THE DYNAMICS OF CONSUMER BEHAVIOR: NOVELTY AND FRAMING EFFECTS

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Abstract

Dynamic consumer responses are an important research topic for managers in assessing short and long-term marketing effectiveness and incentives in behavioral and consumption decisions. Using a field experiment with high frequency data, we investigate consumer responses to information-based marketing interventions designed to encourage conservation behavior in the residential electricity sector. We discuss novelty and framing effects as temporal mechanisms for behavior change, resulting from new consumer innovations in energy metering technologies. We find that a non-monetary health-based decision frame, in which consumers consider the human health effects of their marginal electricity use, induced persistent energy savings behavior; whereas a more traditional cost savings frame, drove sharp attenuation of treatment effects over time. We discuss the implications of our findings for the design of effective information campaigns to engage consumers on household consumption decisions.

Keywords*:* energy consumption, framing, dynamic decision making, randomized controlled trials

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1. Introduction

Scholars have proposed that the framing of information can have important effects on consumer behavior —often helping individuals and organizations overcome cognitive or behavioral biases, and make better consumption or investment decisions (Thaler and Sunstein, 2008; Ratner et al., 2008). Information framing effects take place when the manner in which information is represented or "framed" to consumers affects its evaluation (Tversky and Kahneman 1981). Typical framing interventions provide participants 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, 1984; Levin, Schneider and Gaeth 1998; Keren 2011). Scholars have used information framing strategies in a wide range of decision-making domains, including saving money for retirement (Benartzi and Thaler, 2007); reducing poverty and improving access to financial institutions (Bertrand, Mullainathan, and Shafir, 2006); designing health behavior programs (Rothman and Salovey, 1997; Rothman et al., 2006; Block and Keller, 1995; Keller and Lehman, 2008); and encouraging resource conservation (Schultz, 1999; Schultz et al., 2007). Historically, framing research has been conducted in small-scale lab studies with short trials and one-shot decisions. While more recently, the research has moved to framed field experiments (Harrison and List 2004; Levitt and List 2009), we still have little understanding of the effectiveness of information framing on consumer behavior over longer time periods (Allcott and Rogers, 2014). Studying the dynamics of framing is important for marketing effectiveness because there is a fundamental question about how long framing effects last after initial exposure, and what happens when novelty effects fade or decision frames are repeated, particularly for estimating consumer demand cycles (Sun 2006). In this study, we conduct a field experiment to offer new perspectives on the effectiveness of information framing in repeated decision processes on both consumer engagement and consumption behavior.

Scholars have repeatedly suggested that a temporal lens is essential for long-term marketing effectiveness (Pauwels 2004) and recent literature reflects a growing interest in inference and estimation of dynamic decision models with market data (Valentini, Montaguti and Neslin, 2011). However, prior research on the dynamic effects of marketing variables in consumer research remains limited. This is partly due to the difficulty and cost of collecting longitudinal individual and organizational data. In recent years, however, the development of information and communication technologies (ICT), big data analytics, and lower data storage costs have allowed researchers to collect detailed information about managerial and consumer behavior across broad sectors of the economy from information and communication systems to marketing (Goel, and Goldstein, 2013; Sundararajan, Provost, Oestreicher-Singer, and Aral, 2013; Winer, 2001). Big data analytics can now be used to understand customers' responses to information strategies and message framing over time.

In this article, we make use of big data analytics to analyze how framing interventions can affect consumption behavior over time in the context of residential energy consumption. Understanding the potential mechanisms to reduce energy consumption is an essential part of addressing climate change (Howard-Grenville et al. 2014), since electricity generation accounts for over 40% of the carbon dioxide emitted by the United States and residential and commercial buildings collectively account for over two-thirds of total U.S. energy consumption (EIA, 2014; EPA, 2013). Energy conservation results not only from technological changes in built environments, but also from behavioral changes in consumption (Gillingham and Palmer, 2014).

Guided by aggressive federal and state policy, 493 U.S. electric utilities have installed 50 million advanced ("smart") energy meters nationally through 2014 (Edison Foundation 2014) with $5.2 billion USD in smart grid investments. These technological innovations allow for real-time feedback about electricity usage to consumers and real time observations of household consumption decisions. However, this substantial upgrade in smart meter technology is not yet associated with a sound understanding of behavior change opportunities with these new shifts in technologies. Further research is needed to understand how the design of such innovations shapes its acceptance by consumers and ultimate response in established social systems (Hauser, Tellis and Griffin 2006).

In this study, we use advanced energy metering technologies with real-time consumer alerts, to provide households individualized and more frequent information about the unobserved monetary or social costs related to their electricity consumption. The use of information technologies to deliver information treatments offers new benefits for research: information diffusion is relatively fast; feedback delays to consumers are shortened, particularly versus infrequent paper-based mailings, for example; and analytics data can be deployed to verify when and how managers and consumers interact with information treatments or alerts. These technological innovations allow us to uniquely study the role of framing effects on household consumption decisions over time. We leverage the capacity to collect and analyze data with an unprecedented breadth, depth, and scale to solve real-life problems.

In a randomized controlled trial (RCT), we unpack two mechanisms of behavior change with non-price, information-based strategies: *novelty* effects, learning about household consumption with information and communication technologies; and *persistence* effects, habit-forming behavioral changes over time with repeated information provision, whose magnitudes depend on message framing and psychology-based mental accounts. The behavioral principle we invoke is learning and evolution (Camerer 1999). As in Cervantes' famous tale of *Don Quixote*, new mental accounts can inspire changes in behavior. We explore novelty and persistence under two alternative decision frames, namely a cost savings frame, which focuses decision makers on the monetary costs of electricity consumption, and a health frame, which focuses decision makers on the social costs of electricity consumption.

2. Framing Conservation

In the energy conservation context, there are many reasons to expect that information framing could impact conservation behavior over time. First, conservation behavior requires continuous monitoring and self-regulation. Household curtailment behaviors 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. However, consumers receive infrequent information about the monetary cost of electricity (Jessoe and Rapson, 2012; Ito, 2014). Second, consumers are generally unaware, or unable to observe the negative externalities of their electricity use such as outside air pollution and related environmental health damages (Brunekreef and Holgate, 2002). Further, these social costs are also not necessarily 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 the persistence of induced energy savings behavior over time.

Several groups of researchers have recently demonstrated with direct experimental field evidence that tailored information programs have a tremendous potential for reducing household electricity use (Schultz et al., 2007; Allcott, 2011; Ayres, Raseman, and Shih, 2012; Jacobsen, Kotchen and Vandenbergh, 2012; Costa and Kahn, 2013; Yoeli et al., 2013; Gilbert and Graff Zivin, 2014). These studies report significant conservation effects using social comparisons and other normative information based appeals to conserve energy. These studies build on seminal work in psychology by Robert Cialdini and colleagues (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 strategies. 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 view of behavioral persistence with information-based strategies is lacking. Further empirical research is needed to understand how consumers can stay engaged with information-based interventions and what framing is most effective to keep consumers engaged (Rogers and Frey, 2014). We ask, can information strategies motivate habit-forming behaviors for household energy conservation, and if so, what are the underlying mechanisms of change? We propose a dynamic behavioral model of curtailment using informative feedback and real-time appliance-level metering capabilities not previously available. Before we turn our attention to the details of the experiment and high-frequency results, we develop hypotheses regarding possible mechanisms of behavior change and habit formation. The goal of tailored information programs is to help consumers learn about the external effects of their individual electricity consumption, and hence provide foundations for ways in which psychological motives can influence conservation decisions at the individual level.

