriptive statistics for electricity consumption across the four treatments[16]. Average monthly electricity consumption shows that the group which consumed the least electricity was the boost and modest goal treatment, followed by the boost only treatment.

Table 4 column (c) presents the variation (as a percentage) in households' average electricity consumption across the four treatments. We observe a similar trend of increased average electricity consumption during the period of the experiment for all treatments due to the winter months. We control for this in our econometric model. Highest consumption was by the control group: CG 31% increase in consumption compared to the average consumption of the whole sample. The T1 and T2 groups had the lowest increases at respectively 12% and 7%. A Kruskal

[16] The statistics are based on average electricity consumption. The SMEG data are seasonally adjusted data; SMEG data do not distinguish between electricity used for heating and other electricity consumption. The results of table 4 are preliminary statistical estimations to be confirmed (or not) in the later econometric analysis.

Wallis (K-Wallis)[17] equality test of average monthly electricity consumption among treatments confirms that average electricity consumption during the six months of the observation period differed significantly across treatments (p-value = 0.0001). Also, pairwise comparison by treatment based on a Wilcoxon-Mann-Whitney (WMW) test shows that average electricity consumption over the period of the experiment differed significantly across some treatments (p=0.0001) although the consumption of the pair T3-CG shows no differences during the two first months of the experiment (p= 0.495)[18].

6.2. Efficiency of combination of boosts and goals

Table 5 presents the results of the DID regression for changes to household electricity consumption[19].

[17] Since the distribution of the error terms of our dependent variable does not satisfy the normal distribution criteria, we rely on the K-Wallis and WMW tests as alternatives to one-way analysis of variance (ANOVA). These two non-parametric tests are considered the best alternatives to the traditional t test which requires a normal distribution of the tested variable error terms. The K-Wallis test is used to compare two or more independent samples of equal or different sizes. It is an extension of the MWM U test which is used to compare two groups.

[18] Since the WMW test computes the comparison using the median, we add a pairwise comparison by treatment using the regular t test which compares average electricity consumption. The results show similar effects: T1 vs CG pvalue= 0.077, T2 vs CG pvalue= 0.017, T3 vs CG pvalue = 0.123.

[19] Based on the analytic using one-sided power calculations for DID models (Burling et al., 2020) and assuming $\alpha = 0.05$ and a MDE of 0.7, we observe a minimum effect size of 0.05 for the treatment effects results presented in this study

Table 5: Difference-in-differences estimation results

VARIABLES	Average household energy consumption (column a)	Average household energy consumption (column b)
time ($time_{post_{it}}$)	54.17**	54.17**
Boost & ambitious goal $(T1_i)$	3.152	-15.11
Boost & modest goal $(T2_i)$	-46.84	-69.53
Boost only $(T3_i)$	-38.08	-70.39
Control (CG_i)	*Ref*	*Ref*
time*T1 ($time_{post_{it}} * T1_{it}$)	-56.10*	-56.10*
time*T2 ($time_{post_{it}} * T2_{it}$)	-71.63**	-71.63**
time*T3 $(time_{post_{it}} * T3_{it})$	-43.22	-43.22
Individual characteristics		
Age	10.55	8.69
Higher intellectual profession	-72.59	-53.69
Employee	0.309	18.30
Retired	-9.119	5.78
Household size	48.54*	47.44
High NEP	-22.99	-8.61
Being part of Env. association	-	-84.24
Dwelling' characteristics		
Surface area	0.265	0.224
Individual electric heating system	114.9**	94.33*
Energy curtailment behaviors		
Prewash	-	-9.53
Full washing machine	-	7.205
Turn off heating at night	-	0.737
Turn on heating to avoid wearing thick clothing	-	16.13
Reducing heating for absences of more than 4 hours	-	-2.763
Turn off lights in unoccupied rooms	-	-15.00
Weather temperature²	-0.172***	-0172***
Constant	177.3	303.8*
Observations	708	708
R-squared	0.294	0.343

Table 5 presents the DID ordinary least square estimations equivalent to the regression formulation. The interaction variables time*T1, time*T2, time*T3 represent the effect of the treatments T1, T2, T3 compared to the control group (CG). Robust standard errors are clustered by household. Coefficient statistical significance is *** p<0.01, ** p<0.05, * p<0.1. Column a presents the treatment effect estimation without curtailment behaviors, Column b includes all GEB scale items and membership of an environmental NGO.

Table 5 compares the treated and control groups.[20] First, the coefficients of the interaction variables “time*T1” and “time*T2” for the effect of the treatments during the period of observation are negative and significant. Thus, T1 and T2 reduce household electricity consumption by respectively 56.10 kWh and 71.63 kWh compared to the control group (CG). The coefficient of the interaction “time*T3” is not significant, meaning that the treatment “boosts only” (T3) does not affect household electricity consumption.

Second, electricity consumption is positively and significantly affected by household size (column a) and use of an individual heating system. Intuitively, the size of the household will have a positive effect on electricity use (48.54 kWh on average) and households with individual electric heating systems consume 114.9 kWh more on average than those with a shared heating system. Also, electricity consumption changes based on the weather conditions i.e. higher outside temperatures and more light lead to a reduction in use of heating and lighting in the house and decrease electricity consumption. Household size has a significant and positive impact on electricity consumption i.e. larger household size (more individuals in the household) is related to higher electricity consumption.

