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Report on innovative interventions aimed at facilitating the adoption of energy efficient products

Ellen van der Werff[a], Cristina Cattaneo[b]. & Matthias Rodemijer[c]

[a] University of Groningen, the Netherlands
[b] European Institute on the Economy and the Environment, Italy
[c] WWU Munster, Germany

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1. Summary for policy makers

Goal

To effectively reduce environmental problems caused by fossil energy use policy makers can implement incentives aiming to promote sustainable energy behaviours. We tested the effectiveness of incentives to promote sustainable energy behaviours. In particular, we tested whether a goal setting intervention is scalable and can thereby promote sustainable energy behaviour at large. Next, in the context of financial incentives to promote shifting energy use in time we tested why people are likely to shift their energy use of appliances. Finally, we tested for which type of customers, social information programs are likely to be effective in promoting sustainable energy behaviours.

Method

In three studies conducted in Italy, the Netherlands, and Germany we tested incentives to promote sustainable energy behaviour. We used randomized control trials to ensure that our findings can be attributed to the incentive. We combined the experiments with questionnaires to gain more insight into the underlying processes. We aimed for general samples and collaborated with utilities to increase the external validation of our studies. However, participants voluntarily signed up for the experiments. Therefore, the sample is likely to be somewhat biased towards people who may be more interested in the topic of energy than the general population.

Results

The results from our study in Germany suggest that there is a low demand for energy technologies that can help people to save energy. Specifically, we found that there was a low demand for the energy savings app.

The findings from our study in the Netherlands suggest that people are willing to shift their energy consumption in time. Specifically, our results suggest that people are most likely to shift the use of the dishwasher in time. To a somewhat lesser extent they shift the use of the washing machine, dryer and their electric vehicle. However, people hardly adjust their use of the lights, household appliances (e.g. vacuum cleaner) and the television or music installation to the energy tariffs. Furthermore, in the context of a financial incentive we tested which factors most strongly influence the shifting of energy consumption in time. Interestingly, despite the financial incentive, we found that saving money did not influence people's energy consumption in time. We found that people are more likely to shift their energy consumption in time when they perceive that they can shift their energy consumption and when they think others do so.

The results from our study in Italy suggest that the effectiveness of social information programs differs for different types of customers. Specifically, we found that when baseline consumption is low, it is hard to further reduce it, no matter if the person receiving the information holds high or low environmental values. However, when pre-consumption is high, high environmental values boost the effectiveness of peer comparison. 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.

Implications

- When designing interventions aiming to promote sustainable energy use it is not only important to develop an effective intervention, it is also crucial to ensure that many people are exposed to and participate in the intervention.
- Organizations and governments aiming to promote sustainable energy behaviour could promote the adoption of energy technologies that can help people save energy. However, a key question is how to motivate people to set the goals to save energy.
- Financial incentives may not be the most effective strategy to promote a shift in energy consumption. Instead people may be more likely to shift their energy consumption in time when they receive information about the time of use of others and when the extent to which they can shift their energy use in time is increased. For example, smart appliances that automatically turn on at times when renewable energy is available may help people to shift their energy use in time.
- Policy makers aiming to promote sustainable energy behaviour can provide people with information on the energy behaviour of others. However, these incentives are most likely to be effective when they target those who care about the environment, yet currently do not engage in sustainable energy behaviour.

2. Executive Summary

To effectively reduce environmental problems caused by fossil energy use policy makers can implement incentive aiming to promote sustainable energy behaviours. In this report we aimed to test the effectiveness of incentives to promote sustainable energy behaviours. In three studies conducted in Italy, the Netherlands, and Germany we tested incentives to promote sustainable energy behaviour. Specifically, we tested whether a goal setting intervention is scalable and can thereby promote sustainable energy behaviour at large. Next, in the context of financial incentives to promote shifting energy use in time we tested why people are likely to shift their energy use of appliances. Finally, we tested for which type of customers social information programs are likely to be effective in promoting sustainable energy behaviours. Importantly, we collaborated with utilities to increase the external validation of our studies.

The results from our study in Germany suggest that there is a low demand for energy technologies that can help people to save energy. Specifically, we found that there was a low demand for the energy savings app. Our findings show that organizations and governments aiming to promote sustainable energy behaviour should aim to promote the adoption of energy technologies that can help people save energy. As studies have shown that goal setting interventions can effectively promote sustainable energy behaviour a key question is how to motivate people to set these goals.

The findings from our study in the Netherlands suggest that people are willing to shift their energy consumption in time. Specifically, our results suggest that people are most likely to shift the use of the dishwasher in time. To a somewhat lesser extent they shift the use of the washing machine, dryer and their electric vehicle. However, people hardly adjust their use of the lights, household appliances (e.g. vacuum cleaner) and the television or music installation to the energy tariffs. Furthermore, in the context of a financial incentive we tested which factors most strongly influence the shifting of energy consumption in time. Interestingly, despite the financial incentive, we found that saving money did not influence people's energy consumption in time. We found that people are more likely to shift their energy consumption in time when they perceive that they can shift their energy consumption and when they think others do so. These findings suggest that financial incentives may not be the most effective strategy to promote a shift in energy consumption. Instead people may be more likely to shift their energy consumption in time when they receive information about the time of use of others and when the extent to which they can shift their energy use in time is increased. For example, smart appliances that automatically turn on at times when renewable energy is available may help people to shift their energy use in time.

The results from our study in Italy suggest that the effectiveness of social information programs differs for different types of customers. Specifically, we found that when baseline consumption is low, it is hard to further reduce it, no matter if the person receiving the information holds high or low environmental values. However, when pre-consumption is high, high environmental values boost the effectiveness of peer comparison. 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. Our findings suggest that policy makers aiming to promote sustainable energy behaviour can provide people with information on the energy behaviour of others. However, these incentives are perhaps ineffective among those who care less about the environment. Therefore, they should be directed towards those who strongly care about the environment, yet currently do not engage in sustainable energy behaviour.

3. Aim of the report

3.1 Introduction

In this report, we discuss studies on incentives to promote sustainable energy behaviours. We present the results from three studies: a study on the scalability of energy use goal setting in collaboration with Münster utility (Germany), a study on differentiated electricity tariffs in collaboration with utility Qurrent (the Netherlands), and a study on social information messages in collaboration with utility ENI (Italy). These findings are relevant for policy makers aiming to promote sustainable energy behaviours.

Objectives

- Provide insight into the effectiveness of incentives to promote sustainable energy behaviours;
- Understand the underlying processes explaining why incentives may be effective and under which conditions they may be effective in promoting sustainable energy behaviour;
- Test whether incentives are scalable and can change behaviour on a large scale.

To promote sustainable energy behaviours policy makers can use different incentives. In this report we will focus on three important strategies to promote sustainable energy behaviours: goal setting, financial incentives and social information. We will test if the incentives can effectively promote sustainable energy behaviour by testing whether the incentives are scalable, why they influence behaviour and for which type of people such interventions may be effective.

