Motivating energy conservation among non-rate paying households with feedback and social nudges: A cautionary tale

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Motivating energy conservation among non-ratepaying households with feedback and social nudges: A cautionary tale*

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Abstract

Non-price interventions have been shown to be valuable instruments in reducing energy use among rate paying customers, but their effect on non-ratepayers have received less attention. This study uses a randomized controlled trial research design to examine the effect of feedback and a social nudge on energy consumption of non-rate paying households. Empirical findings are based on 218,387 hourly observations from 62 households gathered over a period of 21 weeks. Our results suggest that neither feedback on energy use or a social nudge in the form of peer comparison are effective instruments to reduce the energy usage of non-rate paying households. The average treatment effect masks heterogeneous effects among households that are low and high users of energy in the pre-treatment period: both interventions increase energy use for high users while feedback decreases usage among low users. The effect of the social nudge among low users depends on their relative usage in the previous period, with above-average users decreasing consumption, and vice versa. We discuss these empirical results in the context of a model of utility that incorporates moral utility and preferences for conformity.

Keywords: energy conservation, social nudges, feedback, residential electricity

1 Introduction

Concerns about climate change and sustainability have prompted many initiatives aimed at reducing energy consumption in the United States. In particular, non-pecuniary behavioral interventions have garnered substantial interest and are now being used as an energy conservation tool in a number of settings (Allcott 2011a; Allcott and Mullainathan 2010). Non-pecuniary interventions are attractive because pecuniary incentives like taxes are politically challenging and costly, and while the effectiveness of subsidies is hard to evaluate (Allcott 2011a). In this paper, we examine the effect of two non-pecuniary interventions, feedback in the form of a weekly energy use report and a social nudge in the form of peer

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comparison, on the energy consumption of residential non-rate paying customers. Residential energy consumption is responsible for 20% of national energy demand and 18% of GHG emissions, and a significant portion of residential customers are non-ratepayers who do not pay directly for their energy use (U.S. Energy Information Agency 2011; U.S. Census Bureau 2013; U.S. Energy Information Agency 2009). It is important to separately examine the effect of conservation incentives for non-ratepayers because the absence of a pecuniary benefit from energy conservation for non-ratepayers may cause them to behave differently from ratepayers. Non-ratepayers are also important to consider because they constitute a non-trivial portion of electricity consumers. The rental market accounts for 34 percent of all occupied housing units in the United States (U.S. Census Bureau 2013). Of this figure, 26 percent of all rental units include the cost of energy in their rent (U.S. Energy Information Agency 2009). Although non-ratepayers account for only 9% of residential energy consumers, the potential for energy savings in this group is large because studies have reported higher energy use among non-ratepayers compared to their rate-paying counterparts. Munley et al. (2014) find that residents who pay for their energy use as part of their rent consumed 32 percent more electricity on average than residents in the same apartment complex who paid for their energy use separately. Levinson and Niemann (2004) report that tenants living in utility-included apartments set their thermostat between one and three degrees warmer during winter months. This finding is reinforced by Maruejols and Young (2011) who report a one-degree daytime temperature difference for residents of multi-family dwellings who do not have to pay directly for their electricity use, compared to those that pay for electricity depending on level of use. Given these characteristics of non-ratepayers it is important to examine what types of non-price interventions will be effective in decreasing energy use among this market segment.

Our research design based on a randomized controlled trial (RCT) enables us to identify the effect of feedback and social nudges on energy consumption. Sixty-two households living in a utility-inclusive housing complex are randomly divided into a control group and two treatment groups. Baseline electricity consumption for all groups was collected for twelve weeks. In Phase 1, which lasted 4 weeks, both treatment groups received weekly home electricity reports (HERs) in a format similar to an electricity bill. In Phase 2, which ran for 5 weeks, the second treatment group received HERs with additional information about their energy consumption relative to their neighbors, while the first treatment group continued to receive the basic HER. We observe hourly electricity consumption for households in the sample. Empirical findings are based on 218,387 hourly observations gathered from 62 households over a period of 21 weeks. Our preferred empirical specification is a random-effects model with controls for temperature, rain, time-of-day, day-of-week, snow days and holidays. We find heterogeneous effects among households that are low and high users of energy in the pre-treatment period: both interventions increase energy use for high users while feedback decreases usage among low users. The effect of the social nudge among low users depends on their relative usage in the previous period: households increase their energy use upon receiving an energy report indicating that they are below average users of energy in the pervious period, or decrease their usage when they are informed that they are above average users. This effect on low-users is consistent with the boomerang effect suggested by Schultz et al. (2007) among a sample of ratepayers, as well as preferences for conformity (Luzzati 1999).

We adapt the framework developed by Allcott and Kessler (2015) to model the choice of energy consumption among non-ratepayers given the presence of moral (dis)utility from energy use. Additionally, we extend this model with the model of conformity (Luzzati 1999) which formalizes the boomerang effect where households who are told they use more energy than average reduce their usage and those who are told they use less than average increase their usage (Schultz et al. 2007). Based on our theoretical model, our results are consistent with feedback decreasing the marginal moral cost of energy use for high-users, while increasing it for low users. Moreover, low users seem to have preferences for conformity, reducing their usage when they received a report indicating that they were above-average users in the previous period, and vice-versa. High users on the other hand increase usage regardless of relative usage status and as such do not seem to be sensitive to conformity.

This paper is most closely related to studies that use a randomized controlled trial (RCT) study design to examine the effect of different energy conservation incentives. The effectiveness of feedback as an energy conservation tool has found support in a number of studies. Other studies suggest that feedback has little or no effect, or that feedback leads to increased usage. However most of these studies are pilot trials or are relatively older studies. For listing of these studies see Delmas and Lessem (2014). Houde et al. (2013) show that real time feedback reduced household electricity consumption by 5.7% although statistically significant effects were limited to four weeks after treatment period ended. Jessoe and Rapson (2014) find that real time feedback increases the price elasticity of demand for electricity by facilitating consumer learning, thereby improving their ability to respond when prices increase.

Peer comparisons have also been shown to affect energy use. Several evaluations of the effect of OPOWER home energy reports that provide neighborhood comparisons alongside the monthly energy bill have found that this program was overall successful and led to decreases in average electricity consumption (Allcott 2011b; Ayres, Raseman, and Shih 2012). Alcott (2011) finds that OPOWER reports reduce electricity consumption by 2%. The reduction in electricity use is greater for households in the highest decile of pre-treatment electricity consumption. These households saw reductions of 6.3% compared to 0.3% for those in the lowest decile. Costa and Kahn (2010) show heterogeneous treatment effects of OPOWER reports. They found the impact to be 2-4 times greater in liberals compared to conservatives. Schultz et al. (2015) find that in-home displays coupling information about kilowatt consumption with a normative message reporting usage of similar households led to a significant reduction of 7% during a three month period, whereas displays that contained information about kilowatt usage or kilowatt usage with its corresponding cost did not lead to any significant effect. Peer comparisons can also have mixed effects. Schultz et al. (2007)

documents a “boomerang effect” in which above-average energy consumers decreased usage while below-average energy consumers increased usage. However, Schultz et al. (2007) find that the boomerang effect can be mitigated by adding an injunctive message to the peer comparison report. The effectiveness of other types of social nudges has been studied in the literature. Asensio and Delmas (2015) study the effect of health and environmental messaging on energy conservation. They find that information about the health and environmental effects of energy consumption led to a greater reduction in electricity use compared to monetary incentives and control. The effect was especially large among families with children, who saw a 19% reduction in electricity consumption relative to control.