3. From Novelty to Persistence

Let us consider three temporally separable hypotheses, each involving the relationship between behavioral responses and information signals received. We propose two distinct mechanisms of behavior change: one increasing and another decreasing over time. The mechanism for increasing returns to information is the *novelty effect*, which encompasses learning with information and communication technologies; and the mechanism for decreasing returns to information is the *persistence effect*, which encompasses habit formation and is subject to the existence of information framing effects that depend on the type of information provisioning. We then discuss novelty and persistence in the context of two framing approaches to energy conservation that consider the unobserved monetary and social costs of electricity consumption, namely, a cost savings frame, and a health frame. We are interested in comparing the immediate and then long run effects of a health frame versus a cost savings frame for energy conservation.

3.1. Novelty Effects

Most households in the United States receive no information over their electricity usage apart from their monthly bills, which 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, the information is not only informative about the external effects of their consumption, but also inculcates learning and motivational effects in the household. In the social psychology literature, learning is a well-studied psychological mechanism resulting from information seeking and acquisition (Bandura, 1977). We postulate that there is a novelty associated with the *content* of tailored information received (e.g. the informational value of learning) and the *mode* of communication in which it is received (e.g. information technologies), which we refer to as the *novelty hypothesis*. We posit that the novelty of receiving electricity usage information with new technologies can increase engagement in the short-run—for example, reducing overall consumption levels or forgoing current for future consumption. Novelty effects amplify an immediate desire to act on alert-based information.

Novelty effects can explain immediate behavioral changes in both magnitude and direction of consumption. Prior research shows for example, that when fans learn that professional sports teams move in to a new stadium, the average attendance during the initial year the teams occupy the new stadium rises 22% (Howard and Crompton, 2003). This is the so-called stadium *novelty effect*. Other examples of novelty effects with information campaigns include the announcement through the national media of Betty Ford's and Happy Rockefeller's breast cancer diagnoses, which led to significant increases in breast cancer screenings in treatment centers in the initial year of media coverage (Fink et al., 1978).

Novelty effects can also lead to decreased consumption behavior. Well publicized health warnings of mad cow disease in 2003 led to short-term reductions in beef sales, and cattle futures (Schlenker and Villas-Boas, 2009); and mass market advertising campaigns about H1N1 swine flu in 2009, led to short-term reductions in the consumption of lean hogs (Attavanich, McCarl and Bessler, 2011). These exogenous events or natural experiments serve as examples where information diffusion was the primary vehicle to incite immediate behavioral responses, and where consumers voluntarily opted to adjust consumption.

When novelty effects are present, we expect to observe short-run conservation behavior. This is because we expect novelty to increase *engagement or involvement*, defined previously by Stone (1984) as the: "time and or intensity of effort expended in the undertaking of behaviors." In prior research, high consumer engagement has been linked with short-run responsiveness to framing interventions (Maheswaran and Meyers-Levy, 1990; Rothman et al., 1993; Millar and Millar, 2000). This reasoning therefore suggests the following hypothesis:

H1: *As households receive tailored information about the effects of their electricity use, novelty effects lead to immediate conservation behavior*.

3.2. Repetition Effects

Our novelty hypothesis opens the question as to what happens over time when information treatments are repeated? We could expect the effects of repetition to lead to either increasing or decreasing conservation behavior over time across a study population. On one hand, if information diffusion is gradual and behavior change occurs relatively slowly, then we could expect to observe increasing conservation behavior over time as more households learn and adopt energy saving practices. On the other hand, if novelty effects dominate and behavior change occurs relatively quickly through the use of technology, then we could expect the effects of repetition to lead to gradually decreasing conservation behavior over time, as households return to their normal consumption patterns. Under fast diffusion with information technologies, we hypothesize the latter—that the effects of normative information feedback should gradually decrease over time.

A reason for the waning effects of tailored information could be that novelty effects simply wear off and/or partial habituation occurs, leading to some long-run persistence of treatment effects, but with decreasing returns due to gradual consumer inattention or outside opportunity costs.

When economic value is placed on time, we posit that inattention or outside opportunity costs may become important sources of decreasing persistence of treatment effects. Consumers may simply lose motivation or gradually become inattentive to cue-based information treatments. We know that in consumption settings such as electricity, cellular phones, health care and debit cards, for example, consumers who have become inattentive to past usage sometimes experience "bill shock"—a term used to describe when consumers unwittingly cross certain consumption thresholds, exceeding plans or contracts, and often these rebounds in consumption result in usage fees or overdraft penalties (Grubb, 2015). If consumers become gradually inattentive to informative feedback about their energy usage, we could expect decreasing persistence as households who have initially taken energy saving actions might return to earlier patterns of consumption. Alternatively, consumers might also face outside opportunity costs, perhaps eventually substituting other sources of behavioral savings in the household budget, which might be perceived to be less costly. There can be a number of alternatives for households to achieve savings. Examples might include choosing to eat out less often (Beverly, McBride and Schreiner, 2003), seeking promotions in supermarkets (Moore, Sherraden, et. al., 2000) substituting generic for brand-name prescription drugs (Haas et al., 2005) etc., without the effort of attention to behavioral changes in their energy consumption habits. Recent supporting evidence for decreasing persistence of treatment effects have been shown in experimental papers by Allcott and Rogers (2014), Gilbert and Graff-Zivin (2014) and Dolan and Metcalfe (2013). These papers highlight the potential long-run persistence of experimental treatment effects with normative information strategies, but with diminishing returns over time.

If novelty effects drive immediate energy saving behavior (Hypothesis 1) and repetition effects lead to gradually decreasing energy saving behavior (Hypothesis 2), we posit that these mechanisms work in sequential, but opposing directions. While these two mechanisms alone might describe a testable paramorphic model of human behavior and underlying mental processes (Hoffman 1960), we argue that the long-run outcomes 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 the relative rates of increasing and decreasing conservation behavior over time. In order to highlight the importance of framing effects on long-run household conservation decisions, in the next section we discuss the two alternative framing approaches used in the experiment. This leads to the following hypothesis:

H2: *As tailored information received by households is repeated, conservation behavior gradually decreases.*

3.3. Moralized Consumers versus Cost Savings

In this study, 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 and even outperform information about private benefits such as cost savings. The authors do not however establish the persistence of these information-based approaches for conservation behavior over time. In this study, we experiment with a health framing approach to study dynamic behavior, which was designed to frame energy conservation as altruistic and raise the moral cost of energy use. The health framing approach to energy conservation re-focuses the consumer's marginal consumption as a moral judgment about the social costs of energy use acting though air pollution. Households receive repeated informational cues about the unobserved harm that their marginal electricity consumption does on others. We posit that our normative health frame leads to different *moral sensitivities* to external health damages from air pollution; which 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; Dietz, 2015). We refer to this as the *moralized consumer hypothesis*.

