THE DYNAMICS OF BEHAVIOR CHANGE:

EVIDENCE FROM ENERGY CONSERVATION

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Abstract

Little is known about the effect of message framing on conservation behavior over time. In a randomized controlled trial with residential households, we use advanced metering and information technologies to test how different messages about household energy use impact the dynamics of conservation behavior down to the appliance level. Our results, based on 374 million panel observations of kilowatt-hour (kWh) electricity consumption for 118 households over 9 months, show that differences in behavioral responses due to message framing become more significant over time. We find that a health-based frame, in which households consider the human health effects of their marginal electricity use, induced persistent energy savings behavior of 8-10% over 100 days; whereas a more traditional cost savings frame, drove sharp attenuation of treatment effects after 2 weeks with no significant savings versus control after 7 weeks. We discuss implications for the design of effective information campaigns to engage households in conservation behavior.

Keywords: energy conservation, decision framing, repeated behavior, randomized controlled trials

JEL: C93, D03, D12, L94, Q41

1. Introduction

Information programs solve problems of imperfect information in markets—often helping individuals and institutions make better consumption or investment decisions, and overcome cognitive or behavioral biases (Thaler and Sunstein, 2008, Ratner et. al., 2008). Information framing has been used in a wide range of decision-making domains, including saving money for retirement (Benartzi and Thaler, 2007); paying for charity and performance (Gneezy and Rustichini, 2000); reducing poverty and improving access to financial institutions (Bertrand, Mullainathan, and Shafir 2006); designing health behavior programs (Rothman and Salovey, 1997; Keller and Lehman, 2008); and encouraging resource conservation (Schultz et.al., 2007). In this paper, we use information-based strategy to motivate household energy conservation. We provide experimental evidence from a randomized trial that non-price based framing interventions can be effective for conservation behavior over time.

Typical framing interventions provide study subjects with alternative representations of a decision problem, e.g. framing a quantity as a gain or loss, shifting reference points, or manipulating a choice set (Tversky and Kahneman, 1981; Kahneman and Tversky, 1979; Levin, Schneider and Gaeth, 1998; Keren, 2011). Information framing effects are defined when the manner in which stimuli are represented or "framed" to decision-makers affects its evaluation. Historically, framing research has been conducted in small-scale studies with short trials and one-shot decisions. While more recently, this research has moved from the laboratory to field experiments in market settings (Levitt and List, 2009; List and Price, 2013), we still have limited understanding of the effectiveness of information framing on behavior over long time periods (Bernedo, Ferraro, and Price, 2014). Studying the dynamics of framing interventions is important because there is a fundamental question about how long framing effects can last after initial exposure, and what happens when decision frames are repeated.

In this paper, we conduct a field experiment to analyze how framing interventions can affect residential energy consumption behavior over time. Understanding the potential mechanisms to reduce energy consumption is an essential part of addressing climate change (Davis and Gertler, 2015), since electricity generation accounts for over 40% of carbon emissions in the United States. Residential and commercial buildings collectively account for over two-thirds of total U.S. energy consumption (EIA, 2014; EPA, 2013). Energy conservation can be achieved not only with technological changes in buildings and appliances, but also with behavioral changes in consumption (Asensio and Delmas 2015; Allcott and Mullainathan, 2010; Gillingham and Palmer, 2014; Harding and Hsiaw, 2014).

In a fast growing experimental literature, scholars have demonstrated that tailored information programs have a tremendous potential for reducing household electricity use (Allcott 2011; Ayres, Raseman, and Shih, 2012; Costa and Kahn, 2013, Davis and Metcalf, 2014; Delmas and Lessem, 2014; Gilbert and Graff Zivin, 2013, Jacobsen, Kotchen and Vandenbergh, 2012). These studies report significant conservation effects using social comparisons and other normative appeals to conserve energy, which build on seminal work in psychology (Cialdini, Reno and Kallgren, 1990; Cialdini, 2003; Schultz et.al., 2007; Nolan et.al., 2008). Despite the popularity of this growing body of research, very little is currently known about the dynamics of household responses to norm-based behavioral interventions, and even less so at the appliance level. Conservation is not a one-time occurrence but requires repeated consumer effort and attention. Some responses may be immediate, others not; and currently, researchers have not been able to differentiate well between short- and long-run behavior change mechanisms in a framing intervention. A dynamic analysis of conservation behavior with real-time information strategies is lacking.

There are many reasons to expect that information framing could have differential impacts on energy consumption over time. First, household conservation behavior such as turning off unused lights, unplugging charging devices or reducing standby power, are habitual or event-based actions that might require timely information feedback to consumers about monetary or social costs. Consumers, however, receive infrequent information about the monetary costs of electricity (Gilbert and Graff Zivin, 2014; Jessoe and Rapson 2012; Ito 2014). Second, consumers are generally unaware, or unable to observe the negative externalities of their electricity consumption such as outside air pollution and related environmental health damages (Brunekreef and Holgate, 2002). These social costs of individual electricity use are also usually not reflected in prices for electricity services (National Research Council, 2010). From the above, we could expect that more salient information regarding these unobserved costs might influence judgments and decisions over time. In the present study, we offer new field evidence that framing effects—e.g. alternative representations of the external effects of household consumption decisions, either in terms of monetary or social costs—can dramatically alter energy savings behavior over time.

We conduct a field experiment using advanced energy metering technologies with real-time energy use information provided to households at the appliance level. We give households information about unobserved monetary and social costs related to their electricity consumption. The use of advanced metering and information technologies offers new benefits for behavioral research (Chen et al., 2014). First, information diffusion and feedback is relatively fast and can improve the salience of prices and quantities (Gilbert and Graff Zivin, 2014). Second, analytics data can be deployed to verify when and how households interact with information treatments or alerts. This is important because engagement analytics allow us to assess the effect of the actual treatment, that is to say when people access their energy feedback information, rather than just measuring the effect of the intent to treat, that is to say sending the email or making the information available on the dashboard.

Our results are based on 374 million high frequency panel observations of kilowatt-hour (kWh) electricity consumption for 118 households observed over 9 months. While households respond immediately to tailored messages about their electricity use, the effectiveness of repeated messages on consumption behavior varies by decision frame. We find that a health-based frame, in which consumers consider the environmental and human health effects of their marginal electricity use, induced more persistent energy savings behavior over a 100-day treatment period; as compared to a more conventional savings frame over the same period. In other words, conservation was short-lived with cost savings framing, but was more persistent with environmental and health framing. These results indicate that framing can be used as a strategy to overcome behavioral barriers, especially in settings where price-based policies may not be politically feasible or effective (Gneezy, Meier and Rey-Biel, 2011).

The rest of the paper proceeds as follows. Section 2 presents some background on possible mechanisms for behavioral changes in responses to high frequency messaging over time. Section 3 discusses the setting of the field experiment and Section 4 describes the experimental design. Section 5 presents the econometric approach. Section 6 discusses the results by framing intervention including appliance dynamics and a concluding discussion follows.

2. Background

2.1. Novelty and Repetition

Most households in the United States receive no information about their electricity usage apart from their monthly bills, which generally do not disaggregate across time periods or sources of usage. Because of this, most households know little about their energy use patterns and its effects (Attari, DeKay, Davidson, and de Bruin, 2010). As consumers receive tailored information about their electricity use in real time and by appliance through a dashboard, we posit that there is a novelty associated with the *content* of tailored information received (e.g. the new information provided) but also with the *mode* of communication in which it is received (e.g. the dashboard). We posit that the novelty effects associated with advanced metering and information technologies might facilitate consumer engagement and amplify the desire to act on alert-based information. In consumer research, high engagement or issue involvement has been linked with short-run responsiveness to framing interventions (Maheswaran and Meyers-Levy, 1990; Millar and Millar, 2000). We expect that as households receive tailored information about the effects of their electricity use with advanced technologies, novelty effects could lead to immediate conservation behavior.

The novelty effect opens the question as to what happens over time when information treatments are repeated. We could expect repetition to lead to either increasing or decreasing conservation behavior over time. On one hand, if information diffusion is gradual and behavior change occurs relatively slowly, then we could expect increasing conservation behavior over time as more households learn and adopt energy saving practices. On the other hand, from a cognitive perspective, it is unlikely that repeated instances of a single intervention would continue to have the same effect each time and produce the same level of a target behavior, as individuals tend to be desensitized to repeated exposure to a given stimuli (Rogers and Frey, 2014).

If novelty effects wear off over time, then we could expect repetition to lead to gradually decreasing conservation behavior over time, as households return to their normal consumption patterns. There are several possible reasons for this. When economic value is placed on time, inattention or outside opportunity costs may lead to a decreasing effect of treatment.

Households may simply lose motivation or gradually become inattentive to the information conveyed via the treatment. Alternatively, households might also face outside opportunity costs, and substitute other sources of behavioral savings in the household budget, which might be perceived to be less costly than monitoring electricity consumption. Recent supporting evidence for diminishing returns to normative information strategies have been shown in experimental research by Allcott and Rogers (2014), Gilbert and Graff-Zivin (2014) and Dolan and Metcalfe (2013). Accordingly, as tailored information received by households is repeated, conservation behavior might gradually decrease.

The long-run outcomes of information strategies will also depend critically on the presentation of the decision problem. In other words, the manner in which the household conservation decision is framed or described to consumers will determine observed conservation levels over time. In this study, we are interested in comparing the immediate and then long run effects of a health frame versus a savings frame.

2.2. Health Frame

We experiment with a health framing approach, which is designed to frame energy conservation as altruistic and raise the moral cost of energy use. We further explore the interest, initiated in Asensio and Delmas (2015) that framing conservation decisions on health externalities—that is, informing consumers about the environmental health damages associated with their individual electricity use, can motivate conservation behavior. A health framing approach to energy conservation focuses household consumption on the social costs of energy use through air pollution. Reframing conservation as a health concern can be motivational for many affected consumers, particularly for at-risk populations such as urban communities, families with children or those with asthmatics in the home (Asensio and Delmas, 2015; Neidell, 2004).

Regarding the long run effectiveness of health framing, we know from a related body of evidence in psychology that individuals tend to resist becoming desensitized to a repeated stimulus if the stimulus is sufficiently intense (Rogers and Frey, 2014). This might be the case when learning that one's excess electricity consumption may be causing direct harm on others (Asensio and Delmas 2015). As such, we posit that health framing might lead to greater information retention, which could translate into more persistent behavioral effects over time. This is consistent with behavioral economic models of decision-making and morally motivated consumption behavior in markets (Fehr and Schmidt, 2006; Uhlmann, Pizarro, Tannenbaum and Ditto, 2009) as a non-price mechanism.

2.3. Cost Savings Frame

By contrast, the cost savings approach to conservation follows standard reasoning about private benefits from household energy savings. Standard economic reasoning predicts that tailored information about private benefits should motivate rational curtailment behavior towards energy efficiency. However, we have several reasons to believe that cost savings information may not have lasting effects. First, consumers may gradually become inattentive to information about electricity costs (Allcott and Greenstone 2012) especially as the savings potential is typically small. Second, cost savings information in market conditions may crowd out intrinsic motivations (Frey and Oberholzer-Gee, 1997; Ariely, Bracha, Meier, 2009; Gneezy, Meier, and Rey-Biel, 2011) particularly in situations where intrinsic motivations could be important considerations to engage in conservation behavior. Further, a recent meta-analysis of energy conservation field studies (Delmas, Fischlein and Asensio, 2013), shows that monetary incentives and information do not always lead consumers to save more and instead often lead to significant energy increases over time.

