Title: Real-time Feedback and Electricity Consumption

Subtitle: A Field Experiment Assessing the Potential for Savings and Persistence

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Abstract: Real-time information feedback delivered via technology has been reported to produce up to 20 percent declines in residential energy consumption. There are however large differences in the estimates of the effect of real-time feedback technologies on energy use. In this study, we conduct a field experiment to obtain an estimate of the impact of a real-time feedback technology. Access to feedback leads to an average reduction of 5.7 percent. Significant declines persist for up to four weeks. In examining time of day reduction effects, we find that the largest reductions were observed initially at all times of the day but as time passes, morning and evening intervals show larger reductions. We find no convincing evidence that household characteristics explain heterogeneity in our treatment effects; we examine demographics, housing characteristics and psychological variables.

Keywords: Feedback Technology, Residential Electricity Consumption, Field Experiment

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1. Introduction

Readily available, easily accessible, real-time information feedback delivered via technology is reported to produce important declines in residential energy consumption (Faruqui et al. 2010; Ehrhardt-Martinez et al. 2010). Designing interventions that use feedback technologies and rely primarily on information as a means of changing energy behaviors have been promoted as cost-effective policies (Fischer 2008; EPRI 2009) and possible alternatives to traditional price incentives (Allcott and Mullainathan 2010).

In its basic form, feedback technologies consist of enhanced monthly bills with various pieces of information such as energy tips and comparison with peers (see Ayres et al. 2009; Allcott 2011). More complex feedback technologies provide real-time information accessible via computers, mobile phones and/or other portable displays. Estimates of the energy savings from feedback technologies vary widely, from none to as much as 20 percent (Faruqui et al. 2010; Ehrhardt-Martinez et al. 2010). There are three main factors at the source of this heterogeneity in outcomes. First, studies have employed different research designs. A fair share of the estimates publicly available come from pilot programs implemented by electric utilities. These pilot programs vary in size, participant selection procedures, duration and evaluation methods, making it difficult to reconcile the large differences in the statistical estimates. Second, the features of the feedback technology, such as timeliness, data display, interactivity, sociability, and controllability play a significant role in inducing energy reductions and have varied substantially across studies. Third, there is significant heterogeneity in the characteristics of the population of consumers participating in feedback interventions.

Although several studies have looked at the impact of feedback technology, providing insights as to how study design, features of the technologies and characteristics of the people using them impact the energy savings estimates, several questions remain. To determine if feedback technologies are cost-effective measures to manage energy demand it is necessary to assess whether they provide persistent energy savings and how they change consumption profiles. Previous studies have remained silent on these questions due to limitation in study design and data available (EPRI 2009).

The goal of this paper is first to provide an estimate of the potential for energy savings for households that have access to real-time feedback technology. Our focus is on electricity consumption only. The feedback technology resembles the technologies being deployed by several utilities in the US and elsewhere. We use a randomized controlled trial to overcome issue of selection bias and to estimate treatment effects. In this paper we exploit our experimental study design and high data resolution to gain insight into the nature of behavior changes that can lead to observed energy reductions. Over the period of the field trial, March through October 2010, we found a statistically significant reduction in electricity use of 5.7 percent. However, an examination of persistence of effects over time shows that there is only a brief period of significant reductions in electricity consumption: by week four all statistically significant reductions have ended. In examining time of day reductions, the largest reductions were observed initially at all times of the day but as time passes, morning and evening intervals show larger reductions. Evening reductions faded but morning reductions were sustained for eight weeks. However, the return to baseline in other day and evening periods cancelled out statistical significance in overall reductions. Thus, overall statistically significant reduction effects lasted for four weeks.

2. Experimental Design

The central goal of this study is to assess the impact of providing real-time whole-home electricity consumption feedback to households. The feedback technology tested was a monitoring device that recorded electricity consumption, and a web application that graphically displayed consumption information in near real-time (information was updated every ten minutes) as well as other related energy information such as cost, and comparative use.

Households participating in this study were recruited in collaboration with Google, a large IT company based in California, with several offices across continental US. Employees (N=1743) from the company continental enrolled their households for the study. Enrollment in the study was voluntary. Participating households were randomly assigned to no-feedback (untreated control) or feedback (treatment) conditions. Only households in the feedback treatment condition were given access to the feedback technology initially. Households in the control condition were given access to the feedback technology after three months. The study took place between February, 2010 and October, 2010.