Scaling a goal setting intervention

Goal setting has been found to be an effective strategy to alter behaviour. One line of reasoning for why goal setting could affect behaviour comes from a model of reference-dependent preferences and loss-aversion (Heath et al. 1999). The argument is that goals create reference points to which agents compare their behaviour. Falling short of a self-set goal by a certain distance reduces utility by more than achieving a goal of the same distance would increase utility (loss aversion). Economic models by Koch & Nafziger (2011) and Hsiaw (2013) showed that with present-biased agents goals can be used as a commitment device to exert discipline over future behaviour. The idea is that "future selves" reduce overconsumption due to the potential pain of falling short of a goal that was set at an earlier point in time by the "previous self".

"In light of its widely-documented effectiveness, it is somewhat puzzling that plan-making has not been more broadly adopted by policy-makers." (Rogers et al. 2019, p. 12).

Studies suggest that goal setting interventions can effectively promote resource conservation. Agarwal et al. (2017) tested smart showering meters that provide real-time feedback on water consumption among 500 households in Singapore. The feedback intervention was complemented by different saving goals of exogenous size. They found an interesting pattern in line with theory of reference dependence and loss aversion: higher goals led to more conservation but the highest goal seemed to de-motivate and discourage savings. Harding & Hsiaw (2014) use an event study to evaluate the effects of an energy-savings program in the United States that asked households to set themselves a target for their electricity consumption. The study found that self-set goals reduced consumption by on average 4%. For consumers who chose relatively realistic goals, the treatment effect was a high reduction in consumption of 11%. Loock et al. (2013) ran an experiment with about 1,800 electricity consumers to test a web portal, which allows participants to set themselves energy saving goals with different default goals as suggestions. Varying default goals significantly influences the self-set goals and affects energy savings. A treatment group with medium default goals (15% savings) realizes statistically significant savings of 4% in comparison to a "no-goal group". The authors conclude that "[…] the savings achievable by goal-setting functionalities are ultimately worth the effort." (Loock et al. 2013, p. 1327).

We built on these promising results by asking an additional question that frequently remains unanswered: Is a goal setting intervention a scalable intervention? That is, can a goal setting intervention lead to energy saving on a large scale? For this purpose, we developed an energy saving app with a goal-setting feature for mobile phones that can be easily accessed by the majority of the population. We ran a large-scale field experiment in which we advertise the app to an entire city of over 310,000 inhabitants.

Incentives to shift energy consumption in time

To promote energy efficiency we need to rely more on renewable energy sources such as wind and solar energy. However, renewable energy is not always available because the sun is not always shining and the wind is not always blowing. Therefore, individuals need to shift their energy use to times when renewable energy is available (Steg, Perlaviciute, & Van der Werff, 2015). However, few studies have tested whether people are willing to shift their energy use in time, for which appliances or behaviours they are most willing to shift their energy use, and which factors influence the shifting of energy use in time. The current study aims to address these questions.

A common approach to encourage sustainable energy behaviour is by introducing a financial incentive. Financial incentives can be effective in promoting such behaviours (e.g. Maki et al., 2016). Yet, financial incentives do not always result in consistent long-term behavioural changes. That is, once the incentive is discontinued, behaviour often returns to baseline (Bolderdijk et al., 2011; Maki et al., 2016). Furthermore, research has shown that financial appeals can be less effective compared to environmental appeals in promoting sustainable energy behaviour (Bolderdijk et al., 2013; Schwartz et al., 2015). For example, advertising an energy saving program by focussing on the environmental benefits was found to be more effective in promoting participation in the energy saving program than focussing on the financial benefits. Monetary benefits of environmental behaviour are often small, and may therefore not be perceived as worth the effort (Dogan, Bolderdijk, & Steg, 2014). The financial benefits of shifting one's energy consumption in time may not be worth the effort. Financial incentives to shift energy use in time are likely to be small. However, shifting one's energy consumption in time may be relatively effortful. For example, when people want to switch the use of their washing machine in time they need to plan this behaviour. They need to turn on the washing machine and handle the washed cloths at a time that may not be very convenient for them. Therefore, a crucial question is whether people think it is worth the effort to shift their energy consumption in time for the financial savings. In the context of a financial incentive to shift energy consumption in time we will test which factors influence shifting one's energy consumption in time. Specifically, we will, amongst others, test the influence of financial and environmental motivations to do so.

Smart appliances can help consumers to shift their energy consumption in time. For example, smart appliances can automatically turn on when renewable energy is available and when energy tariffs are low. Smart appliances can also help consumers by providing clear information on when renewable energy is available and when energy tariffs are low. The aim of this study is to test if people are likely to use such smart appliances and whether they can help consumers to shift their energy consumption in time.

Under which circumstances do social information programs promote sustainable energy behaviour?

Social information programs are increasingly used by policy makers to nudge behavioural change. Within such programs people for example receive information about the energy consumption of others (social norms) which can promote sustainable energy behaviour. Social norms can effectively induce behavioural change (Schultz et al. 2007). When people realize they consume more energy than other they become motivated to change their behaviour to be in line with others and reduce their energy consumption. However, relatively little is known about the sources of heterogeneity in the effect of social information programs. This study aims to answer the question which customers' characteristics make customers more likely to respond to social information programs. The current study examines the role played by two sources of heterogeneity: individual values and initial energy consumption levels.

Values are antecedents of preferences, intentions, and behaviour and represent guiding principles in everyone's life (Schwartz, 1992). People with strong environmental values care about nature and the environment. People with strong environmental values are more likely to engage in sustainable energy behaviour. As values determine behaviour they represent a crucial source of heterogeneity in response. However, despite their important role in guiding behaviour, the differential response to social information with respect to values has rarely been studied. Information is more effective when it resonates with people's central values (Steg et al. 2015). Therefore, we will test if people with strong environmental values are more likely to respond to the social information.

When initial energy consumption of customers is low the cost for conservation is likely to be higher, because they are likely to 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. Therefore, we will test if social information is particularly likely to promote sustainable energy behaviour among those with higher initial energy consumption.

Values are stable characteristics that are difficult to change. Identity, which is the label used to describe yourself, can be changed by reminding people of their past behaviour (Van der Werff et al., 2014). Specifically, environmental self-identity is defined as the extent to which one sees oneself as a type of person who acts environmentally-friendly (Van der Werff et al., 2013). Past environmental behaviour is a driver of environmental self-identity, which in turn is related to future environmental behaviour, such as energy conservation (van der Werff et al., 2014b). Drawing from this literature, we will test if a message making past pro- environmental actions salient increases the effect of social information programs on behaviour. Specifically, we will test whether adding an identity message to social information programs makes values more effective in influencing behaviour.

3.2 Acknowledgements

We would like to express our thanks to our contact persons at Eni, Qurrent, and Münster utility for the fruitful collaboration.

