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Information provision and energy consumption: Evidence from a field experiment

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ABSTRACT

Energy consumption and the residential real estate market are closely related, leading to a multitude of policy interventions targeted to reduce the carbon externality from the housing market. Feedback provision regarding household energy consumption is considered a low-cost strategy for promoting energy conservation. Although various studies investigate the impact of information feedback on energy consumption, less is known about the heterogeneity of these responses. In this paper, we report the findings from a field experiment where participants are exposed to consumption feedback through the use of in-home displays during two discrete stages. The results show that information provision reduces electricity consumption by around 20%, on average, relative to a sample of non-treated households. Importantly, we also show that this average effect significantly differs based on the time of day and across the treatment group. Most of the feedback effect occurs during off-peak hours, and clusters among households that are older and that are most focused on energy conservation.

1. Introduction

The residential housing market is on a trajectory towards "net zero" energy consumption, at least from a policy perspective. Given that over 30% of all energy is consumed within homes, a combination of new technologies and an expanding set of regulations and incentives have been implemented to stimulate consumers to minimize their utility bills. In 2020, all newly constructed homes in the EU need to generate as much energy as they consume.[2] For the existing capital stock, a multitude of policies is put into place to achieve significant reductions in the use of energy. Such policies include information provision, subsidies, and financing of energy efficiency investments.

However, research shows that technology alone will not be enough to make the mark. First, it has been documented that engineering predictions regarding energy savings are often not realized due to the rebound effect – consumers tend to increase their energy consumption when using more efficient technologies (Aydin et al., 2017). Second, the diffusion of new energy efficiency technology is rather slow due to the hurdle of myopic discounting and a lack of consumer awareness (Jaffe and Stavins, 1994; Brounen et al., 2013). Clearly, behavioral factors are important, as consumers need to adopt and adapt to achieve residential energy savings. As compared to technological changes, behavioral changes can lead to immediate energy savings without additional costs. Therefore, in recent years, there has been a growing interest in the interventions to increase households' energy awareness and knowledge in order to achieve positive behavioral changes (see, for example, Allcott, 2011b; Allcott and Rogers, 2014; Jessoe and Rapson, 2014).

One such intervention is the provision of feedback to households about their energy consumption. Feedback is considered an important tool for behavioral change, and has been implemented and proven to be successful in a variety of fields, such as public health, education, and organizational behavior. In the field of energy conservation, feedback has received increasing attention due

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2 In California, similar legislation is in place for 2050.

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to recent developments in information technologies and energy infrastructure.[3] However, the effectiveness of feedback on energy consumption is still an important topic of policy discussion because of the variety of results in the literature, as well as the wide range of feedback mechanisms.

The literature has documented evidence showing that feedback can promote favorable changes in energy consumption behavior. Abrahamse et al. (2005), Darby et al. (2006), Fischer (2008), Faruqui et al. (2010) and Ehrhardt-Martinez et al. (2010) provide reviews of empirical studies on the effect of energy feedback. Using the data from 42 empirical studies, Karlin et al. (2015) document that feedback is effective, with an average of seven percent reduction in energy consumption. The estimated effects range between 0.8% increase to 48% reduction in energy consumption (See, for example, Matsukawa, 2004; Houde et al., 2013; Lynham et al., 2016; Gans et al., 2013; Carroll et al., 2014). However, the effectiveness of feedback in reducing energy consumption varies widely across studies. In fact, some of the studies document that feedback alone is not sufficient for energy savings. Given the variety in reported results, it is essential to understand the mechanisms behind residential demand response behavior, and to identify under which conditions feedback can alter consumption behavior.

This study contributes to the literature by further investigating the determinants of households' response to feedback on energy consumption. We empirically analyze the effect of information provision using a sample of households from the Netherlands. Using the settings of a field experiment on the Dutch island of Texel, we track the electricity consumption patterns of 158 households over a period of 8 months. The sample is split into a treatment and a control group, where treatment consists of two consecutive periods during which feedback is offered about household electricity consumption: first, regarding households' own consumption levels accompanied by goal-setting, and in the latter three months, regarding consumption levels relative to other households. The latter period also includes energy saving tips. Households are also provided with two smart energy plugs that they can use to monitor the electricity consumption of individual appliances.

We examine how household's average electricity consumption changes in response to high-frequency feedback offered by in-home displays (IHDs). The findings indicate that providing feedback, accompanied with a goal, through in-home displays leads to a significant reduction in electricity consumption of the households in our sample. We document that digital information provision and setting a goal reduce electricity consumption by 20% relative to the control group. This effect is larger than what has been documented for normative messages by regular mail, although the longer-term persistency of the effect needs further research. The effect remains persistent in the second phase of the experiment, during which households are provided with energy saving tips and information in relative terms, in addition to high frequency information on energy consumption.