In the moral psychology literature, Nichols and Mallon (2006) consider 3 factors driving such moral judgments: (a) rule based norms (the societal norms of right and wrong, that is, learning that one's contribution to public health damages are bad), (b) mental assessment of costs and benefits, and importantly for information retention, (c) emotional activations. We know from a related body of evidence in neuroscience of the established link between emotions and moral judgments (Prinz, 2006). Emotional activations are known to facilitate long-term retention of information (Kleinsmith and Kaplan, 1963; Sharot, Delgado and Phelps, 2004; Sharot and Phelps, 2004) and this finding has been widely replicated in experimental psychology with several decades of research (see Heuer and Reisberg, 1992 for a review). For instance, injuring someone in a car accident will not be easy to forget. Likewise, learning that one's excess electricity consumption may be causing direct harm on others might lead to greater information retention, which we posit could translate into more persistent behavioral effects over time especially among those sensitized consumers for whom the information is salient. These three psychology-based rationalizations (societal norms of right/wrong, mental assessment of costs/benefits, and emotional responses to harm-norms) are consistent with behavioral economic models of decision-making and morally motivated behavior in markets (Fehr and Schmidt, 2006; Uhlmann, Pizarro, Tannenbaum and Ditto, 2009) as a non-price mechanism.

By contrast, the cost savings approach to conservation follows standard reasoning about private benefits from household energy savings. Standard theory 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 be crowded out (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. Further, a recent meta-analysis of energy conservation field studies (Delmas, Fischlein and Asensio, 2013), shows that monetary incentives and information do not necessarily lead consumers to save more and instead often lead to significant energy increases over time, rather than induce conservation. For these reasons, we predict the dynamics of behavior under the cost savings frame could under-perform relative to the health frame. Thus, we posit our third hypothesis:

H3: *As households receive repeated information feedback about their household electricity use, the health frame produces more lasting conservation effects versus a cost savings frame.*

In the next section, we describe the experiment and provide empirical tests of our behavioral hypotheses for novelty and persistence under two alternative framing approaches. We expect novelty effects to lead to immediate behavioral changes under both information strategies, but the persistence of the effects on consumers should differ by the decision frame. We expect consumers who receive health-based messaging to have a higher level of engagement, and more persistent behavior change over time versus the cost savings frame, especially for those consumer groups for whom health impacts on others might be particularly salient; in particular, urban communities and families with children, which we target in this study.

4. The Field Experiment

A randomized controlled trial was conducted with residential consumers to test our behavioral hypotheses. We provided real-time, appliance-level smart metering energy feedback to residential households in a large residential community in Los Angeles over 8 months, with 118 family apartments and 440,059 panel observations of hourly kilowatt-hour (kWh) electricity consumption. We monitored electricity usage directly in each of the participant households. 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, see Chen, Delmas and Kaiser (2014). We note that before the availability of advanced metering infrastructure (AMI) 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.

Our field experimental site, University Village, is located in proximity to public transportation, local businesses, parks and schools. It is a multiple building, family apartment/condo-style housing complex with 1,103 units. 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 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. Residents are younger and more educated than the U.S. population, 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. We note that our experimental results represent outcomes of real-life consumptions decisions in their natural settings. All residents pay their own electricity bills.

Randomly selected households were assigned into one of two treatment groups. One group of households received energy use feedback with cost savings information compared with the top 10% most efficient neighbors of similar size. Another group of households received energy use feedback with tailored information about the environmental health consequences of their consumption, specifically, pounds of air pollutants and a listing of health consequences, namely, childhood asthma and cancer.

As in standard framing theory, we maintain *logical equivalence* by translating consumed kilowatt-hours into dollars or health costs. For example, 1 unit of a consumed kilowatt-hour of electricity can be converted into either equivalent costs using electric utility rates, or equivalent pounds of air pollutants using local power plant emission factors. Other potential equivalencies for energy conservation, such as equivalent cars on the road, pounds of coal burned, trees saved, or other emissions related metrics are possible, but tested lower in stated willingness-to-save estimates in our survey pre-tests.[‡] Weekly updating treatment messages were sent to participants via e-mail alerts and were accessible via a website with information graphics and consumer-friendly design (Appendix 1). Both treatment groups received weekly e-mail alerts and real-time access to energy use data. A third randomly assigned group was monitored for electricity use, but only received information feedback through their electricity bill. 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.

[‡] A thorough listing of emissions equivalencies and calculation methodologies is available at the U.S. EPA's Green Power Equivalency Calculator website (http://www.epa.gov/greenpower/pubs/calculator.htm). For further discussion of logical equivalence in framing theory, see Keren (2011), Chong and Druckman (2007) and Levin, Schneider and Gaeth (1998).

We provided households with factual, evidence-based numbers that depended on their weekly consumption and were specific to their community. The representative messages for our two decision frames are shown below:

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.

All social and monetary costs were presented to households in numerical and scientifically verifiable terms. The 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 emitted air pollutants for a median 2-bedroom apartment was about 979 lbs. and ranged between 131 lbs. and 4058 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 note that these quantified savings opportunities are typically unobserved by consumers between billing periods or are not available at all, as we normalized the savings estimates to achievable benchmarks of households of similar size and occupancy in the community. Our treatment messages were also pre-tested in a series of questionnaires for clarity, comprehension and stated willingness-to-save energy with independent populations.

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 state these two assumptions formally in Appendix 2 and then discuss the empirical strategy in the next section.

5. Empirical Model

To test our behavioral hypotheses, we estimate dynamic treatment effects over time, following a 6-month baseline-monitoring period. For household *j*, in treatment group *i*, at time *t*, we estimate treatment effects of information provision with the following econometric model:

$$E_{ijt} = \sum_{h_t} \tau^{h_t} P_{it} T_i + \boldsymbol{\Gamma H}_j + \boldsymbol{\Theta \Psi}_t + \gamma_t + \varepsilon_{jt}, \quad h_t = \{0, \ldots, t\} \tag{1}$$

We regress the hourly 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 an event-time indicator equal to 1 during the post-treatment period, and 0 during the baseline period. Treatment status is identified exclusively 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 produce a time series of average treatment effects (ATEs), τ^{h_t}, over a window of analysis from $h_t = \{0, \ldots, t\}$. We include a vector of observable household characteristics $\boldsymbol{H}_j$, weather controls $\boldsymbol{\Psi}_t$, and $\boldsymbol{\Gamma}$ and $\boldsymbol{\Theta}$ are coefficient vectors. Time fixed effects are denoted by γ_t and the residual error is captured in ε_{jt}. Errors are clustered at the household level. In the absence of informative feedback, we assume counterfactual consumption levels follow a matched control group sample or statistical reference level, which is standard practice in evaluating RCTs.