Study 1

We developed an energy savings app with a goal-setting feature for mobile phones that can be easily accessed by the majority of the population. In collaboration with the main utility provider in the city of Münster we ran a field experiment in which we advertised the app to an entire city with over 310,000 inhabitants. In the field experiment we tested the effect of goal setting on electricity consumption. Please note that electricity consumption data of most German households is only available on an annual basis.

4. Method Study 1

4.1 Procedure

Our experiment was run between May and November 2018. To recruit subjects to use the app, about 69,000 utility customers received direct and personalized mails encouraging them to use the new energy savings app (see Figure 1) and participate in the lottery. Furthermore, 14,000 flyers advertising the new app were put into the mail of annual electricity bills. The same flyer was put into a print of a local newspaper that was distributed to 18,000 households. In addition, we put an advertisement in another local newspaper with 48,000 prints and contracted a local radio station to play frequent advertisement spots. We also used public advertisement in the main student canteen (1,600 students per day) where posters were presented and about 200 flyers were distributed for two weeks. Upon signing up, subjects get randomly assigned to a control group and a treatment group with equal probability.

Figure 1: Example of Flyer

4.2 Measure of electricity consumption

We hired a professional IT company to develop a feature for mobile applications which allows users to more conveniently report their consumption to the utility. As depicted in Figure 2 the app automatically recognizes and reads the electricity meter if the user points the camera of her phone at the meter. The user then only needs to press an "upload"-button on her phone in order to upload the data to the server of the utility provider. In case of technical issues with the scanning process, they could also manually type the value into the app. All participants received a reminder to scan their meter one day prior to, one day after and exactly on the due date (see Figure 2d). If subjects failed to scan the meter 2 days after the due date, they did not gather the lottery ticket for that particular scan. They could, however, continue to use the app and get lottery tickets for all upcoming scans.

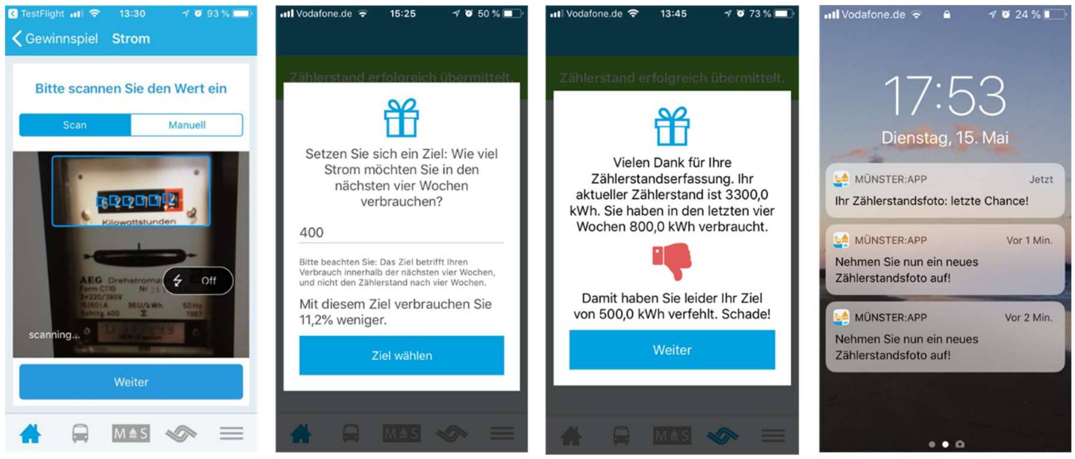

Figure 2: Screenshots of Energy Savings App

4.3 Experimental manipulation

Figure 3 gives an overview of the experimental design. In the control group subjects received three short energy savings tips and were asked to scan their meter every month.

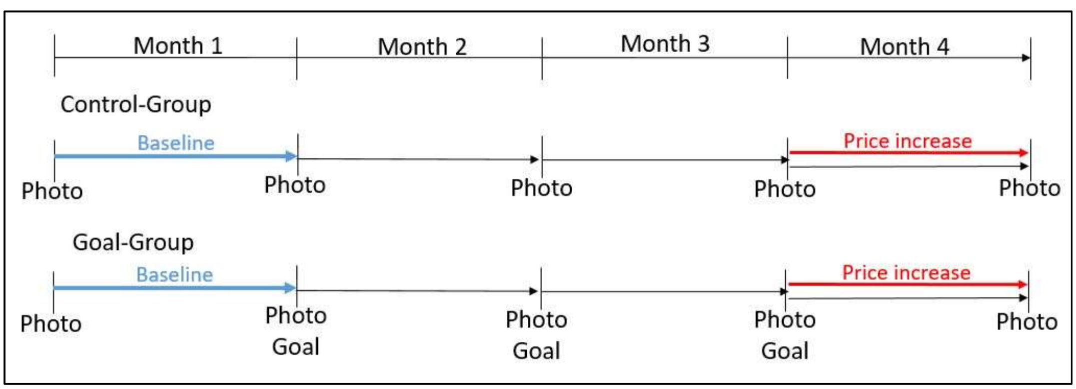

Figure 3: Experimental Design

After subjects completed the meter reading, they were informed that the next scan is due in 30 days and that they can automatically save the due date in the calendar on their phone. In the treatment group the process was the same for the first month.

In the second months, just after having completed the second scan, subjects were asked to set themselves an energy consumption goal for the upcoming 30 days. Figure 2b shows a screenshot of the goal setting screen. Subjects entered their desired consumption in kilowatt-hours for the next 30 days and the app told them how much less/more they would consume in per cent relative to the baseline month. This way subjects may try out different values and get a feeling for a realistic goal as a percentage of monthly consumption.

After the third scan had been completed at the beginning of month 3, subjects in the treatment group were informed about whether they reached their consumption goal in the last month (i.e. in month 2). If subjects consumed less than or exactly the planned amount, they were congratulated and shown a “thumbs up”. They were also told how many kilowatt-hours they saved on top of the intended goal. If they fell short of their goal by consuming more than intended, they were told by how many kilowatt-hours they missed the goal and were shown a “thumbs down” (see Figure 2c).

In our final experimental period (month 4), we compared our goal setting treatments with a financial incentive to conserve energy. In month 4, a subset of the treatment and the control group received an implicit increase in the price of electricity. With a probability of ½ the subject was informed that she participates in an additional lottery. If she wins the lottery, she receives 1 Euro per kilowatt hour saved in month 4 relative to her electricity consumption in month 3. The chances to win in the lottery are calculated based on the current number of app users and were communicated to the subject. The total amount she may receive is limited to 100 Euros. Prizes were paid out in the form of vouchers for the online shop Amazon.com. This additional treatment allowed us to compare the effectiveness of goal setting to a more classical fiscal intervention by increasing the expected price of electricity.