Thus, as households receive repeated information feedback about their household electricity use, we test empirically whether a health frame will produce more lasting conservation effects versus a savings frame.

3. The Field Experiment

A randomized controlled trial was conducted with residential consumers to test our hypotheses. We provided real-time, appliance-level smart metering energy feedback to 118 residential households in a large residential community in Los Angeles over 9 months, which includes a 6-month baseline period and a 100-day treatment period (14 consecutive weeks). We tested the effectiveness of two different messaging approaches based either on the environmental and health impacts of electricity consumption, or on the monetary savings of reducing electricity consumption.

3.1 Experiment location and recruitment

Our field experimental site, University Village, is a multiple building, family apartment/condo-style housing complex in Los Angeles with 1,103 units. All residents pay their own electricity bills. The community spans two census block groups serviced by the Los Angeles Department of Water and Power (LADWP).

On a per capita electricity use basis, University Village residents are representative of middle-income California multi-family renter populations and are only slightly below the national average, due to the milder climate in the State of California. Our 118 participating households consist of single, married and domestically partnered graduate college students with and without children in the home. Many residents are younger and more educated than the U.S. population (e.g. bachelor’s degree or higher), but are representative of users of information devices who fall in our target population of urban dwellers with and without children in the home; and who increasingly rely on electronic communications in their daily lives. Thus, our experimental results are indicative of how future residential electricity consumers can respond to high frequency information, especially as electric utilities begin utilizing smart metering data with information and communication technologies (Edison, 2014). We note that our experimental results represent outcomes of real-life consumptions decisions in their natural settings.

All units in the community are furnished with a common set of major appliances—a refrigerator, dishwasher, gas stove and microwave of similar make and model, which allows for standardization in the housing capital stock. This is an important feature of our field site and experimental design. With standardization in major appliances, we achieve more precise estimates of behavioral savings than is otherwise possible without standardization in appliances. For an engineering overview of the real-time appliance level energy metering technology developed for this experiment, see Chen et al., (2015). We note that before the availability of advanced smart metering technology, there was also no readily available way to observe electricity consumption in real time, or perhaps at a high enough sampling frequency to identify novelty effects with non-lasting actions, making it difficult to draw conclusions about the speed and magnitude of demand changes by individual consumers (Reiss and White, 2008).

Households were recruited to participate in the study. No direct environmental messaging was used in order to prevent biases in recruitment selection. The recruitment process occurred within the context of several community events and information campaigns during the summer months prior to the start of the academic year. To meet Institutional Review Board (IRB) ethics requirements regarding research with human subjects, participation was strictly voluntary and no personally identifiable information was collected or shared. We conducted an enrollment survey to capture basic apartment demographics and occupancy characteristics for the community at-large, including households who opted in and those who opted out of the study. We recruited many more willing participants than there were active equipment allotments. Among the 1,103 households at University Village, 226 households volunteered to participate and another 88 households in our entry survey chose not to participate. This equals a participation rate of 20%. We randomly selected 118 participating households from these 226 volunteers. The participating households in our experiment represent 10.7% of the population at University Village. No households entered into or dropped from the study for the entire duration of the experiment. No monetary rewards or financial incentives were offered for participation.

We tested for potential differences in baseline characteristics between the total population of households at our field site and our sample of volunteer households. We compared the monthly electricity meter readings of the entire population of University Village with those of our participants, along with other observable characteristics, such as the size of the apartment, the number of occupants in each unit, the apartment floor and the location of the apartment in the complex. As shown in Table 1, there are no significant differences between participating and non-participating households. This analysis is based on electricity meter readings for 12 months prior to the start of the experiment.

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Insert Table 1 about Here

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4. Experimental design

Each participating household was randomly assigned to either one of the two treatment groups or to the control group. One group of households received energy use feedback with cost savings information. Another group of households received energy use feedback with tailored information about the environmental health consequences of their consumption, specifically, pounds of air pollutant emissions and a listing of health consequences, namely, childhood asthma and cancer. Both treatment groups had access to an online dashboard that displayed real time electricity use data. The electricity consumption of the control group was observed, but this group did not receive any information feedback about their electricity consumption apart from their normal monthly electricity bills.

4.1. Information Display and Messaging

With the exception of the treatment messages, the dashboards for the health and financial groups were identical. The data presented on the dashboard included electricity consumption data for the past month, week, and day as well as real-time readings that would update every thirty seconds. In addition, a pie chart provided information about appliance usage. Lastly, electricity consumption for the 10% most efficient apartments was calculated and presented on each apartment's dashboard as a benchmark for energy efficiency.[1] The online dashboard can be seen in Appendix 1 and was accessible to the participants any time. In addition, personalized weekly emails were sent to each household in both treatment groups. These emails summarized electricity consumption in the past week and provided a private, password-protected link to view their online personal energy dashboard. The end-to-end architecture system designed to measure real-time, appliance-level data and provide feedback to the households is described in Chen et al. (2015).

The treatment messages translated consumed kilowatt-hours into dollars or health costs. We provided households with factual, evidence-based numbers that depended on their weekly consumption. The representative messages for our two decision frames are shown below:

[1] Since there was variation in occupancy across apartments, energy consumption was scaled by the number of occupants in each household for the benchmark comparison to the most efficient apartment.

1. *Health frame:* Last week, you used XX% more/less electricity than you efficient neighbors. You are adding/avoiding XX pounds of air pollutants, which contribute to known health impacts such as childhood asthma and cancer.

2. *Cost Savings frame*: Last week, you used XX% more/less electricity than your efficient neighbors. In one year, this will cost you (you are saving) $XX dollars.

The typical savings potential for a median 2-bedroom apartment was about $79 per year, and ranged between $11 and $328 in 2012 USD. The typical amount of reduced emitted air pollutants for a median 2-bedroom apartment was about 979 lbs. and ranged between 131 lbs. and 4,058 lbs. of criteria pollutants. These consider only annual non-baseload output emissions, e.g. the locally generated emissions attributed to meeting excess energy demand. Equivalent pounds of air pollutant emissions were calculated using emission factors from the Emissions & Generation Resource Integrated Database (eGRID) maintained by the U.S. EPA and based on LADWP electricity mix. Equivalent cost savings were calculated using household-level kWh consumption data and the published LADWP electric rate schedules for residential customers.

We make two identifying assumptions for the estimation of treatment effects. First, treatment selection is independent of the behavioral response function, which is given by random assignment. Second, treatments are independent and mutually exclusive. We discuss consumer engagement and the use of Google Analytics page tracking to validate whether treatment assigned equals treatment received in Section 6.5.

4.2. Timeline and randomization

The randomized controlled trial was conducted from October 2011 to July 2012. The baseline period lasted 6 months and was followed by 100 days (14 weeks) of treatment. In the baseline period, we observed the households' electricity consumption but did not provide energy use information to the households. We initially allocated an equal number of units to each condition: 42 units in the control group and 42 and 43 households respectively for health and cost savings groups. However, due to technical issues with some of the units in the control group, which were installed first, the final number of working units was 36 for the control group.[2]

Table 2 shows descriptive statistics by group for both treated and control households during the 6-month baseline period. The covariates and electricity consumption are reasonably balanced between treated and control households. In particular, the average electricity consumption reported in average kWh per day is statistically indistinguishable between groups along with other important household characteristics. The last column in Table 1 shows the results of a regression testing for significant differences between groups similar to the approach used in Allcott (2011). As given by the *F*-test *p*-value of 0.2485, we reject a hypothesis of imbalance between groups, which provides an important check on randomization. One exception is the variable representing membership in an environmental organization, a proxy for environmentalist households, which is significant at the 10 percent level (Table 1, last column). Households who report membership in an environmental organization in our sample represent a very minor share (~8%) of households in the study. In separate analyses, we computed the effects for households belonging to an environmental organization in our experiment. These results show no significant interaction of environmentalist households with either treatment, meaning these households do not drive the study's primary results.

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Insert Table 2 about Here

[2] Some of the units installed were omitted from the analysis due to technical issues with the metering equipment in these households. These technical issues mainly affected participants in the control group, who were the first set of households to have their metering kits installed. Six households assigned to the control group were affected and therefore omitted from the analysis in consultation with the engineering team. See Chen, et al., (2015).

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5. Econometric Approach

Our experimental approach addresses methodological concerns identified in a meta-analytic review of the behavioral literature in energy conservation, namely, inclusion of an independent control group, randomization in experimental assignment, household demographic controls, and weather and seasonality controls (Delmas, Fischlein and Asensio, 2013) for residential field studies.

Evidence of the effectiveness of a randomized trial is may change over time. We carefully considered two alternative approaches to analyze the consumption dynamics: a moving window of analysis, with for instance, week-to-week energy savings in which prior history does not matter; or alternatively, a cumulative window of analysis from the start of treatment where the prior consumption history does matter. We decided to use a cumulative window of analysis to estimate energy savings over time because cumulative energy savings is often the final metric of interest when measuring returns to behavioral interventions, particularly for policy and program evaluation.[3]

For household *j*, in treatment group *i*, at time *t*, we estimate treatment effects of information provision with the following econometric model:

$$E_{ijt} = \sum_{h} \tau^{h} P_{it} T_{i} + \boldsymbol{\Gamma H}_{j} + \boldsymbol{\Theta \Psi}_{t} + \gamma_{d} + \varepsilon_{jt}, \quad h = \{0,\ldots,z\} \qquad (1)$$

We regress the electricity loads in kilowatt-hour per unit time E_{ijt} on a series of treatment group and event time indicators, where T_i is equal to 1 if the household belongs to treatment group *i*, and 0 otherwise; and P_{it} is a post-treatment indicator equal to 1 during the post-treatment period, and 0

[3] In supplemental analyses, we also estimated weekly performance using a moving window. These results are available upon request from the authors.

during the baseline period. For convenience, the electricity usage has been normalized by dividing by the average post-period control group consumption in the experiment and multiplying by 100, which allows for direct interpretation of coefficients as percentage change (Allcott 2011). Treatment status is identified when the group-event time dummy is equal to 1, and 0 otherwise, which allows for estimation of treatment effects by difference-in-differences (DID) with a control group of metered households who receive an electricity bill, but receive no additional information treatment. We estimate a series of treatment effects, τ^h over a cumulative window of analysis from $h=\{0,\ldots,z\}$. The sampling rate for the kilowatt-hour electricity loads is 1/30 Hz, which is one reading every 30 seconds for all independently metered appliance signals in the community. We include household characteristics $\boldsymbol{H}_j$ weather controls Ψ_t, and where Γ and Θ are coefficient vectors. Day-by-week fixed effects are denoted by γ_d and the residual error is captured in ε_{jt}. Robust standard errors are clustered at the household level using the Arellano (1987) heteroskedasticity and autocorrelation-consistent covariance matrix. In the absence of informative feedback, we assume counterfactual consumption levels follow a matched control group sample or statistical reference level, which is a standard practice in evaluating RCTs.