Household Level 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 an important statistical control for household environmentalist ideology. 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.

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 quality-controlled, local weather data provided by the National Oceanic and Atmospheric Administration (NOAA). Outside dry bulb 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, making our hourly kWh observations compatible with outside weather variation. The hourly updating weather vector is $\boldsymbol{\Psi}_t = [\Psi_t^H, \Psi_t^C]$:

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

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

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 θ_{OUT} and the indoor base temperature θ_b, 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 of the week dummies to capture common time trends (or cycles) in the data and any calendar shocks on consumption. Our experimental approach addresses key 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.

We carefully considered the effects of a large effective sample size for this case given a fixed N and large T dimension across households. 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. 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 DID papers implement 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.

Our standard errors improve as our sampling window grows and they are satisfactory due to a number of important design considerations. First, we have very high-resolution measurement, down to individual appliances, in which both make and model of all appliances has been standardized across the community. This provides for more precise behavioral estimates than is otherwise possible in comparable studies with monthly residential billing data, in which the stock of buildings and ordinary household appliances such as the refrigerator, dishwasher or programmable thermostats is very heterogeneous. Second, we control for time-varying characteristics on consumption very precisely by the use of rigorous degree hours, which offers a finer resolution controls for weather variability than typical approaches that use aggregated heating and cooling degree-days, or that have no weather controls at all.

[Insert Table 1 about here]

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6. Results

Table 1 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 fixed effects. Column VI in Table 1 shows the results of a regression testing for significant differences between groups. 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 our randomization procedure. One exception is the variable representing membership in an environmental organization, which is significant at the 10 percent level (Table 1, Column VI). 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 of belonging to an environmental organization as a proxy for green behavior. These results show no significant interaction of environmentalist households with either treatment, meaning these households do not drive the study's primary results.

We also tested for potential differences in baseline characteristics between the total population of households at our field site and our sample of volunteer households. Among the 1,103 households at University Village, 226 households volunteered in our experiment and another 88 households in our entry survey chose not to participate. This reflects a participation rate of 20%. We then randomly selected 118 participating households in our field experiment from these 226 volunteers. 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. We conducted an ex-ante analysis of electricity meter readings for 12 months prior to the start of the experiment and found no significant differences between participating and non-participating households. These additional results are available upon request from the authors. Next, we evaluate the dynamic effects on behavior.

6.1. The First 48 Hours: The Salience of Novelty

In this section, we study the hypothesis that novelty effects increase consumer engagement leading to immediate behavioral changes in consumption. In Figure 2, we plot the hourly treatment effects and 95% confidence intervals in event time for the first 48 hours after the start of information treatments. The dynamic treatment effects (DTEs) are shown in percentage change versus the control group and net of all observable controls, including outside weather variation, which can be a significant source of estimation error at this high time-resolution. By convention, negative values in percentage change mean energy savings (conservation) and positive values in percentage change mean energy increases (splurging behavior) relative to control.

Behavioral changes are immediate. Consistent with our predictions, we observe rapid and increasing conservation behavior under both decision frames as shown in Figure 2. Our dynamic treatment effects are negative, meaning consumers take immediate energy savings actions, and we report significant effects after only 12 hours for the health group, and after 13 hours for the cost savings group when the upper 95% confidence intervals thresholds become negative. Figure 2 shows that short-run adjustments in consumption occur within the first day of treatment and these effects persist throughout the day, which indicates both immediate load shifting and conservation behavior.

The novelty of receiving information feedback about electricity use with information technologies has increased salience for treated households, and as a result, we observe dynamic changes in consumption at very high temporal resolution. In classic habit-formation models, the utility derived from current consumption is typically modeled as weighted values of past consumption (Duesenberry, 1949; Brown, 1952; Pollak, 1970; Ryder and Heal, 1973; Becker and Murphy, 1988). These models provide excellent theoretical support for monotonically rising, falling or hump-shaped consumption profiles (Carrol, Overland and Weil, 2000; Fuhrer, 2000) in which behavioral changes in consumption are typically slow to adjust in the short-term, but not in the long term. Our finding of immediate and significant energy savings behavior is quite remarkable as it occurs after a time lapse of only hours (not days, weeks or months) since the first notification e-mail and website was made available to participants. This immediate savings behavior observed with use of information technologies also appears to work favorably across treatment types, as both cost savings and health groups respond immediately to the treatment. Thus, we provide evidence that novelty effects with information and communication technologies can be observed in multiple decision frames (at least two); and appear to be limited only by the speed of information diffusion, and the time it takes for any immediate behavioral actions to take effect. We show that consumers respond immediately to the treatment.

6.2. Peak Energy Savings

Having demonstrated that electricity usage feedback can drive immediate behavioral savings, we monitored the treatment effects in event time to understand what can be learned about the maximum savings potential under our two framing approaches. We estimated hourly DTEs using a high frequency analysis. Treatment status for the experiment begins at approximately 9:30 a.m. on Tuesday mornings, when weekly e-mail alerts were sent to participants for about 13 weeks. In Figure 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 in Table 2.

[Insert Table 2 about here]

We find that peak energy savings occurs quickly within 12 and 13 hours, respectively for treated households randomly assigned to receive health and cost savings messages. By time-of-day, peak conservation occurs at approximately 9:00 p.m. (21:00) and 10:00 p.m. (22:00) in the evening, when most residents are home and peak consumption occurs for the community-at-large. At these peak community usage hours, the magnitudes of the energy savings are considerable: 14.9% peak conservation potential under the cost savings frame and 27.2% peak conservation potential under the health frame (Table 2) although there is considerable variance in the behavioral estimates in the first few hours. In the next section, we explore the magnitudes of the energy savings in terms of the underlying appliance behaviors. It turns out peak conservation occurs very quickly for both treatment groups, within half a day from the start of treatment. These results are consistent with experimental evidence by Gilbert and Zivin (2014) and Allcott and Rogers (2014) who also document that the greatest magnitudes of energy savings occurs on the first day households receive their home energy reports; although the exact time of information delivery are typically unobserved in these studies, as the authors report *intent-to-treat* effects around a fixed window surrounding the mailing of the home energy report. 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 (Appendix 3) in which we show very high compliance to our information-based alerts among participant households.

6.3. Behavioral Persistence

We extended our high frequency analysis to 100 days of treatment, which is the approximate duration of a typical information campaign during peak winter or summer months. Figure 3 shows the dynamic treatment effects and 95% confidence intervals over the full treatment horizon. Figure 4 shows the distribution of daily treatment effects in the study. The supporting point estimates are also shown in Table 3A and 3B at regular intervals for the first week of treatment (novelty period- Table 3A) and subsequent weeks (persistence 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).