Thus far, the empirical literature on the topic has mainly focused on total energy savings.[4] However, from the perspective of electricity suppliers and network companies, another important concern is the peak in electricity demand at certain times of the day. Potential reductions in peak demand can help to reduce the risk of rolling blackouts, which has critical social and economic implications. Therefore, to improve the efficiency and stability of the electricity supply system, there is a growing interest in reducing peak demand for electricity by eliminating part of electricity use, or shifting it to lower demand times. In the context of this study, it is therefore also interesting to test whether feedback provision has heterogenous effects on peak and off-peak electricity consumption. Our findings indicate that, although feedback leads to energy savings, households do not alter their electricity demand behavior during the peak hours.

We then examine the underlying mechanism of the feedback effect. We investigate the drivers of energy reductions by using the information obtained from questionnaires that are carried out at the end of each treatment phase. We document that the effect of feedback is stronger among "energy conservative" households, who declares that they have been purchasing energy efficient products in the past. This finding implies that information feedback is more effective among households who are already interested in energy conservation. In other words, information helps to raise awareness across all households, but only yield energy conservation when households are genuinely interested ex-ante. We also find that older households are more likely to respond to the provision of feedback, a difference that we explain by the variation in the time available to process the feedback information. Time that is perhaps more abundant for the older, retired participants in the experiment. Finally, we document that the households who frequently checked the IHD and made use of offered saving tips are more likely to realize energy savings at the end of the feedback treatment.

This paper has some implications for policy makers. Even though feedback helps to reduce domestic energy consumption and induces behavioral changes, it only appears to affect consumers that are interested, able and willing. It is therefore important to provide customized information to the consumer and select precise feedback tools for specific household groups. In addition, the findings on peak demand imply that utilities may need to combine feedback intervention with time-of-use pricing schemes, in order to avoid the increasing gap between peak and off-peak demand levels.

The remainder of the paper is structured as follows: we first discuss the research design and data, providing details about the Texel experiment in Section 2. After presentation and discussion of our methodology and empirical results in Section 3, we conclude the paper with a summary of key findings and their policy implications in Section 4.

2. Experimental design and data

Texel is the most western island of a small archipelago in the north of the Netherlands. Although the remains of the first inhabitants of Texel date back to 5000 BCE, the island received city rights in 1415 CE. Ever since, Texel has played a modest role in Dutch history, as the stage for various battles during the different Anglo-Dutch, Napoleonic, and World Wars. Today, the island is home to about 14,000 inhabitants clustered across seven villages, spread over an area of some 463 km^2. About 70% of economic activities on Texel are in some way related to tourism, which is partly due to its relatively friendly climate, with winter lows between 0–4 °C, summer highs from 16–23 °C, and 1650 sun hours a year (more than anywhere else in the Netherlands).

During 2014, Texel was selected for one of twelve field trials by one of the nation's largest energy grid providers, Liander. In this field trial, Liander cooperated with a local energy supplier "Texel Energie," and IT-specialists of Capgemini, a consulting company. The field trial entailed piloting of novel technologies, focused on information provision related to energy consumption through in-home displays

[3] According to the U.S. Energy Information Administration, in 2014, there are 52 million smart meters installed by U.S residential customers, which provide detailed information on households' electricity consumption.

[4] Although there is a literature on the effect of feedback on demand shifting through dynamic pricing, none of these studies examine the effect of simple feedback (without price incentives) on peak and off-peak demand separately. Analyzing the impact of real-time feedback on households' energy consumption, Houde et al. (2013) document that the impact of feedback on energy saving is larger during the morning and evening time periods.

Table 1
Descriptive statistics for treatment and control groups.

	Treatment sample		Control sample	
Number of observations	104		54	
Variables	Mean	Std. dev.	Mean	Std. dev.
Net monthly electricity consumption from the grid (kWh)				
Pre-experiment period (January, February)	401.4	(197.0)	375.8	(309.9)
Respondent characteristics				
Age	54.9	(10.6)		
Education = secondary school	0.08			
Education = high school	0.21			
Education = vocational school	0.25			
Education = university	0.31			
Education = master/Phd	0.15			
Energy behavior (fraction)				
Willing to pay for renewable energy	0.31			
Knows the amount of energy consumed	0.81			
Thinks energy conservation is important	0.92			

(IHD), smart meters and price incentives. Texel was targeted for this trial, as the island aims for energy neutrality by 2020, an ambitious goal which requires various innovative measures and trials that help to achieve real progress.