We performed specification tests on the choice between fixed or random effect estimators in our panel data set. Our results are not sensitive to either specification. A Hausman test favored the use of random effects with covariates so we used this in the current study. This approach is generally consistent with the prior experimental literature estimating heterogeneous population treatment effects and also avoids potential biases in estimating the time series error component (Nickell, 1981).

5.1 Household controls

We condition on observable household characteristics that includes: apartment size, ranging from 1 to 3 bedrooms; the number of adults in the household, ranging from 1 to 3; the number of children in the household, ranging from 0 to 4; building floor in the residential complex ranging from 1 to 3; and apartment floor plan measured in nominal square footage. Because political leaning or ideology can also significantly impact energy efficiency attitudes and behaviors (Gromet, Kunreuther and Larrick, 2013; Costa and Kahn, 2013), we include a proxy variable equal to 1 when the head of household reports being a member of an environmental non-governmental organization (NGO), and 0 otherwise. In this way, we condition on greener participating households and capture an important source of heterogeneity. Additional unobservable characteristics that may be common to the community are also captured in the control group variation.

5.2 Seasonality and autocorrelation

Electricity demand in kWh per unit time exhibits seasonality and serial correlation that depend on outside factors such as time of day or weather. Modeling electricity loads with high time-resolution data requires special consideration of seasonality and time-varying characteristics on consumption, most notably, the effects of outside temperatures on hourly energy demand. Even with the milder climate in Los Angeles, heating and cooling hours capture significant seasonal variation on electricity consumption. We calculate heating and cooling degree hours, using local weather data provided by the National Oceanic and Atmospheric Administration (NOAA). Outside temperatures were recorded hourly at the Santa Monica Municipal Airport weather station, located less than 1 mile from the study site. Degree-hours capture seasonal heating or cooling requirements at a finer resolution than degree-days, and is a common approach in energy economics to model the influence of outside temperature fluctuation on patterns of energy demand (Reiss and White 2008, Appendix B). The hourly updating weather vector is $\mathbf{\Psi}_t = [\Psi^H, \Psi^C]$:

$$\Psi^H = \max\left\{0,\ \sum_{h=1}^{24}\left(65-\theta_{outside}\right)\right\} \quad \text{heating degree hours}$$

$$\Psi^C = \max\left\{0,\ \sum_{h=1}^{24}\left(\theta_{outside}-65\right)\right\} \quad \text{cooling degree hours} \tag{2}$$

As shown in Eq. (2), the larger the indoor heating or cooling requirement, the larger is the linear distance between the measured mean hourly outside temperature $\theta_{outside}$ and the indoor base temperature, which by U.S. convention is defined as 65˚F/18.3˚C (Day and Karayiannis 1998). When outside temperatures rise above the base temperature, cooling degree hours are strictly positive and heating degree hours are zero. Conversely, when outside temperatures fall below the base temperature, heating degree hours are strictly positive and cooling degree hours are zero. In this way, the differential effects of heating and cooling on kWh electricity consumption are decomposed in a meaningful way over a 24-hour period. In addition to seasonal degree-hours, we also specify day-by-week dummies to capture common time trends (or cycles) in the data and any calendar shocks on consumption.

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Insert Figure1 about Here

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6. Results

We obtained data on electricity consumption at high frequency of 1/30 Hz, one reading every 30 seconds, which we note is currently the state-of-the-art in high-frequency smart metering technology. We obtained an unbalanced panel of 53,437,110 kWh observations at the 30-second sampling frequency.[4] Across all 6 measured appliance categories (e.g. *heating and cooling*, *lighting*, *plug load* [e.g. all items plugged into wall outlets], *refrigerator*, *dishwasher* and *other kitchen appliances*), this gives a total sample size in this study of 374,059,770 panel observations. At 374 million kWh observations, our sample is one of the largest and highest resolution data sets to date in a behavioral study. We also begin to shed light on conservation behavior for individually metered appliances.

6.1. The Salience of novelty

In this section, we study the hypothesis that novelty effects with advanced metering and information technologies can lead to immediate behavioral changes in consumption. In Figure 1, we plot the dynamic treatment effects (DTEs) after the start of information treatments. The DTEs are shown in percentage change versus the control group and net of all controls, including outside weather variation. The thin lines in Figure 1 denote upper and lower 95% confidence intervals. By convention, negative values in percentage change mean energy savings (conservation behavior) and positive values in percentage change mean energy increases (splurging behavior) relative to control.

Consistent with the novelty hypothesis, there is a large and immediate conservation effect under both decision frames as shown in Figure 1. We report significant effects within the first day of treatment for the health group, and within 2 days (approximately 43 hours) for the cost savings group. For both treatment groups, we observe substantial adjustments in consumption within 48 hours of the initial treatment. These effects also persist throughout the day and early evening, which indicates both immediate load shifting and conservation behavior.

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[4] Some observations were lost due to wireless signal transmission from the metering equipment. These were relatively short periods reflecting the number of working units and aggregate signal. We tested to confirm these time observations were missing at random and uncorrelated with treatment status or household characteristics.

6.2. Peak Energy Savings

Having demonstrated that electricity usage feedback can drive immediate behavioral savings, we estimated hourly treatment effects in event time to understand what can be learned about the magnitudes of savings under our two framing approaches. Treatment status for the experiment begins at approximately 9:30 a.m. on Tuesday mornings, when the weekly e-mail alerts were sent to participants for 14 consecutive weeks (~100 days). In Table 2, we report *peak conservation*, which we define as the highest energy savings achieved after the start of information treatments. The resulting peak conservation times, magnitudes, and elapsed hours are all summarized by group in Table 2.

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[Insert Table 2 about here]

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By time-of-day, peak conservation occurs between 6:00 p.m. (18:00) and 7:00 p.m. (19:00) in the evening, when most residents are getting home and this is just before peak consumption occurs for the community-at-large at approximately 9:00pm (21:00). At peak consumption for the community, the relative magnitudes of the energy savings are considerable: we observe -15.7% peak conservation under the cost savings frame and -21.7% peak conservation under the health frame (Table 2). However, as shown in Table 2, the amount of time to reach peak savings differs substantially by group. Peak energy savings occurs after 176 hours (7 days of treatment) for the cost savings group but occurs after only 8 hours (within 1 day) for the health group. We do find evidence for rapid behavioral changes in consumption by both groups in the short run, however, the health group responded more quickly to the treatment.

What would a household need to be doing to achieve this level of conservation? For example, at standard nameplate wattages for common household appliances, to achieve 15-22% savings at peak conservation would require all treated households at University Village apartments to simultaneously reduce the equivalent energy as consumed in 24-30 minutes of 2 compact fluorescent light bulbs, 12-18 minutes of a laptop use, or 5-6 minutes of a 40 inch flat panel TV per day. In the next section, we further explore the magnitudes of the energy savings in terms of the underlying appliance categories. In related work, Reiss and White (2008) provide an excellent discussion of how much households would have to do to conserve a large amount as a result of price shocks and other public appeals.

Our results are generally consistent with experimental evidence by Gilbert and Zivin (2014) and Allcott and Rogers (2014) who also document that the greatest magnitudes of energy savings occur early in an information-based intervention, often on the first day households receive their home energy reports. Although in prior studies, the exact time of information delivery is typically unobserved, as the authors report *intent-to-treat* effects around a fixed window surrounding the mailing of the home energy reports. We distinguish these dynamic treatment effects from our own results because in our experimental setup, we are additionally able to track live page views with Google Analytics data (Figure 3; Appendix 3) in which we show very high compliance to treatment using information technologies. We discuss implications of analytics tracking on strategies for consumer engagement in Section 6.5

6.3. Behavioral Durability

We extended our analysis to 100 days of treatment, which is the approximate duration of a typical information campaign during peak winter or summer months (Delmas, Fischlein, Asensio 2013). Figure 1 shows the dynamic treatment effects and 95% confidence intervals over the full treatment horizon. Figure 2 shows the distribution of daily treatment effects in the study. The supporting point estimates are shown in Table 3A and 3B at regular intervals for the first week of treatment (novelty period - Table 3A) and for subsequent weeks (repetition period - Table 3B). Here we evaluate what is referred to as in-treatment persistence, that is, the persistence of treatment effects while households are still receiving information. Persistence during the in-treatment period is also sometimes referred to as the *durability* of treatment. In this study, we do not report behavioral effects after information treatments have been lifted, although this is promising area of further study (see Allcott and Rogers, 2014).

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[Insert Table 3A and 3B about here]

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Following peak conservation, we observe significant but decreasing durability of treatment effects over time. This is consistent with decreasing returns to information, although the dynamic responses follow markedly different consumption profiles, depending on the household assignment. For households who received cost savings messages, the effects decay very rapidly. Consumption patterns for cost savings households are not statistically different from the control group after about 7 weeks (Table 3B). By the end of 100-day experimental monitoring period, we observe no significant conservation behavior for cost savings households. As such, we say that the cost savings frame has poor durability.

For households randomly assigned to receive health messages, the effects decay at a much lower rate from peak conservation. The health strategy has very high durability. By the end of the experimental monitoring period, the net energy savings are approximately range between 8-10%, which is on the high end of prior experimental studies with social norm-based approaches.

6.4. Appliance Dynamics

We can additionally decompose the dynamic responses at the appliance level. Here we document that conservation behavior may be simultaneously observed in certain appliance-level consumption categories and not others. Appendix 2 for example shows the appliance dynamics for the lighting, heating and cooling, plug load [i.e. all items plugged into the wall outlets], refrigerator, dishwasher and other kitchen appliances. Lighting conservation is the most persistent form of behavior change observed experimentally for both treatment groups. While this is certainly evidence that households have adopted new energy savings practices particularly in lighting consumption versus the control group, interestingly, we observe markedly different appliance behaviors over time by decision frame.

In the health frame, the strong persistence of energy savings behavior is mainly driven by household changes in (a) plug load management, (b) lighting conservation and (c) space heating and cooling (Appendix 2). It turns out that as a share of household appliances, plug load is the largest share (28-32%) of total energy use in the community, so plug load management, heating/cooling (19-26%), and lighting (14-15%) conservation drive the strong behavioral durability in the health group over time.

In contrast, the weak behavioral durability of energy savings in the cost savings frame is mainly attributable to strong energy consumption rebounds at the appliance level, particularly in heating and cooling and plug load usage (Appendix 2). For heating and cooling, we initially observe conservation and then after about 40 days of treatment we observe evidence of a direct “rebound” that produces an increase in consumption. Energy rebounds are known and commonly discussed in the literature on energy efficiency (Gilliangham, Kotchen, Rapson, Wagner, 2013; Azevedo 2014), but to our knowledge, this is the first direct evidence of a rebound at the appliance level. However, these rebounds in consumption were not strong enough to compensate for significant behavioral changes in lighting conservation, which were effective but represent a relatively low appliance share (14-15%) versus the other appliance categories.