5. Results Study 1

5.1 Sign up and meter scans

Table 1 reports the number of subjects who sent in their first to fifth scan of the meter. Only 1,627 subjects signed up for the energy savings app and send in the first scan. This is a striking result given our large efforts to contact the majority of the city and making the app salient. Since every subject might have received a variety of advertisements, we cannot pin down a particular response rate. Recall, however, that we at least contacted 83,000 individual households (69,000 + 14,000) through direct mailing, meaning that the lower bound for the response rate is 1.96%. This indicates that our mobile app is a poor device to scale up the goal-setting nudge and that our intervention only benefited - if anything - a small portion of the population.

	Number of Subjects		
Number of Meter Scans	Goal	Control	Total
1	803	824	1627
2	307	314	621
3	167	171	338
4	108	121	229
5	81	100	181

Table 1: Time Series of Number of Participants

Another astonishing result is the sharp attrition rate among subjects who signed up. Of the 1,627 subjects who participated, only 181 remained in the app for the experimental period and sent in all 5 scans. The data provides no evidence of differences in attrition between the control and goal group.

In sum, demand for energy savings devices is extremely low as at most 1.96% signed up for the program and of those only 1.1% actually completed the program.

5.2 Influence of goal setting on energy use

Since we need 3 scans to evaluate the effect of our intervention on consumption in month 2, we can only analyse those 338 subjects that remained in the sample until the beginning of month 3. Our analysis compares the change in electricity consumption relative to the baseline period (month 1) between treatment and control group. This approach eliminates individual-specific fixed effects and thereby reduces noise due to substantial heterogeneity in usage behavior. Due to large variance in consumption, we restrict our sample to subjects with a baseline consumption above the 5th percentile and below the 95th percentile. Table 2 shows results of an OLS regressions of the form:

$$\Delta Y_{(i,t)}=\alpha_i+\beta_t T_{(i,t)}+\epsilon_i$$

Where $\Delta Y_{it}=Y_{it}-Y_{(i,t=1)}$ is the change in consumption (in kilowatt-hours) of individual i in month $t\in\{2,3,4\}$ relative to our baseline month t=1. Since some subjects send in their scan one day too early or too late, we normalized the outcome variable by dividing by the actual number of days and then multiplying by 30. The coefficient β_t is the average treatment effect on the treated

(ATT) of the goal set at the beginning of month t on consumption during month t. The treatment indicator is denoted by T_it and equals 1 if subject i was asked to set a goal at the beginning of month t; and zero otherwise. Column 1 and 2 report the results of the effect of the first and second goal on the change in consumption in the respective consumption period. Column 3 shows the effect of the third goal, the monetary incentive and the interaction effect between the two. Note that due to the large attrition rates, standard errors increase as we move from the left to the right in each row.

As can be seen in Table 2 subjects in the control group reduced their consumption on average by 1.85 kwh from month 1 to month 2. Control group consumption increased in month 3 and substantially increased in month 4. The sign of the goal-setting treatment coefficients varies and is only negative for the third period. The coefficient of the monetary incentive is negative and economically large. Note, however, that the standard errors on all of the treatment coefficients are large, as well. Despite the fact that we are looking at changes in consumption, there still seems to be a substantial degree of unexplained heterogeneity among subjects, making Type II errors a concern. Due to this large noise in the data we are not able to statistically identify sizeable effects of our goal setting and monetary intervention. We are therefore careful to not interpret these results as evidence for no effects of our treatments on consumption.

	Dependent Variable: Change in Consumption relative to Baseline		
	Month 2 (first goal)	Month 3 (second goal)	Month 4 (third goal)
Goal Treatment	0.0935	-2.428	4.823
	(3.073)	(3.713)	(5.954)
Monetary Incentive			-5.232
			(5.402)
Goal × Monetary Incentive			0.946
			(8.273)
Constant	-1.848	2.674	12.03***
	(2.036)	(2.541)	(3.911)
N	304	205	161

Table 2: Average Treatment Effects on the Treated

Overall, the findings suggest that digital saving technologies are not effective on a large scale because participants do not engage with the technologies. However, there are a number of concerns that might explain the limited success of the current technology. First, subjects might dislike scanning their meter because of privacy reasons. If this is the case, the question is whether privacy concerns would not also be present with most other digital technologies, such as smart meters or mobile apps that monitor eating, sleeping and exercising behaviour. If privacy concerns are an issue for consumers, we actually want to capture this effect in our study. Second, more subjects could have signed up for the app, had we explicitly advertised the goal setting feature instead of just promoting it as an "energy savings app". This difference matters if subjects with preferences for an energy-goal technology are particularly unlikely to be interested in using a more general energy savings app. We view this correlation of preferences to be

unlikely but cannot rule it out. Note that a research design that would have advertised the goal setting feature explicitly would not have allowed us to randomize the intervention among users. While such a campaign possibly attracts more users, it leaves us with substantial uncertainty as to whether goals have any causal effect of consumption in our sample.
Third, it could certainly be the case that our mobile app was not designed in a way that attracted consumer's interest. While this is true for any research study, it is important to remember that details in the design may matter and affect attrition rates. We tried to minimize this issue by closely working together with experts in the market. We designed the app in cooperation with a major utility and an IT developer that has specialized on creating energy-related apps. While it generally may be the case that our particular implementation was unattractive, the question is whether policy makers would be able to come up with a more appealing design.
Even though we cannot rule out that other designs would have been more successful, we think that our study captures the behavioural reaction of a policy campaign that is addressed at promoting an energy savings technology designed by market experts.

4.3 Conclusion Study 1

We built on the promising results in the literature on goal setting and plan-making and implemented a large field experiment to see whether energy saving goals are scalable with a mobile application. In particular, we hired market experts to develop a new energy savings app that asks randomly selected subjects to choose an energy consumption goal. The rollout of the app was promoted through a mass marketing campaign where we targeted an entire city in Germany by radio spots, flyers, posters and direct mailing. Despite our substantial efforts to promote this new app, less than two per cent of the households signed up. Furthermore, the number of users decreased to 1% after 4 months.
The low demand for the energy savings app also reduces our ability to identify the causal effect of goals on energy conservation. Even though our treatment effects are statistically insignificant, we do not interpret our results as strong evidence for a null-effect due to the lack of statistical power. Instead, we rather view our results as a useful insight for policymakers in that our energy savings campaign failed to deliver on what we would have expected based on studies in the literature. Even if the true treatment effect for the small number of participants is relatively large, our intervention is unlikely to be a cost-effective policy tool.
Our results also add to the recent policy debates on digital consumer technologies – referred to as "smart saving devices" - as potential measures to reduce energy consumption. We contribute to this debate by showing evidence of a strikingly low interest for one of these technologies.
Our results may certainly be specific to energy conservation and we want to highlight that studies on goal setting in other fields (in particular on health-related behaviour) showed successful implementations at large scale. Our results do not stand in contrast to these studies but rather show the importance of distinguishing the fields in which goal setting and planning prompt nudges can be scaled up by technological innovations.
Since our intention was to simulate a behaviourally-motivated policy campaign as closely as possible, we refrained from a random encouragement design that tests the effectiveness of different types of promotion strategies. This way, we were able to use radio spots, flyers and other mass marketing tools to maximize the number of contacted households. The drawback of such a design is that one cannot identify whether different promotion designs would have been

more effective. We encourage future research to identify the particular factors that influence the success of behavioural policy campaigns.