In 2013, Liander launched their pilot project under the title "Texel smart self-supplying." This project was organized in 5 stages; *preparation* (1) until September 2013, which mainly involved contracting with partners and communicating with trial participants; *recruiting* (2) until February 2014, where applicants were gathered; *selection and registration* (3) until March 2014, where 300 applicants were selected on a first come basis; *pilot communication* (4) until December 2014, during which participants' usage was monitored and their feedback on the project was collected by means of surveys and interviews; *closure communication* (5) until January 2015, during which the results of the pilots were analyzed and disseminated. Participants were recruited by advertisements in local newspapers, attracted by the perspective of free hardware (IHD) with the name "KIEK," which provides them with feedback and insights regarding their residential energy use. A screenshot of the IHD is presented in Appendix A, and shows the way in which a selection of basic but immediate details regarding energy usage and expenses are conveyed to participants.

The experiment is conducted in two phases. Starting on March 15, 2014, the households in the treatment sample were supplied with the IHD and started to receive information about their energy use levels and expenses. Participants were also supplied with smart energy plugs that helped them to detect the energy-intensive appliances within their home. In addition to the high-frequency feedback (every 15 min), participants were asked to set goals for their energy consumption at the beginning of the experiment. Using the IHD, households can monitor their real consumption and compare it to their goals.[5]

In the second phase of the experiment, which started on May 15, 2014, participants started to receive weekly messages regarding the best way to use their IHD, as well as high frequency feedback on their energy consumption. Personal advice was provided three times a week, through the IHD, for saving energy. During this period, households also received information regarding their consumption levels relative to other households.[6] All communication about consumption, energy saving advice and relative comparisons were provided through the IHD.

In total, 288 households were subscribed for the installation of an IHD. We exclude holiday homes from the analysis, as their consumption patterns contain seasonality effects and irregular occupancy spikes. Liander also collected data on the monthly electricity consumption of 54 randomly selected households in Texel that were not part of the field trial, households which serve as a control group in our analysis. In order to properly identify the treatment effect, we apply a monthly analysis, as the control group data is only collected on a monthly basis. We limit our sample to the households for which the data is available for all months from January to August, resulting in a sample of 158 households (104 in the treatment group, 54 in the control group).[7]

Table 1 documents the average monthly energy consumption data for the period before the field experiment. These statistics show that, before the start of the experiment, the average monthly electricity consumption of the treatment group is slightly higher as compared to the average consumption of the control group. However, this difference is not statistically significant ($t = -0.63$). Liander, the network company, also surveyed the treated households at the start of the pilot and at the end of each treatment to capture subjective information on household motivation and household response to the information provision.[8] The average age of the participants is around 55. According to the survey, 21% of the respondents have graduated from high school (this compares to 25% in the Netherlands, NL), 25% of the respondents have a vocational school diploma (32% in NL),

[5] Feedback theory suggests that feedback can be more effective on energy consumption behavior when it is accompanied by a goal (Locke and Latham, 2002; Schultz et al., 2015; Karlin et al., 2015).

[6] Schultz et al. (2007) document that a descriptive normative message, detailing average neighborhood usage, produced either desirable energy savings or the undesirable boomerang effect, depending on whether households were already consuming at a low or high rate. Adding an injunctive message (conveying social approval or disapproval) eliminated this boomerang effect. Allcott (2011b) expanded upon this work with an evaluation of a series of programs run by a company called "OPOWER," sending home energy report letters to residential utility customers, comparing their electricity use to the consumption of neighbors. Using data from a randomized field experiment on some 600,000 treatment and control households across the U.S., it was estimated that the program reduced energy consumption by two percent, on average.

[7] We note that selection of the treated households is semi-random, where recruitment took place through advertisement, and selection was not through a lottery. If energy conserving households are more likely to sign up for the experiment, our results may be biased upwards.

[8] The information on respondent characteristics is not available for the control sample.

31% of the respondents have a university diploma (25% in NL) and 15% of the respondents graduated from a higher education system (18% in NL). The sample distribution of education at levels closely mimics that of the Dutch population as a whole. Energy conservation is important for 92% of participants. Moreover, 31% of participants are willing to pay for renewable energy. When asked how much participants know about their current energy usage, 30% of participants claim to have an exact overview on their current consumption levels, while 51% indicate that they are less certain of their current consumption. Similarly, Brounen et al. (2013) document that 44% of the households have no information about the cost of their monthly energy use.

