How Households Respond to Residential Energy Feedback? Evidence from a Quasi-Experiment

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Abstract

In this paper, we report the findings from a field experiment on the residential electricity usage of 150 Dutch households on the island of Texel. In this experiment, participants are exposed to consumption feedback through the use of in-home displays during two discrete stages of three months. Our results show that information incentives reduce electricity use by 18 percent, and that this effect is stronger among older and energy conservative households.

JEL Codes: Q30, Q40, R22
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I. Introduction

The residential energy market is getting involved in a race to zero. After supply chain managers have raced to zero in attempts to minimize their corporate cost inefficiencies, and after high frequency stock traders have raced to zero by implementing the newest technologies to reduce their lag time to the diffusion of stock relevant news into financial market, we now find the residential energy market in the middle of a race that also involves technology, costs and efficiency. Given that over 30 percent of all energy is consumed within our homes, and given that international treaties have been signed to reduce the associating carbon dioxide consequences of this energy consumption, a strong push for energy efficiency has started in the mid nineties. Therefore a combination of new technologies and an expanding set of regulations and incentives has been put into place to stimulate consumers to minimize their utility bills towards zero.

Research shows, however, that technology alone will not be enough to make the mark. On the one hand, we find that engineering predictions regarding energy savings are often not realized due to the rebound effect – consumers tend to increase their future energy consumption after facing projections of more efficient technologies (**?**). On the other hand, we find that the diffusion of new energy efficiency technology is rather slow due to the hurdle of myopic discounting and a lack of consumer awareness (**?**). Clearly, the human factor in this race to zero is important, as consumers need to adopt and adapt to turn this corner in residential energy savings. Hence, more emphasis is needed on informing consumers and observing their responses to this information.

The power of information is vital when constructing policies that aim to effectively change behavior. **?** reviewed 38 studies within the field of social and environmental psychology, all targeting household energy conservation. Interestingly, most studies focus on voluntary behavioral change in energy consumption by improving the knowledge and perceptions of individuals, rather than changing contextual factors (e.g., the pay-off structure) that may determine households' behavioral decisions. Information provision tends to result in higher knowledge levels, but not necessarily in behavioral changes or energy savings. Rewards effectively encourage energy conservation, but with rather short-lived effects. Feedback has also proven its merits, in particular when provided frequently.

? ran a field experiment in which normative messages are used to promote household energy conservation. 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. **?** recently 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 their neighbors. Using data from randomized field experiment on some 600,000 treatment and control households across the U.S., it is estimated that the program reduces energy consumption by two percent, on average. This effect is equivalent to that of a short-run electricity price increase of 11 to 20 percent, illustrating that non-price interventions can substantially and cost-effectively change consumer behavior.

Two very recent and related contributions to this rich literature on residential energy experiments have stressed the importance of information in price elasticity. **?** analyzed the electricity consumption of 437 households in the Bridgeport and New Haven areas of Connecticut. These households participated in a careful experiment to test the effects of high-frequency information about residential electricity usage on the price elasticity of demand. There results show that households adapt their consumption levels a lot more (three standard deviations more) to varying electricity prices if they are exposed to simple high frequency information regarding their usage. This evidence points to learning as a likely mechanism for the treatment differential. **?** ran a comparable experiment with a sample of 863 households across the Japanese cities of Kitakyushu and Kyoto. Here the sample is split across two groups with two types of policy interventions: social pressure and private incentives. Their results show that social pressure itself reduces electricity consumption by three to four percent. However, the reduction is much larger when consumers are exposed to dynamic pricing, in which the highest marginal price results in a reduction of 15 percent, and effect which is strongest among consumers that are well informed.

In this paper, we empirically analyze the power of information within the residential energy market. More specifically, we are going to analyze how household's electricity consumption responds to the feedback that is offered to them by in-home displays (IHD). Using the settings of a field experiment on the Dutch island of Texel, we track the electricity consumption patterns of over 150 households over the period of 8 months. The sample is split across a treatment and a control group, where treatments consists of two consecutive periods of three months during which feedback is offered on the electricity consumption levels, first regarding the own consumption levels and in the latter three months regarding consumption levels relative to other households and energy saving tips. This study contributes to an already rich literature by further investigating the determinants of households's response to energy feedback.

Our findings indicate that providing consumption feedback through in-home displays is an effective means to reduce energy consumption. We document that information incentives reduce electricity use by 18 percent, and that this effect is stronger among energy conservative and older households who have checked the display frequently and have used the saving tips.

The paper continues as follows. We first discuss our research design and data, by detailing the Texel experiment. After a careful presentation and discussion of our methodology and empirical results, we conclude our paper with a summary of key findings and their implications.