Study 2

We conducted a study in collaboration with utility Qurrent in the Netherlands. The study aimed to test a financial incentive for shifting energy use in time. Qurrent offered new customers the 'smart energy contract' with which they pay electricity tariffs that vary every hour depending on supply and demand instead of fixed electricity tariffs. Participants would have insight in the tariffs via a mobile application. The tariffs per hour would be available from 3 pm on the day before. The aim of this study was to test for which appliances people shift their energy consumption in time. Importantly, we aimed to test why people may be motivated to switch their electricity use in time. Furthermore, a few participants received a smart light bulb. The light bulb provided feedback on the energy tariffs by changing colour. We aimed to evaluate the smart light bulb.

6. Method Study 2

6.1 Procedure and sample characteristics

A link to an online questionnaire (the premeasure at T1) was sent to about 200 customers of Qurrent who signed up for the differentiated tariffs scheme. The link was sent between September and December 2017. In total 53 participants filled out the premeasure. In the premeasure age ranged from 33 to 80 (Mean = 57, Standard deviation = 13). In total 40 men filled out the premeasure, 12 women and 1 participant indicated 'other/ prefer not to say'. Most participants were living with a partner (N=24), or with a partner and children (N=18). Furthermore, 8 participants lived alone and 3 participants were single parents. In total, 41 participants finished a university of applied sciences or a higher level of education, 10 participants finished vocational education, and 2 participants finished primary school or lower. Most participants were working (N=33) or retired (N=16), four participants indicated they do not work or 'other'.

Of the participants who filled out the premeasure 28 participants were randomly selected to receive a smart light bulb. In April 2018 all participants received the post measure questionnaire (T2). In total, 15 participants completed the post questionnaire. Of those, six did not receive a smart light bulb and nine did receive a smart light bulb. In the post measure age ranged from 48 to 80 (M=65, SD=10) and 13 men and two women filled out the post measure.

6.2 Materials

6.2.1 Smart light bulb

In total 28 participants were sent the smart light bulb. They received a letter explaining that they could place the light bulb in a normal fitting in their home. The light bulb would colour green when tariffs are low, orange when tariffs are average, and red when tariffs are high (see pictures below).

Figure 4: Example of the smart light bulb when tariffs are high (left) and when tariffs are low (right)

6.2.2 Measures

Measures at T1 and T2
For nine appliances participants were asked whether participants are willing to adjust the use of the appliance to the energy tariffs (washing machine; dryer; dishwasher; lights; household appliances e.g. vacuum cleaner; television and music installation; electric vehicle; e-bike; charging appliances). Participants could answer on a scale from 1 (totally agree) to 7 (totally disagree).

We asked to what extent people know when they should adjust their energy use to the tariffs, which we label timing efficacy, with one question ('I know when I should adjust my energy use'). Participants could answer on a scale from 1 (totally agree) to 7 (totally disagree).

We asked to what extent people think they are capable of adjusting their energy use 'shift efficacy' with two items ('I have the feeling that I can adjust my energy use'; 'I am capable to adjust my energy use'). Participants could answer on a scale from 1 (totally agree) to 7 (totally disagree).
We asked participants to what extent they think adjusting their energy use is worth the money and worth the environmental benefits. Participants could answer on a scale from 1 (totally not worth the effort) to 7 (totally worth the effort).

We asked participants about four different reasons why they decided to participate in the differentiated energy tariffs: money, sustainability, fun or because others do so. Participants could answer on a scale from 1 (totally disagree) to 7 (totally agree).

As can be seen in Table 3, on average participants feel capable to shift their energy use in time and somewhat know when they should shift their energy consumption. Participants indicate that they find it worth the effort to shift their energy use in time for the environment and to a lesser extent for the money. Finally, they signed up for the smart energy contract to save money, for sustainability and because they liked it. However, they indicated that they did not sign up for the smart energy contract because others do so.

		T1		**T2**	
		Mean	Standard deviation	Mean	Standard deviation
	Timing efficacy	4.81	1.85	4.80	1.90
	Shift efficacy	4.58	1.49	5.00	.91
Worth the effort for…	…the money	3.92	1.65	4.07	1.91
	…the environment	4.94	1.31	4.40	1.81
Reasons to participate in the smart energy contract	To save money	4.77	1.72	5.67	1.29
	To promote sustainability	5.55	1.42	5.33	1.29
	Because others do it	1.58	1.28	1.67	1.59
	For fun	5.08	1.83	5.20	1.78

Table 3: Means and standard deviations for efficacy, worth the effort and reasons to participate at time 1 (T1) and time 2 (T2).

Measures at T2
We asked if people installed the smart light bulb ('yes' or 'no'). Only five out of the nine participants who responded installed the light bulb. We asked participants why they did not install the light bulb. One person did not receive the light bulb, one person was concerned about privacy issues, one person thought they could not do more to save energy and one person did not want to act upon the light bulb.

As the number of participants is too low to evaluate the influence of the light bulb we did not conduct any further analyses.

7. Results Study 2

The use of which appliances is shifted in time?
The results show that people only adjust the use of certain appliances to the energy tariffs. As can be seen in Figure 5 below people are most likely to shift the use of the dishwasher in time. To

a somewhat lesser extent they shift the use of the washing machine, dryer and their electric vehicle. People hardly adjust their use of the lights, household appliances (e.g. vacuum cleaner) and the television or music installation to the energy tariffs. For these appliances people became even less likely to adjust their use over time. However, please note that the post measure is only filled out by a few participants (N=15).