3. Methodology and results

In order to identify the impact of treatment on household electricity consumption, we estimate a difference-in-differences model. The standard econometric model used to estimate this relationship can be defined as:

$$\ln(E_{it}) = \beta_0 + \beta_1 T_i + \beta_2 Phase1_i + \beta_3 Phase2_i + \beta_4 T_i * Phase1_i + \beta_5 T_i * Phase2_i + \varepsilon_{it} \quad (1)$$

where i is the household identifier, t is the month, and E is the net monthly electricity consumption from the grid.[9] T is a dummy variable which is equal to one for the households in the treatment group and is equal to zero for the households in the control group. The variables $Phase1$ and $Phase2$ control for the effects of seasonal variation on electricity consumed from the grid. Interacting T with $Phase1$ and $Phase2$, we are able to identify the impact of treatments that are implemented in phase 1 and phase 2 on the amount of electricity consumed from the grid. The difference between the coefficients of these interactions can be interpreted as the additional impact of treatment in phase 2.[10] ε_{it} denotes a normally distributed error term.

3.1. Difference-in-differences estimation

We first graphically examine the average electricity use of the treatment and control groups during the period of observation. Fig. 1, Panel A shows that consumption patterns over time are quite similar across both groups, a similarity that is most likely the outcome of common seasonality in weather patterns (and solar energy generation). Although the patterns are similar, the reduction of electricity consumption in the treatment group is clearly higher during the first and second phase of the experiment.

In Table 2, column 1, we present the results of the estimation of the model specified in Eq. (1). The results show that "phase 1 treatment" has a significant impact on electricity consumption with a decrease in energy consumption of 20%, a result that remains stable during phase 2 (23%). The stability of effects across stages might indicate that the provision of energy saving advice and conveying information in relative terms (relative to neighbors) does not have a significant additional impact on the electricity use, beyond providing high frequency information about household energy consumption. It might also be the case that the effect of these additional treatments in the second phase is cancelled out by the diminishing effect of the first treatment. Therefore, we further investigate the effect of different type of treatments, based on the self-declared statements of the treated households.

To verify whether our findings are in line with the statements of households regarding their energy savings, we divide the treatment group based on declared savings. In the survey, households are asked to indicate whether they saved energy through the information provided by the IHD. We separate the treatment group in two samples, based on the answer to this question. One group includes the households who reported "no savings" and the other group includes the