The previously discussed evaluations of the effect of behavioral interventions on energy use have been done in the context of households that pay for electricity depending on their consumption level (ratepayers). One of the few studies of non-ratepayers that also employ RCT is a field experiment by Delmas and Lessem (2014) whose study participants are students living in campus dorms. Delmas and Lessem (2014) study the effect of private and public information on electricity consumption. They find that private information in the form of real time appliance-level feedback was ineffective in reducing electricity consumption. However, private information coupled with public information showing residents' conservation rating induced a 20% reduction in electricity use.

The main difference between our study and prior literature using RCTs to examine the impact of feedback and peer comparison on energy use is that we focus on the effect of interventions on non-ratepaying households. Except for Delmas and Lessem (2014) who use dorm room students as their study population, all of the previous studies on the effect of feedback and peer comparison are on ratepaying households. As discussed earlier, non-ratepayers are important to consider because they constitute a non-trivial portion of electricity consumers and the potential for energy savings in this group is large because they typically consume more than their ratepaying counterparts.

This paper is also related to the broader literature investigating the effect of information and social nudges on other aspects of environmental conservation including towel reuse in hotels (Goldstein, Cialdini, and Griskevicius 2008), littering (Cialdini, Reno, and Kallgren 1990), water conservation (Ferraro and Miranda 2013), and recycling (Schultz 1999).

2 Theory

We use the framework developed by Allcott and Kessler (2015) to model the effect of feedback and social nudges on energy choices, and adapt the model for our case where households are not ratepayers. As in Allcott and Kessler (2015) we allow for a numeraire good (x), and focus on energy usage (e). Energy usage generates consumption utility $f(e;\alpha)$ where α is a taste parameter that represents preferences for indoor temperature, lighting, and other factors that effect energy use. The information a household has about electricity usage is the critical treatment variable of our RCT. As in Allcott and Kessler (2015) we posit the existence of perceived utility from energy consumption ($\hat{f}(e;\alpha,\gamma)$), $\hat{f}' > 0, \hat{f}'' < 0, \hat{f}'(0) = \infty$. That is, although information does not effect the utility households derive from energy consumption, it does effect their perceived utility. The perceived utility that households derive from energy consumption is contingent on their level of knowledge γ that represents what the consumers know about the level and cost of energy consumption.

Utility also depends on moral utility which is the utility consumers derive from being "good citizens." Allcott and Kessler (2015) model moral utility as $M = m - \mu e$, where m is a fixed level of moral utility (unrelated to energy use) and μ is the moral price of energy usage (Levitt and List (2007)). Energy may generate positive moral disutility if consumers are aware of, and care about externalities related to energy use such as greenhouse gas emissions and air pollution. Unlike Allcott and Kessler (2015), we assume that μ also depends on γ, $\mu(\gamma)$, i.e. acquiring knowledge about the level and unit cost (price) of energy may affect the disutility from each additional unit of energy use. Our second treatment investigates the effects of peer comparison. As such, we further modify the definition of moral utility to include the term $\eta(e-s)$, where s is average usage of peers, to denote disutility from consumption above or below the average consumption level of peers.[1] This is consistent with Schultz et al.'s (2007) boomerang effect, models of conformity (Luzzati, 1999), as well as inequality aversion as presented in Fehr and Schmidt (1999). As in Allcott and Kessler (2015) we allow for a budget constraint where the consumer's income must be at least as large as their expenditure on the numeriare good and energy. We ues p_e for the price of energy, but note that for our households, who are not rate-payers, it is zero.

The consumer maximization problem is given by

$$\max_{x,e} U = x + \hat{f}(e;\alpha,\gamma) + m - \mu(\gamma)e - \eta(e-s) \quad \text{s.t.} \quad y \geq x + ep_e \tag{1}$$

and the first order condition (FOC) is given by

$$\hat{f}'(e;\alpha,\gamma) = \mu(\gamma) + \eta + p_e. \tag{2}$$

which indicates that consumers will use energy up to the point where their perceived marginal utility from energy consumption equals the marginal cost of using energy.

2.1 Effect of treatments on energy use

In our experiment, the feedback treatment improves information our households have regarding their energy usage. More specifically, households are told both how much energy they used and the cost of this usage, including the price of each unit of energy (see Figure A.1). We denote the information available to those in the treatment groups as $\hat{\gamma}$. Under the feedback treatment, the FOC and optimal energy use is given by: $\hat{f}'(e;\alpha,\hat{\gamma}) = \mu(\hat{\gamma})$ and $e^*(\alpha,\hat{\gamma},\mu)$, respectively.[2] Our model predicts that if knowledge from the feedback treatment increases

[1] Velez, Stranlund, and Murphy (2009) model this as a quadratic function so that allows the marginal disutility to increase linearly in the size of the deviation.

[2] We assume that absent any information about peer usage, $\eta = 0$ and does not affect the level of energy use in the feedback treatment.

marginal disutility from energy use, then we would expect energy use to decrease (i.e. $\mu(\hat{\gamma}) > \mu(\gamma)$ then $e^*(\alpha, \hat{\gamma}, \mu) < e^*(\alpha, \gamma, \mu)$ and if $\mu(\hat{\gamma}) < \mu(\gamma)$ then $e^*(\alpha, \hat{\gamma}, \mu) > e^*(\alpha, \gamma, \mu)$). The effect of feedback on marginal disutility may have to do with the difference between expected and actual price of energy. We would expect households to reduce usage if the actual price is greater than the expected price, and vice versa. Information about the level of energy use can also increase marginal disutility if this causes the negative effects of energy consumption such as pollution and greenhouse gas emissions to become more salient to households.