2.1 The Feedback Technology

The feedback technology tested in this study consisted of a hardware device that allowed the display of ten minute interval electricity consumption data. The data were provided to the households via a web interface developed by Google, and called Google Powermeter. The main feedback feature of the interface is a graph that presents the ten minute interval and historical electricity consumption data. The interface also has a number of other features, including: (1) an annual electricity budget tracker, (2) a forecast of the annual electricity bill, (3) a display of total daily kWh, (4) an estimate of the baseload consumption, (5) a projection of electricity consumption during the night, morning, afternoon, and evening based on previous uses, (6) a comparison at the day level of current consumption to past consumption, (7) a link to a web page with energy conservation tips and (8) an email reminder.

2.2. Assignment to Experimental Conditions

Figure 1 illustrates the experiment procedure. Participants who met the eligibility criteria completed an online survey. The survey included questions on demographics, housing characteristics, appliance saturation, psychological questions, and energy related behaviors. Once participants completed the survey, they received the hardware device that was used to record electricity consumption. Participants were responsible for hardware installation; hiring a certified electrician, or installing it themselves. Once the hardware device was properly working, the web application could be installed. Up until seven days after the installation of the web application, all participating households performed exactly the same steps and were unaware of their assignment to experimental conditions. At the end of the seven days, after web application activation, participants were randomized to experimental conditions. For households in the treatment group, the web application automatically switched on and started displaying information. Households assigned to the control group had a blank interface and were sent an email informing them of assignment and received $10 compensation.[1] Assignment to the control condition was stratified by region (West Coast, Central, and East Coast), assignment probabilities were 20 percent.

After three months (on May 28, 2010), participants in the control group also were given access to the web application. The treatment group continued to receive feedback about energy use.

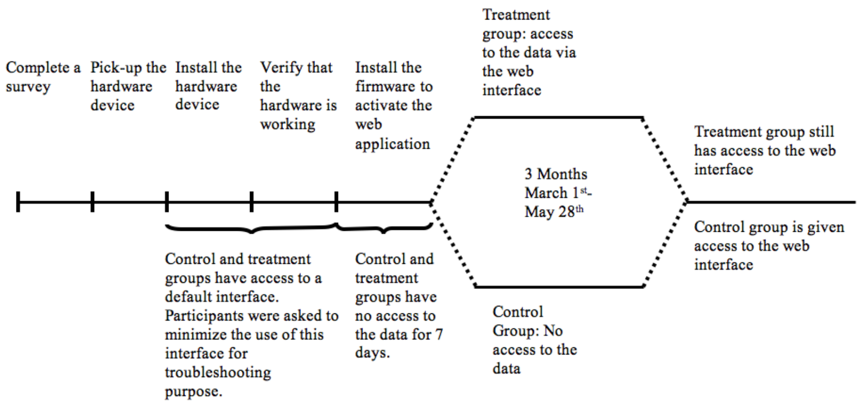

Figure 1: Experimental Design

2.2 Interim-Survey

On May 28, 2010, an interim online survey was distributed to all participants. The goal of this interim-survey was to assess changes in moderators and mediators of energy consumption. Participation in the post survey was low. Only 21 percent of households that participated in the study (N=1628) completed the interim-survey.

2.4 Validity of the Experimental Design

Of the households (N=1628) who met the eligibility criteria, completed the pre-survey, and agreed to be randomized, 1089 households (67 percent)

[1] The compensation for being assigned to the control group was not pre-announced.

installed the device at some time during the first three months of the experiment. Of these, 24 households were excluded from the analysis because they reported having significant problems with the technology or data were recorded for fewer than three days. This left 1065 households, of which 752 were in the feedback condition and 313 were controls.[2]

Table 1 presents a comparison of participants by condition and compares the experimental sample to California and US demographics. We found no statistically significant differences in the mean of each variable in Table 1 except for the proportion of households with an income less than $100,000. Overall, groups were well balanced.[3]

In Table 1 we also compare the study sample to California and the US population. Fifty-three percent of participants resided in California (and about 65 percent in the corresponding census division). Households in our study sample are more affluent and more highly educated than the average household in California and in the US. Average electricity consumption in our sample lies between California and US averages. Household size, square footage and the proportion of single family detached units in our sample are also close to US population averages. The primary threats to external validity in our sample are that at least one member of each participating household is an employee from a large IT company and most of these employees are engineers.