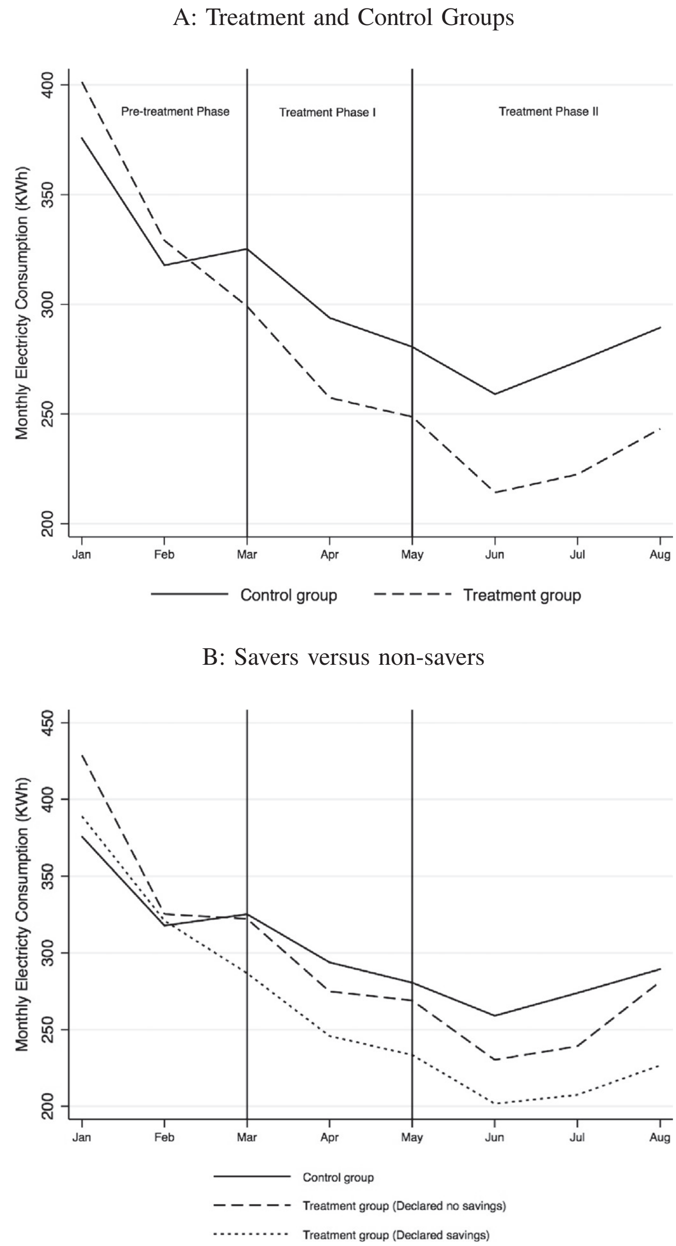

Fig. 1. Monthly net electricity consumption. Notes: Panel A represents the average electricity consumption from the grid for each month for the treatment and control groups. Panel B represents the average electricity consumption from the grid for each month for treatment groups ("declared savings" and "declared no savings") and control group separately. Treatment group (declared saving): group of households who declared that the treatments helped to save energy. Treatment group (declared no saving): group of households who declared that the treatments did not help to save energy. Phase 1 treatment takes place between March 15th–May 15th, and phase 2 treatment starts on May 15th.

[9] Since all dwellings in the treatment and control groups have solar panel installations, we might expect that the electricity consumption from the grid highly depends on the season. However, since we include a control group, we are able to isolate the impact of seasonal variation in energy generation from solar panels on the electricity consumption from the grid.

[10] We should note that we are not able to isolate the additional impact of second phase treatment from the first phase treatment as the effect of first treatment might be diminishing during the second phase. In that case, the effect of second treatment will be underestimated.

Table 2
Difference-in-differences estimation results.

Variables	(1) Simple DID	(2) Savers versus non-savers	(3) Peak	(4) Off-peak
Treatment * Phase1	−0.205*		−0.033	−0.388***
	(0.115)		(0.121)	(0.120)
Treatment * Phase2	−0.229**		0.038	−0.520***
	(0.086)		(0.090)	(0.089)
Treatment group	0.178**		−0.013	0.371***
	(0.066)		(0.070)	(0.069)
Treatment (declared no savings) * Phase1		−0.102		
		(0.239)		
Treatment (declared savings) * Phase1		−0.218*		
		(0.123)		
Treatment (declared no savings) * Phase2		−0.096		
		(0.178)		
Treatment (declared savings) * Phase2		−0.268***		
		(0.091)		
Treatment group (declared no savings)		0.119		
		(0.138)		
Treatment group (declared savings)		0.158**		
		(0.071)		
Phase1	−0.162*	−0.162*	−0.215**	−0.101
	(0.093)	(0.093)	(0.098)	(0.097)
Phase2	−0.270***	−0.270***	−0.379***	−0.158**
	(0.070)	(0.070)	(0.073)	(0.072)
Constant	5.616***	5.616***	5.012***	4.806***
	(0.054)	(0.054)	(0.057)	(0.056)
Observations	948	852	948	948
R-squared	0.110	0.112	0.068	0.157

Notes: Table 2, Column 1 reports the simple difference-in-differences (DID) estimation results. Dependent variable is the logarithm of monthly net electricity consumption. Table 2, Column 2 reports the DID estimation results for the households that reported positive savings and no savings, separately. Dependent variable is the logarithm of monthly net electricity consumption. Treatment group (declared saving): group of households who declared that the treatments helped to save energy. Treatment group (declared no saving): group of households who declared that the treatments did not help to save energy. Table 2, Columns 3 and 4 report the DID estimation results separately for the peak and off-peak periods of the day. Dependent variables are the logarithm of monthly net electricity consumption during the peak (1) and off-peak (2) periods of the day, respectively. Phase 1 treatment takes place between March 15th–May 15th, and phase 2 treatment starts on May 15th. Months included in phase 1: April, and months included in phase 2: June, July and August. March and May are excluded from the analysis as the treatments are started at the middle of these months.

* $P < 0.1$.

** $P < 0.05$.

*** $P < 0.01$.

households who reported "positive savings" (by the help of IHD). We limit our treatment sample to those households for which the survey data is available. This leads to a sample of 88 households in our treatment group (10 reported "no savings", 78 reported "positive savings"). Fig. 1, Panel B documents that, although the electricity consumption patterns are quite similar across the three groups (the "treatment – declared no savings", "treatment – declared savings" and the control group), the households that declared positive savings are associated with the largest reductions in energy consumption.

To test the statistical significance of these subgroup differences, we repeat the difference-in-differences analysis by interacting the treatment effect with respondent's saving declaration. Table 2, column 2 reports the estimates of the treatment effect for the two subgroups. The results indicate that the effect of feedback is significant for the households who declared that the intervention in phases 1 and 2 helped them save energy. The reduction in electricity consumption of households who declared that treatments did not help to reduce their electricity consumption is not statistically significant for either phase. These results show that the treatment is not effective for a (small) subgroup of households in the sample, in line with the declarations of the households.