The social nudge treatment provides subjects with information regarding their consumption relative to peers. The FOC and optimal energy use is given by: $\hat{f}'(e; \alpha, \hat{\gamma}) = \mu(\hat{\gamma}) + \eta$ and $e^*(\alpha, \hat{\gamma}, \mu, \eta)$, respectively. Assuming that households have a preference for conformity in energy usage, households who are given information that they are above-average consumers of energy will decrease energy use while households who find out that they are below-average consumers of energy will increase usage. That is, if $\eta > 0$ and $e > s$ then $e^*(\alpha, \hat{\gamma}, \mu, \eta) < e^*(\alpha, \gamma, \mu)$. If $\eta > 0$ and $e < s$ then $e^*(\alpha, \hat{\gamma}, \mu, \eta) > e^*(\alpha, \gamma, \mu)$. It is also possible that $\eta < 0$, i.e. households gain utility from deviating from average energy use. In this case above-average consumers will further increase usage and below-average consumers will further decrease usage.

3 Experimental Design

The setting of the field experiment is a family housing complex for students, faculty, and staff of a large public university in the Northeast. The most important characteristic of the housing complex with regards to our experiment is that the cost of energy is included in the rent. Heating and hot water are electric so total electricity consumption can be equated with total energy consumption.

The housing complex is composed of 120 one-bedroom units and 120 two-bedroom units.

One-bedroom apartments are grouped into housing blocks of six apartment units while two-bedroom units are grouped into housing block of four apartment units.[3] To maintain homogeneity in housing characteristics, only households in one-bedroom units were eligible to participate in the study. The apartment complex is metered and billed as one unit. To obtain data on energy consumption of individual households, we installed eGauge electricity meters on all one-bedroom units. We observe hourly electricity consumption for all households in our sample.

Out of 120 potential participants, 64 households agreed to participate in the study.[4] These households were randomly divided into a control group and two treatment groups. The experiment was conducted in several phases: In the pre-treatment phase, baseline electricity consumption for all groups was collected for twelve weeks. Information collected during the pre-treatment period enables analysis on key characteristics of the sample such as block differences and attributes of vacant housing, among others. During the first phase of the experiment, residents in the two treatment groups received feedback on their electricity consumption through weekly Home Electricity Reports [HERs] that were delivered to each residents' mailbox. These HERs conveyed the type of information one would expect to find in an electricity bill, such as information on total consumption and pricing (see Appendix Figure A.1). This phase lasted for a total of four weeks. During the second phase of the experiment the effects of a social nudge on electricity consumption habits is evaluated. The social nudge tells the consumer whether he or she is an above-average or below-average consumer of electricity (for example: "This week you consumed 21 percent less electricity than your neighbors"). In Phase 2 residents in both treatment groups continued to receive the information they received in Phase 1, the only difference being that treatment group 2 was provided with additional information about their energy-consumption in relation to their neighbors (see Appendix Figure A.2). This phase of the experiment lasted for five

[3] One-bedroom apartments are 371 square feet in area; two-bedroom apartments are 505 square feet in area. Rent is between $760-$880 per month depending on apartment size and the resident's affiliation with the university.

[4] Participants were required to sign a consent form to participate in the study.

weeks.

The organization of the treatments and experimental phases are outlined in Table 1.

Table 1: Experimental design

	Pre-Treatment Period 11/11/14-02/11/15 (approx. 13 weeks)	**Phase 1 02/12/15-03/11/15 (4 weeks)**	**Phase 2 03/12/15-04/15/15 (5 weeks)**
Control Group (21 Households)	No Intervention	No Intervention	No Intervention
Treat Group 1 (21 Households)	No Intervention	Feedback on Electricity Use	Feedback on Electricity Use
Treat Group 2 (22 Households)	No Intervention	Feedback on Electricity Use	Feedback on Electricity Use & Social Nudge

4 Data

In total 225,871 observations of hourly electricity consumption were collected from the 64 apartment units participating in the study, from November 11, 2014 to March 15, 2015. Two units with total electricity consumption that is one to two standard deviations above the mean hourly electricity consumption were dropped from the sample bringing the total number of households to 62. Table 2 presents aggregate data on electricity consumption while Table 3 groups observations according to experimental phase and experimental group.

Table 2: Hourly/Daily/Weekly electricity consumption

	n	**Mean**	**SD**	**Min**	**Max**
kWh/hour	218387	2.277	1.168	0.0003	10.575
kWh/day	9104	54.627	17.097	0.262	118.028
kWh/week	1335	370.878	118.362	30.934	694.718

Number of observations vary by household due to different days of meter installation in the pretreatment period.

Since households in the sample were randomly assigned to treatment and control groups, we expect trends in their mean electricity consumption in the pre-treatment period to be similar. Figure 1 plots average daily electricity consumption according to each experimental group. For the most part we see that the three groups follow roughly the same pattern over time. Weekly seasonality is visible in the data, as is the the decrease in electricity

Table 3: Hourly electricity consumption (kWh/hour) by experimental group and period

	HH		Pre-Treatment 11/11/14-02/11/15 (13 weeks)	Phase 1 02/12/15-03/11/15 (4 weeks)	Phase 2 03/12/15-04/15/15 (5 weeks)	Total Obs 11/11/2014-04/15/15 (approx 18 weeks)
Control	20	Mean	2.387	2.739	1.908	2.336
		(SD)	(1.211)	(1.200)	(1.161)	(1.228)
		n	*40760*	*12748*	*16800*	*70308*
Treat 1	20	Mean	2.266	2.594	1.898	2.239
		(SD)	(1.110)	(1.122)	(1.163)	(1.148)
		n	*39682*	*13084*	*16800*	*69566*
Treat 2	22	Mean	2.255	2.711	1.915	2.259
		(SD)	(1.087)	(1.134)	(1.091)	(1.126)
		n	*45607*	*14426*	*18480*	*78513*
ALL	62	Mean	2.301	2.682	1.907	2.277
		(SD)	(1.137)	(1.153)	(1.137)	(1.168)
		n	*126049*	*40258*	*52080*	*218387*

HH refers to the number of households assigned to each group at the start of the experiment. Changes in vacancy status were taken into consideration and two outliers were removed.

consumption that occurred over Winter Break (December 14, 2014 through January 19, 2015) and Spring Break (March 14, 2015 through March 22, 2015). It is clear that the trend of the data is determined in large part by temperature changes. Figure 2, which tracks average daily consumption and average daily temperature over time, shows that electricity consumption is at its highest during the cold winter months and then drops as temperature rises.

5 Results and Discussion

We now proceed to examine treatment effects. The model we estimate with a random effects estimator is the following: [5]

$$lnkWh_{it} = \gamma_1 Treat1_i + \gamma_2 Treat2_i + \gamma_3 Phase1_t + \gamma_4 Phase2_t + \beta_1 Fdbk_{it} + \beta_2 Sn_{it} + \boldsymbol{\zeta X} + \epsilon_{it},$$

$$\epsilon_{it} = u_i + e_{it},$$

[5]We also estimated the model using a fixed-effects estimator. The coefficients are close to identical. The Hausman test indicates that the random-effects model is efficient relative to the fixed-effects model with a chi-square statistic of 0.68 and p-value of 1.