Surprisingly, treatment appears to cause an increase in energy use of the refrigerator in both treatments. Conservation behavior as it relates to refrigerator usage consists mostly of adjusting the refrigerator temperature settings. Surprisingly, we observe an average 8% increase in refrigerator loads for both treatment groups versus control. We verified all measurements with the engineering team to confirm the appliance consumption. Discussion during our focus group conducted after the study revealed that people were unclear on how to operate the analog refrigerator controls. As a result, many treated households wrongly adjusted the refrigerators settings to what they thought would be warmer temperatures, but in fact were colder temperatures, thereby increasing rather than decreasing their electricity use. Due to a less than optimal design in the control system, it seems that treated households increased their consumption versus the control group, which we interpret as an opportunity for the manufacturer to improve designs. This finding is consistent with the work of Attari et al. (2010) that highlights the importance of consumer perception and cognitive ability on the effectiveness of environmental behaviors.

In conclusion, our results show that framing has dramatic implications with regard to effectiveness and changes in underlying appliance behaviors. While this phenomenon certainly raises new questions and need for further research about why framing should lead to variation in appliance-level responses, we provide new evidence on the effectiveness of appliance-level behaviors in response to a causal treatment.

6.5. Consumer Engagement

In many empirical settings, scholars often assume that treatment assigned equals treatment received (Manski 1996). In practice however, some subjects comply with randomly assigned treatments, while others do not.

Using Google analytics data, we provide evidence for high compliance rates to our information treatments by using a unique household identifier for each login when participants visited our website. Google analytics can track users in real-time as they navigate a website and provide metrics to characterize the interactions between users, the displayed content and revealed activity patterns in response to information treatments. This information can be useful to understand the effectiveness of a treatment and also to verify whether treatment effects on populations should be adjusted to reflect low compliance rates. A similar capability should become available at scale as electric utilities deploy smart meters and online billing schemes (Edison, 2014).

We observe a high level of website engagement. In our study, 100% of treated households visited the website to view the displayed treatment messages at least once and sometimes multiple times per day, most commonly by clicking through our weekly feedback emails. We list descriptive statistics for new page entrances and other metrics by treatment group in Appendix 3. Page entrances, as defined by Google, are counted on the first pageview or screenview hit of an individual session. Our health treatment group had 752 total page entrances. Over approximately 98 days of tracking, this was an average engagement of 1.27 page entrances per week per household. Over the same period, the cost savings group had 260 page entrances for an average engagement of 0.43 page entrances per week per household. Households in the health group were therefore significantly more engaged than those in the cost savings group.

Appendix 3 shows descriptive statistics for various measures of engagement by treatment group and by day of the week. We report several measures of website engagement including weekly pageviews by group, unique pageviews (which do not count repeat visitors in a single session), time on page in milliseconds, and total events (which count all website interactions within pages such as clicks and mouseovers). While all visual information between treatment groups was identical, except for the treatment message itself, we see that the health group dominates the cost savings group in all the reported measures of engagement. Households in the health group viewed the pages more often, clicked more often and stayed longer on the website. These differences are statistically significant at the 1% level (Table 4A in Appendix 3).

We also observe the greatest number of initial page entrances on Tuesdays, which was the particular day of the week in which we sent participants weekly reminders with their electricity usage feedback (Appendix 3). This is also depicted in Figure 3, which shows weekly spikes of daily visits. This result suggests that alert-based reminders can be effective at directing users and that the timing of these reminders is an important factor driving engagement with information technologies. We also conducted a series of supplemental analyses to understand whether greater conservation effects could be identified for households with higher engagement metrics. We examined both cross-sectional results and engagement over time and found no interaction or additive effect of marginal page entrances (or other measures of engagement) on conservation beyond the primary treatments. This suggests that user engagement appears to be a necessary but not sufficient criterion for conservation behavior.

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Insert Figure 3 about here

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6.6 Robustness Checks

As robustness checks on our estimates, we considered both sampling intervals and clustering options in order to distinguish statistically trivial from substantively important treatment effects. First, we compared results based on different sampling frequencies. We carefully considered the effects of a large effective sample size for this case given a fixed N and large T dimension across households. We aggregated electricity consumption over fifteen- and thirty-minute intervals as well as hourly and daily electricity readings in order to validate our statistical inference at various sampling intervals, which upheld our general results. We report results at our native sampling frequency of 1/30 Hz, and also provide supplemental regressions using fixed effects models with hourly data in Tables 6A and 6B in Appendix 4. The results and response dynamics are quantitatively similar.

Serial correlation can have a large downward bias on standard errors in difference-in-difference models because the right-hand-side variables may be highly correlated through time. This problem is irrelevant for DID models when only two time periods are compared, but it can lead to a severe bias to conventional standard error estimates in longer series. This common time series pitfall of ignoring error correlation within group or time clusters has been well-documented in Bertrand, Duflo, Mullainathan (2004) and as a result, many empirical papers adjust standard errors by implementing one-way clustering on the panel's group dimension, adding time fixed effects to absorb any common shocks as standard practice—an approach we advocate in this paper with the introduction of more rigorous weather controls. We further explored double clustering on both the panel's group and time dimension to compute more conservative standard errors that may be robust to correlation along two dimensions. In supplemental analyses, we implemented multi-way clustering using procedures described in Cameron, Gelbach and Miller (2011) and Thompson (2011) to account for dependence in group and time dimensions. Our results are robust to sampling frequency, double clustering and various assumptions about the variance-covariance matrix with respect to inference.

7. Discussion

Scholars have only recently started to investigate the long-term effects of information-based behavioral interventions on conservation behavior. This study contributes to a developing body of work that examines the most effective information strategies to motivate lasting conservation behavior. Our analysis builds upon prior work by Asensio and Delmas (2015) but extends this earlier work along three important experimental dimensions. First, we include data at a 30 second sampling interval, which allows us to identify changes in behavior at a very high resolution. Second, we report data on website analytics, which allows us to observe household engagement with the treatment to confirm that the households accessed the information provided. Third, we shed light on dynamic responses at the appliance level.

We wish to emphasize four principal results. First, framing has important implications for the dynamics of energy conservation behavior and the evolution of treatment effects over time. We document that framing interventions can nudge consumers to change electricity use behavior in aggregate and at the appliance level. By introducing orthogonal framing treatments, we build on the earlier observation by Gilbert and Graff Zivin (2014) that some behavioral "nudges" are transitory, while others can shift the steady state and lead to new patterns of consumption. With experimental evidence from a randomized trial, we show very strong in-treatment persistence with a health-based framing approach to energy conservation, and very weak in-treatment persistence with the more commonly used cost savings frame. By introducing framing into the conservation problem, we demonstrate the power of information as a non-price mechanism for behavior change. Second, consistent with our novelty hypothesis, behavior change with information technologies can be immediate. We show that when novelty effects are present and feedback delays are short, the behavioral savings by consumers can be immediate:

within a matter of hours, and not over a span of weeks or months as observed in prior literature. This implies that information-based alerts are not only effective potential means of achieving curtailment goals, but are also effective at shifting electricity use load patterns from peak to off-peak periods. This latter point, however, requires further study. Third, given the timescale for behavioral changes in the current study, we show that peak behavioral savings with norm-based policy instruments are typically under-identified without the appropriate measurement frequency, particularly in standard 30-day residential billing cycles. Some treatments may last, others not. Finally, dynamic responses to framing interventions can occur without changes to existing billing rates, pricing structures or available monetary incentives. Timely information about consumption and its external effects can provide great value to consumers. We argue that behavioral interventions with information strategies can be important complements to price-based policies.

The emergence of real-time consumer data should bring a shift in the research agenda on how to design and enhance the timing and duration of information framing approaches to meet energy conservation or policy goals. We note that our randomized trial allows for direct causal interpretations of framing effects over time, while controlling for observable community characteristics and other unobservable characteristics to the extent they are represented in the control group. Our results described in this study are generally indicative of anticipated behavior in urban, multi-family renter populations with and without children in the home.

Our research is not without limitations. First, while we expect some attenuation of treatment effects in larger study populations, we acknowledge that other possible sources of heterogeneity (for example, political affiliation, computer literacy, Internet availability, age of the capital stock of household appliances, and kWh distribution of household energy uses) may become important sources of variation in larger populations. We have controlled for these characteristics to the best of our ability, notably by extending previous methodologies to include, but not limited to: standardized appliances in the residential field site which allow for more precise estimates, rigorous weather controls, a political proxy for environmental leaning, and unrestricted access to Internet in households. Further research can be scaled to other residential communities, particularly urban households or susceptible populations for which concerns about air pollution or high energy costs may be particularly salient. Second, while our study covers changes in energy conservation over 9 months, we do not study the persistence of these behavioral changes after the conclusion of the study. Further research should test how interventions can produce changes in behavior that persist even after the interventions are discontinued (Rogers and Frey, 2014).

Another important limitation on generalizability is the cause-effect attribution of the unobserved externalities. As in standard framing theory, we convert consumed kilowatt-hours into equivalent costs or pounds of air pollutant emissions. In the health decision frame, the main mechanism linking electricity consumption to environmental health damages is the calculated pounds of equivalent emissions, which is tailored to the individual household and region. We acknowledge that emissions and health impacts can be geographically separate from the originating point of use. Thus, some caution must be taken in ascribing tailored individual household emissions to specific health impacts on the community.

The current study provides a starting point for unanswered theoretical questions on the role of framing theory and habit-forming behavior at the appliance level. While outside the initial scope of this investigation, further research should seek to understand the nature of information framing effects and the psychological basis of persistence in important appliance categories, which we identified in this study. Finally, we recognize that if the monetary incentives are large enough, consumers will change behavior. In our experiment, the average monthly cost savings potential for a typical 2 bedroom family apartment versus the top 10% most energy efficient neighbors of similar size ranges between \$6.00-\$8.00 USD per month (\$72.00 to \$96.00 USD per year). Thus, while energy costs are small relative to the U.S. household budget, the potential energy savings achieved by participating households could be larger or longer lasting with larger magnitudes of savings. Further research to understand thresholds, either in terms of cost savings or size of emissions externalities might shed further light on the sensitivity of information provision to the persistence of conservation behaviors.

8. Conclusion

In this paper, we use information-based strategy to motivate consumer decision-making about household energy conservation. We show that tailored information disclosures about the environmental and health implications of household electricity use can be very salient with residential consumers and lead to more lasting behavioral effects versus framing based on cost savings. Conservation is short-lived when the curtailment decision is framed as a monetary reward and is more persistent when it is framed as a health-based community concern. We build on a body of literature by behavioral economists and psychologists on the importance of social utility in household consumption decisions, particularly in settings where monetary incentives may not work to modify behavior (Frey and Oberholzer-Gee, 2002; Gneezy, Meier and Rey-Biel, 2011). We show that the framing of choices can play an important role in the behavioral persistence of curtailment behaviors. These differences become more significant over time.