[Insert Table 3A and 3B about here]

Following peak conservation, we observe significant but decreasing persistence of treatment effects over time. This result is consistent with our predictions in Hypothesis 2, which predicts decreasing returns to information during the persistence period, although the dynamic behavior follows markedly different consumption profiles depending on the household assignment. For households randomly assigned to receive cost savings messages, the effects decay very rapidly. By the end of 100-day experimental monitoring period, we observe no significant conservation behavior after about 6 weeks (Table 3B). 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 6%, which is on the high end of prior experimental studies with social norm-based approaches. These dynamic treatment effects by framing intervention are summarized in Appendix 4.

6.4. Appliance Dynamics

We can additionally decompose the dynamic treatment effects at the appliance level for apartments in the study. Here we document that conservation behavior may be observed in certain appliance-level consumption categories and not others. Appendix 5 for example shows the appliance dynamics for the lighting, heating and cooling, plug load and other kitchen appliances. Lighting conservation is the most persistent form of behavior change observed during the experiment for both treatment groups. While this is certainly evidence that households have adopted new energy savings practices versus the control group due to a causal treatment, 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 and (b) lighting conservation, but not space heating and cooling (Appendix 5). It turns out that as a share of household appliances, plug load is the largest share of total energy use in the community, so plug load management drives the primary results and strong behavioral persistence of household conservation in the health group over time. By contrast, the weak behavioral persistence 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. We see that framing has dramatic implications with regard to effectiveness and underlying appliance behaviors. While this behavior certainly raises new questions about why framing should lead to variation in appliance-level responses, we provide partial support for new habit-forming behaviors from a causal treatment, particularly for the health-based frame. While we make important strides in understanding the role of framing on the dynamics of consumption, further research is needed to understand the drivers of conservation at the appliance level. These results are the first known experimentally measured conservation treatment effects at the appliance level.

6.5. Consumer Engagement

In this section, we analyze dynamic behavior with various measures of engagement. Several scientific articles have begun reporting the use of Google Analytics as a web analytics tool (Plaza, 2009; Goncalves and Ramasco, 2008) to learn about revealed consumer behavior. Google analytics can track users in real-time as they navigate a website and hence characterize the interactions between users, website content and the activity patterns of a population. All treated households had unrestricted Internet access in the community. For households assigned to either treatment, we monitored their website interactions with our information treatments using Google analytics. Our aim here is to learn about their revealed behavior through interactions with information technologies.

Information framing can lead to different website behavior and engagement. Table 61 in Appendix 6 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 unique page entrances, total events, count of sessions, time on page, exit rates and bounce rates for their individual dashboards (see sample screenshot in Appendix 1). Interestingly, 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 our reported measures of engagement. They viewed the pages more often, clicked more often, stayed longer on the website and had lower exit rates and lower bounce rates. These differences are statistically significant at the 5% level (Table 62 in Appendix 6). Households assigned to receive health messages were significantly more engaged with the electricity usage information than those households who received cost savings information (Table 61).

We also observe the greatest number of page entrances on Tuesdays, which was the particular day of the week in which we sent participants weekly reminders with their electricity usage feedback. 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. In our experiment, the timing of the reminders was weekly. 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 dynamics 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.

7. Discussion

We wish to emphasize three 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 household conservation problem, we demonstrate the power of information as a non-price mechanism for behavior change and more sustainable consumption. 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 days, 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, these dynamic framing effects with tailored information provision can occur without changes to existing billing rates, pricing structures or available monetary incentives. The principal value delivered to consumers is in the value of information. We argue that behavioral savings 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, 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 standard errors, 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 8 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 maintain *logical equivalence* of our decision frames by converting 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 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; Tully and Winer, 2014). 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 and big data analytics for behavioral research in management and energy conservation. 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 of 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 for a better understanding of consumers' response to innovation (Hauser, Tellis, and Griffin, 2006). From a managerial perspective, to provide useful insights and decision-making support, managers must be capable of framing the appropriate analytical solutions. The importance of an organization-wide culture for informed fact-based decision making for business analytics is emphasized by Davenport (2006). To support such a culture, managers need to know not only how to turn raw data and information (through analytics) into meaningful and actionable knowledge for an organization, but also how to properly interact with and communicate this knowledge to the other members of the organization.

More generally, this paper contributes to an emerging literature on behavioral "nudges" as non-pecuniary strategies for behavior change (Camerer et al., 2003; Thaler and Sunstein, 2003; Ratner et al., 2008). We introduce framing and provide new methodologies 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 literature on non-price incentives for energy conservation and pro-environmental behavior with novelty and persistence effects as temporal mechanisms to overcome biases and existing patterns of behavior using repeated information strategies (Steg and Vlek, 2009; Kollmus and Agyeman, 2010; Delmas, Fischlein and Asensio, 2013). Information framing can be used as a general consumer strategy, particularly in settings where price-based policies may not be politically feasible or effective. We argue that the relative importance of the environmental health effects of air pollution on household electricity consumption decisions 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 Baseline Usage 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. $Y_0^T - Y_0^C$ (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 Treatment	Net Conservation after 100 days
Monetary Savings Group	-14.9%	9:00-10:00pm	12 hrs.	Not significant
Health Group	-27.2%	10:00-11:00pm	13 hrs.	-6.0%
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: Total hourly kWh	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(7)**	**(9)**	**(10)**
	1 hour	**6 hours**	**12 hours**	**18 hours**	**24 hours**	**36 hours**	**48 hours**	**1 week**
Experimental								
Post-Treat*Cost Savings Group	**-8.658**	**-6.552**	**-14.07*** **	**-9.545** **	**-9.267*** **	**-4.603**	**-4.516***	**-10.98*** **
	(17.10)	(6.579)	(4.813)	(3.980)	(3.468)	(2.841)	(2.461)	(1.325)
Post-Treat*Health Group	**-23.78**	**-16.79** **	**-27.21*** **	**-18.97*** **	**-15.87*** **	**-10.86*** **	**-9.442*** **	**-8.485*** **
	(16.98)	(6.547)	(4.782)	(3.956)	(3.446)	(2.824)	(2.452)	(1.320)
Household Characteristics								
Adults	-11.73***	-11.47***	-11.46***	-11.46***	-11.43***	-11.40***	-11.42***	-11.65***
	(0.543)	(0.544)	(0.543)	(0.542)	(0.541)	(0.539)	(0.537)	(0.521)
Children	13.66***	13.63***	13.60***	13.59***	13.59***	13.58***	13.56***	13.43***
	(0.195)	(0.194)	(0.194)	(0.194)	(0.193)	(0.193)	(0.192)	(0.187)
Apartment Size (No. of bedrooms)	36.88***	36.86***	36.87***	36.81***	36.83***	36.78***	36.58***	35.95***
	(0.785)	(0.784)	(0.783)	(0.782)	(0.781)	(0.778)	(0.776)	(0.754)
Floor Plan (nominal square footage)	-0.0429***	-0.0430***	-0.0427***	-0.0425***	-0.0426***	-0.0425***	-0.0420***	-0.0401***
	(0.00261)	(0.00261)	(0.00261)	(0.00260)	(0.00260)	(0.00259)	(0.00258)	(0.00251)
Building Floor	6.600***	6.618***	6.598***	6.596***	6.598***	6.562***	6.548***	6.588***
	(0.171)	(0.171)	(0.171)	(0.171)	(0.171)	(0.170)	(0.170)	(0.165)
Member of Environmental Organization	-1.077**	-1.206***	-1.232***	-1.241***	-1.234***	-1.232***	-1.234***	-1.936***
	(0.427)	(0.428)	(0.427)	(0.427)	(0.426)	(0.424)	(0.423)	(0.411)
Weather Controls								
Heating Degree Hours	0.965***	0.966***	0.969***	0.966***	0.959***	0.963***	0.955***	0.955***
	(0.0349)	(0.0348)	(0.0349)	(0.0348)	(0.0348)	(0.0347)	(0.0347)	(0.0341)
Cooling Degree Hours	0.0485	0.0488	0.0520	0.0455	0.0403	0.0461	0.0400	0.0256
	(0.0682)	(0.0681)	(0.0682)	(0.0681)	(0.0681)	(0.0680)	(0.0679)	(0.0674)
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	74.74***	74.29***	74.07***	73.88***	73.93***	73.91***	73.76***	73.35***
	(1.664)	(1.663)	(1.663)	(1.660)	(1.657)	(1.653)	(1.647)	(1.604)
Number of Observations	256,606	257,236	257,877	258,491	259,114	260,373	261,627	273,794
Number of Apartments	118	118	118	118	118	118	118	118
Wald chi-square (d.f. > 40)	35,631***	35,619***	35,752***	35,805***	35,892***	36,085***	36,270***	37,882***