Estimating the detailed treatments effects based on the quarterly data reveals some interesting features (appendix 7). Specifically, boosts on their own have small but significant effects on energy behavior after some time whereas boosts combined with goals have an immediate and stronger effect on reducing electricity consumption. Precisely, during the first three months and compared to the control group, an ambitious goal plus boosts (T1) reduces electricity consumption by 81.12 kWh on average while a modest goal plus boosts (T2) reduces consumption by 90.09 kWh on average. Both these effects disappear in the second three months of the experiment. Households in the T3 group which received only boosts showed an average reduction in their electricity consumption in the second three months of 34.01 kWh. These differences can be explained by the novelty of having a goal to work towards which resulted in higher commitment in the first three months of the experiment. Alternatively, the time taken to learn from the boosts (without a goal) (T3) is reflected in the fact that the energy reductions showed up only in the second three months of the experiment. These findings highlight the need to motivate participants continuously to avoid loss of interest in trying to reduce their electricity usage.

[20] Due to some missing values for the variable “number of inhabitants”, we reduced the number of observations to 708. We ran the estimations including and the results did not change. However, we prefer to present the estimations with no missing values.

6.3. *Boosts and goals combined with environmental concern*

The treatments that produced the best results were boosts plus goals (T1 and T2) which had significant effects on reducing electricity consumption. To investigate whether NEP scores played a part, we estimate DID for two different sub-samples of individuals based on their different NEP profiles. This allows us to identify for which groups the treatments had a stronger effect and to compare the effect based on high NEP or low NEP profile.

Table 6: Treatments estimation with the NEP profile

VARIABLES	Average household electricity consumption (high NEP) (a)	Average household electricity consumption (low NEP) (b)
time ($time_{post_{it}}$)	69.97***	30.80
Boost & ambitious goal ($T1_i$)	-62.4***	75.00***
Boost & modest goal ($T2_i$)	-140.3***	-60.51*
Boost only ($T3_i$)	-72.00*	-7.244
Control (CG_i)	*Ref*	*Ref*
time*T1 ($time_{post_{it}} * T1_{it}$)	-80.33**	-27.73
time*T2 ($time_{post_{it}} * T2_{it}$)	-96.04***	-47.29
time*T3 ($time_{post_{it}} * T3_{it}$)	-62.47	-9.134
Individual characteristics		
Age (45-55 years old)	-81.36***	-125.9***
Higher intellectual profession	-280.3***	-170.1***
Employee	-197.9***	-13.65
Retired	36.27	-450.5***
Household's size	36.60***	-9.398
Membership of an environmental NGO	-150.4***	-232.9***
Dwelling characteristics		
Surface area	1.182***	-0.245
Indiv electric heating system	14.78	197.9***
Curtailment behaviors		
Prewash	29.96***	-23.17***
Full washing machine	-23.24**	80.88***
Turn off heating at night	-7257	-0.505
Turn on heating to avoid wearing thick clothing	11.98*	14.07**
Reducing the heating for 4 hours absence	-9.2444	-8.781*
Turn off the lights in unoccupied rooms	-96.17***	-11.15
Weather temperature	-0.249***	-0.0914
Constant	-1064***	-284.2***
Observations	360	348
R-squared	0.636	0.589

Table 6 presents the DID estimations for the equivalent regression formulations for the effect of the treatment. The sample is divided into high level of concern for the environment (n=39 households observed) and low level of concern for the environment (38 households observed). Columns (a) and (b) report the respective ordinary least square estimates for the first and second groups. Robust standard errors are clustered by household. Coefficient statistical significance is based on the standard thresholds*** p<0.01, ** p<0.05, * p<0.1.

The results in table 6 show the impact of the NEP profile. Column (a) shows the estimated impact of the treatments for the high NEP profile. For this profile, T1 and T2 are effective for reducing electricity use. If we compare the impact of the three treatments, T2 boosts and modest goal has the strongest effect and reduces electricity consumption by 96.04 kWh on average (compared to the control group). T1 comes next with 80.33 kWh electricity consumption reduction. In this profile, a professional job, being retired, or belonging to an environmental association increases the chances of reducing electricity consumption. Using an individual electric heating system does not increase electricity consumption significantly which suggests that a high NEP profile is related to better management of electricity use.

Column (b) presents the treatments effect for low NEP and shows that this group is not significantly sensitive to any of the treatments. For the low NEP profiles, some curtailment behaviors such as not using the prewash program, are significant for reducing electricity consumption - 23.17 kWh on average. In addition, being retired and having more time, and membership of an environmental NGO have a positive impact on reducing electricity consumption, showing some other forms of environmental citizenship for this profile. If we compare high and low NEP profiles, we observe the same effects for most of the control variables. However, use of an individual electric heating system is positively significant for the low NEP profile. Households with a low NEP profile consume more electricity (197.9 kWh on average) if they have an individual electric heating system.

Overall, our results confirm those obtained from our main regression, and more precisely that a combination of goals and boosts is more relevant for lowering household electricity consumption. However, the efficiency of the treatments depends on the NEP profile. Households with a high NEP profile are more likely than low NEP profile households to reduce their electricity consumption.

7. Discussion

Our empirical findings are fourfold. First, when implemented in combination with a goal (ambitious or modest), boosts can have a significant effect on reducing electricity use. In other words, setting a precise goal and providing boosts incentivizes the household to act and to reduce its electricity consumption. That is, a boost increases the household’s knowledge about electricity usage and providing suitable means for steering households in the presence of goals (Martela, 2015). In this case, boosts and goals seem to be mutually reinforcing. That is, the combination of a modest (realistic) goal and boosts produces more significant results than a more ambitious goal and boosts. Therefore, a step-by-step strategy with a long-term perspective delivers better outcomes. These results are in line with the findings in Harding and Hsiaw (2014) on the need to set realistic goals.