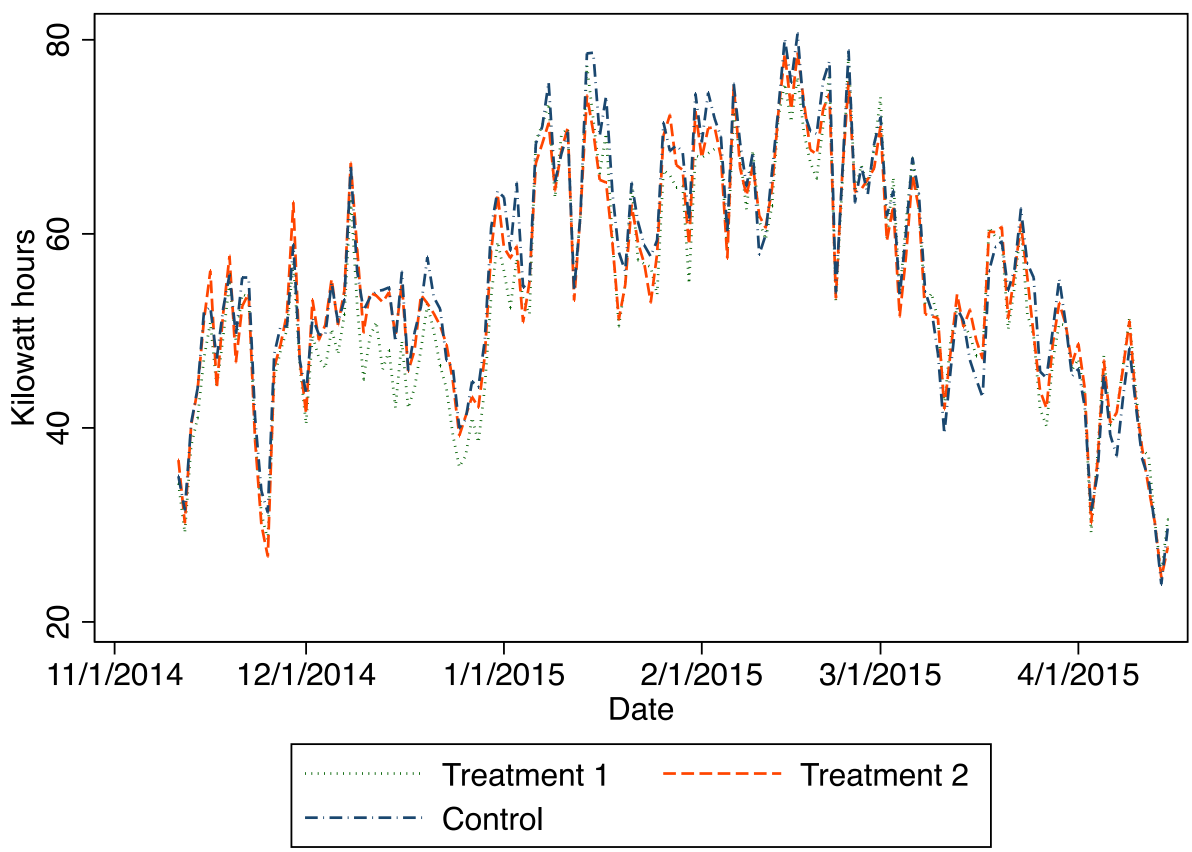

Figure 1: Average Daily Electricity Consumption, by Experimental Group

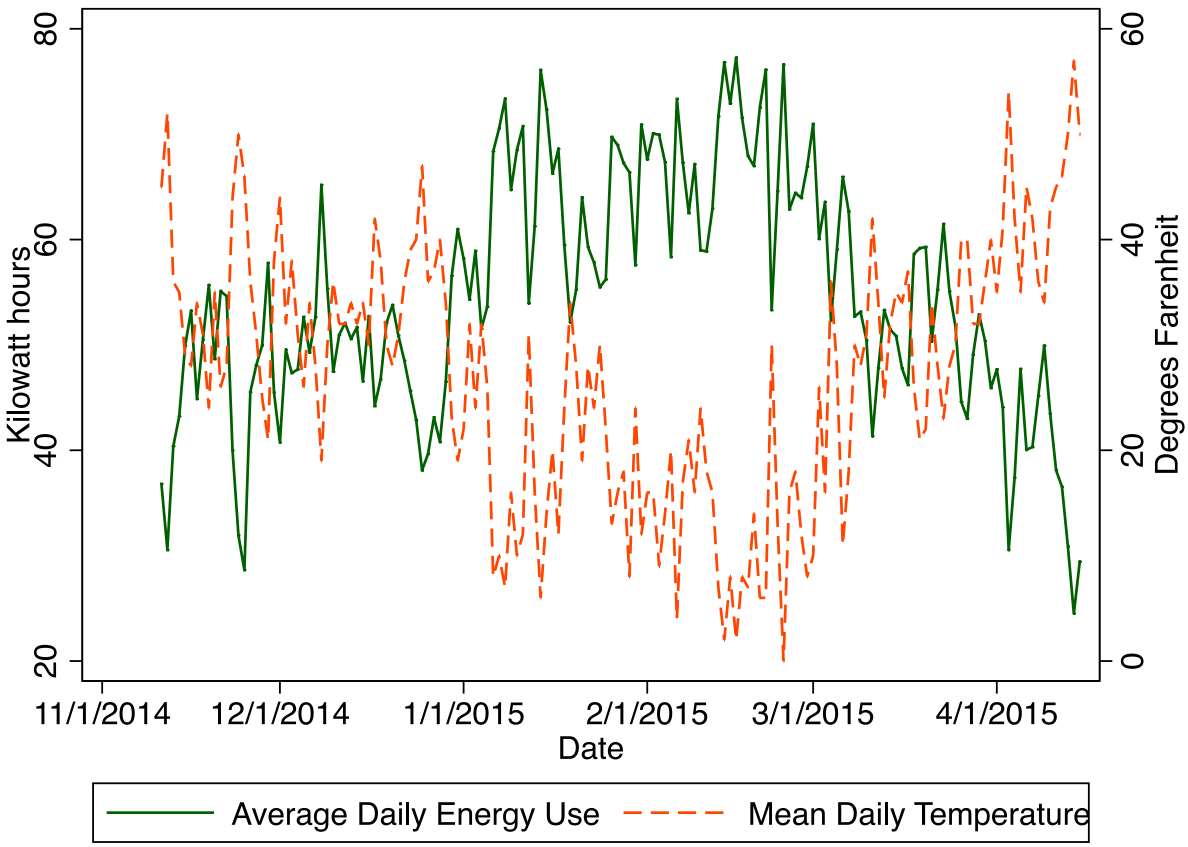

Figure 2: Average Daily Electricity Consumption and Temperature

where $lnkWh_{it}$ is the log of hourly electricity consumption, $Treat1_i$ is a dummy variable equal to one if household i is assigned to treatment group 1, $Treat2_i$ is a dummy variable equal to one if household i is assigned to treatment group 2, $Phase1_t$ indicates the time period when the feedback treatment is given to treatment groups 1 and 2 and $Phase2_t$ indicates the time period when the social nudge treatment is given to treatment group 2 while treatment group 1 continues to receive the feedback treatment. The vector $\boldsymbol{X}$ contains control variables such as temperature, rain, time-of-day, day-of-week, snow days and holidays. Details on control variables are given in Appendix Table A.1. Regressing control variables on the dependent variable indicates that the sign of parameter estimates meet our expectations: electricity use is higher at end-units, decreases with temperature, increases during evening hours, and increases on snow days. The variable $Fdbk_{it}$ is a dummy variable which indicates whether or not the household received feedback. Notice (Table 1) that all of the household in both treatments 1 and 2 receive feedback during phases 1 and 2. The variable Sn_{it} indicates whether a household receives the peer-comparison (i.e. is in treatment group 2 during phase 2 of the experiment period).

The parameters of primary interest are β_1 and β_2 which give the average treatment effects of feedback and the social nudge respectively. Table 4 presents estimates for average treatment effects. In all cases we present the results from random effects regressions both with and without controls, $\boldsymbol{X}$ and with conventional and cluster-robust standard errors. The coefficients for β_1 and β_2 in the model with full controls indicate that on average feedback increases energy consumption by 4.5% while the social nudge increases energy consumption by 6.2%. Based on our theoretical model, these results suggest that on average feedback decreases marginal disutility (moral cost) from energy use. If households' expected price of energy is greater than the actual price, the lower cost may signal lower negative externalities from energy use, leading to decreased marginal disutility and increased consumption. Other studies among ratepayers find a negative relationship between real-time feedback and energy use (Houde et al. 2013; Jessoe and Rapson 2014), while Delmas and Lessem (2014) find a negative but insignificant effect of private real time feedback on the energy consumption of dorm-room students. As previously noted, there is no a priori reason to suggest that ratepayers will respond differently to feedback when compared to non ratepayers.

With regards to the social nudge, if households have a preference for consumption at or near the average group consumption, we would expect below average users to increase consumption and above average users to decrease consumption. The positive effect of the social nudge treatment suggests that the increase in consumption by below average users dominated the effect of the treatment. The effect of above or below average user status on the effect of the social nudge treatment is further explored in Section 5.2.

Table 4: Average treatment effect

Dependent variable: lnkWh				
	(1)	(2)	(3)	(4)
Treatment 1	-0.036	-0.036	-0.113	-0.113
	(0.069)	(0.069)	(0.087)	(0.071)
Treatment 2	-0.054	-0.054	-0.108	-0.108
	(0.068)	(0.069)	(0.089)	(0.079)
Phase 1	0.164***	0.164***	-0.041***	-0.041
	(0.005)	(0.036)	(0.011)	(0.037)
Phase 2	-0.317***	-0.317***	-0.108***	-0.108*