II. Experimental Design and Data

Texel is the most Western island of the argipelago at the North of the Netherlands. Although the remains of first inhabitants of Texel date back to 5,000 B.C., the island received city rights only in 1415. Ever since, Texel played a modest role in Dutch history, as it was home to Ada, countess of Holland when prisoned at Texel by her uncle William, and was stage for various battles during the different Anglo-Dutch, Napoleontic, and World Wars. Today, the island is home to 13,566 inhabitants clustered across seven villages spread over an area of 463 squared kilometers. About 70 percent of economic activities on Texel are in some way related to tourism, which is partly due to its relatively friendly climate with winter lows in the range of 0-4 °C, summer highs of 16-23 °C, and with 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 managers, Liander. In this field trial, Liander cooperated with a local energy supplier "Texel Energie", and the IT-specialists of Capgemini. The field trial entails the pilot of novel technologies both regarding energy consumption in-home displays (IHD), smart meters and price incentives. Texel was targeted for this trial, as the municipality announced in 2008 to aim for energy neutrality by 2020. An ambitious goal which requires various innovative measures and opens up the door to trials that help to realize progress.

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

The experiment is conducted in two phases. Starting on March 15, the households in the treatment sample are supplied with the KIEK IHD and start reading about their energy use levels and expenses. Besides the high-frequency feedback (every 15 minutes), participants receive every week a message regarding how to use their KIEK display. Every month they receive an overview of their use, all communication runs through the IHD. In the second phase, which starts on May 15, participants are supplied with smart energy plugs that help them to detect the high use appliances within their home. Three times a week personal advice is given through the IHD for saving energy.

By February 17th of 2014, 288 households were subscribed for the installation of KIEK. Among these, we exclude the holiday homes from our analysis. On the other side, Lliander collected data on the monthly electricity consumption of 57 households, which serves as a control group in our analysis. In order to disentangle the treatment effect, we apply a monthly analysis as the control group data is collected only on a monthly basis. We also limit our sample with the households, for which the data is available for all months from January to August, which results in a sample of 150 households (100 in the treatment group, 50 in the control group).

Table 1 presents the average monthly energy consumption data for the period before the field experiment. These statistics show that, before the start of experiment, the average monthly electricity consumption of the treatment group is significantly higher compared to the average consumption of the control group. Liander also surveyed the households at the start of the pilot and at the end of each treatment to capture their motivations and their reactions to information provision.[2] The average age of the respondents is around 55. According to survey answers, 28 percent of the respondents are graduated from high school, 21 percent of them has a vocational school diploma, 30 percent of them has a university diploma and 23 percent of them are graduated from a higher education system. For 92 percent of the participants, the energy conservation is important. Moreover, 31 percent of participants are willing to pay for renewable energy. When asked about their current knowledge of their energy usage, 30 percent of participants claim to have a very exact overview on their current consumption levels, while

[1]Participants were recruited by advertisements in local newspapers.

[2]Unfortunately, we do not have information on the characteristics of the households in the control group.

51 percent indicates to be less certain of themselves.

[Insert Table 1: Summary Statistics]

Households are also investigated based on their attitudes towards different treatments. The survey answers show that 71 percent of the households check the KIEK on a daily basis in the first phase, and this share decreases to 62 percent in the second phase of the experiment. The plugs, which are used to get detailed information about the energy efficiency of the appliances, are used by 85 percent of the households. Finally, 52 percent of the households declared that they used the saving tips which are provided by KIEK in the second phase. As a result of these treatments, 48 and 52 percent of the households reported a positive energy saving in the first and second phases of the experiment, respectively.

III. Methodology and Results

In order to identify the impact of treatments on households electricity consumption, we estimate a simple 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 month, and E is the electricity consumption from the grid.[3] 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 factors on electricity consumed from the grid. When we interact 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. ε_{it} denotes a normally distributed error term.

A. Impact of Feedback

We start our analysis with a visual examination of the electricity use numbers of our treatment and control groups during the period of analysis. Figure 1 shows that consumption patterns

[3] Since all houses in the treatment and control groups have solar panel installations, we might expect that the electricty consumption from the grid highly depends on the seasons. However, since we include a control group, we are able to isolate the impact of seasonal variation on the electricty consumption from the grid.

match up across both groups, a similarity that is most likely the outcome of common seasonality. Although the patterns are similar, we also detect a clear reduction in the gap between these groups, which can be attributed to the impact of treatments. The reduction in the electricity consumption of treatment group is more apparent during the first months of feedback treatment in phase-1.