We started by emphasizing the potential benefits of the development of information technologies for behavioral and experimental research to evaluate social programs. As our research indicates, the successful use of these technologies requires a deeper understanding of individual behavior and the factors that drive the private provision of public goods. While the research so far has emphasized macro effects on the diffusion of greener technologies (Bollinger and Gillingham, 2012; Rubin, et al., 2004), our research demonstrates the advantages of a more micro and dynamic approach to understanding consumer responses to innovation and technology-assisted behavior change. From a managerial perspective, to provide useful insights and decision-making support in meeting energy conservation goals, managers must be capable of framing the appropriate analytical solutions.

This paper contributes to an emerging literature on behavioral “nudges” as non-monetary strategies for behavior change (Camerer et al., 2003; Thaler and Sunstein, 2003; Ratner et al., 2008). We introduce framing and provide new technology-based approaches to evaluate both the duration and magnitude of information framing effects, specifically in consumption settings that enhance consumer welfare through disclosure of unobserved externalities. This paper also extends framing theory (Soman, 2004; Chong and Druckman, 2007) by designing equivalency frames in the residential electricity sector that can alter behavior. We also contribute to the resource conservation literature on intrinsic motivations for pro-environmental behavior (Steg and Vlek, 2009; Kollmus and Agyeman, 2010; Delmas, Fischlein and Asensio, 2013; Van der Linden 2015). Information framing can be used as a general consumer strategy, particularly in settings where price-based policies may not be politically feasible or effective. With regard to the effectiveness of behavioral strategies, we argue that the relative importance of the environmental health effects of air pollution on household electricity consumption has been under-emphasized in consumer decision-making; and the relative importance of cost savings information has been over-emphasized.

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Table 1. Comparison of Participating versus Non-Participating Households at University Village (Meter Readings Data)

	Participating Households (S.D.)	Non-Participating Households (S.D.)	Difference Participating vs. non-participating (S.D.)	Test for significant Differences Participating vs. non-participating (S.E.)
Electricity Consumption §				
Average kWh per day	8.429 (15.2)	8.737 (28.7)	.3070 (32.5)	-.0004 (.0004)
kWh per square foot	.2007 (.339)	.2043 (.479)	.0036 (.587)	.0833 (.198)
kWh per person	42.53 (68.5)	44.72 (108.8)	2.18 (128.6)	-.0003 (.0009)
Square Footage	859.79 (106.3)	868.83 (98.54)	9.04 (144.9)	-.0001 (.0002)
Number of bedrooms	1.97 (.379)	1.97 (.343)	-0.003 (.511)	-.0263 (.160)
Number of bathrooms	1.60 (.490)	1.65 (.474)	.05 (.681)	.0143 (.040)
Number of occupants	4.03 (.566)	4.01 (.512)	-.02 (.763)	-.0107 (.126)
Building Floor	2.08 (.808)	2.08 (.786)	.002 (1.12)	-.0308 (.021)
Location in Complex (1 if Sawtelle, 0 if Sepulveda)	.543 (.498)	.596 (.491)	.053 (.699)	-.041 (.040)
Number of Households	118	986	1,104	1,104
Number of Observations	5,533	46,184	51,718	51,718
F-test *p*-value	-	-		0.669

§ Based on 12 months of independent electricity meter readings. Coefficients for kWh per square foot and kWh per person are based on independent regressions. No significant differences are found.

Table 2 Comparison of Baseline Characteristics Between Treated and Control Households

	I. Control Group (S.D.)	II. Treatment Group 1: (S.D.)	III. Treatment Group 2: (S.D.)	IV. Difference Treat 1-Control (S.D.)	V. Difference Treat 2 – Control (S.D.)	VI. Test for significant Differences Participating vs. non-participating (S.E.)
Average kWh usage/Day	8.660	7.543	7.457	-1.118	-1.204	-0.000377
	(7.623)	(6.485)	(6.672)	(10.01)	(10.13)	(0.00195)
Apartment Size (bedrooms)	2.043	1.980	1.914	-0.063	-0.128	-0.153
	(0.394)	(0.339)	(0.358)	(0.520)	(0.532)	(0.205)
No. of Adults	1.968	1.970	1.847	0.002	-0.122	-0.105
	(0.175)	(0.271)	(0.360)	(0.322)	(0.401)	(0.106)
No. of Children	0.653	0.425	0.480	-0.227	-0.172	-0.0562
	(0.800)	(0.874)	(0.713)	(1.184)	(1.072)	(0.0572)
Floor Plan (Square Footage)	877.66	867.17	846.04	-10.49	-31.62	0.000203
	(97.451)	(97.019)	(108.761)	(137.51)	(146.03)	(0.000674)
Building Floor	2.163	1.919	2.103	-0.244	-0.060	-0.0494
	(0.861)	(0.813)	(0.760)	(1.184)	(1.148)	(0.0501)
Member Environmental Organization	0.024	0.119	0.082	0.096	0.058	0.157*
	(0.152)	(0.324)	(0.274)	(0.358)	(0.313)	(0.0835)
Number of Observations	119,609	187,684	183,701	307,293	426,902	371,385
Number of Households	33	43	42	76	75	118
F-test *p*-value						0.2485

6 month baseline period (no electricity use feedback) *** p<0.01, ** p<0.05, * p<0.1

Table 2. Peak Conservation

Strategy	Peak Conservation (% energy savings vs. control)	Peak Conservation Time of Day	Elapsed Hours After Initial Treatment	Net Conservation after 100 days
Monetary Savings Group	-15.7%	6:00-7:00pm	176 hrs.	Not significant
Health Group	-21.7%	6:00-7:00pm	8 hrs.	-10.0%

Control Group*	N/A	N/A	N/A	N/A

* By experimental design, control group receives no information.

Table 3A. Dynamic Treatment Effects by Framing Intervention

	First Treatment Period: Novelty							
Dependent variable: kWh @ 1/30	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	1 hour	**6 hours**	**12 hours**	**18 hours**	**24 hours**	**36 hours**	**48 hours**	**1 week**
Experimental								
Post-Treat*Cost Savings	**-5.474**	**-8.394**	**8.103**	**-0.869**	**-3.202**	**-2.074**	**-8.064*****	**-15.56*****
	(-13.69)	(-10.93)	(-6.88)	(-4.996)	(-4.034)	(-3.578)	(-3.088)	(-3.369)
Post-Treat*Health Group	**-19.57*****	**-21.43*****	**-5.999**	**-9.411****	**-10.59*****	**-9.523****	**-13.03*****	**-9.962*****
	(-5.987)	(-5.202)	(-4.127)	(-4.361)	(-3.886)	(-3.893)	(-3.915)	(-3.037)
Household Characteristics								
Adults	-1.325	-1.404	-1.447	-1.443	-1.491	-1.446	-1.425	-2.025
	(-8.963)	(-9.009)	(-8.992)	(-8.978)	(-8.958)	(-8.931)	(-8.894)	(-8.726)
Children	10.24**	10.24**	10.23**	10.22**	10.22**	10.25**	10.27**	10.33**
	(-4.288)	(-4.285)	(-4.282)	(-4.277)	(-4.276)	(-4.265)	(-4.258)	(-4.221)
Apartment Size (No. of bedrooms)	44.82**	44.64**	44.49**	44.38**	44.33**	44.19**	43.91**	43.21**
	(-18.21)	(-18.21)	(-18.2)	(-18.2)	(-18.19)	(-18.14)	(-18.1)	(-17.85)
Floor Plan (nominal square	-0.0436	-0.0434	-0.0426	-0.0424	-0.0422	-0.042	-0.0413	-0.0403
	(-0.0627)	(-0.0626)	(-0.0626)	(-0.0626)	(-0.0626)	(-0.0625)	(-0.0624)	(-0.0615)
Building Floor	9.286***	9.255***	9.214***	9.178***	9.158***	9.088***	9.009***	9.111***
	(-3.438)	(-3.435)	(-3.434)	(-3.432)	(-3.431)	(-3.418)	(-3.405)	(-3.356)
Member of Environmental	-8.181	-8.099	-7.967	-7.84	-7.823	-7.767	-7.553	-8.444
	(-9.144)	(-9.191)	(-9.234)	(-9.264)	(-9.264)	(-9.259)	(-9.299)	(-8.982)
Weather Controls								
Heating Degree Hours	0.656**	0.658**	0.666**	0.653**	0.653**	0.666**	0.650**	0.644**
	(-0.274)	(-0.274)	(-0.274)	(-0.274)	(-0.274)	(-0.273)	(-0.273)	(-0.273)
Cooling Degree Hours	-0.840***	-0.838***	-0.829***	-0.839***	-0.841***	-0.827***	-0.835***	-0.834***
	(-0.209)	(-0.209)	(-0.209)	(-0.209)	(-0.209)	(-0.208)	(-0.208)	(-0.205)
Day-by-Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	33.62	33.91	33.68	33.88	33.99	33.95	34.22	35.58
	(-31.42)	(-31.46)	(-31.44)	(-31.4)	(-31.37)	(-31.29)	(-31.2)	(-30.77)
Number of Observations	27,531,13	27,601,36	27,669,23	27,735,09	27,802,42	27,941,28	28,079,52	29,404,74
Number of Apartments	118	118	118	118	118	118	118	118
R^2	0.0231	0.0232	0.0232	0.0232	0.0232	0.0233	0.0233	0.0241

Robust standard errors clustered at the household level in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3B. Dynamic Treatment Effects by Framing Intervention