	(0.005)	(0.052)	(0.016)	(0.056)
Feedback	0.040***	0.040	0.045***	0.045
	(0.006)	(0.050)	(0.006)	(0.049)
Social Nudge	0.066***	0.066	0.062***	0.062
	(0.007)	(0.056)	(0.006)	(0.056)
Constant	0.730***	0.730***	0.998***	0.998***
	(0.049)	(0.049)	(0.131)	(0.136)
Controls	No	No	Yes	Yes
Cluster-robust S.E.	No	Yes	No	Yes
N	218387	218387	218387	218387
R^2	0.0523	0.0523	0.2267	0.2267

Standard errors (S.E.) clusted by household in parentheses.

* $p < .1$, ** $p < .05$, *** $p < 0.01$

5.1 High and low users

To further examine the behavioral response driving our results, we classify participants as high users and low users. Households are considered high users if their electricity consumption is above average in the pretreatment period. Households are considered low users if their electricity consumption is below average in the pre-experimental period. Table 5 shows the regression results when we estimate equation 1 separately for high and low users. [6]

Table 5: Treatment effect by high and low user

Dependent variable: lnkWh	High Users		Low Users	
	(1)	(2)	(3)	(4)
Treatment 1	-0.027	-0.027	-0.103	-0.103
	(0.123)	(0.073)	(0.136)	(0.067)
Treatment 2	-0.030	-0.030	-0.069	-0.069
	(0.113)	(0.090)	(0.134)	(0.070)
Phase 1	-0.038***	-0.038	-0.038**	-0.038
	(0.014)	(0.051)	(0.017)	(0.048)
Phase 2	-0.112***	-0.112	-0.097***	-0.097
	(0.023)	(0.077)	(0.023)	(0.061)
Feedback	0.128***	0.128**	-0.047***	-0.047
	(0.008)	(0.058)	(0.008)	(0.063)
Social Nudge	0.074***	0.074	0.052***	0.052
	(0.010)	(0.059)	(0.008)	(0.085)
Constant	1.130***	1.130***	1.009***	1.009***
	(0.170)	(0.099)	(0.174)	(0.158)
Controls	Yes	Yes	Yes	Yes
Cluster-robust S.E.	No	Yes	No	Yes
N	95302	95302	123085	123085
R^2	0.2324	0.2324	0.2557	0.2557

Standard errors (S.E.) in parentheses.

* $p < .1$, ** $p < .05$, *** $p < 0.01$

[6] Results of regressions using interaction terms are consistent with those from Table 5 (see Appendix Table A.2). Separate regressions (Table 5) allow all coefficient estimates to differ between high users and low users, whereas using interaction terms (Appendix Table 5) restrict coefficients other than those of the interaction terms to be the same.

Among high users, feedback increases electricity use by 12.8% while the social nudge increases electricity consumption by 7.4% relative to control. Among low users, feedback decreases electricity use by 4.7% while the social nudge increases electricity use by 5.2%. These results suggest that the effect of feedback on marginal disutility of energy use is different for high users and low users. For low users, feedback appears to have increased marginal disutility, leading to lower energy use. The expected price of energy could be lower than the actual cost for low users. Furthermore, a significant portion of low users may be those who are environmentally conscious. Thus, increased awareness of energy usage may have made the negative externalities associated with energy consumption more salient, leading to lower energy use.

5.2 Positive and negative messaging

Over the course of the experiment, 110 HERs with the social nudge were distributed. Forty-eight of these HERs reported that the household was a below-average consumer of electricity; sixty-two HERs reported that the household was an above-average consumer of electricity. [7] While there was no explicit value judgment present in the HER with the social nudge, it may be the case that receiving an HER with a positive message (that the household consumed less than their neighbors) had a different effect than receiving an HER with a negative message (that the household consumed more than their neighbors). This is consistent with a preference for conformity and the boomerang effect (Luzzati (1999), and Schultz et al. (2007)).