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3B. Dynamic Treatment Effects by Framing Intervention

Dependent variable: Total hourly kWh	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
	Repeated Weekly Treatment: Persistence											
	2 weeks	**3 weeks**	**4 weeks**	**5 weeks**	**6 weeks**	**7 weeks**	**8 weeks**	**9 weeks**	**10 weeks**	**11 weeks**	**12 weeks**	**13 weeks**
Experimental												
Post-Treat*Cost Savings Group	**-9.259*** **	**-5.740*** **	**-3.697*** **	**-1.600*** **	**-0.670**	**-0.273**	**-0.514**	**0.0345**	**0.867** **	**0.527**	**0.495**	**0.387**
	(0.935)	(0.761)	(0.660)	(0.592)	(0.539)	(0.495)	(0.463)	(0.437)	(0.414)	(0.398)	(0.384)	(0.372)
Post-Treat*Health Group	**-9.146*** **	**-6.517*** **	**-5.764*** **	**-5.034*** **	**-4.860*** **	**-5.524*** **	**-6.327*** **	**-5.777*** **	**-5.323*** **	**-5.267*** **	**-5.316*** **	**-5.920*** **
	(0.925)	(0.754)	(0.656)	(0.587)	(0.533)	(0.489)	(0.455)	(0.429)	(0.407)	(0.393)	(0.378)	(0.364)
Household Characteristics												
Adults	-10.52***	-10.06***	-10.04***	-9.431***	-8.996***	-8.302***	-7.858***	-6.756***	-6.350***	-5.280***	-4.638***	-4.212***
	(0.499)	(0.476)	(0.460)	(0.441)	(0.426)	(0.412)	(0.400)	(0.391)	(0.383)	(0.377)	(0.369)	(0.363)
Children	13.30***	13.33***	13.22***	13.12***	12.79***	12.81***	12.66***	12.55***	12.67***	12.51***	12.47***	12.64***
	(0.179)	(0.173)	(0.167)	(0.161)	(0.156)	(0.152)	(0.147)	(0.144)	(0.140)	(0.138)	(0.135)	(0.134)
Apartment Size (No. of bedrooms)	36.13***	34.75***	34.22***	33.37***	32.79***	31.79***	30.20***	30.03***	28.94***	30.39***	30.33***	30.16***
	(0.723)	(0.695)	(0.673)	(0.650)	(0.630)	(0.611)	(0.593)	(0.581)	(0.568)	(0.566)	(0.556)	(0.545)
Floor Plan (nominal square footage)	-0.0411***	-0.0379***	-0.0373***	-0.0352***	-0.0334***	-0.0296***	-0.0235***	-0.0216***	-0.0176***	-0.0210***	-0.0197***	-0.0189***
	(0.00241)	(0.00232)	(0.00225)	(0.00217)	(0.00211)	(0.00205)	(0.00199)	(0.00195)	(0.00191)	(0.00190)	(0.00186)	(0.00183)
Building Floor	6.592***	6.648***	6.687***	6.752***	6.795***	6.733***	6.866***	6.914***	6.989***	7.045***	7.008***	7.057***
	(0.159)	(0.153)	(0.148)	(0.143)	(0.139)	(0.135)	(0.132)	(0.129)	(0.126)	(0.124)	(0.121)	(0.119)
Member of Environmental Organization	-2.477***	-2.423***	-2.444***	-2.812***	-3.037***	-3.318***	-3.513***	-3.705***	-3.938***	-4.645***	-4.917***	-4.938***
	(0.393)	(0.379)	(0.367)	(0.356)	(0.346)	(0.335)	(0.327)	(0.325)	(0.326)	(0.325)	(0.322)	(0.316)
Weather Controls												
Heating Degree Hours	0.923***	0.906***	0.899***	0.907***	0.905***	0.915***	0.921***	0.934***	0.925***	0.936***	0.944***	0.968***
	(0.0331)	(0.0323)	(0.0314)	(0.0307)	(0.0302)	(0.0298)	(0.0295)	(0.0294)	(0.0289)	(0.0288)	(0.0284)	(0.0282)
Cooling Degree Hours	-0.0147	0.0691	0.0513	0.0282	0.0140	0.0166	-0.0126	-0.0141	-0.00254	0.0101	0.00527	0.0291
	(0.0659)	(0.0630)	(0.0622)	(0.0615)	(0.0601)	(0.0597)	(0.0591)	(0.0585)	(0.0577)	(0.0577)	(0.0569)	(0.0566)
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	71.71***	70.27***	70.08***	67.96***	66.52***	63.72***	60.05***	55.93***	53.54***	51.30***	48.89***	47.17***
	(1.540)	(1.483)	(1.436)	(1.392)	(1.351)	(1.312)	(1.281)	(1.255)	(1.232)	(1.212)	(1.191)	(1.171)
Number of Observations	291,038	308,164	324,705	342,253	359,450	377,266	394,844	412,452	429,784	446,028	462,369	477,876
Number of Apartments	118	118	118	118	118	118	118	118	118	118	118	118
Wald chi-square (d.f. > 40)	40,892***	43,466***	45,920***	48,492***	51,146***	54,215***	57,066***	59,548***	61,803***	64,587***	66,656***	69,153***

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figure 1. Peak Energy Savings: The First 48 hours.