3. Analysis and Results

Analysis strategy and results are presented according to study goal: main treatment effects, heterogeneity of response to treatment, and persistence of treatment effects.

3.1 Average Treatment Effect

Our first goal is to obtain an internally valid estimate of the effect of real time electricity feedback on energy consumption. Figure 2 shows the average daily electricity consumption of the treatment and control groups over the experimental period, March 1, 2010 to May 28, 2010, and six months after the experiment (i.e. when controls also received feedback). Immediate and over time

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[2] Because at most 24 of the drop-outs occurred after the randomization, attrition bias based on knowledge of treatment is negligible. Of the 24 participants that were excluded because of problems with the technology, some were knowledgeable of their assignment. For these households we cannot conclude a priori that attrition was uncorrelated with their assignment to experimental conditions. To rule out this potential concern, we ran a probit regression to estimate the probability of being one the 24 households that did not have a sufficient amount of data collected. A latent variable depending on demographics, housing characteristics, psychographics and a dummy for the assignment to the experimental conditions was assumed to determine the decision to comply or not. The coefficient for the dummy to the assignment to the experimental conditions was not significant.

[3] We also performed a probit regression where the probability of being assigned to the treatment is a function of the observable characteristics listed in Table 1 and failed to reject the multiple hypothesis that all covariates are equal to zero (Likelihood ratio test, LR=77.42, p=.33).

reductions can be seen throughout the experimental period. Once control households received feedback they replicated reductions seen in the experimental period, while treatment households in the post experimental period had higher consumption than the `new' feedback (previously control) households. Table 2 shows the main treatment effect across 5 different specifications.

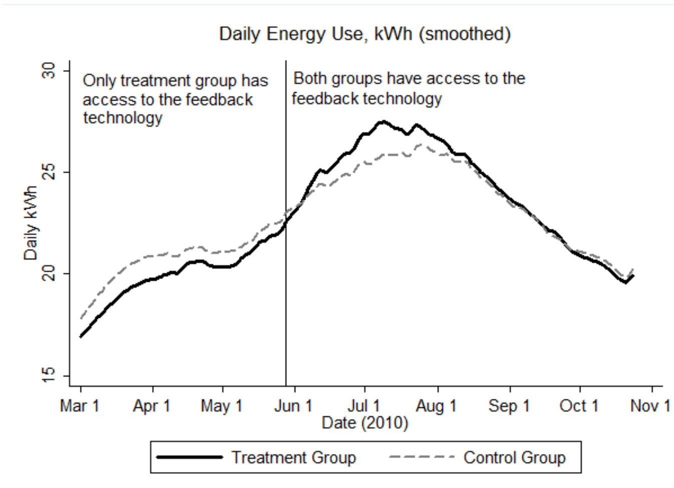

Figure 2: Electricity consumption in Treatment and Control groups

Our preferred specification regresses the log of hourly electricity consumption averaged over the day and includes household fixed effects, day fixed effects and controls for weather (mean daily temperature and a dummy that takes the value 1 if precipitations were received on day *t*):

$$\log(Electricity_{it}) = \alpha + \gamma_i + \psi_t + \rho Treatment_{it} + \beta Weather_{it} + \varepsilon_{it} \qquad (1)$$

The dummy *Treatment* takes the value 0 for households in the control group before May 28, 2010 (when they did not have access to the feedback technology), and 1 thereafter; and takes the value 1 for households in the treatment group for the entire time after the first seven days after installation (when they had access to the feedback technology). Standard errors are clustered at the household level to account for serial correlation.

The estimate of the average treatment effect, ρ, is a measure of the average percentage difference in electricity consumption between households that are exposed to feedback and those that are not.