To explore the effect of receiving a positive or negative message, we replace the variable Sn with Sn_{below} and Sn_{above} where Sn_{below} is a dummy variable equal to one if the household received an HER that week indicating that they were a below-average consumer of electricity in the previous period and Sn_{above} is a dummy variable equal to one if the household received an HER that week indicating that they were an above-average consumer in the previous

[7] None of the households were exactly at the average throughout the experiment period.

period. While the variables are mutually exclusive (the household could not receive a one for both Sn_{good} and Sn_{bad}), a households' below-average or above-average designation can change from week to week. Table 6 shows regression results. On average, regardless of the message received, electricity consumption increases, which is inconsistent with both preferences for conformity and the boomerang effect.

To further examine the effect of positive and negative messaging, we run separate regressions for high and low users.[8] Table 7 shows that a message communicating that the household is a below-average user of electricity increases electricity use by 8.2% for high users and 7.5% for low users. A message communicating that the household is an above-average user also increased electricity use by 7.3% for high users but decreased electricity consumption by 2.5% for low users. Low users appear to exhibit behavior consistent with preferences for conformity. On the other hand, the behavior of high users do not conform with our expectations. Although high users with below-average status increased usage in the following period, those with above-average status also increased usage.

[8]Results of regressions using interactions are presented in Appendix Table A.3.

Table 6: Treatment effect by type of message

Dependent variable: lnkWh	(1)	(2)
Treatment 1	-0.115	-0.115
	(0.077)	(0.072)
Treatment 2	-0.110	-0.110
	(0.078)	(0.080)
Phase 1	-0.043***	-0.043
	(0.011)	(0.037)
Phase 2	-0.109***	-0.109*
	(0.016)	(0.057)
Feedback	0.045***	0.045
	(0.006)	(0.049)
SN-Below Average	0.087***	0.087
	(0.008)	(0.066)
SN-Above Average	0.037***	0.037
	(0.008)	(0.054)
Constant	1.002***	1.002***
	(0.116)	(0.137)
Controls	Yes	Yes
Cluster-robust S.E.	No	Yes
N	218387	218387
R^2	0.2258	0.2258

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < 0.01$

Table 7: Treatment effect by user type and message content

Dependent variable: lnkWh				
	High Users		Low Users	
	(1)	(2)	(3)	(4)
Treatment 1	-0.028	-0.028	-0.104	-0.104
	(0.123)	(0.073)	(0.141)	(0.068)
Treatment 2	-0.031	-0.031	-0.070	-0.070
	(0.113)	(0.090)	(0.139)	(0.071)
Phase 1	-0.039***	-0.039	-0.039**	-0.039
	(0.015)	(0.053)	(0.017)	(0.048)
Phase 2	-0.113***	-0.113	-0.098***	-0.098
	(0.023)	(0.077)	(0.023)	(0.061)
Feedback	0.129***	0.129**	-0.047***	-0.047
	(0.008)	(0.058)	(0.008)	(0.063)
SN - Below Average	0.082***	0.082*	0.075***	0.075
	(0.030)	(0.049)	(0.009)	(0.079)
SN - Above Average	0.073***	0.073	-0.025*	-0.025
	(0.010)	(0.060)	(0.013)	(0.129)
Constant	1.131***	1.131***	1.018***	1.018***
	(0.170)	(0.100)	(0.181)	(0.159)
Controls	Yes	Yes	Yes	Yes
Cluster-robust S.E.	No	Yes	No	Yes
N	95302	95302	123085	123085
R^2	0.2323	0.2323	0.2557	0.2557

Standard errors (S.E.) in parentheses

* $p < .1$, ** $p < .05$, *** $p < 0.01$

6 Conclusion

We provide evidence based on a randomized controlled trial of the effect of feedback and social nudges on energy use among non-rate paying residents of a family housing complex at a major Northeastern public university over the winter heating months. Non-ratepayers are important in the sense that they represent a significant portion of renters and they have the potential for greater reductions in energy use as they tend to use more energy than ratepayers (Munley et al. 2014; Maruejols and Young 2011; Levinson and Niemann 2004).

Overall our results are quite concerning–feedback on energy usage and a social nudge in the form of peer comparison both result in non-ratepayers increasing their energy usage. That said, when we examine the data more closely, we find that individual households differ in their responses to feedback and peer comparison depending on their usage in our pre-treatment period. Those who used less energy than average over the pre-treatment period tend to reduce their usage when they are provided feedback, and when they are told that they are using more than average. They do however increase their usage when they are told that they are using less than average. This is consistent with a model of moral utility where information about the household's level of energy use increases their marginal disutility of energy use perhaps by making negative externalities more salient. The behavior of our low usage households is also consistent with preferences for conformity in energy use which suggests that households who use less than average will increase their usage while those who use more than average will reduce their usage (Luzzati (1999), and Schultz et al. (2007)). The behavior of households who use more energy than average in the pre-treatment period suggests that information about their usage does not increase their moral disutility as feedback increases their consumption. Moreover, they increase consumption regardless of their usage status relative to peers. This suggests that to the extent that households are not sensitive to externality concerns or conformity in energy use, providing them with information about their usage and their usage relative to others may have perverse effects.

We do not have information on environmental preferences of households in our sample.

Low users likely represent a type of household that is more sensitive to environmental concerns and negative externalities associated with energy use. For these types of households, our results suggest that the negative effect of feedback may be enhanced by providing information about the health and environmental effects of energy use, similar to Asensio and Delmas (2015). On the other hand, incentives aimed at landlords to provide weatherproofing or to install more efficient lighting and appliances may be more effective for high users, and the utility-inclusive rental market in general.

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Appendices

Appendix A

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NVA Unit

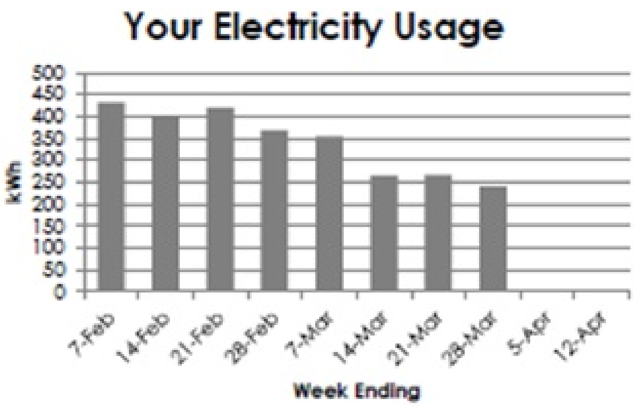
Home Electricity Report°

03/22/15 – 03/28/15

°This is not an electricity bill.