[Insert Figure 1]

In Table 1, we present the results of the estimation of model specified in equation (1). The results in column (1) show that "Phase-1 treatment" has a significant impact on the electricity consumption. The estimated effect remains stable during the Phase-2, which indicates that provision of energy saving tips does not have a significant impact on the electricity use of the households.

[Insert Table 1]

To verify whether our findings are in line with the declarations of the households regarding energy savings, we divide the treatment group based on declared savings. In the survey, the households were asked to indicate whether they saved energy by the help of the treatments. We separated the treatment group in two, based on the answer to this question. One group includes the households who reported "no saving" and the other group includes the households who reported "positive saving" (by the help of treatment). We limit our treatment sample to the households for which the survey data is available. This leads to a sample of 85 households in our treatment group (30 reported "no saving", 55 reported "positive saving"). As can be seen from figure 2, we find electricity consumption patterns that are similar across the three groups – the "treatment – declared no saving", "treatment – declared saving" and the control group. Figure 2 shows also that the declared savers are associated with largest energy use reductions.

[Insert Figure 2]

To test the statistical significance of these subgroup differences, we repeat our impact regressions analysis while including a "declared saver" dummy. Table 3 reports the estimates of the effect of treatment for these two sub-groups. The results indicate that there is a significant treatment effect for the households who declared that the intervention in phase 1 and 2 helped them in saving 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 both phases. These results show that the treatment is stronger for a sub-group of households in the treatment group, and that this effect appears to be permanent. In the next steps of the analysis, we will explore the characteristics of the people in this subgroup.

[Insert Table 3]

Now that we understand the extent and longevity of the effect of feedback, we utilize the set-up of the household survey to analyze the variation of the effect across our sample. In Table 4, we estimate the same model in Table 3. This time we construct the sub-groups based on other survey questions. Frequency refers to the question: how often do you check the KIEK? Tips refers to the reply to the question: did you use the energy saving tips? And Plugs refers to the question: did you use the plugs? Based on the answers of these questions, we divide the treatment sample in two sub-groups for each model in Table 4.[4] The results are in line with the expectations and our findings in Table 3. The treatment leads up to significant energy savings among households, who used the tips and plugs to lower their energy consumption. Clearly, a more energy aware and active subgroup of households appears from these results.

[Insert Table 4]

B. Heterogenity in the Effect of Feedback

Besides relating the survey question responses to the electricity savings, we also examine whether the energy behavior questions can help us to understand the observed variation in households' reported savings. In Table 5, we therefore estimate the determinants of the probability of declaring positive savings (by the help of KIEK). Here, we use only the survey data. Therefore, the sample size is different from the previous estimations (106 instead of 85). According to these results, the frequency of checking KIEK and using the tips significantly increase the probability of reporting positive saving. So, these can be considered as the two main drivers of the energy savings. According to calculated marginal effects, high frequency of checking KIEK increases saving probability by around 18 percent. Similarly, using the energy saving tips also increases this probability by around 21 percent.

[Insert Table 5]

In Table 6, we estimate the determinants of the probability of declaring positive saving (by the help of KIEK). For this, we use only the survey data. Therefore, the sample size is different

[4] We split the sample according to the survey questions by grouping them: high-low frequency of checking KIEK, used tips-did not use tips, used plugs-did not use plugs

from the previous estimations (130 instead of 85). This time, we generate new variables based on some characteristics and motivations of the households. We use the following survey questions to construct the variables: What is the importance of “saving money” motivation for attending the project?, How much are you willing to pay (WTP) for the environment?, Questions about energy conservation behavior: buying efficient light bulbs, shower time, etc., Do you know how much electricity you consume in a year (energy literacy)?, Age, and Education level. We generate dummy variables based on the median values of the answers or the yes/no answers.[5] According to the results, energy conserving behavior and age significantly increases the probability of reporting positive saving. So, these can be considered as the two main household characteristics that lead to energy saving as a result of feedback provision. According to calculated marginal effects, high level of energy conserving behavior increases saving probability by around 16 percent. Being older than 55 increases this probability by around 29 percent.

[Insert Table 6]

IV. Conclusion

The results of our random field experiment on the residential electricity usage shows that providing consumption feedback through in-home displays is an effective means to reduce energy consumption. Our analysis shows that information incentives reduce electricity use by 18 percent, and that this effect is stronger among energy conservative and older households who have checked the display frequently and used the saving tips.