Ideally, the household fixed effects model would be identified using electricity billing data for the months preceding the experiment; however, we did not have access to this data. Identification of ρ with household fixed effects relies on the fact that after May 28, 2010 both the control group and the treatment group had access to the feedback technology. Under the assumption that the treatment effect is constant over time, when households in both groups have access to the technology, any differences in average consumption levels can be attributed to household specific fixed effects. In the next section, we use a similar identification strategy while relaxing the assumption that the treatment effect is time invariant.

Results from the estimation of the fixed effects model are presented in Table 2 (Model 1): the average treatment effect consists of a decrease in electricity use of 5.7 percent per hour (this works out to about 0.05kwh in absolute terms), significant at the 5 percent level. We assess the robustness of this result using five other specifications, all presented in Table 2.

We first estimated Model 1 restricting the sample to households living in California, which constitute about 65% of our sample (Table 2, Model 2). This specification notably allows us to reduce the variations in weather and climatic conditions and yields an estimate of the average treatment effect that replicates the one of Model 1 closely.

We then look at the first three months of observations and compare electricity consumption between households in the control group and treatment group, controlling for day fixed effects and weather. In this specification the dummy *Treatment* takes the same value for a given household. Variation over time of the treatment variable is thus not a source of identification. We find an average treatment effect corresponding to a larger reduction: -8.9 percent and less precise (Table 2, Model 3).

Next, using all the data from March to October, we estimate a sequence of specifications. The simplest includes only a dummy for the treatment effect. As we can see in Table 2 (Model 4), the coefficient on *Treatment* is positive. This result underlines the importance of controlling for day fixed effects and weather while using variation over time to identify the treatment effect. In the present case, the fact that summer months induce higher electricity consumption leads to an upward bias in the estimation of ρ.

Adding weather[4] and daily time fixed effects (Model 5, Table 2) yields an average treatment effect similar to Model 1, with a decrease of 9.4 percent, but not significant at the 5 percent level.

Finally, if we consider a specification that includes household information that might explain household specific (time-invariant) energy use, such as house size, age of the building, family size, etc.,[5] we get a decrease of 7 percent (Table 2, Model 6) similar to that in Model 1. This estimate is insignificant, suggesting that the household information at our disposal is insufficient to explain idiosyncratic differences in each household's level of energy use.

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[4] We experimented with the controls for weather. For instance, we added to the model the daily minimum temperature and the daily maximum temperature and quadratic terms. This had marginal effects on the estimates of the treatment effect.

[5] The complete list of survey variables and responses can be requested to the authors.

3.2 Treatment effect - Time of Day

An aspect of our primary research goal is to use our unique real time data to inform our understanding of time specific electricity use and reductions. We use the high resolution of the data to estimate the feedback treatment effects for each hour of the day. We aimed to distinguish between periods of high and low household membership activity, which allows us to infer whether savings are attributable to habitual behavioral change (such as turning off lights) or to one time behaviors that are more structural in nature (such as installing energy efficient appliances or house insulation). Change in habitual behaviors should lead to reductions that are observable at periods of high occupancy while the latter class of actions should lead to reductions in the baseload levels of consumption.

Figure 3 plots the hourly average treatment effects by time of day with their 95% confidence intervals (over all days of the week). Hourly treatment effects are obtained by using hourly data and estimating the following model which controls for day of the year fixed effects, weather and household fixed effects.

$$\log(Electricity_{it}) = \alpha + \gamma_i + \psi_t + \rho_h Treatment_{it} + \beta Weather_{it} + \varepsilon_{it} \quad (2)$$

The largest reductions in electricity consumption due to feedback occur during the morning and evening peak periods: between 5 am and 10 am, electricity consumption decreases by 12.2 percent in average and between 8 pm and 11 pm electricity consumption decreases by 8.2 percent on average. While energy savings during the middle of the day and night are insignificant, savings during the morning and evening peaks are large and significant. Savings occur at periods when household members occupy the house and engage in household functions, such as eating, entertainment, cleaning and household maintenance. Based on this finding, we argue that electricity use reduction during household activity is consistent with changes in energy behaviors that pertain to habits. Shorter showers, less heating or air conditioning, or a myriad of other singly less impactful behaviors such turning off lights, turning off/unplugging small appliances, less oven use but reduced in combination can bring about large reductions and thus explain our finding. Alternatively, households could have purchased energy efficient appliances that are mostly used at times when most household members are present, e.g. dishwashers, washing machines, hot water heaters, stoves, and air conditioners.