Your Electricity Usage:

Period: from	to	Total Usage(kWh)	Price of Electricity($/kWh)	Total Cost($)
03/22/15	03/28/15	240.84	0.18	43.70



<u>This period:</u>

- Your average electricity consumption was **34.41 kWh** per day.
- Your average electricity cost was **$6.24** per day.

<u>Since February 1st, 2015:</u>

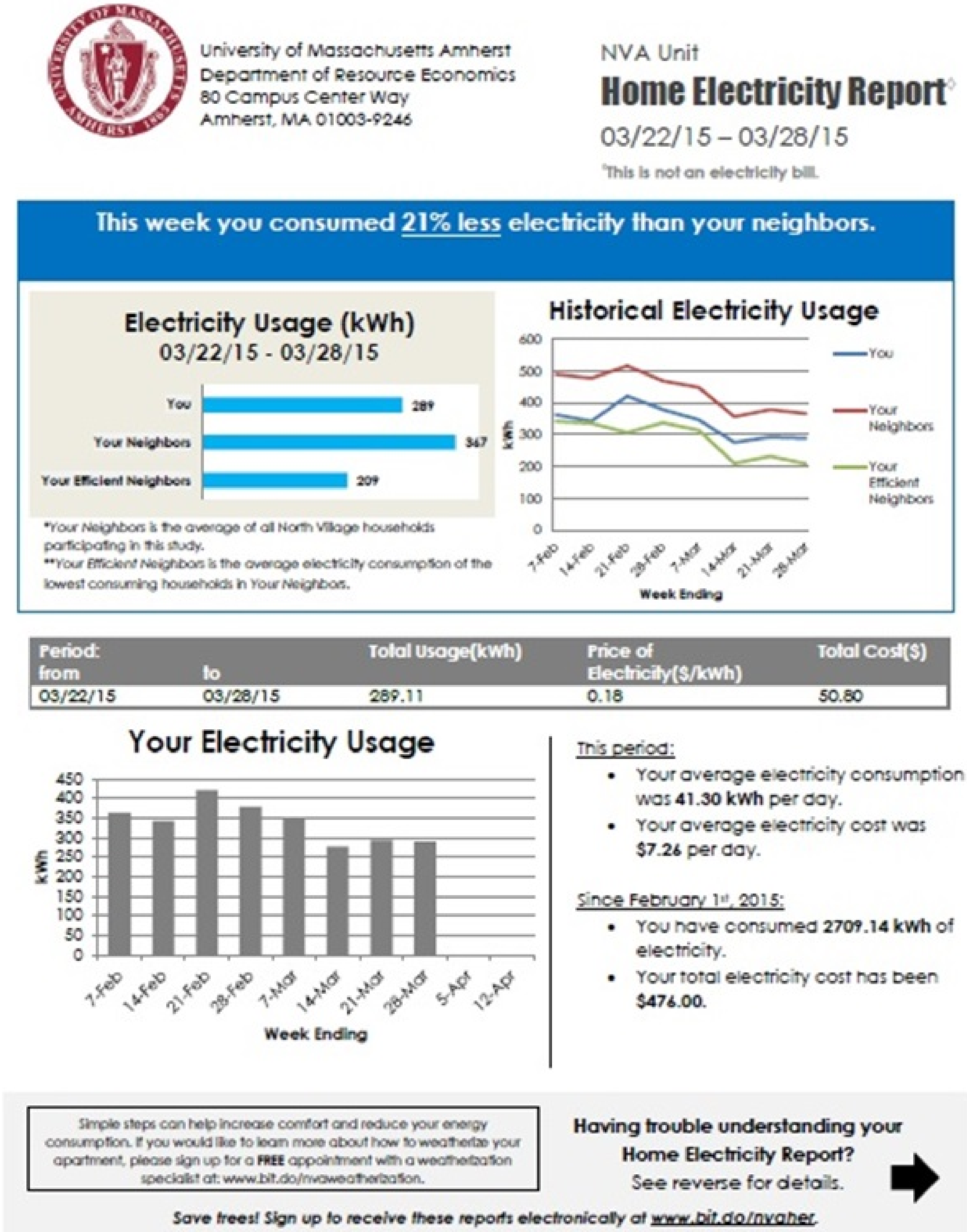
- You have consumed **2746.81 kWh** of electricity.
- Your total electricity cost has been **$485.14**.

Simple steps can help increase comfort and reduce your energy consumption. If you would like to learn more about how to weatherize your apartment, please sign up for a **FREE** appointment with a weatherization specialist at: www.bit.do/nvaweatherization.

Having trouble understanding your Home Electricity Report?
See reverse for details.

Save trees! Sign up to receive these reports electronically at <u>www.bit.do/nvaher</u>.

Figure A.1: Feedback treatment



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Amherst, MA 01003-9246

NVA Unit

Home Electricity Report

03/22/15 – 03/28/15

*This is not an electricity bill.

This week you consumed 21% less electricity than your neighbors.

*Your Neighbors is the average of all North Village households participating in this study.
**Your Efficient Neighbors is the average electricity consumption of the lowest consuming households in Your Neighbors.

Period: from	to	Total Usage(kWh)	Price of Electricity($/kWh)	Total Cost($)
03/22/15	03/28/15	289.11	0.18	50.80

This period:

- Your average electricity consumption was **41.30 kWh** per day.
- Your average electricity cost was **$7.26** per day.

Since February 1st, 2015:

- You have consumed **2709.14 kWh** of electricity.
- Your total electricity cost has been **$476.00.**

Simple steps can help increase comfort and reduce your energy consumption. If you would like to learn more about how to weatherize your apartment, please sign up for a **FREE** appointment with a weatherization specialist at: www.bit.do/nvaweatherization.

Having trouble understanding your Home Electricity Report?
See reverse for details.

Save trees! Sign up to receive these reports electronically at www.bit.do/nvaher.