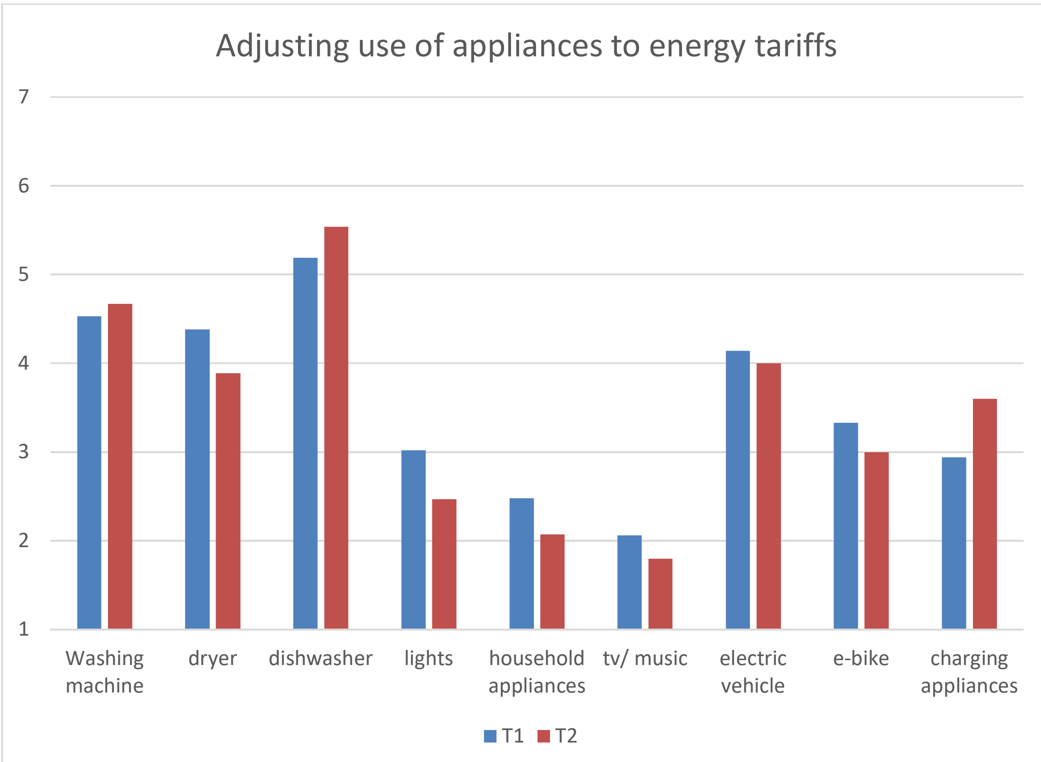

Figure 5: Adjusting the use of nine appliances to the energy tariffs on a scale from 1 to 7.

Which factors predict shifting energy use in time?

Next, we tested which factors predict the adjusting of appliances to the energy tariffs. We only used the data from the premeasure as more participants filled out this measure. We combined all appliances into one variable. However, when we combine all appliances the scale is not very reliable (Cronbach's alpha = .61), when we remove adjusting the lights the scale becomes reliable (Cronbach's alpha = .81). We calculated the mean of adjusting the time of use of all appliances expect the lights (M=3.52, SD=1.51).

	Efficacy		Worth the effort		Reasons			
	Switch efficacy	Timing efficacy	For the money	For the environment	To save money	To promote sustainability	Because others do it	For fun
Shifting electricity use in time	.64**	.48**	.41**	.18	.32*	.31*	.35*	.21

Table 4: The correlation between shifting the use of appliances in time and efficacy, worth the effort, and reasons.

As can be seen in Table 4, participants are more likely to shift their use of appliances in time when more strongly think that they can shift the use of these appliances in time and when they know when to use the appliances. The more participants think it is worth the effort to shift electricity use in time for money, the more likely they are to shift their electricity use in time. However, whether they think it is worth the effort for the environment is not related to shifting their energy use. Finally, the more people indicate that saving money, promoting sustainability and because other do it is a reason for them to shift their energy use in time, the more likely they are to shift their use of appliances in time.

We tested which factors are the most important predictors of shifting energy use in time by conducting a regression analysis. All factors together explain 58% of the variance in adjusting one's electricity consumption ($F(8, 41) = 7.04$, $p < .001$). Switch efficacy, and because others do it are the only significant predictors of adjusting one's energy use when all other factors are controlled for. The more people perceive they are capable of adjusting their energy use, the more likely they are to adjust their energy use ($b = .45$, $p < .01$). Furthermore, the more people think others adjust their energy consumption they more likely they are to do so ($b = .37$, $p < .05$).

Interestingly, these findings suggest that in the context of a financial incentive to shift energy use in time financial reasons are not motivating people to shift their energy use in time. The financial benefits of shifting energy use may not be worth the effort. These findings are in line with studies suggesting that financial incentives to promote environmental behaviour are often not worth the effort. Instead, people are more likely to shift their energy use the more they feel capable to do so and the more they think others do so. Our findings suggest that helping people to shift their energy use in time may be more effective to change behaviour. For example, by providing people with smart energy technologies that automatically turn on at times when renewable energy is available. Furthermore, providing people with information on the extent to which others shift their energy may be more effective in changing behaviour.

Study 3

We evaluated a program providing energy utility customers with information on their energy use, relative to that of their neighbors (Allcott, 2011; Allcott and Rogers, 2014). We conducted the study in collaboration with a European electricity utility. The information on energy use is included in a Home Energy Report, which is distributed to customers via email (eHER). We aimed to study

the role of environmental values in shaping response to the program. We also aim to test an augmented message sent by the utility including an environmental self-identity prime.
The analysis of the field experiment combines data from three sources: a randomized program on a large pool of customers from a European electricity utility, survey data collected from a sub-sample of the program recipients and control group and online survey, conducted using Prolific Academic.

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. Online data include information on environmental self-identity, self-reported behaviour and intention, and an incentivized decision.

8. Method Study 3

8.1 Procedure and sample characteristics

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

In November and December 2017, we augmented the eHER by including a message in the marketing module. In particular, customers were randomized to receive either an environmental self-identity message in which participants were reminded of their past environmental behaviour or a control message.

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 6 shows the sample flow diagram.

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. 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.