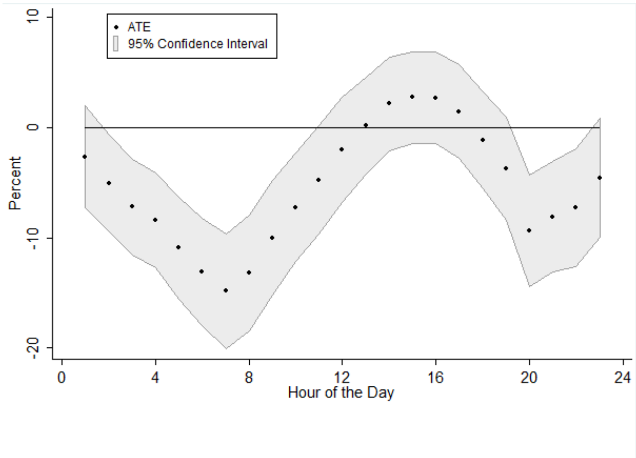

Figure 3: Average Treatment Effect at Different Time of the Day

3.3 Persistence

Figure 1 suggests that the impact of feedback fades over time. During the first three months of the experiment, with only the treatment group receiving feedback, the treated households have lower electricity use than the controls. When the control group initially receives feedback (after May 28, 2010), their electricity use drops below the longer term feedback and original treatment group. At the end of the eight months the two groups converge, having similar levels of electricity consumption. To further investigate this pattern of results, we relax the assumption that the treatment effect is constant, and test if the feedback effect persists over time.

Table 3 presents the estimation results of different models that allow the treatment effect to vary across time. Each model allows the treatment to vary non-parametrically in the initial weeks and then assumes that the treatment effect stabilizes after a number of weeks. That is, the average treatment effect varies as a function of the time since the households in the treatment group had access to the feedback technology. Under the assumption that the treatment effect stabilizes starting the fifth week after receiving the treatment (Model 2), the model that we estimate is:

$$\begin{aligned} \log(Electricity_{it}) &= \alpha + \gamma_i + \psi_t + \rho_1 TrWk1_{it} + \rho_2 TrWk2_{it} \\ &+ \rho_3 TrWk3_{it} + \rho_4 TrWk4_{it} + \rho_5 TrWk5_{it} + \beta Weather_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

where *TrWk1* takes a value of 1 during the first week of treatment and 0 otherwise, *TrWk2-TrWk4* are similar, and *TrWk5* takes a value of 1 for all weeks after the fourth week that household *i* is treated and 0 otherwise, so that *Treatment* in the previous section is the sum of all of these *TrWk* variables. In this specification, identification of household fixed effects relies on the assumption that in the *long-term*, the treatment effect stabilizes. This assumption is motivated by our view that a process of behavioral change enacted by feedback technologies, although dynamic, should reach a long-run steady-state after an extended exposure to feedback. How *long term* should be defined in this context is subject to interpretation. For this reason, we use different number of weeks, respectively five, six, seven and eight as thresholds to determine when the treatment effect is stable.

Model 1 assumes that the treatment effect is constant (same specification than Model 1 in Table 2) and models 2, 3, 4, and 5 in Table 3 allow the treatment to vary up to the 5th, 6th, 7th, and 8th week, respectively. Estimates of these models show a significant decrease in energy consumption of around 7 to 8 percent in the first two weeks after treatment. The effect declines and become insignificant starting the third week after the treatment. In sum, access to real time electricity feedback leads to an immediate decrease in electricity consumption, but in the long term these electricity savings decrease and disappear.

Taken together, the fact that reductions due to feedback occur primarily during peak household activity periods, but on average do not persist over time suggests that reductions might be primarily due to temporary changes in habitual behaviors.