Although our findings indicate that feedback, on average, is effective in saving energy, an important question that remains is how feedback affects energy demand during different time periods of the day. This is of importance, as shifting peak electricity demand to off-peak periods can create substantial economic benefits (Boiteux, 1960; Williamson, 1966; Kahn, 1988). In order to meet the energy demand at peak time periods, utility companies have to invest more in incremental capacity, transmission, and distribution. Thus, the marginal cost of electricity supply is significantly higher at certain times of the day, as energy providers and the network companies need to plan their capacity based on the peak demand levels (Joskow, 2012; Joskow and Wolfram, 2012). Considering that failure to match supply and demand will result in blackouts, which might have critical effect on economy, the economic benefits of reduction in peak demand can be quite significant.

One of the common approaches to reduce peak energy demand is encouraging households to eliminate a part of their peak energy-using activities, or shift these activities to other periods of the day. In order to incentivize such behavioral change, many utilities have proposed a change in the residential electricity rate structure – a higher price during periods of higher demand, and a lower price at other times of the day. Indeed, there is a growing body of literature examining households response to different energy price structures.[11]

In the context of this study, as feedback is provided without any price incentives, one may assume that feedback has similar effects on the energy consumption at the peak and off-peak hours. The graphs do not show distinct differences in peak versus off-peak patterns during the experiment. However, this symmetry assumption may not be true, as household's attention or interest in energy savings

[11] See, for example, Ida et al. (2013), Jessoe and Rapson (2014), Savolainen and Svento (2012) and Allcott (2011a).

might be less during the peak demand hours. In order to test this, we estimate the effect of feedback on peak and off-peak energy demand separately.

Fig. 2 presents that the relative change in electricity consumption of the treatment group compared to the control group is stronger during the off-peak hours. When we formally test the feedback effect on electricity demand during peak and off-peak hours separately, we document that the effect is significant only during the off-peak time period (see Table 2, columns 3 and 4). This implies that energy savings are realized mostly during the low-demand hours of the day. Therefore, the gap between peak and off-peak demand increases by the feedback treatment, keeping the peak demand level unchanged.

3.2. Household-related heterogeneity

In line with results documented by Schultz et al. (2007), Allcott (2011b) and Jessoe and Rapson (2014), we find that providing information feedback on electricity use triggers a reduction in households' subsequent energy consumption. The reduction reported in our experiment is quite large as compared to previous findings, and may well be due to the fact that the island of Texel contains a population that is more responsive than the average population, driven by the ongoing and active policy to convert the island to energy neutrality. We also document that the effect of the treatment differs across households, and the feedback is not effective for a small group of households.

To better understand why some of the participants indicate experiencing no savings, we examine whether the energy behavior questions can help to disentangle the observed variation in households' reported savings. Using the survey data, we generate new variables based on characteristics and motivations of the sampled households. We use the following survey questions to construct the variables: "What is the importance of saving money for joining the project?," "What is the importance of environmental concerns for joining the project?," "How much are you willing to pay (WTP) for the environment?," "Do you know how much electricity you consume in a year (energy literacy)?," as well as questions about energy conservation behavior (e.g. buying efficient light bulbs, shower time, etc.), age and education level. We generate dummy variables based on the median values of the answers or the yes/no answers.[12]

Table 3 presents the descriptive statistics for the sample of households who declared positive savings and the sample that declared no savings, separately. Households who declared savings by the help of treatment are older as compared to the sample of households who declared no savings. Another important difference relates to the previous energy conservation behavior of the households. Households who reported energy savings also have a higher energy conservation tendency prior to the experiment. The environmental motivations for participating the experiment is slightly higher among the households who reported positive energy savings.

In order to analyze the determinants of the probability of declaring positive savings (by the help of IHD), we estimate a simple logit model. The results in Table 4 indicate that the effect of feedback is stronger among energy conservative households (higher probability of reporting energy saving) who declared that they have