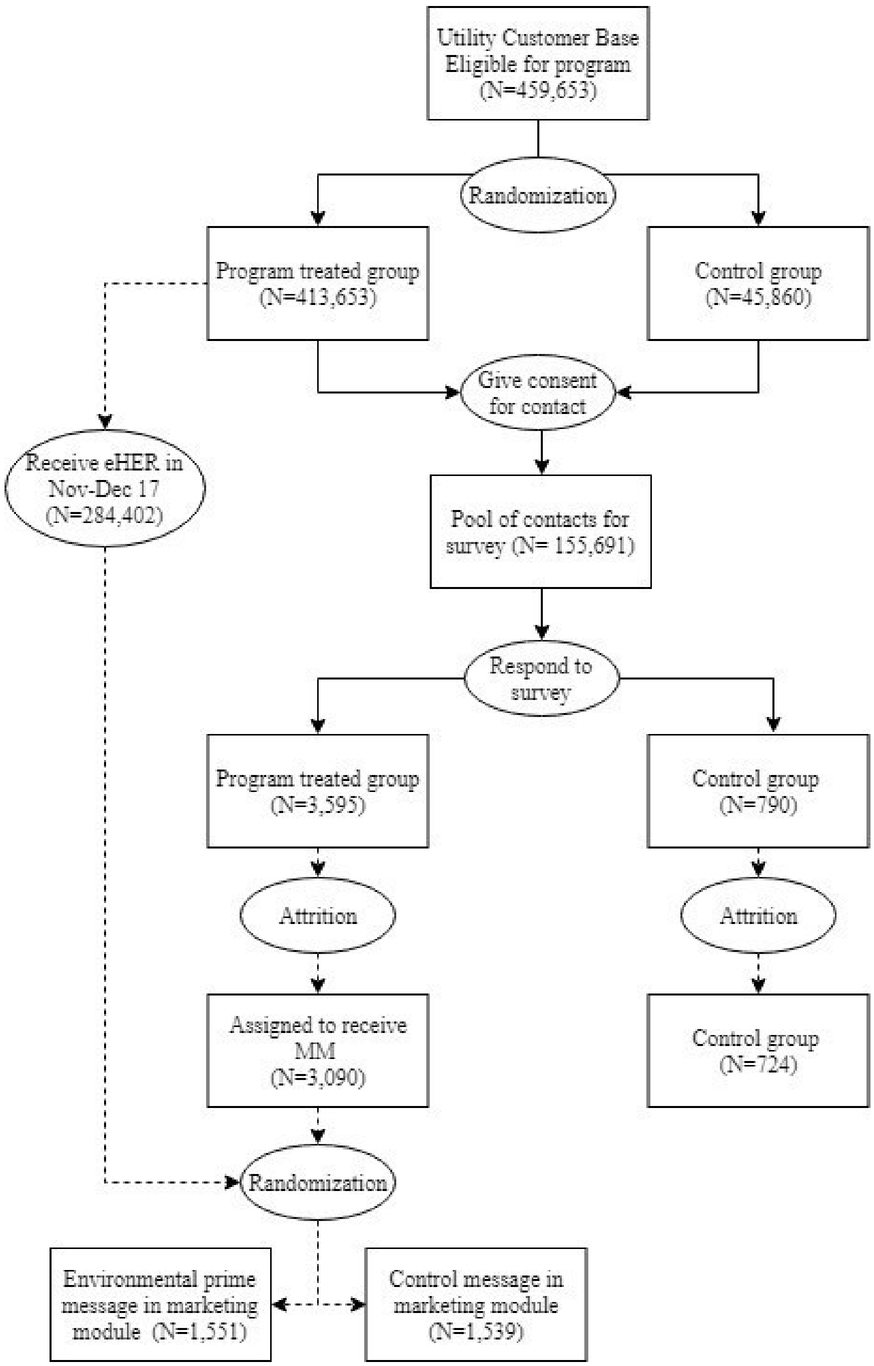

Figure 6: A schematic overview of the sample flow.

8.2 Materials

8.2.1 Experimental conditions

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). It consists primarily of the Home Energy Report, which customers in the treatment group receive by email (eHER) every two months. The eHER features a static neighbour comparison, whereby one's own previous month consumption is compared with that of 100 similar homes nearby and of the 20 most efficient similar homes nearby. Besides information on neighbours' behaviour 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 neighbours or of the average neighbour. 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 neighbour 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 they are registered to the website. As such, the experimental design relies on an encouragement design.

Furthermore, the eHER contains a section labelled 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. Customers were randomized to receive either an environmental self-identity message in which participants were reminded of their past environmental behaviour or a control message in the marketing module:

• Self-identity message: "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 7 shows examples of the self-identity message and control eHER.

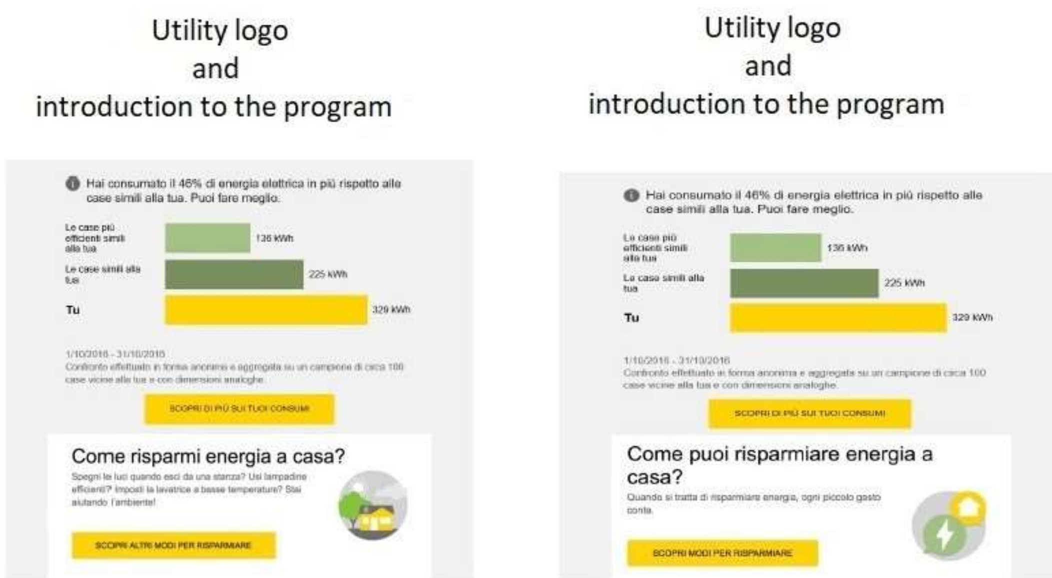

Figure 7: Example of the eHER sent on November 2017 containing environmental prime (left) and control message (right) in the marketing module area

8.2.2 Measures

Electricity measure
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.

Surveys
We collected data from a sub-sample of the large survey participants (see report 1.3) 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, and on environmental self-identity. 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 is to people. We classify a customer as having high environmental values if her score is above the median. We classify about 34 per cent of customers as having high environmental values.

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 collected socioeconomic 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.

We also collected data using an online survey, namely Prolific Academic. We collected information on environmental self-identity, self-reported behaviour and intention, and an incentivized decision (respondents' donation to a non-profit organization). The online survey serves different purposes. First, we test different ways to encourage pro-environmental behaviour, and select the best performing message for the field experiment. Second, we use the online data to perform a manipulation check on the prime. Third, we wanted to pre-test whether people that report to be concerned about climate change or the environment do also try to perform pro-environmental behaviours.

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, 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.

9. Results Study 3

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:

$$y_{it} = \beta_1 DD_{it} + h_t + g_i + \varepsilon_{it} \quad (1)$$

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. The regression also includes month-by-year fixed effects, h_t , and household fixed effects gi. 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 5, we present the results from estimating the first equation. The average treatment effect is negative but it is not statistically significant. The point estimate is -0.060. The findings suggest that the feedback does not influence energy consumption. However, 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. Second, the estimated effect of Table 5 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.

	(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.

Table 5: The impact of the program on electricity usage, main and heterogeneous effects.

Program impact depending on pre-treatment energy consumption
Next, we tested if the effectiveness of the program depends on pre-treatment energy consumption. To test this hypothesis we estimate the first 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 5 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.

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.