We further examine this hypothesis by assessing if and how treatment effects at different hours of the day vary over time. Figure 4 shows that starting the sixth week after receiving the feedback technology, there is a clear separation in the treatment effects between the peak and off-peak periods. The pattern of treatment effects across the different hours of the day suggests a shift in consumption across different times of the day. This is surprising if we consider an economic interpretation of reduction in use, however, given that most households in our sample do not face time-of-use electricity tariffs we consider alternative interpretations, such as actions adopted by household members during mornings and evenings become consolidated as habits and are maintained.

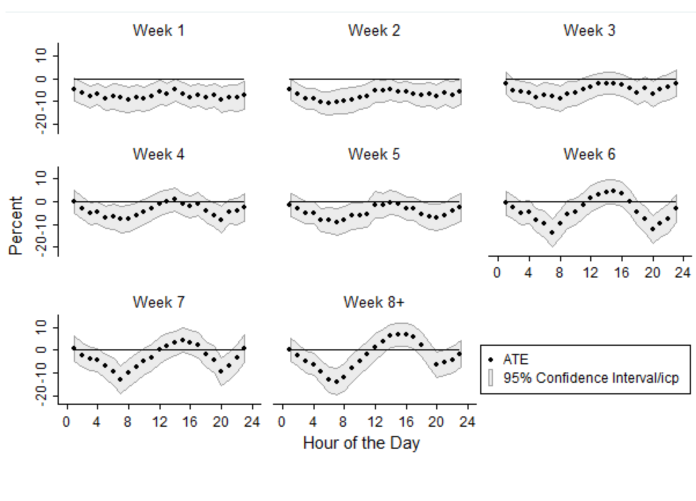

Figure 4: Persistence of Average Treatment Effect at Different Time of the Day

To assess the robustness of our results, we test different specifications. Figure 4 plots the estimates of a model identical to our preferred specification (equation 1) except that we estimate the model separately for each week since households have access to the feedback technology. All data for weeks greater or equal to eight are pooled together. We find that in the first two weeks after having access to real time electricity feedback, electricity consumption decreases in all time periods. Starting the third week, reductions during the day (10 am -4 pm) and the night (11 pm -4 am) start to fade away. In the long-run, only reductions during the morning and evening peak periods persist.

3.4 Self-Reported Behaviors

To understand the source of reductions in electricity consumption, we conducted a interim-survey at the end of initial feedback period (3 months after the beginning of the study) where participants were asked to report energy efficiency home investments and energy conservation behaviors. These results must be interpreted with caution; only 342 households completed the interim-survey at the end of the experimental period. Representativeness of this sample of the overall group of 1064 is of necessity suspect. Households in the treatment group were significantly more likely to perform an energy audit. Although performing an energy audit does not by itself immediately impact electricity consumption, this is an important step towards achieving larger reductions. While not significant, there are also indications that households in the treatment group were more likely to purchase CFLs. We find no statistical differences in other behaviors related to investments in energy efficiency.[6] Comparing the treatment and control groups with respect to individual habitual behaviors,[7] we find no statistically significant differences, except for the use of power strips. We fail to reject the joint null hypothesis that all behavior indicators are different in the control and treatment groups.

4. Conclusion

We find exposure to real-time feedback technology produces reductions in electricity consumption an average of 5.7 percent. This estimate is smaller than the estimates obtained in several other studies that consider similar type of feedback technology. For instance, Ehrhardt-Martinez et al. 2010 report average savings of the order of 12 percent for real-time feedback technology. We argue that our results are more realistic because use of an experimental design reduces the possibility of selection bias and allows us to compute an internally valid

[6] We ask participants if they purchased CFL, made an home energy audit, made major energy efficiency improvements such as insulating their home or replacing windows, and purchased a new TV, dishwasher, AC, refrigerator, washing machine, laptop and/or dryer.

[7] We ask participants if they were more likely to turn off computer(s), TV, gaming console, lights, power strip, AC and/or heating when not needed. We also asked if they were more likely to wear warmer clothes to compensate for lower use of heating, use dishwasher and washer at full capacity, wash clothes in cold water and use a clothes line.

estimate of the effect of the feedback technology. Moreover, we have a larger sample size than the ones typically used in pilot programs run by electric utilities. On the other hand, our results should be interpreted with the important caveat that a specific technology has been tested on a group of households that is not fully representative of the whole US population.