Dependent variable: kWh @ 1/30 Hz	Repeated Weekly Treatment: Persistence												
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
	2 weeks	3 weeks	4 weeks	5 weeks	6 weeks	7 weeks	8 weeks	9 weeks	10 weeks	11 weeks	12 weeks	13 weeks	14 weeks
Experimental													
Post-Treat*Cost Savings Group	**-14.23*** **	**-13.38*** **	**-12.18*** **	**-9.816*** **	**-8.288*** **	**-6.826** **	**-5.236**	**-3.932**	**-2.931**	**-1.870**	**-1.087**	**-0.639**	**-0.212**
	(-3.518)	(-3.609)	(-3.031)	(-3.008)	(-3.166)	(-3.39)	(3.678)	(3.846)	(3.934)	(4.050)	(4.149)	(4.236)	(4.297)
Post-Treat*Health Group	**-12.31*** **	**-11.67*** **	**-11.52*** **	**-11.79*** **	**-11.54*** **	**-11.17*** **	**-10.96*** **	**-10.80*** **	**-10.97*** **	**-10.56*** **	**-10.09*** **	**-9.980** **	**-10.12** **
	(-3.021)	(-3.032)	(-2.959)	(-3.059)	(-3.184)	(-3.249)	(3.348)	(3.419)	(3.630)	(3.731)	(3.837)	(3.889)	(3.934)
Household Characteristics													
Adults	-1.02	-0.752	-0.879	-0.603	-0.719	-0.545	-0.655	-0.0741	0.216	0.227	0.308	0.611	0.724
	(-8.548)	(-8.369)	(-8.197)	(-8.01)	(-7.836)	(-7.806)	(7.884)	(7.924)	(7.948)	(8.062)	(8.235)	(8.272)	(8.166)
Children	10.49**	10.54**	10.42**	10.41***	10.22**	10.25**	10.24***	10.27***	10.34***	10.30***	10.33***	10.45***	10.56***
	(-4.154)	(-4.097)	(-4.072)	(-4.037)	(-4.011)	(-3.983)	(3.973)	(3.976)	(3.984)	(3.997)	(4.006)	(4.006)	(4.007)
Apartment Size (No. of bedrooms)	42.29**	40.57**	39.99**	38.31**	36.48**	34.42**	32.18*	31.05*	29.70*	29.19*	28.42*	27.61	26.81
	(-17.59)	(-17.42)	(-17.29)	(-17.08)	(-16.96)	(-16.9)	(16.92)	(16.93)	(16.97)	(17.04)	(17.12)	(17.19)	(17.26)
Floor Plan (nominal square footage)	-0.0408	-0.0394	-0.0391	-0.0356	-0.0303	-0.0239	-0.0165	-0.0124	-0.00914	-0.00727	-0.00543	-0.00313	0.000313
	(-0.0605)	(-0.06)	(-0.0597)	(-0.0595)	(-0.0594)	(-0.0596)	(0.0600)	(0.0604)	(0.0606)	(0.0611)	(0.0617)	(0.0620)	(0.0623)
Building Floor	9.010***	8.771***	8.588***	8.659***	8.673***	8.707***	8.992***	9.101***	9.198***	9.184***	9.208***	9.315***	9.387***
	(-3.292)	(-3.226)	(-3.19)	(-3.152)	(-3.123)	(-3.116)	(3.129)	(3.143)	(3.158)	(3.184)	(3.219)	(3.253)	(3.279)
Member of Environmental Organization	-8.377	-8.259	-8.265	-8.852	-9.044	-9.418	-9.711	-9.681	-9.495	-9.471	-9.232	-9.177	-9.064
	(-8.803)	(-8.638)	(-8.611)	(-8.497)	(-8.398)	(-8.393)	(8.473)	(8.582)	(8.666)	(8.836)	(9.025)	(9.054)	(8.999)
Weather Controls													
Heating Degree Hours	0.615**	0.573**	0.569**	0.548**	0.506*	0.441*	0.367	0.301	0.234	0.168	0.117	0.0990	0.0824
	(-0.268)	(-0.263)	(-0.261)	(-0.26)	(-0.259)	(-0.259)	(0.261)	(0.262)	(0.264)	(0.265)	(0.266)	(0.266)	(0.266)
Cooling Degree Hours	-0.839***	-0.745***	-0.746***	-0.775***	-0.809***	-0.860***	-0.954***	-0.956***	-0.949***	-0.975***	-0.917***	-0.905***	-0.886***
	(-0.202)	(-0.193)	(-0.193)	(-0.191)	(-0.184)	(-0.185)	(0.186)	(0.188)	(0.188)	(0.188)	(0.191)	(0.194)	(0.195)
Day-by-Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	36.07	38.16	39.62	39.35	39.22	38.17	36.58	34.32	33.49	33.68	33.72	32.42	30.74
	(-30.19)	(-29.73)	(-29.41)	(-29.02)	(-28.69)	(-28.67)	(28.89)	(29.00)	(29.09)	(29.42)	(29.87)	(30.05)	(30.03)

Number of Observations	31,323,860	33,219,246	35,026,028	36,980,245	38,879,906	40,865,886	42,834,067	44,792,397	46,713,091	48,503,721	50,305,792	52,010,717	53,437,110
Number of Apartments	118	118	118	118	118	118	118	118	118	118	118	118	118
R^2	0.0253	0.0257	0.0255	0.0254	0.0251	0.0249	0.0247	0.0244	0.0241	0.0238	0.0234	0.0234	0.0237

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figure 1. Dynamic Treatment Effects by Framing Intervention

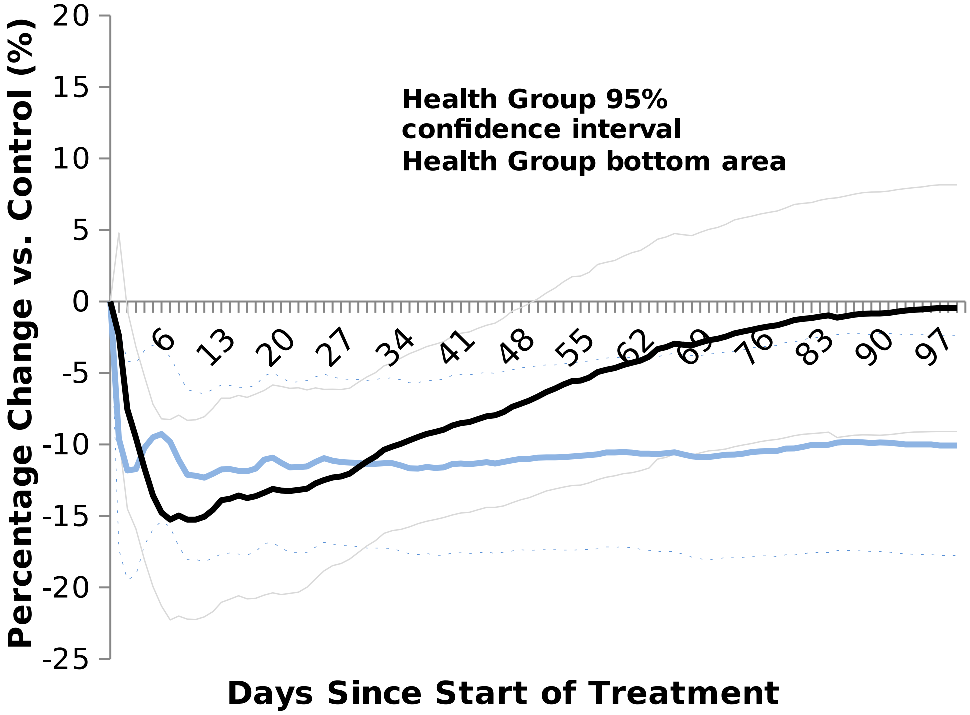


Figure 2. Distribution of Daily Treatment Effects

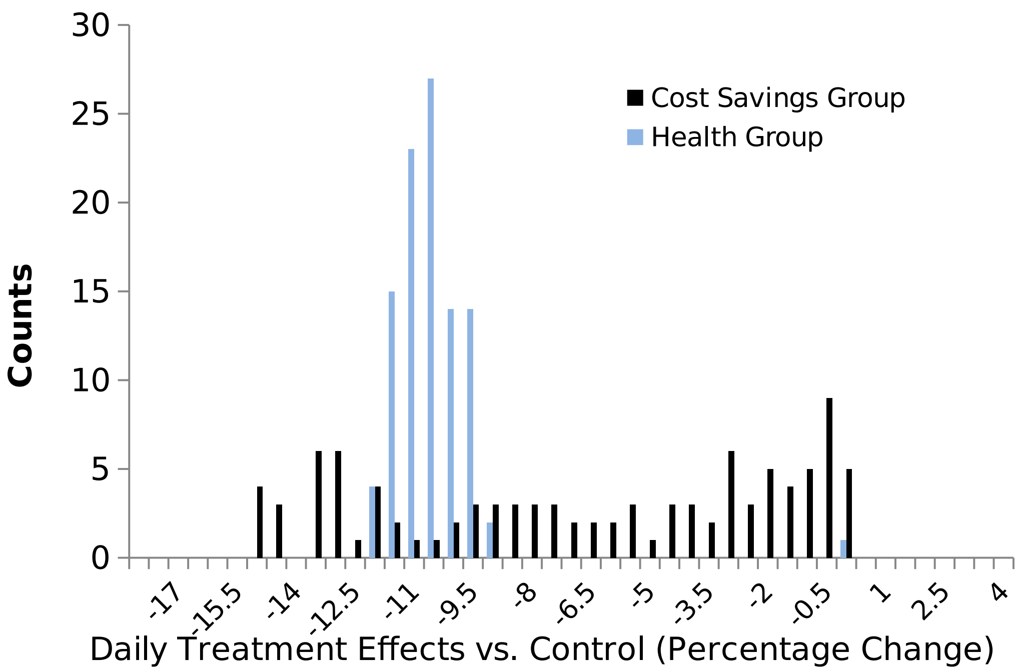
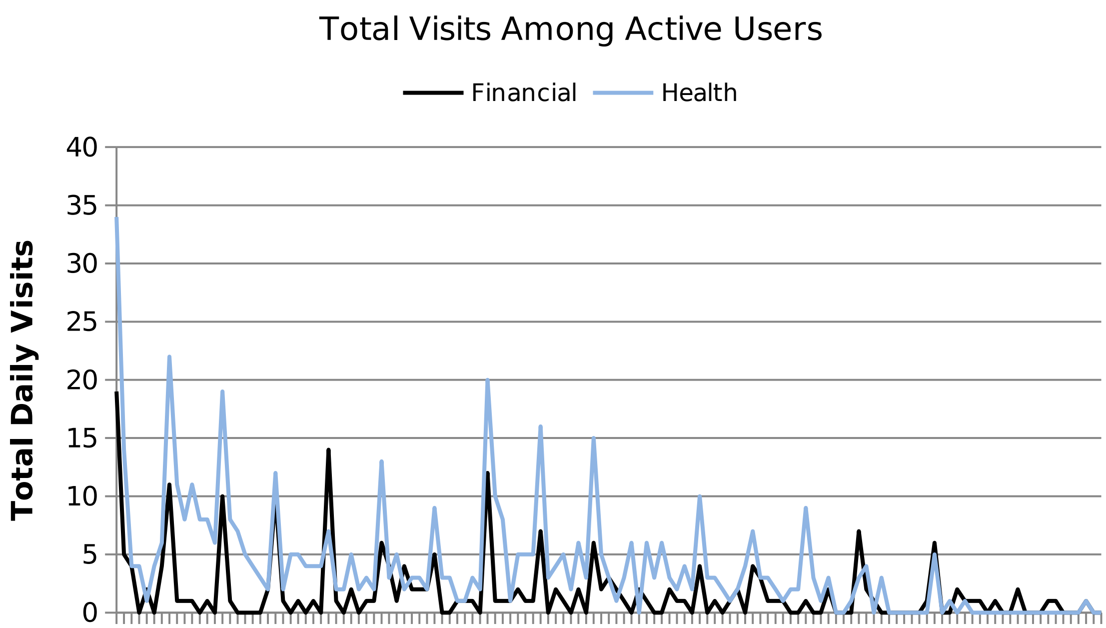