Second, although boost only (treatment T3) reduces electricity use, this result is not statistically significant for any profile. This is in line with Abrahamse et al. (2005) who recommend combining behavioral tools with goal setting. We extend this idea by combining goal setting with boosts which have long lasting effects on knowledge. If we focus only on boosts, we find this is effective for high NEP households but not significant for low NEP households. This exemplifies the complexity of the causality link between ecological concern and electricity behaviors shown by Nauges and Wheeler (2017). It also emphasizes the need to combine boosts with an objective span and to implement these behavioral tools in the right context.

Third, in the case of high NEP profiles, our results show that all the treatments promote electricity saving. Being retired, being a professional, and belonging to a green NGO appear to be important for promoting electricity saving. These relations suggest that individuals with more time will be more likely to have the resources and motivation to change their electricity use behavior and that higher education and greater environmental commitment are good predictors of such actions. Although the findings from our behavioral treatments are novel, the empirical findings on the effect of education and retirement (having more time) are in line with prior results. For instance, Pullinger (2014) shows that working time, sustainable consumption and well-being should be considered together. More precisely, being retired or having shorter working hours has a positive effect on sustainable consumption by allowing the household more time to learn and providing the enabling conditions to study the environment and act on it (for a similar discussion see Shove et al., 2020).

Fourth, among low NEP profiles, we found that none of the treatments were significant although education, retirement, environmental commitment, and curtailment behaviors (variable “prewash”) matter. This result is in line with the findings in Nauges and Wheeler (2017) on the difference between curtailment and energy efficient behaviors. The latter explain why the relationship between curtailment behavior and concern for climate change is difficult to identify and requires long learning combined with non-monetary and monetary tools to increase its potential efficiency. In the case of citizens with low intrinsic motivation towards environmental issues, some other forms of environmental commitment are at work. These findings also illustrate the complexity between electricity behaviors and environmental concern and the dependence on dwelling characteristics and diverse forms of actions beyond solely green values (Welsch and Kuhling, 2009; Woersdorfer and Kaus, 2011; Babutsidze and Chai, 2018).

More generally, following the recommendations in Buckley (2020) and Ander and Fels (2018), we provide new evidence on the effectiveness of boosts and goals for driving potential electricity reductions. In Monaco and elsewhere, there is an urgent need to increase electricity use transparency through the provision of information and education and by "increasing means and reducing barriers to increase capability or opportunity" (Belaid and Joumni, 2020: 9). Thus, studying the effectiveness of goals combined with boosts is relevant to increase individual capability to transform a stated concern for the environment into concrete action. Our results show that modest goals combined with specific information can translate concern for the environment into green behavior. A goal of between a 15% and 25% reduction in energy use is efficient for households already concerned about the environment and committed to greener behaviors.

8. Conclusions and policy implications

Boosts seem to be a promising and novel tool which require some pre-conditions before being implemented. Goal setting is a classic tool which has good outcomes and a greater impact when combined with other tools. Our results show the effect of goals and boosts on energy conservation, and their complementarity and effectiveness for steering individuals to reduce their electricity consumption. Outcomes for high NEP profile households show their inherent limits which policy makers should consider if they want to change individual behaviors. Let's elaborate further these points.

Our empirical findings highlight that there are no good or bad behavioral tools but only instruments adapted to a local context and targeted to a specific population (Bradt, 2019). Our field work showed that the right combination of a modest goal and boosts can produce significant results. This suggests that researchers and policy makers should not overlook the importance of instruments such as goal setting and focus only on boosts; on the contrary, they need to observe the focal population to determine whether goals combined with boosts will produce better results, and why. Having chosen a particular behavioral tool, it may be necessary to find the goal level and to co-design this process with local actors. Here knowledge of the field and the level of trust among the participants will be critical (see Kendel et al., 2017 for a suggested balance).

It is important also to determine what participants consider to be a realistic and an ambitious goal. An ambitious goal involves the degree of pressure that can be exerted on individuals and the length of time that they will be able to sustain this effort. Our research in the field shows that volunteers set an ambitious goal were initially highly motivated but found it difficult to maintain this level of effort over the long run which shows that extrinsic motivation has limits. However, several goal levels should be tested to establish which provides the most significant results. Sample size and other conditions matter for the goals levels set in experiments.

Finally, it is well known that environmental profile matters. The fact that those most involved in environmental issues are the most responsive to behavioral tools, creates new problems related to inclusiveness. As Hertwig and Ryall (2020) point out, the notion of emancipation through education, and increasing individual capabilities are both important and may increase the pressure to innovate to include all citizens in an ecological-transition-for-all agenda (DellaValle and Sareen, 2020). Economists and decision-makers must study these new behavioral tools to identify which will include the largest range of the population, and replicate experience in different and larger contexts to obtain robust results. This requires both ambitious but cautious efforts since each context is unique, and some tools may work only in certain contexts. This leads to the limitations of our study.

The evidence on the efficacy of combining boosts with goals raises questions about behavioral strategies and their enforcement. We need more in-depth investigation of the efficiency of behavioral tools for promoting electricity saving behaviors which considers the different levels of households' concern for the environment. To increase its generalizability to other fields such as mobility and nutrition, and to investigate the right combination of behavioral tools, (see Banerjee and Duflo, 2009) our field experiment should be replicated with a larger sample and a more diverse populations of volunteers. We also cannot exclude a Hawthorne effect (Schwartz et al., 2013) i.e., the fact of being observed increasing motivation and possible biasing our results. These limitations are discussed in Harrison and List (2004) and are important. For instance, in some field experiments the control group is not neutral. This is highlighted by Kendel et al. (2017) in the context of their experiment on electrical consumption and their finding of 13% decreased energy use in the control group and a 26% decrease in the treatment groups. This suggests that being observed may induce some behavioral changes in some contexts. In our experiment, we cannot exclude a framing effect on the volunteers. For example, the ex-ante survey asked about energy systems and heating, some energy practices, and environmental concerns and may have influenced the sample by revealing some implicit assumptions of our experiment. These limitations are inherent to a field experiment methodology and are both a force and a constraint and may moderate some results (see Harrison and List 2004 for a longer discussion).