[5]Based on the answers of our survey questions we generate the variables: Money saving: median, WTP: 0 or positive, Energy conservation behavior: median of the index, Energy literacy: yes or no, Age: median, and Education level: “university and upper” or “lower”

Figure 1: Monthly electricity consumption from the grid (Treatment and control sample)

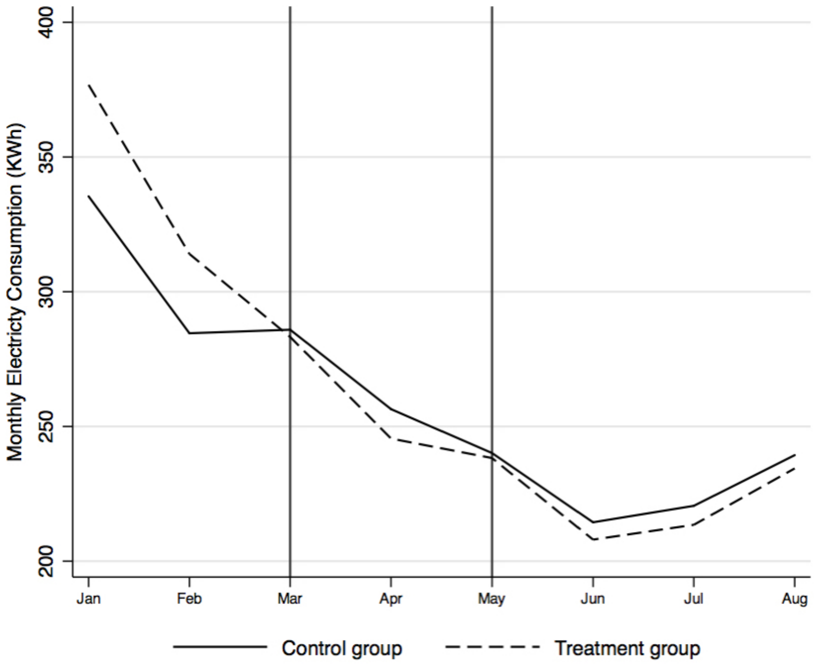

Figure 2: Monthly electricity consumption from the grid (Savers versus non-savers)

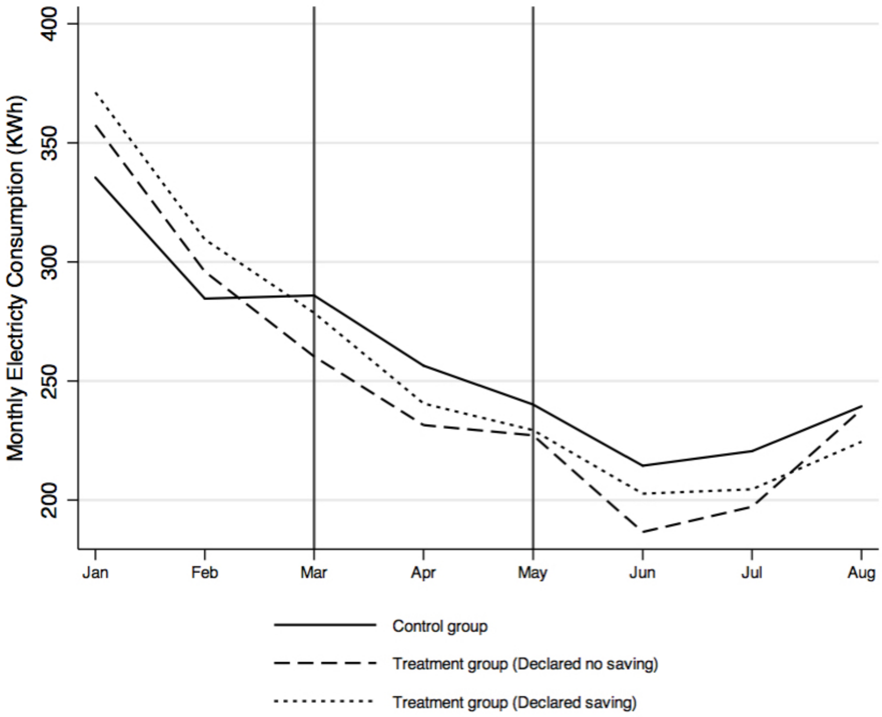

Table 1: Descriptive Statistics for Treatment and Control Groups

	Treatment Sample		Control Sample	
Number of Observations	*100*		*50*	
Variables	Mean	Std.Dev.	Mean	Std.Dev.
Electricity consumption from the grid (KWh)				
Pre-experiment period (January, February)	376.7	(150.7)	335.4	(141.8)
Respondent characteristics				
Age	54.9	(10.6)		
Education (0)	0.08			
Education (1)	0.21			
Education (2)	0.25			
Education (3)	0.31			
Education (4)	0.15			
Energy behavior				
Willing to pay for renewable energy	0.31			
Knows the amount of energy they consumed	0.81			
Thinks energy conservation is important	0.92			
Response to treatment				
Checking KIEK on a daily base in phase 1	0.71			
Checking KIEK on a daily base in phase 2	0.62			
Used plugs	0.85			
Used saving tips	0.59			
Saved electricity by the help of treatment in phase-1	0.48			
Saved electricity by the help of treatment in phase-2	0.52			