Figure 3. Participant Engagement

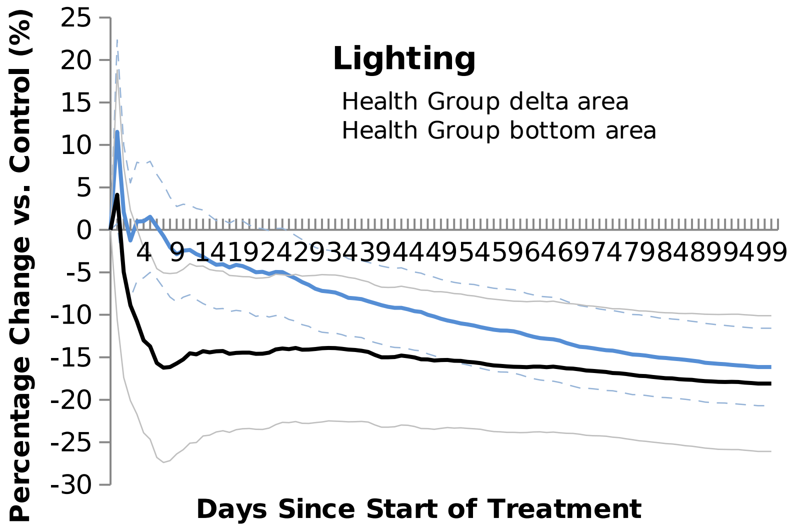
Google Analytics

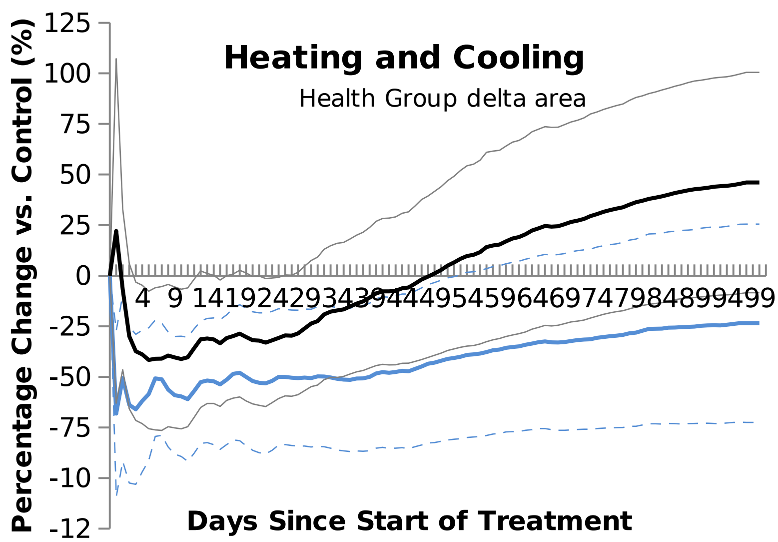


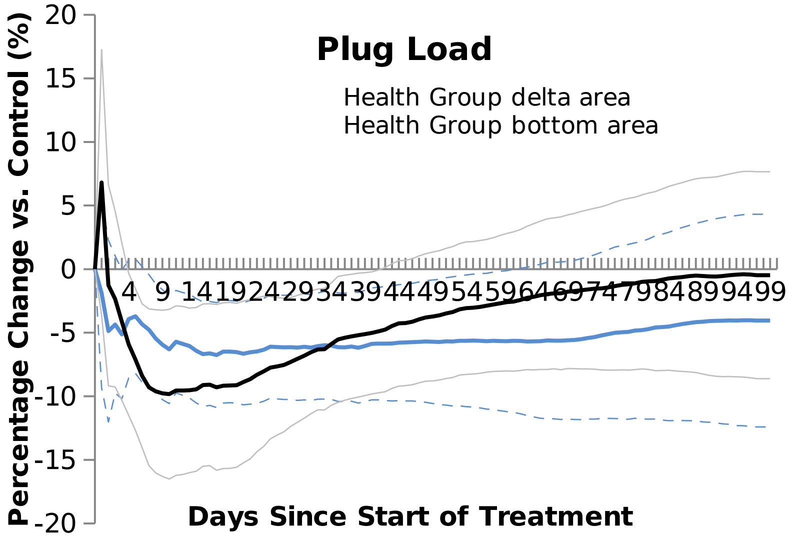
Appendix 1. Energy Dashboard

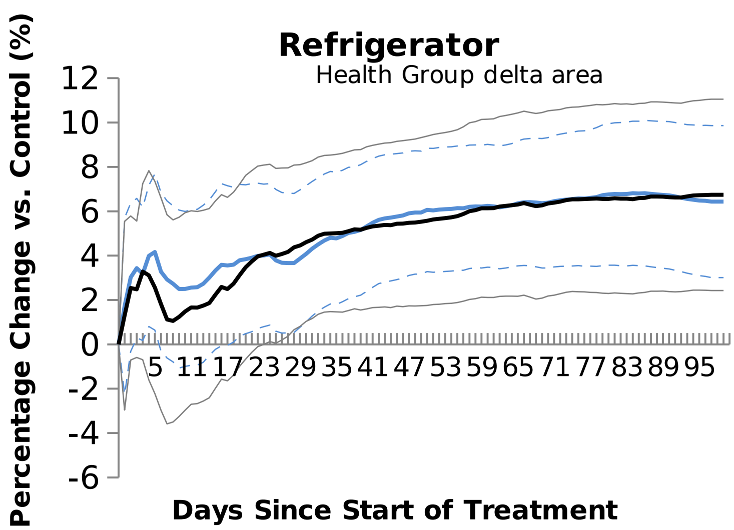
Appendix 2 Appliance Dynamics

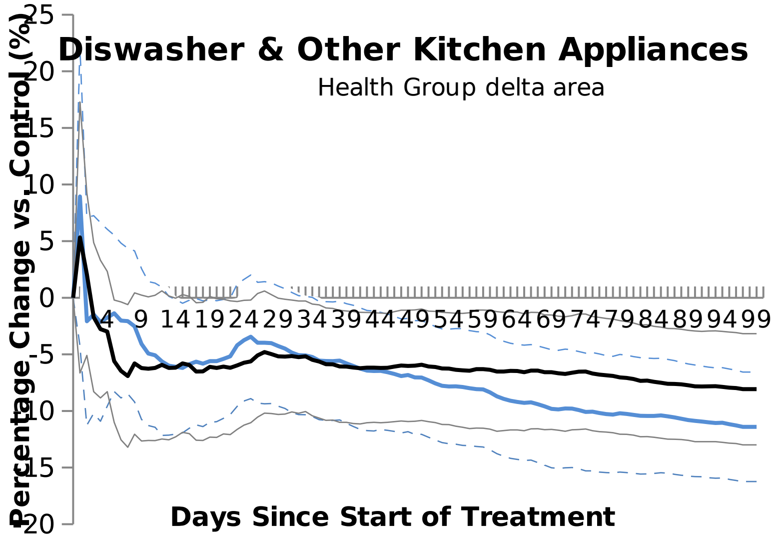
Dynamic Treatment Effects at the appliance-level.






Plug Load
Health Group delta area
Health Group bottom area
Percentage Change vs. Control (%)
20
15
10
5
0
-5
-10
-15
-20
4 9 14 19 24 29 34 39 44 49 54 59 64 69 74 79 84 89 94 99
Days Since Start of Treatment


Refrigerator
Health Group delta area
Percentage Change vs. Control (%)
12
10
8
6
4
2
0
-2
-4
-6
5 11 17 23 29 35 41 47 53 59 65 71 77 83 89 95
Days Since Start of Treatment


Diswasher & Other Kitchen Appliances
Health Group delta area
Percentage Change vs. Control (%)
25
20
15
10
5
0
-5
-10
-15
-20
4 9 14 19 24 29 34 39 44 49 54 59 64 69 74 79 84 89 94 99
Days Since Start of Treatment

Appendix 3 Website Analytics

Table 4A. Weekly Engagement Metrics by Group

	Cost Savings Group 260 page entrances*				**Health Group 752 page entrances***				
Variable	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max	*T-test p-*value
Pageviews	16.7	10.9	1	49.3	40.3	23.8	2	91.8	.001
Unique Pageviews	14.8	9.1	1	41	32.6	16.1	2	66.3	.000
Time on Page (ms)	5,391	7,516	58	24,681	25,983	22,399	76	71,945	.002
Total Events**	166.1	245.8	5	717.8	2,093.8	2,485.1	7	6,936.8	.004

* Page entrances are the number of initial dashboard entries by households via unique login. Pageviews track all website page visits
** Total events count all click interactions throughout the website.

Table 4B. Website Page Entrances by Day of Week

Day of Week	**Cost Savings Group** Panel Freq.	Percent %	Cum. %	**Health Group** Panel Freq.	Percent %	Cum. %	*T test p-*value
Monday	350	8.7	8.7	786	10.2	10.2	.469
Tuesday*	**2,045**	**50.9**	**59.7**	**3,444**	**44.7**	**55.0**	**.161**
Wednesday	400	10.0	69.6	985	12.8	67.8	.363
Thursday	326	8.1	77.7	817	10.6	78.4	.433
Friday	432	10.8	88.5	633	8.2	86.6	.344
Saturday	190	4.7	93.2	408	5.3	91.9	.818
Sunday	272	6.8	100.0	624	8.1	100.0	.084
Total	4,015	100.0		7,697	100.0		

* Weekly e-mail reminders were sent to participants on Tuesday mornings

Appendix 4 Supplemental Analyses: Hourly Sampling

Table 5A. Dynamic Treatment Effects by Framing Intervention

	First Intervention Period							
Dependent variable: kWh @ 1 hr.	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	1 hour	**6 hours**	**12 hours**	**18 hours**	**24 hours**	**36 hours**	**48 hours**	**1 week**
Experimental								
Post-Treat*Cost Savings	**8.845**	**2.931**	**7.188**	**8.592**	**3.139**	**1.948**	**-2.446**	**-11.97*** **
	(9.423)	(12.80)	(8.530)	(6.281)	(4.930)	(4.412)	(3.810)	(3.676)
Post-Treat*Health Group	**-9.369**	**-15.93*** **	**-10.13** **	**-8.888** **	**-10.76*** **	**-11.63*** **	**-13.15*** **	**-9.879*** **
	(8.049)	(5.291)	(4.626)	(4.232)	(3.995)	(3.929)	(3.979)	(3.247)
Household Characteristics								
Adults	-2.815	-2.915	-2.998	-2.928	-2.944	-2.939	-2.903	-3.495
	(9.351)	(9.393)	(9.390)	(9.386)	(9.372)	(9.350)	(9.319)	(9.220)
Children	10.59**	10.60**	10.59**	10.57**	10.57**	10.60**	10.61**	10.65**
	(4.370)	(4.373)	(4.369)	(4.367)	(4.367)	(4.360)	(4.351)	(4.332)
Apartment Size (No. of bedrooms)	45.30***	45.12**	44.99**	44.90**	44.89**	44.78**	44.53**	43.35**
	(17.54)	(17.54)	(17.54)	(17.54)	(17.55)	(17.53)	(17.51)	(17.45)
Floor Plan (nominal square	-0.0463	-0.0461	-0.0456	-0.0454	-0.0455	-0.0454	-0.0448	-0.0428
	(0.0608)	(0.0608)	(0.0608)	(0.0608)	(0.0608)	(0.0607)	(0.0606)	(0.0599)
Building Floor	9.049***	9.025***	8.983***	8.957***	8.927***	8.862***	8.806***	8.891***
	(3.350)	(3.350)	(3.347)	(3.345)	(3.346)	(3.336)	(3.327)	(3.297)
Member of Environmental	-3.526	-3.413	-3.415	-3.311	-3.329	-3.385	-3.284	-4.308
	(10.01)	(10.04)	(10.04)	(10.10)	(10.10)	(10.07)	(10.12)	(9.639)
Weather Controls								
Heating Degree Hours	0.778***	0.779***	0.784***	0.782***	0.769***	0.783***	0.766***	0.757***
	(0.258)	(0.258)	(0.258)	(0.259)	(0.259)	(0.258)	(0.258)	(0.258)
Cooling Degree Hours	-0.734***	-0.733***	-0.727***	-0.728***	-0.739***	-0.725***	-0.736***	-0.734***
	(0.199)	(0.198)	(0.198)	(0.198)	(0.198)	(0.197)	(0.197)	(0.195)
Day-by-Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	36.56	36.92	37.05	36.94	37.21	37.36	37.39	39.03
	(34.19)	(34.22)	(34.21)	(34.20)	(34.17)	(34.10)	(34.03)	(33.68)
Number of Observations	256,606	257,132	257,770	258,390	259,010	260,269	261,525	273,693
Number of Apartments	118	118	118	118	118	118	118	118
R^2	0.0479	0.0479	0.0480	0.0479	0.0478	0.0479	0.0478	0.0480