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APPENDIX

Appendix 1-a: Recruitment letter the participants received.

Take part in the Smartlook experience!

Join our CNRS team

Live a unique experience in favor of energy transition

Act for change

- Volunteers' anonymity ensured
- Study launch in June 2018
- Scientific study for non-commercial purposes

THE PROJECT

According to the Principality of Monaco energy transition White Paper, everyone must act to cut "greenhouse gas emissions by 50% by 2030". Control and reduce energy consumption require individual efforts and changes to habits for better management of energy usage.

We invite you to contribute to the energy transition by participating in Smartlook, a unique scientific study.

Smartlook is a project led by the GREDEG laboratory (Groupe de Recherche en Droit, Economie, Gestion) of the Côte d'Azur University and CNRS, in partnership with the SMEG. It assesses usage of new digital services provided to households in the Principality of Monaco.

Sign up now

via email:

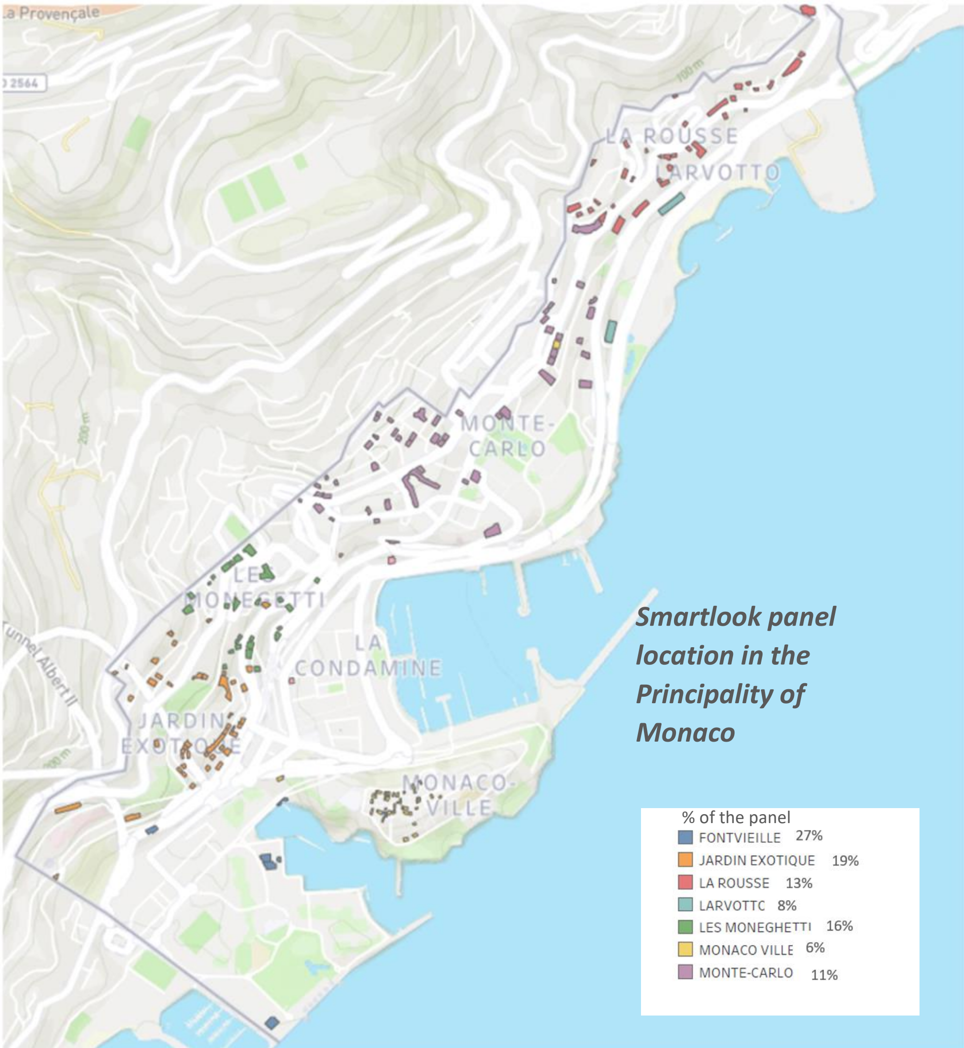
via telephone: XXX

via mail: by returning the reply to coupon to the given address

A project presentation session will be organized to allow you to meet the research team.

Appendix 1-b: Panel location in the Principality of Monaco

Distribution of the households participating in the field experiment across the Principality.