There is significant heterogeneity in the treatment effect with respect to time of the day and time since the feedback has been installed. In the initial weeks after receiving access to feedback, reductions are observed at all hours of the day. There is evidence that behaviors performed during the peak periods are the ones that tend to persist. However, after about four weeks, reductions were however not statistically significant.

Households characteristics may be at the source of heterogeneity. We investigated whether the average treatment effect where correlated with effect of income, ownership status, occupancy, political affiliation, donations to environmental groups, appliance intensity, baseline knowledge and values pertaining to energy, and baseline energy related behaviors. We find no convincing evidence that any of our baseline survey variables explain variation in treatment response. The reasons for lack of explanatory variables for treatment response variability could attributed to variable selection, weaknesses of self-report measures, as well as the possibility that the size of our sample was too small to detect correlations. Interestingly, other feedback studies with much larger sample size have also found that observable variables tend to poorly predict heterogeneity in energy savings from feedback (e.g. Davis 2011). Consistent with previous studies, we find some albeit weak evidence that households that consume more *ex ante* reduce more in terms of kwh. In percentage terms, reductions are however about the same size across quartile groups.

Overall, our results are cause for restrained optimism for the role of providing information alone in designing policies to reduce household energy use. Evidently households do respond to feedback and are able to reduce electricity consumption, indicating that there seems to exist room to change habits and behaviors. Clearly, the challenge is to prevent these reductions from weakening with time. Future research should focus on both the development of rigorous research designs to detect change as well as the development of powerful feedback interventions and strategies that can maintain reductions.

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Table 1: Summary Statistics: Treatment and Control Groups

	Treatment[a]	Control[a]	T-C	Pop CA[d]	Pop US
Electricity Consumption					
Baseline mean (kwh)	0.89	0.92	-0.03	0.81	1.28
	(0.73)[b]	(-0.71)	(0.02)[c]		
Demographics					
Household size	2.96	3.08	-0.11	2.92	2.61
	(1.37)	(1.3)	(0.09)		
% with children (0-18 y)	47.6	51.1	-3.5	38.0	34.3
% income <100,000	9.3	4.8	4.5*	-	-
% income >100,000 and <150,000	18.8	16.9	1.9	-	-
% income >150,000 and <250,000	30.1	34.5	-4.4	-	-
% income >250,000	21.4	20.8	0.6	-	-
median income	-	-	-	61,154	52,175
% engineer	79.4 [e]	76.7 [e]	1.7	-	-
% employed in the IT industry	100 [e]	100 [e]	-	3.1 [f]	2.5 [f]
% white	56.1 [e]	55.3 [e]	0.8	60.9	74.3
% in CA	65.0	69.6	-4.6	-	11.6
% owner	79.3	79.2	0.1	57.8	67.1
Housing Characteristics					
% single family detached	64.2	68.1	-4.9	-	64.9
% < 1,000 sq. ft.	15.3	11.2	4.8	-	-
% > 2,000 sq. ft.	38.7	36.4	2.3	-	-
Average floor space sq. ft.	-	-	-	-	2,171
% heating with electricity	19.5	16.3	3.2	23.2	33.5
Psychographics					
% democratic or leaning	50.4	53.7	-3.3	47.0	44.0
% donation to environment	23.9	28.8	-5.9	-	-
Behavioral Factors					
% turn off lights if not needed	86.5	87.2	-0.7	-	92.0
% turn off power strips	7.5	7.0	0.5	-	74.0
% wash laundry in cold water	48.0	45.7	2.3	-	76.0
Nb of Households	752	313			

Significance levels: *: 5%

Note. (a) Only households in the treatment and control groups post attrition considered. (b) S.D. in parentheses for means. (c) S.E. in parentheses for difference in means. (d) Baseline electricity consumption from the Energy Information Administration (2008 statistics). Household size, percentage of household with children, household income, employment in the IT sector, percentage of white and percentage of home owner from the US Census, 2006-2008 American Community Survey. Party identification from Gallup January-July 2010 polls. Self-reported energy conservation behaviors from Leiserowitz et al. 2009, Global Warming's Six Americas survey (2008). Type of home and square footage from the 2005 Residential Energy Consumption Survey, Energy Information Administration. (e) The survey respondent in each household was the household member employed at Google. (f) Percentage of civilian population. (g) Percentage of respondents that reported to almost always or often perform the behavior.