Robust standard errors clustered at the household level in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5B. Dynamic Treatment Effects by Framing Intervention (Hourly Sampling)

Dependent variable: kWh @ 1 hr. sampling	Repeated Weekly Intervention: Persistence												
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
	2 weeks	3 weeks	4 weeks	5 weeks	6 weeks	7 weeks	8 weeks	9 weeks	10 weeks	11 weeks	12 weeks	13 weeks	14 weeks
Experimental													
Post-Treat*Cost Savings Group	**-10.99*** **	**-10.10*** **	**-9.137*** **	**-6.694** **	**-5.026* **	**-3.485**	**-1.804**	**-0.350**	**0.781**	**1.946**	**2.696**	**3.252**	**3.785**
	(3.709)	(3.727)	(3.044)	(2.866)	(3.035)	(3.286)	(3.623)	(3.813)	(3.913)	(4.079)	(4.200)	(4.316)	(4.391)
Post-Treat*Health Group	**-11.15*** **	**-10.50*** **	**-10.53*** **	**-10.61*** **	**-10.33*** **	**-9.938*** **	**-9.542*** **	**-9.133** **	**-9.220** **	**-8.768** **	**-8.223** **	**-8.088** **	**-8.214** **
	(3.263)	(3.319)	(3.249)	(3.377)	(3.496)	(3.516)	(3.626)	(3.684)	(3.861)	(3.958)	(4.053)	(4.100)	(4.120)
Household Characteristics													
Adults	-3.940	-2.954	-2.450	-1.788	-1.198	-0.657	-0.388	0.115	0.502	0.561	0.691	0.776	1.130
	(7.727)	(7.729)	(7.686)	(7.673)	(7.661)	(7.672)	(7.688)	(7.691)	(7.705)	(7.703)	(7.712)	(7.731)	(7.741)
Children	-6.362	-5.484	-4.867	-4.191	-3.619	-3.107	-2.928	-2.432	-2.000	-1.951	-1.852	-1.783	-1.493
	(8.076)	(8.052)	(8.015)	(8.004)	(7.991)	(7.992)	(8.000)	(7.996)	(8.022)	(8.018)	(8.028)	(8.041)	(8.042)
Apartment Size (No. of bedrooms)	-2.409	-2.159	-2.130	-1.823	-1.765	-1.476	-1.477	-0.550	-0.0682	-0.0592	0.0170	0.337	0.456
	(9.120)	(8.956)	(8.826)	(8.669)	(8.540)	(8.518)	(8.633)	(8.701)	(8.736)	(8.869)	(9.076)	(9.142)	(9.053)
Floor Plan (nominal square footage)	10.74**	10.77**	10.67**	10.62**	10.43**	10.48**	10.51**	10.60**	10.64**	10.59**	10.57**	10.70**	10.82**
	(4.296)	(4.283)	(4.253)	(4.241)	(4.239)	(4.226)	(4.227)	(4.231)	(4.245)	(4.268)	(4.287)	(4.294)	(4.293)
Building Floor	42.06**	40.15**	39.66**	38.20**	36.67**	34.96**	32.93*	32.16*	30.97*	30.56*	30.09*	29.39*	28.74*
	(17.48)	(17.44)	(17.29)	(17.13)	(17.04)	(17.00)	(17.01)	(17.02)	(17.06)	(17.14)	(17.21)	(17.30)	(17.37)
Member of Environmental Organization	-0.0422	-0.0399	-0.0392	-0.0356	-0.0308	-0.0248	-0.0176	-0.0144	-0.0115	-0.00994	-0.00890	-0.00684	-0.00363
	(0.0593)	(0.0590)	(0.0586)	(0.0586)	(0.0586)	(0.0588)	(0.0592)	(0.0595)	(0.0598)	(0.0604)	(0.0609)	(0.0614)	(0.0616)
Weather Controls													
Heating Degree Hours	0.733***	0.703***	0.700***	0.683***	0.656***	0.603**	0.547**	0.496**	0.434*	0.365	0.315	0.296	0.284
	(0.254)	(0.249)	(0.248)	(0.247)	(0.247)	(0.248)	(0.250)	(0.251)	(0.252)	(0.253)	(0.254)	(0.254)	(0.255)
Cooling Degree Hours	-0.737***	-0.659***	-0.653***	-0.676***	-0.691***	-0.731***	-0.802***	-0.795***	-0.800***	-0.846***	-0.828***	-0.820***	-0.811***
	(0.190)	(0.185)	(0.183)	(0.184)	(0.178)	(0.181)	(0.185)	(0.185)	(0.185)	(0.184)	(0.184)	(0.187)	(0.186)
Day-By-Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	39.20	40.00	39.99	38.48	36.93	34.84	32.49	29.02	27.99	28.02	27.98	26.65	24.35
	(33.25)	(32.84)	(32.52)	(32.14)	(31.85)	(31.83)	(32.04)	(32.18)	(32.23)	(32.54)	(32.94)	(33.16)	(33.14)
Number of Observations	290,935	308,059	324,605	342,148	359,349	377,160	394,736	412,351	429,685	445,933	462,275	477,789	490,994
Number of Apartments	118	118	118	118	118	118	118	118	118	118	118	118	118

R^2	0.0487	0.0484	0.0481	0.0475	0.0468	0.0464	0.0460	0.0455	0.0447	0.0442	0.0435	0.0437	0.0444

Robust standard errors clustered at the household level in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6A. Dynamic Treatment Effects by Framing Intervention (Hourly Sampling - Fixed Effects)

	First Intervention Period							
Dependent variable: kWh @ 1 hr.	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	1 hour	**6 hours**	**12 hours**	**18 hours**	**24 hours**	**36 hours**	**48 hours**	**1 week**
Experimental								
Post-Treat*Cost Savings	8.842	2.927	7.185	8.589	3.137	1.946	-2.447	-11.97***
	(9.423)	(12.80)	(8.531)	(6.283)	(4.931)	(4.413)	(3.811)	(3.676)
Post-Treat*Health Group	-9.371	-15.93***	-10.13**	-8.891**	-10.77***	-11.63***	-13.16***	-9.885***
	(8.049)	(5.291)	(4.624)	(4.229)	(3.992)	(3.927)	(3.977)	(3.245)
Weather Controls								
Heating Degree Hours	0.778***	0.779***	0.784***	0.782***	0.769***	0.783***	0.766***	0.757***
	(0.258)	(0.258)	(0.258)	(0.259)	(0.259)	(0.258)	(0.258)	(0.259)
Cooling Degree Hours	-0.734***	-0.733***	-0.727***	-0.728***	-0.739***	-0.725***	-0.736***	-0.734***
	(0.198)	(0.198)	(0.198)	(0.198)	(0.198)	(0.197)	(0.197)	(0.195)
Day-by-Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	99.47***	99.46***	99.40***	99.43***	99.56***	99.41***	99.58***	99.68***
	(2.529)	(2.524)	(2.520)	(2.529)	(2.533)	(2.518)	(2.519)	(2.485)
Number of Observations	256,606	257,132	257,770	258,390	259,010	260,269	261,525	273,693
Number of Apartments	118	118	118	118	118	118	118	118
R^2	0.0041	0.0041	0.0042	0.0041	0.0041	0.0042	0.0043	0.0047

Robust standard errors clustered at the household level in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6B. Dynamic Treatment Effects by Framing Intervention (Hourly Sampling - Fixed Effects Model)

	Repeated Weekly Intervention: Persistence												
Dependent variable: kWh @ 1 hr. sampling	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**	**(21)**
	2 weeks	**3 weeks**	**4 weeks**	**5 weeks**	**6 weeks**	**7 weeks**	**8 weeks**	**9 weeks**	**10 weeks**	**11 weeks**	**12 weeks**	**13 weeks**	**14 weeks**
Experimental													
Post-Treat*Cost Savings Group	-10.98***	-10.10***	-9.138***	-6.696**	-5.028	-3.487	-1.806	-0.353	0.779	1.944	2.693	3.250	3.783
	(3.710)	(3.727)	(3.044)	(2.866)	(3.035)	(3.286)	(3.623)	(3.813)	(3.913)	(4.079)	(4.200)	(4.316)	(4.391)
Post-Treat*Health Group	-11.16***	-10.50***	-10.53***	-10.61***	-10.33***	-9.939***	-9.543***	-9.134**	-9.221**	-8.769**	-8.224**	-8.089*	-8.215**
	(3.263)	(3.318)	(3.248)	(3.377)	(3.496)	(3.516)	(3.626)	(3.684)	(3.861)	(3.958)	(4.053)	(4.100)	(4.120)
Weather Controls													
Heating Degree Hours	0.733***	0.703***	0.700***	0.683***	0.656***	0.602**	0.547**	0.495*	0.433*	0.365	0.315	0.296	0.284
	(0.254)	(0.249)	(0.248)	(0.247)	(0.247)	(0.248)	(0.250)	(0.251)	(0.252)	(0.253)	(0.254)	(0.254)	(0.255)
Cooling Degree Hours	-0.737***	-0.659***	-0.653***	-0.676***	-0.691***	-0.731***	-0.802***	-0.795***	-0.801***	-0.846***	-0.828***	-0.820***	-0.811***
	(0.190)	(0.185)	(0.183)	(0.184)	(0.178)	(0.181)	(0.185)	(0.185)	(0.185)	(0.184)	(0.184)	(0.187)	(0.186)
Day-By-Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	100.1***	99.85***	99.54***	99.44***	99.55***	100.2***	100.5***	100.8***	101.4***	102.0***	102.3***	102.4***	102.4***
	(2.353)	(2.274)	(2.225)	(2.166)	(2.072)	(2.006)	(1.949)	(1.911)	(1.869)	(1.818)	(1.776)	(1.770)	(1.773)
Number of Observations	290,935	308,059	324,605	342,148	359,349	377,160	394,736	412,351	429,685	445,933	462,275	477,789	490,994
Number of Apartments	118	118	118	118	118	118	118	118	118	118	118	118	118
R^2	0.056	0.0062	0.0061	0.0062	0.0062	0.0062	0.0060	0.0054	0.0052	0.0050	0.0047	0.0048	0.0050

Robust standard errors clustered at the household level in parentheses *** p<0.01, ** p<0.05, * p<0