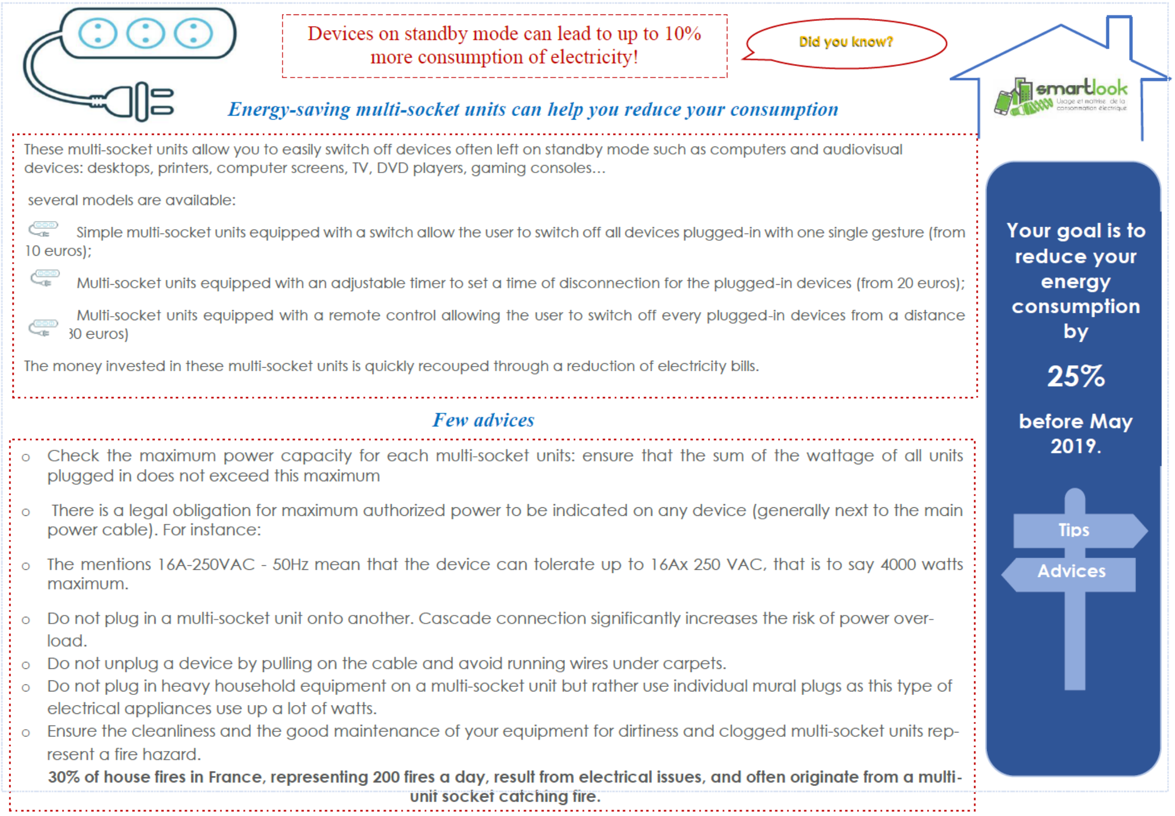


Source: SMEG Monaco.

Appendix 2: Boosts sent to citizens

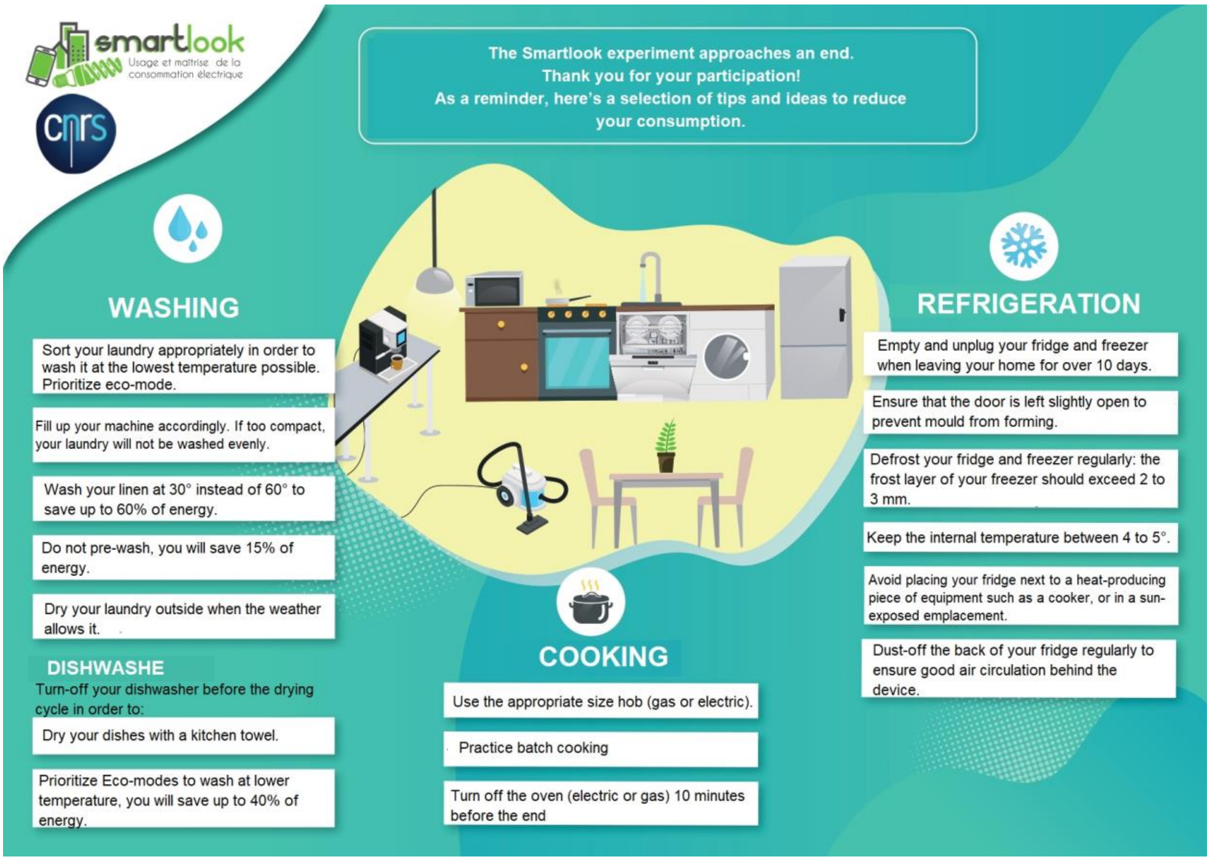
Boosts	Content	Developed idea
Boost 1	Prepare for winter	Check insulation in the apartment. Have boilers cleaned and maintained.
Boost 2	A green Christmas	Check how much electricity Christmas lights are consuming. Use alternative non-electrical decorations.
Boost 3	Do laundry at 30 °	Check efficiency of washing machine and adjust wash temperatures. Use energy-efficient drying alternatives.
Boost 4	Kitchen appliances (1)	Check fridge/freezer temperatures, run dishwasher only when full or on an economy cycle. Have machines serviced regularly.
Boost 5	Kitchen appliances (2)	Try to use energy efficient cooking methods.
Boost 6	Consumption of standby devices	Hidden consumption caused by devices on standby.
Boost 7	Small appliances	Use energy efficient light bulbs.
Boost 8	Prepare for spring (1/2)	Spring cleaning tips (1).
Boost 9	Prepare for spring (2/2)	Spring cleaning (2).
Boost 10	Use of multi-socket units	Multiple sockets allow more control over individual electrical devices.
Boost 11	Ecolabels	Interpretation of ecological labels on household equipment.
Boost 12	Top tips	Summary of provided tips.