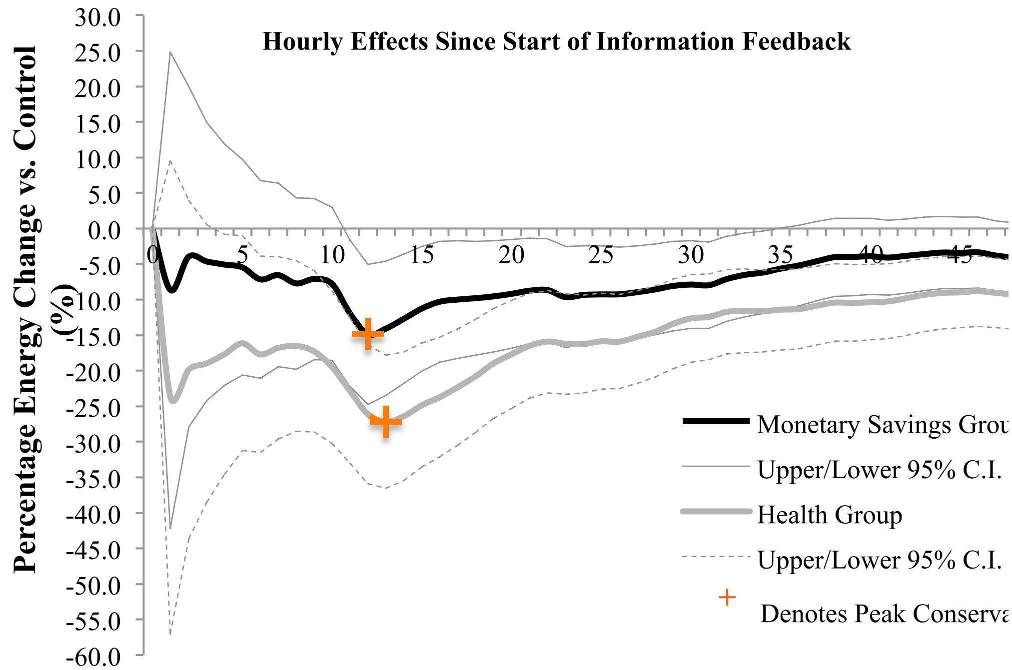
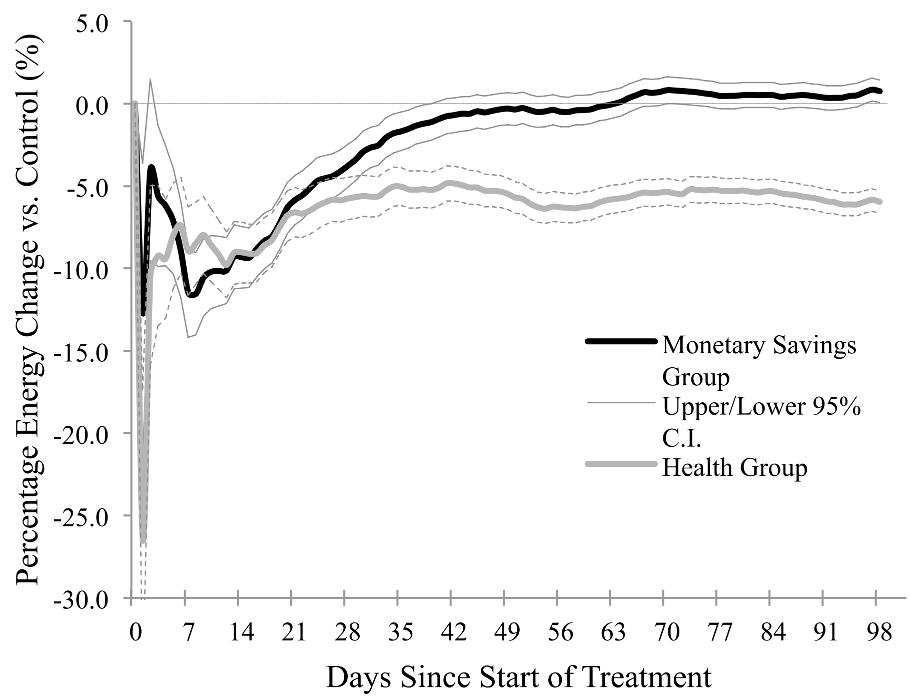
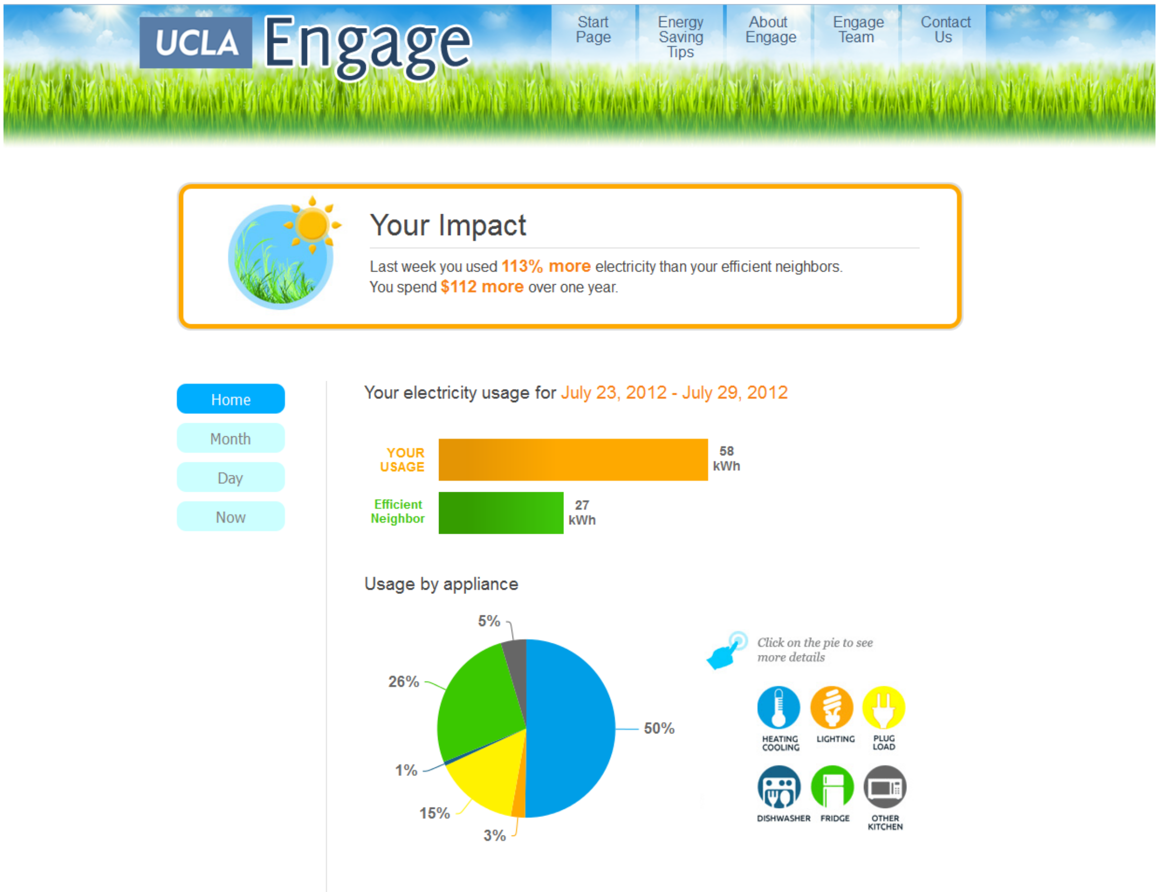