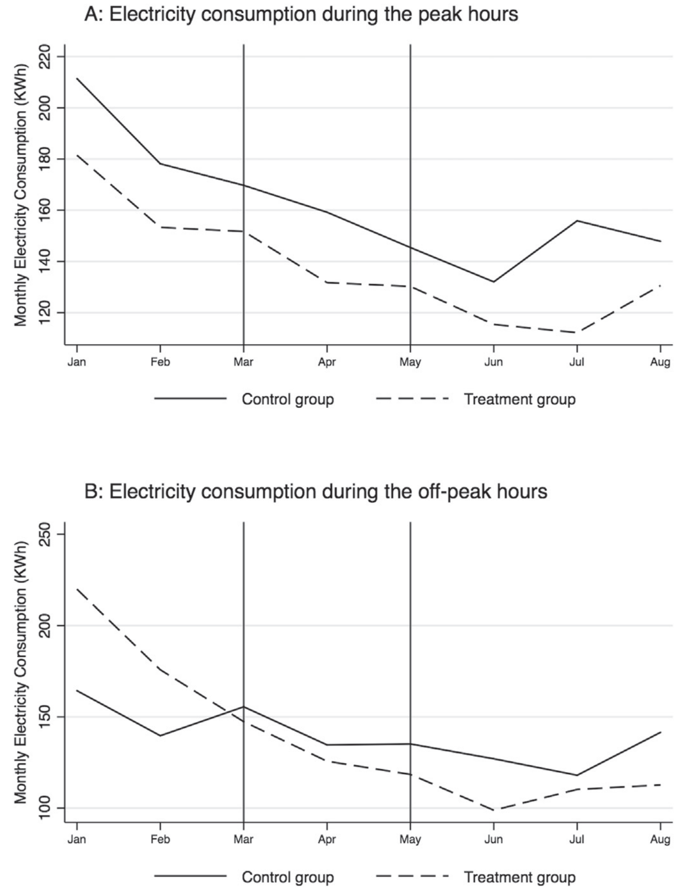

Fig. 2. Monthly net electricity consumption (peak and off-peak hours). Notes: Figure represents the average electricity consumption from the grid during the peak and off-peak hours separately for treatment and control groups. Phase 1 treatment takes place between March 15th–May 15th, and phase 2 treatment starts on May 15th.

been purchasing energy efficient products in the past. This finding implies that information feedback is more effective among households who are already interested in energy conservation. In other words, feedback is more likely to lead to energy conservation when households are genuinely interested ex-ante. We also document that older households are more likely to respond to the provision of feedback. This finding may be explained by the variation in the time available to process the feedback information, as time may be more abundant for the older participants in the experiment.

As a final step in the analysis, we investigate the effect of different feedback treatments on energy savings, again based on household saving declarations. In the survey, households are asked to report their level of involvement with the treatment, by indicating at which level they actively used different aspects of the treatments. The related survey questions are: "How often do you check the IHD?," "Did you use the energy saving tips?," "Did you use the smart plugs?." According to the statistics in Table 3, households who reported energy savings also declared that they checked the IHD more often as compared to the households who reported no savings. The share of households who used energy saving tips is also larger for the households who reported savings. The energy saving expectations before the treatment is slightly higher for the households who reported energy savings after the treatment.

In Table 5, we estimate a logit model including these variables as determinants of reporting positive energy savings. The results are in line with the expectations. The treatment leads to higher self-reported energy savings among households who checked the IHD at

[12] Based on the answers of our survey questions we generate the variables: Age > 55: 1 if respondent's age is above 55, 0 otherwise. Higher education: 1 if "university and higher", 0 otherwise. Motivation to participate (money saving): 1 if above the median score, 0 otherwise. Motivation to participate (environment): 1 if above the median score, 0 otherwise. Willing to pay for renewable energy: 1 if positive, 0 otherwise. Energy conservation behavior in the past: 1 if above the median score, 0 otherwise.

Table 3
Descriptive statistics.

	Declared saving		Declared no savings	
Number of observations	89		17	
Variables	Mean	Std. dev.	Mean	Std. dev.
Age > 55	0.62	(0.49)	0.31	(0.47)
Higher education (university or higher)	0.50	(0.51)	0.50	(0.50)
Motivation to participate = money saving	0.30	(0.46)	0.31	(0.47)
Motivation to participate = environment	0.52	(0.47)	0.41	(0.42)
Willing to pay for renewable energy	0.35	(0.48)	0.37	(0.49)
Knows the amount of energy consumed	0.27	(0.45)	0.27	(0.45)
Energy conservation behavior in the past > median score	0.62	(0.49)	0.42	(0.50)
Positive energy saving expectations before treatment	0.58	(0.50)	0.41	(0.51)
Checking IHD at least once a day	0.71	(0.46)	0.29	(0.47)
Used smart plugs	0.88	(0.33)	0.82	(0.39)
Used saving tips	0.66	(0.48)	0.18	(0.39)

Notes: Declared saving: group of households who declared that the treatments helped them to save energy. Declared no saving: group of households who declared that the treatments did not help them to save energy. Age > 55: 1 if respondent's age is above 55, 0 otherwise. Education level: 1 if "university and higher", 0 otherwise. Money motivation: 1 if above the median score, 0 otherwise. Environmental motivation: 1 if above the median score, 0 otherwise. Willing to pay for renewable energy: 1 if positive, 0 otherwise. Energy conservation behavior in the past: 1 if above the median score, 0 otherwise.

least once a day and who used the energy saving tips. Clearly, these results define a more energy-aware and active subgroup of households. We do not find a significant effect of using energy plugs and positive expectations on the outcome of the experiment.