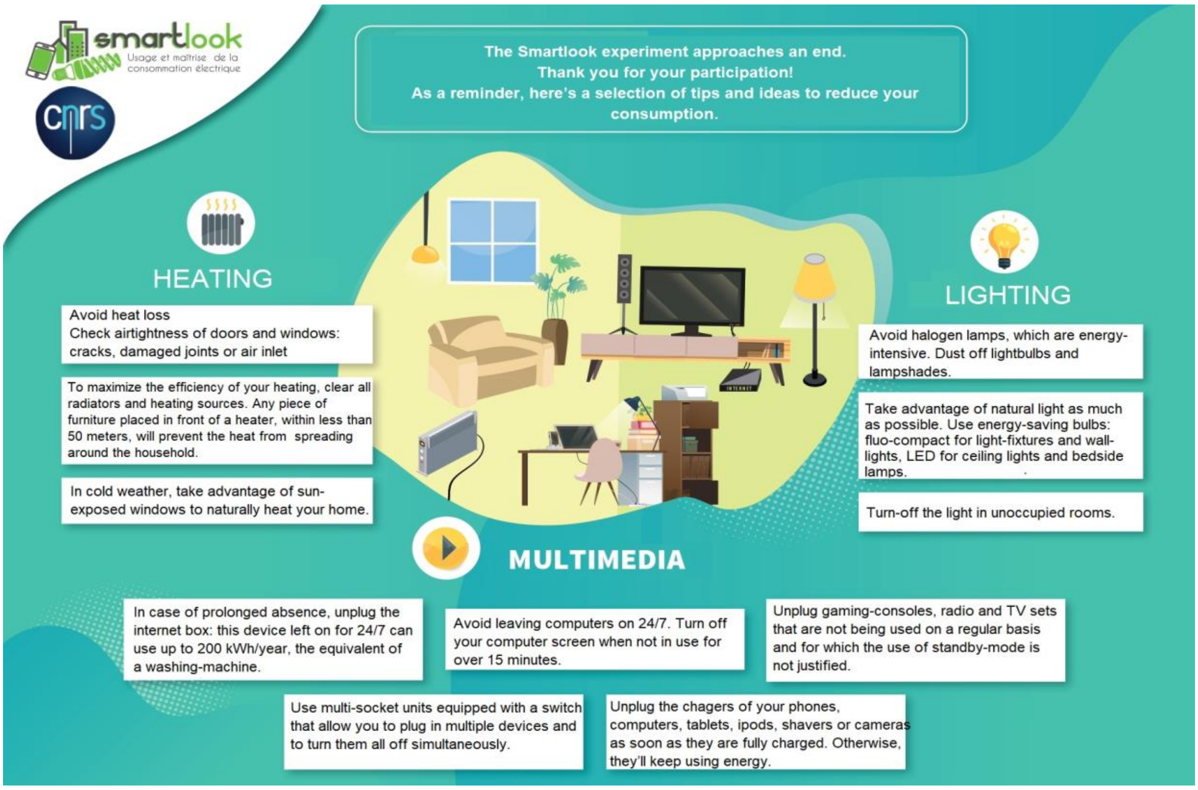
Appendix 3- a: Example of boost n° 10 on use of multi-sockets (English version)