Program impact depending on environmental values

We tested if individuals, who endorse high environmental values, respond more strongly to the treatment or not. The coefficient of this interaction is reported in Column (4) of Table 5 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 (see Table 5). We plotted 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 8. 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.

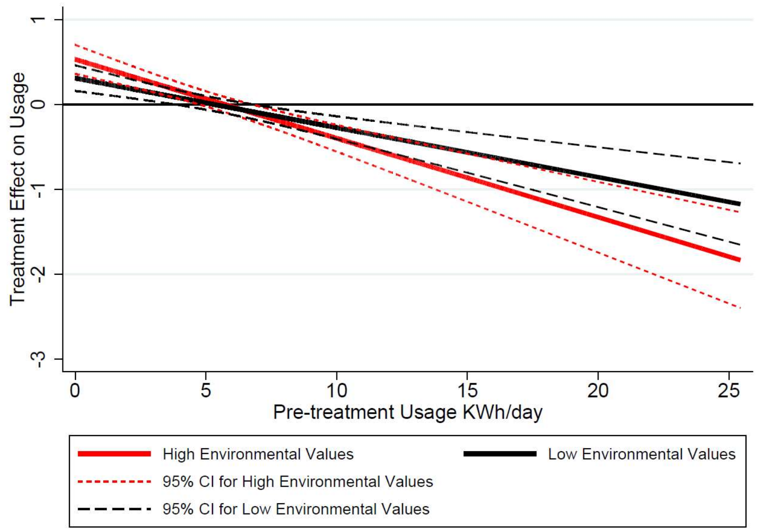

Figure 8: The influence of the social information program for people with strong and weak environmental values.

The underlying mechanism

We tested if the information contained in the eHER makes people focus on the consequences, in terms of energy use, of their own actions. First, if the eHER indeed affects behaviour through this mechanism, its effectiveness should be higher among individuals with a strong environmental self-identity: the stronger their environmental self-identity, 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.

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

$$y_i = \beta_0 + \beta_1 Program_i + X_i + \varepsilon_i \quad (2)$$

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.

We added 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 6.

	(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.

Table 6: The impact of the program on environmental self-identity.

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). However, we found an interaction between 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 environmental self-identity among those with low environmental values, it does increase identity if customers care a lot about the environment. For instance, when a person has strong 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.
We furthermore found that environmental identity is significantly higher among treated customers who recently received the eHER. This suggests that the increased salience of environmental self-identity induced by the eHER is short-lived. These results are in line with the time-varying effects of the HER reported in Allcott and Rogers (2014).

The environmental identity message
Next we tested the influence of the environmental self-identity message within the eHER, we tested if can strengthen the effect of values on the desired behavioural 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. Through the environmental self-identity message 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 message 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 p m an indicator variable for whether month m is in period p:

$$Yim = \tau\ 1Programi \times P\ 1\ m + \tau\ 2Programi \times P\ 2\ m + \alpha\ 1Primei \times P\ 1\ m + \alpha\ 2Primei \times P\ 2\ m + hm + gi + \varepsilon itm$$

here Programi is equal to one for customers in the eHER program treatment group. Primei is equal to one for treated customers also receiving the environmental self-identity message 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 message was sent. The second line identifies the treatment effect for the group of households receiving the eHER augmented with the environmental identity message, in the post message 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 message 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 message in period 2. hm and gi 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. 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. 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. We also tested heterogeneous treatment effects of the identity message with respect environmental values, and found no 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 behavioural consistency or to moral licensing depends on how important behaviour is to one’s moral self (Miller and Effron, 2010; Thøgersen, 2004; Thøgersen and Crompton, 2009). According to these studies, strengthening 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.

	(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.

Table 7: The impact of the environmental message on electricity usage, main and heterogeneous effects.

Our result suggests that the environmental identity message 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 9 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, strengthening environmental self-identity through recalling past pro-environmental actions, can boost the effect of the eHER on energy conservation. The figure also indicates that the message is able to counteract the boomerang effect of the standard eHER.

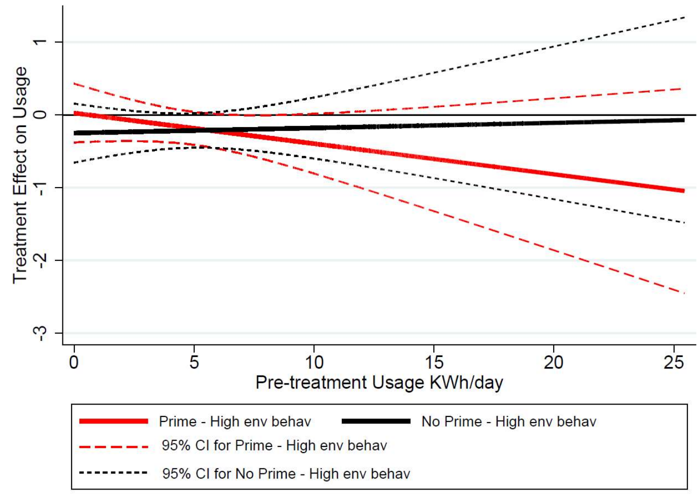

Figure 9: The conditional average treatment effect of receiving the eHER coupled with the prime (red line) versus receiving the eHER without the prime (black line) for individuals who behaved pro-environmentally.

In Figure 10 we plot the conditional average treatment effect of receiving the environmental self-identity message eHER for individuals who behaved (red line) or did not behave (blue line) pro-environmentally in the past. The graph indicates that the message backfires if it is addressed to people who hardly engage in pro-environmental behaviours. This result further highlights how important effective targeting of information treatments is.

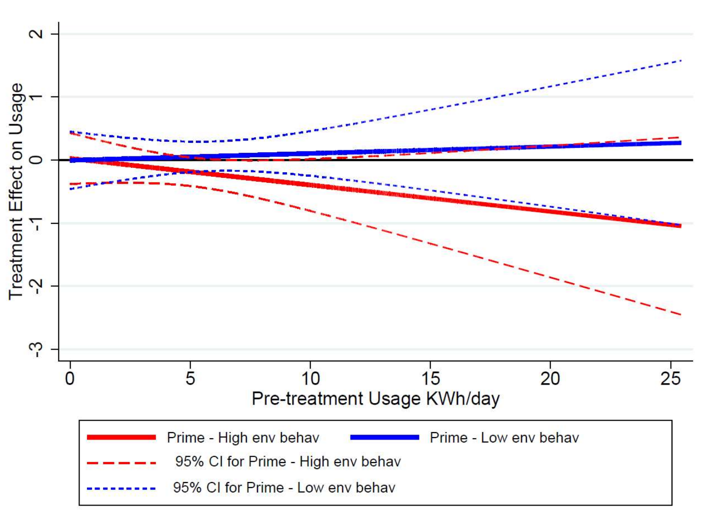

Figure 10: Conditional average treatment effect of receiving the environmental self-identity message for individuals who behaved (red line) or did not behave (blue line) pro-environmentally in the past.

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