Table 2: Main Effects

	(1) t FE, i FE	(2) t FE, i FE CA Only	(3) t FE, i FE 3 months	(4) OLS	(5) t FE	(6) t FE
Treatment	-0.0567**	-0.0497*	-0.0891	0.0221	-0.0939	-0.0704
	(0.0210)	(0.0239)	(0.0574)	(0.0482)	(0.0574)	-0.0669
Temp. (daily)	0.0155***	0.00229*	0.00486		0.0232***	0.0121***
	(0.000751)	(0.00113)	(0.00346)		(0.00282)	-0.0017
Precipitation	0.0738***	0.0125	-0.452***		-0.489***	-0.108**
	(0.00647)	(0.0183)	(0.0521)		(0.0487)	-0.0412
Day Year FE	Yes	Yes	Yes	No	Yes	Yes
Demographics	No	No	No	No	No	Yes
HH FE	Yes	Yes	No	No	No	No
Observations	161542 [a]	92213 [b]	51088 [c]	161542	161542	110188 [d]
R^2	0.075	0.028	0.050	0.000	0.085	0.398
Nb of Households	1064	570	1052	1064	1064	734

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable for all regressions is the log of the hourly kwh for each household, averaged over each day.
R-squared is computed as proportion of variation explained by all variables, including the FE.
Treatment is a dummy variable that is 1 when a household received treatment and 0 otherwise.
Temperature is the daily average temperature for each zip code. Precipitation is a dummy variable taking 1 when there was any precipitation and 0 otherwise, by zipcode.
(a) Observations for all households during the period March to October 2010.
(b) Observations for households living in California during the period March to October 2010.
(c) Observations for all households during the period March to May 2010.
(d) Observations for all households with complete demographic information during the period March to October 2010.

Table 3: Persistence of Treatment Effect

	(1) t FE, i FE	(2) Persistence, 5wk	(3) Persistence, 6wk	(4) Persistence, 7wk	(5) Persistence, 8wk
Treatment	-0.0567**				
	(0.0209)				
Week 1		-0.0804***	-0.0789***	-0.0770***	-0.0756***
		(0.0212)	(0.0211)	(0.0211)	-0.0212
Week 2		-0.0753***	-0.0739***	-0.0719***	-0.0704***
		(0.0210)	(0.0210)	(0.0211)	-0.0211
Week 3		-0.0510*	-0.0493*	-0.0473*	-0.0457*
		(0.0218)	(0.0217)	(0.0218)	-0.0218
Week 4		-0.0382$^+$	-0.0363	-0.0340	-0.0324
		(0.0231)	(0.0230)	(0.0230)	-0.0231
Week 5+		-0.0380			
		(0.0236)			
Week 5			-0.0493*	-0.0467*	-0.0449$^+$
			(0.0237)	(0.0238)	-0.0238
Week 6+			-0.0324		
			(0.0242)		
Week 6				-0.0436$^+$	-0.0416$^+$
				(0.0241)	-0.024
Week 7+				-0.0258	
				(0.0251)	
Week 7					-0.0326
					-0.0253
Week 8+					-0.021
					-0.026
Temp. (Daily)	0.0155***	0.0155***	0.0155***	0.0155***	0.0155***
	(0.000749)	(0.000747)	(0.000747)	(0.000747)	-0.000747
Precipitation	0.0738***	0.0737***	0.0737***	0.0737***	0.0737***
	(0.00645)	(0.00645)	(0.00645)	(0.00645)	-0.00645
Day Year FE	Yes	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes	Yes
Observations	161542	161542	161542	161542	161542
Nb of Households	1064	1064	1064	1064	1064

Standard errors in parentheses

$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dependent variable is the log of the hourly kwh for each household, averaged over each day. Treatment is a dummy variable that is 1 when a household received treatment and 0 otherwise. Temperature is the daily average temperature for each zip code. Precipitation is a dummy variable taking 1 when there was any precipitation and 0 otherwise, by zipcode. Week j is a dummy variable taking 1 in the jth week after the household received the treatment and 0 otherwise.