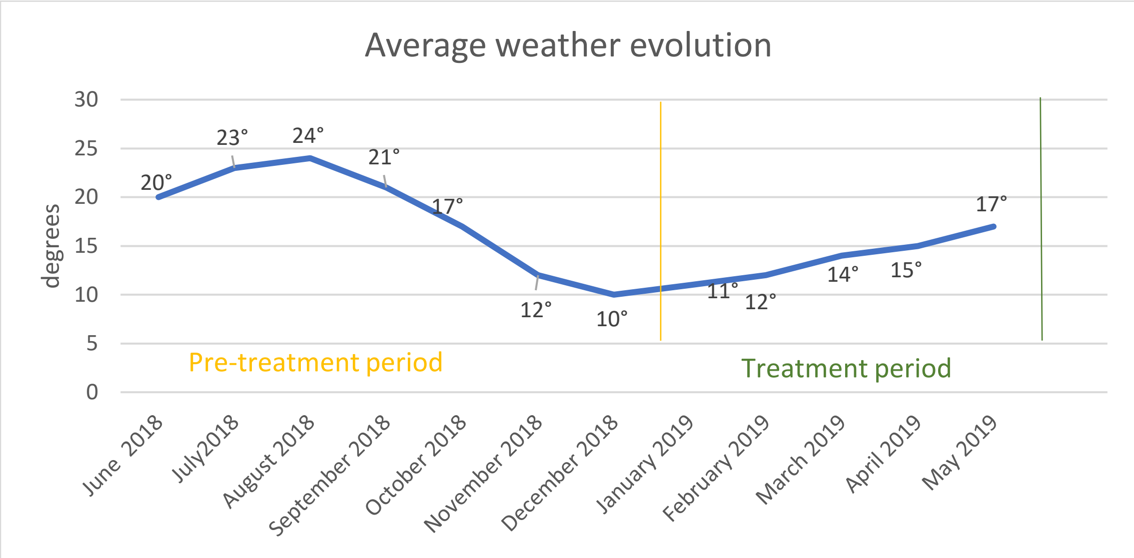
Note: The boosts are phrased in such a way as to draw the attention of the household to a behavior which either is causing unnecessary consumption of energy or would reduce energy consumption. The further information and tips increase the household's knowledge about possible cognitive biases and provide advice on how to overcome them and allow more sustainable consumption of electricity.

Appendix 3-b: Top tips





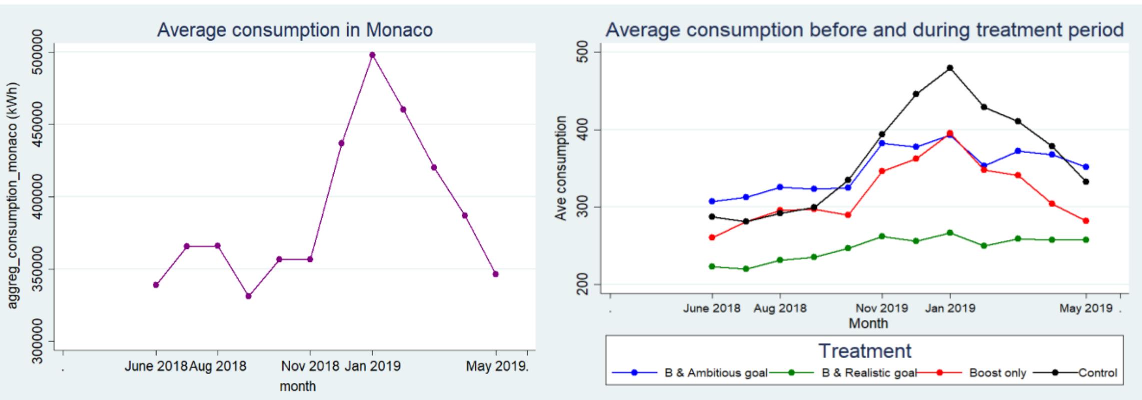
Appendix 4-a. Temperatures changes during the experiment



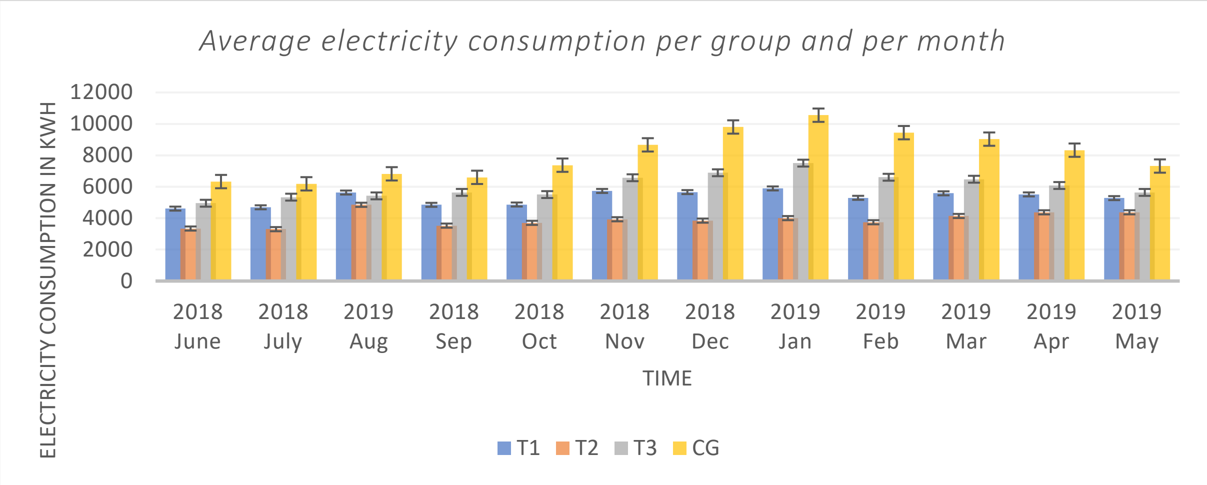
Appendix 4-b. Energy consumption in the Principality of Monaco

Energy consumption in the Principality of Monaco (based on SMEG data on average consumption among Monegasque households).