Figure A.2: Feedback and Social Nudge treatment

Table A.1: Control Variables

Variable Group	Variable	Variable Name	Description
Household Attributes (HH Attr):	**Housing Block End Unit**	end_i	Equal to one if apartment is located on either end of the housing block.
Omitted: Block 1 ($Block\_1_i$)	**Block 2**	$Block\_2_i$	Equal to one if apartment is located in housing block 2.
	Block 3	$Block\_3_i$	Equal to one if apartment is located in housing block 3.
	Block 4	$Block\_4_i$	Equal to one if apartment is located in housing block 4.
	Block 5	$Block\_5_i$	Equal to one if apartment is located in housing block 5.
	Block 6	$Block\_6_i$	Equal to one if apartment is located in housing block 6.
	Block 7	$Block\_7_i$	Equal to one if apartment is located in housing block 7.
	Block 8	$Block\_8$	Equal to one if apartment is located in housing block 8.
	Block 9	$Block\_9_i$	Equal to one if apartment is located in housing block 9.
	Block 10	$Block\_10_i$	Equal to one if apartment is located in housing block 10.
	Block 11	$Block\_11_i$	Equal to one if apartment is located in housing block 11.
	Block 12	$Block\_12_i$	Equal to one if apartment is located in housing block 12.
	Block 13	$Block\_13_i$	Equal to one if apartment is located in housing block 13.
	Block 14	$Block\_14_i$	Equal to one if apartment is located in housing block 14.
	Block 15	$Block\_15_i$	Equal to one if apartment is located in housing block 15.
	Block 16	$Block\_16_i$	Equal to one if apartment is located in housing block 16.
	Block 17	$Block\_17_i$	Equal to one if apartment is located in housing block 17.
	Block 18	$Block\_18_i$	Equal to one if apartment is located in housing block 18.
	Block 19	$Block\_19_i$	Equal to one if apartment is located in housing block 19.
	Block 20	$Block\_20_i$	Equal to one if apartment is located in housing block 20.
Weather:	**Mean Temperature**	$temp_t$	The daily average temperature measured in degrees Fahrenheight
	Rain	$precip_t$	Equal to one if the precipitation for that day exceeded zero inches.
Time-of-Day (TOD):	**1:00 AM**	TOD_1_t	Equal to one if the time was 1:00 AM.
Omitted: 12:00 AM (TOD_0_t)	**2:00 AM**	TOD_2_t	Equal to one if the time was 2:00 AM.
	3:00 AM	TOD_3_t	Equal to one if the time was 3:00 AM.
	4:00 AM	TOD_4_t	Equal to one if the time was 4:00 AM.
	5:00 AM	TOD_5_t	Equal to one if the time was 5:00 AM.
	6:00 AM	TOD_6_t	Equal to one if the time was 6:00 AM.
	7:00 AM	TOD_7_t	Equal to one if the time was 7:00 AM.
	8:00 AM	TOD_8_t	Equal to one if the time was 8:00 AM.
	9:00 AM	TOD_9_t	Equal to one if the time was 9:00 AM.
	10:00 AM	TOD_10_t	Equal to one if the time was 10:00 AM.
	11:00 AM	TOD_11_t	Equal to one if the time was 11:00 AM.
	12:00 PM	TOD_12_t	Equal to one if the time was 12:00 PM.
	1:00 PM	TOD_13_t	Equal to one if the time was 1:00 PM.
	2:00 PM	TOD_14_t	Equal to one if the time was 2:00 PM.
	3:00 PM	TOD_15_t	Equal to one if the time was 3:00 PM.
	4:00 PM	TOD_16_t	Equal to one if the time was 4:00 PM.
	5:00 PM	TOD_17_t	Equal to one if the time was 5:00 PM.
	6:00 PM	TOD_18_t	Equal to one if the time was 6:00 PM.
	7:00 PM	TOD_19_t	Equal to one if the time was 7:00 PM.
	8:00 PM	TOD_20_t	Equal to one if the time was 8:00 PM.
	9:00 PM	TOD_21_t	Equal to one if the time was 9:00 PM.
	10:00 PM	TOD_22_t	Equal to one if the time was 10:00 PM.
	11:00 PM	TOD_23_t	Equal to one if the time was 11:00 PM.
Day-of-Week (DOW):	**Tuesday**	Tue_t	Equal to one if the day was Tuesday.
Omitted: Monday (Mon_t)	**Wednesday**	Wed_t	Equal to one if the day was Wednesday.
	Thursday	Thu_t	Equal to one if the day was Thursday.
	Friday	Fri_t	Equal to one if the day was Friday.
	Saturday	Sat_t	Equal to one if the day was Saturday.
	Sunday	Sun_t	Equal to one if the day was Sunday.
Holiday/Snow Days:	**Thanksgiving**	$Thanks_t$	Equal to one if classes were canceled for Thanksgiving Break.
	Winter Break	$Winter_t$	Equal to one if classes were canceled for Winter Break.
	Monday Holiday	$HolidayM_t$	Equal to one if classes were canceled for Veterans' Day or Presidents' Day.
	Spring Break	$Spring_t$	Equal to one if classes were canceled for Spring Break.
	Snow Days	$Snow_t$	Equal to one if classes were canceled due to snow.

Table A.2: Treatment effect by high and low user: interacted regression

	lnkW	lnkW
Treatment 1	-0.110	-0.110
	(0.094)	(0.071)
Treatment 2	-0.078	-0.078
	(0.091)	(0.076)
Phase 1	0.063***	0.063
	(0.012)	(0.054)
Phase 2	0.009	0.009
	(0.017)	(0.063)
Feedback	-0.048***	-0.048
	(0.008)	(0.062)
Social Nudge	0.052***	0.052
	(0.008)	(0.085)
High User	0.224**	0.224***
	(0.093)	(0.065)
High User*	0.150	0.150
Treatment 1	(0.143)	(0.095)
High User*	0.087	0.087
Treatment 2	(0.124)	(0.093)
High User*	-0.175***	-0.175***
Phase 1	(0.010)	(0.061)
High User*	-0.199***	-0.199**
Phase 2	(0.009)	(0.088)
High User*	0.178***	0.178**
Feedback	(0.011)	(0.085)
High User*	0.198***	0.198*
Social Nudge	(0.014)	(0.119)
Constant	0.918***	0.918***
	(0.120)	(0.125)
Controls	Yes	Yes
S.E. clustered by household	No	Yes
N	218387	218387

Standard errors (S.E) in parentheses

* $p < .1$, ** $p < .05$, *** $p < 0.01$

Table A.3: Treatment effect by user type and message content: interacted regression

	lnkW	lnkW
Treatment 1	-0.111	-0.111
	(0.092)	(0.071)
Treatment 2	-0.080	-0.080
	(0.089)	(0.076)
Phase 1	0.061***	0.061
	(0.012)	(0.054)
Phase 2	0.006	0.006
	(0.017)	(0.063)
Feedback	-0.047***	-0.047
	(0.008)	(0.062)
High User	0.224**	0.224***
	(0.091)	(0.066)
High User*	0.148	0.148
Treatment 1	(0.139)	(0.096)
High User*	0.084	0.084
Treatment 2	(0.121)	(0.093)
High User*	-0.199***	-0.199**
Phase 2	(0.009)	(0.088)
High User*	0.178***	0.178**
Feedback	(0.011)	(0.085)
SN-Below Average	0.074***	0.074
	(0.009)	(0.079)
High User*	0.043	0.043
SN-Below Average	(0.030)	(0.094)
SN-Above Average	-0.022*	-0.022
	(0.013)	(0.123)
High User*	0.091***	0.091
SN-Above Average	(0.016)	(0.136)
Constant	0.926***	0.926***
	(0.117)	(0.126)
Controls	Yes	Yes
S.E. clustered by household	No	Yes
N	218387	218387

Standard errors (S.E.) in parentheses

* $p < .1$, ** $p < .05$, *** $p < 0.01$