Table 2: Difference-in-differences Estimation Results

Variables	
Treatment group	0.133**
	(0.058)
Phase1	-0.178**
	(0.083)
Phase2	-0.309***
	(0.062)
Treatment group*Phase1	-0.184*
	(0.101)
Treatment group*Phase2	-0.175**
	(0.075)
Constant	5.624***
	(0.048)
Observations	900
R-squared	0.145

Notes:
Dependent variable is logarithm of monthly electricity consumption from the grid.
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 moths.
* P<0.1. ** P<0.05. *** P<0.01

Table 3: Difference-in-differences Estimation Results for Sub-groups (reported saving)

Variables	
Phase1	-0.178**
	(0.082)
Phase2	-0.309***
	(0.061)
Treatment group (declared no saving)	0.007
	(0.076)
Treatment group (declared saving)	0.125**
	(0.062)
Treatment group (declared no saving)*Phase1	-0.096
	(0.131)
Treatment group (declared saving)*Phase1	-0.192*
	(0.108)
Treatment group (declared no saving)*Phase2	-0.073
	(0.098)
Treatment group (declared saving)*Phase2	-0.205***
	(0.080)
Constant	5.624***
	(0.047)
Observations	810
R-squared	0.148

Notes:
Dependent variable is logarithm of monthly electricity consumption from the grid.
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.
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 moths.
* P<0.1. ** P<0.05. *** P<0.01

Table 4: Difference-in-differences Estimation Results for Sub-groups (others)

Variables	KIEK freq.	Used tips	Used plugs
Phase1	-0.178**	-0.178**	-0.178**
	(0.081)	(0.080)	(0.081)
Phase2	-0.309***	-0.309***	-0.309***
	(0.060)	(0.060)	(0.060)
Treatment group (non-user)	0.114	0.158**	0.027
	(0.076)	(0.074)	(0.106)
Treatment group (user)	0.112*	0.081	0.128**
	(0.067)	(0.067)	(0.062)
Treatment group (non-user)*Phase1	-0.210	-0.153	-0.148
	(0.132)	(0.129)	(0.184)
Treatment group (user)*Phase1	-0.194*	-0.232**	-0.209*
	(0.116)	(0.116)	(0.107)
Treatment group (non-user)*Phase2	-0.228**	-0.146	-0.180
	(0.099)	(0.096)	(0.137)
Treatment group (user)*Phase2	-0.200**	-0.256***	-0.216***
	(0.086)	(0.087)	(0.080)
Constant	5.624***	5.624***	5.624***
	(0.047)	(0.046)	(0.047)
Observations	768	768	768
R-squared	0.159	0.172	0.161

Notes:
Dependent variable is logarithm of monthly electricity consumption from the grid.
Treatment group (user): group of households who declared that they checked KIEK frequently and/or used saving tips and/or used plugs. Treatment group (non-user): group of households who declared that they did not check KIEK frequently and/or did not use saving tips and/or did not use plugs.
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 moths.
* P<0.1. ** P<0.05. *** P<0.01

Table 5: Determinants of Energy Savings (Logit Analysis)

Variables	Coef.	Marginal effects
Positive expectations about the KIEK	0.574	0.048
	(0.616)	(0.054)
Frequency of checking KIEK	1.775***	0.185**
	(0.644)	(0.080)
Used tips	2.116***	0.214***
	(0.711)	(0.075)
Used plugs	-0.562	-0.039
	(0.822)	(0.048)
Constant	0.113	
	(0.314)	
Observations	106	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

Table 6: Energy Savings and household characteristics (Logit Analysis)

Variables	Coef.	Marginal effects
Motivation to save energy: money	0.212	0.048
	(0.447)	(0.099)
Willing to pay for environment	-0.077	-0.018
	(0.420)	(0.096)
Energy conservative	0.724*	0.165*
	(0.399)	(0.090)
Know the amount of energy consumed	-0.145	-0.033
	(0.444)	(0.103)
Age>55	1.330***	0.296***
	(0.416)	(0.087)
High education	0.463	0.105
	(0.419)	(0.095)
Constant	-0.689	
	(0.514)	
Observations	130	130

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

Appendix A: The KIEK in-home display

Source: TexelEnergie