Energy consumption increased in the panel and in the Principality starting in November 2018. From January 2019 consumption decreased among the households in the panel and the Principality. We believe that the consumption behavior of the panel of households participating in the experiment is typical of the whole Principality.



Appendix 4-c. Panel monthly energy consumption



Appendix 5. GEB scale: energy conservation behaviors (Kaiser and Biel, 2000)

- I wait until I have a full load before doing my laundry (Q23-a)
- I do not use the prewash facility on my washing machine (Q23-b)
- The heating is turned off during the night (Q26)
- In winter, I turn up the heating, so I do not have to wear heavy clothes (Q26)
- In winter, I reduce the heating when I leave home for longer than 4 hours (Q26)
- I turn off lights in unoccupied rooms (Q28)
- I mainly use eco efficient light bulbs (Q27)

Appendix 6. Model variables

Variable names	**Definition**
Dependent variable	
Energy consumption	Each household's average monthly electricity consumption
Independent variables	
Boost & high goal (T1)	1 if the household received a high energy reduction goal coupled with boosts and 0 otherwise
Boost & low goal (T2)	1 if the household received a low energy reduction goal coupled with boosts and 0 otherwise
Boost only (T3)	1 if the household received boosts and 0 otherwise
High NEP	1 if the NEP score is greater than median of NEP score of the panel and 0 otherwise
Men	1 for men and, 0 otherwise
Monegasque	1 if the respondent is a native Monegasque and 0 otherwise
French	1 if the respondent has French nationality and 0 otherwise
Italian	1 if the respondent has Italian nationality and 0 otherwise
Owner	1 if the respondent is the homeowner and 0 otherwise
Single	1 if the respondent is single and 0 otherwise
Married	1 if the respondent is married and 0 otherwise
Post-secondary diploma	1 if the respondent has completed 2 years of higher education and 0 otherwise
Higher education	1 if the respondent has completed 3 years of higher education and 0 otherwise
Master's/Engineer	1 if the respondent has an engineering or a master's degree and 0 otherwise
Employee	1 if the respondent is an employee and 0 otherwise
Higher intellectual professions	1 if the respondent is a professional and 0 otherwise
Surface (Area)	Apartment size
No. of household members	Number of members of the household during the period of the experiment
Environmental commitment	1 for membership of an environmental NGO and 0 otherwise.
Individual heating system	1 if the household has an individual heating system and 0 otherwise
Previous participation in an experiment	1 if the household has previously participated in an experiment related to energy consumption
Individual electric heating system	1 if the household has an individual electrical heating system.

Appendix 7. Difference-in-differences estimation results by trimester

VARIABLES	***Household average energy consumption per trimester***
First trimester	*-22.29*
Second trimester	*ref*
Third trimester	*84.46***
Fourth trimester	*23.18*
B & ambitious goal (T1)	*-26.16*
B & modest goal (T2)	*-83.62*
Boost only (T3)	*-77.64*
Control (T4)	*ref*
*First trimester*T1*	*22.10*
*First trimester*T2*	*28.17*
*First trimester*T3*	*14.50*
Second trimester	*ref*
*Third trimester*T1*	*-81.12**
*Third trimester*T2*	*-90.09***
*Third trimester*T3*	*-37.94*
*Fourth trimester*T1*	*-9.99*
*Fourth trimester*T2*	*-25.00*
*Fourth trimester*T3*	*-34.01**
Age	*8.686*
Higher intellectual profession	*-53.69*
Employee	*18.30*
Retired	*5.781*
Household size (No. in household)	*47.44*
High NEP	*-8.610*
Surface area	*0.224*
Individual electric heating system	*94.33**
Full washing machine	*7.205*
Prewash	*-9.533*
Turn off heating at night	*0.737*
Turn on heating to avoid heavy clothes	*16.13*
Reducing the heating for 4 hours absence	*-2.763*
Turn off the lights in unoccupied rooms	*-15.00*
Being part of Env. association	*-84.24*
Using eco efficient light bulbs	*-14.79*
Weather temperature	*-0.122***
Constant	*318.5**
Observations	*708*
R-squared	*0.349*
Robust standard errors in parentheses	
**** p<0.01, ** p<0.05, * p<0.1*	

VARIABLES	Household average energy consumption
time ($time_{post_{it}}$)	35.03
B & ambitious goal *($T1_i$)*	-15.11
B & modest goal *($T2_i$)*	-69.53
Boost only *($T3_i$)*	-70.39
Control *(CG_i)*	Ref
time*T1 ($time_{post_{it}} * T1_{it}$)	-56.10*
time*T2 ($time_{post_{it}} * T2_{it}$)	-71.63**
time*T3 *($time_{post_{it}} * T3_{it}$)*	-43.22
Individuals' characteristics	
Age	8.686
Higher intellectual profession	-53.69
Employee	18.30
Retired	5.781
Household's size	47.44
High NEP	-8.610
Being part of Env. association	-84.24
Dwelling's characteristics	
Surface (Area)	0.224
Individual electric heating system	94.33*
Energy curtailment behaviors	
Full washing machine	7.205
Prewash	-9.533
Turn off heating at night	0.737
Turn on heating to avoid heavy clothes	16.13
Reducing the heating for 4 hours absence	-2.763
Turn off the lights in unoccupied rooms	-15.00
Weather temperature²	-0.134***
Average consumption in Monaco	0.000378***
Constant	155.5
Observations	708
R-squared	0.347

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

Appendix 8.

Table 8 provides a robustness check. We re-ran the estimations presented in table 5 including average consumption in Monaco as a control. The following table shows that the results do not change, and the coefficients remain significant which confirms our main results.