4. Conclusions and policy implications

Reducing the carbon externality from the residential housing market requires a combination of technology diffusion and behavioral change. The results of our field experiment on residential electricity usage show that providing households with consumption feedback through in-home displays (IHDs) is an effective means to reduce energy consumption. The analysis reveals that information provision can reduce electricity demand by 20%, an effect that is immediate and generally remains constant over the treatment period. This result is economically significant and higher than results documented for feedback provision through, for example, paper mailing campaigns (Allcott, 2011b).

We document that energy savings are realized only during the low-demand hours of the day, which implies that gap between peak and off-peak demand increases by the feedback treatment, keeping the peak demand level unchanged. This finding raises the need for other instruments in conjunction with provision of feedback, such as dynamic pricing schemes. In order to shift part of the peak demand to the off-peak hours, utilities may benefit from IHDs to inform households about time-varying rates. Two recent and related contributions to the literature on residential energy experiments have stressed the importance of information on price elasticity. Jessoe and Rapson (2014) document that households adapt their consumption levels substantially more (up to three standard deviations) to varying electricity prices if they were exposed to simple high frequency information regarding their usage. This evidence points to learning as a likely mechanism for the treatment differential. Ida et al. (2013) find that the effect of social pressure on energy consumption is much larger when consumers are exposed to dynamic pricing, in which the highest marginal price results in a reduction of 15%, an effect which is strongest among consumers that are well-informed. Overall, the available evidence indicates that use of IHDs and dynamic pricing programs together may lead to a reduction in total energy use and

Table 4
Logit analysis: energy savings and respondent characteristics.

Variables	Coef.	Marginal effects
Motivation to participate: money saving	0.212	0.048
	(0.447)	(0.099)
Willing to pay for renewable energy	−0.077	−0.018
	(0.420)	(0.096)
Energy conservation behavior in the past > median score	0.724*	0.165*
	(0.399)	(0.090)
Knows the amount of energy consumed	−0.145**	−0.033
	(0.444)	(0.103)
Age > 55	1.330***	0.296***
	(0.416)	(0.087)
Higher education (university or higher)	0.463	0.105
	(0.419)	(0.095)
Constant	−0.689	
	(0.514)	
Observations	106	106

Notes: Dependent variable is a dummy variable which is one for the households who declared positive savings and zero otherwise. Age > 55: 1 if respondent's age is above 55, 0 otherwise. Education level: 1 if "university and higher", 0 otherwise. Money motivation: 1 if above the median score, 0 otherwise. Willing to pay for renewable energy: 1 if positive, 0 otherwise. Energy conservation behavior in the past: 1 if above the median score, 0 otherwise.
* $P < 0.1$.
** $P < 0.05$.
*** $P < 0.01$.

Table 5
Logit analysis: energy savings and involvement with the treatments.

Variables	Coef.	Marginal effects
Positive expectations before treatment	0.574*	0.048
	(0.616)	(0.054)
Checking IHD at least once a day	1.775***	0.185**
	(0.644)	(0.080)
Used saving tips	2.116***	0.214***
	(0.711)	(0.075)
Used smart plugs	−0.562	−0.039
	(0.822)	(0.048)
Constant	0.113	
	(0.784)	
Observations	106	

Notes: Dependent variable is a dummy variable which is one for the households who declared positive savings and zero otherwise.
* $P < 0.1$.
** $P < 0.05$.
*** $P < 0.01$.

peak demand at the same time. Thus, feedback can contribute to energy conservation, while providing smoother load profiles and better electricity grid stability.

We also document that the treatment effect differs across households within the treatment group. The treatment effect is stronger among older and more "energy conservative" households. Based on households' declarations, we document that households who made use of energy saving tips and installed the smart energy plugs realized higher energy savings.

In efforts to maximize the effectiveness of energy conservation measures, policymakers should distinguish between households that are more responsive to the information that is offered to them. This does not need to be difficult, as we find that this responsiveness does not relate to implicit willingness to pay, or saving motives that are hard to capture, but cluster mostly along age groups and energy conservation profiles. Targeting the older, more active conservers first will help to yield the largest effects. On the other hand, other consumer groups may benefit more from smart technology – or automation over information. In line with the rich literature on "nudges," large groups of consumers will not alter behavior, even when exposed to information. Perhaps technology may help achieve savings for these consumers, similar to the "woodheads" identified by Deng and Quigley (2012).

Appendix A. The KIEK in-home display

Source: TexelEnergie

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2018.03.008.

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