Figure 2. Dynamic Treatment Effects by Framing Intervention



Appendix 1. Consumer Website



Appendix 2 Proof of Identification

Following Manski (1996), we extend the proof of identification for classical experiments in the case of two independent, randomly assigned treatments with known treatment shares (e.g. the fraction of households receiving treatment) and high compliance to treatment. Let $\Re$ denote the randomization treatment rule which specifies treatments received by all households j=1,2,...N. For each household, let ξ_j denote the *received* information treatment by each household in the study population. The population outcome for each household in the study $y_j^{\Re}$ can be represented as,

$$y_j^{\Re} \equiv \sum_{t \in T} y_j(t) \cdot 1[\xi_j = t] \tag{1}$$

where 1 is an indicator function, equals 1 if $\xi_j = t$ and 0 otherwise. Under rule $\Re$, the outcome distribution conditional on observed covariates X is:

$$P(y_j^{\Re} \mid X) = \sum_{t \in T} P[y_j(t) \mid X, \xi_j = t] \cdot P(\xi_j = t \mid X), \qquad \forall t \in T \tag{2}$$

The first term on the RHS in (2) is the experimentally observed outcome distributions, conditioning on X and received information treatments ξ_j. The second term on the RHS is the conditional probability of receiving treatment. Elements of the set of feasible treatments $t \in T$ are independent of one another. Write

$$P[y_j^{\Re}(t)] = P[y_j^{\Re}(t) \mid X, \xi_j = t] \cdot P(\xi_j = t \mid X)$$

$$+ P[y_j^{\Re}(t) \mid X, \xi_j \neq t] \cdot P(\xi_j \neq t \mid X) \quad \text{(by law of Total Probability)} \tag{3}$$

But $P[y_j^{\Re}(t) \mid X,\ \xi_j = t] \equiv P[y_j^{\Re}(t) \mid X]$ by conditional independence, which maintains the statistical independence of the household's behavioral $y_j(\cdot)$ response function from treatment selection. For feasible treatments, $T = \{t_0, t_1, t_2\}$, the outcome distribution becomes:

$$P[y_j^{\Re}(t) \mid X] \quad = P[y_j^{\Re}(t_0) \mid X] \cdot P(\xi_j = t_0) \quad \text{(control)}$$

$$+P[y_j^{\Re}(t_1)\,|\,X]\cdot P(\xi_j = t_1) \text{ (treatment 1)}$$

$$+P[y_j^{\Re}(t_2)\,|\,X]\cdot P(\xi_j = t_2) \text{ (treatment 2)} \qquad (4)$$

By design, known fractions p_1, p_2 of the study population receive treatments t_1 and t_2 respectively. The ex-ante treatment shares are $P(\xi_j = t_1) \equiv p_1$ for treatment 1, $P(\xi_j = t_2) \equiv p_2$ for treatment 2, and its complement, $P(\xi_j = t_0) \equiv 1 - p_1 - p_2$ for the non-treated control group.

Since treatment shares are known, the probabilites $P(\xi_j = t)$ are identified for each $t \in T$. Household outcomes $P[y_j^{\Re}(t_i)\,|\,X]$ are also experimentally observed for each treatment group *i*. Therefore, each term on the RHS of (4) is point-identified for the study population.

It follows that the the identification region, *H* for all treated households is:

$$H\{P[y_j^{\Re}(t_{1,2})\,|\,X]\} \text{ (monetary savings or health group)}$$

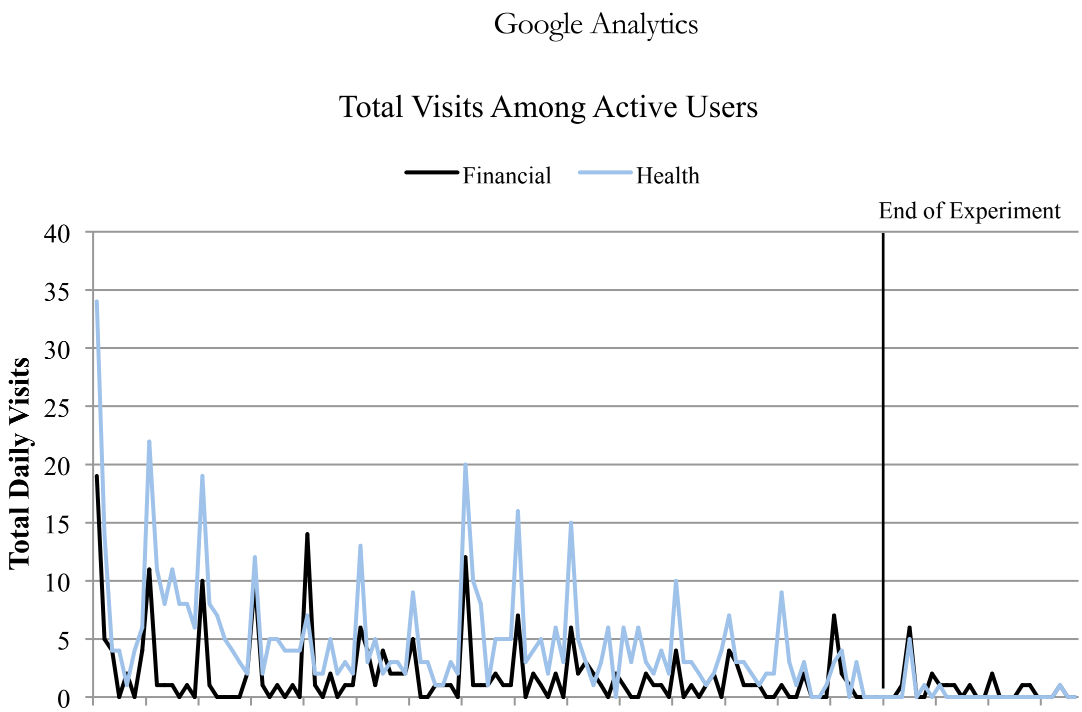
$$= [0,1] \cap \left[\{P[y_j^{\Re}(t_1,t_2)\,|\,X, \xi_j = (t_1,t_2)] - (1 - p_1 - p_2)\} / p_1 + p_2,\ P[y_j^{\Re}(t_1,t_2)\,|\,X / (1 - p_1 - p_2)] \right] \quad (5)$$

The identification region, *H* for non-treated control households is:

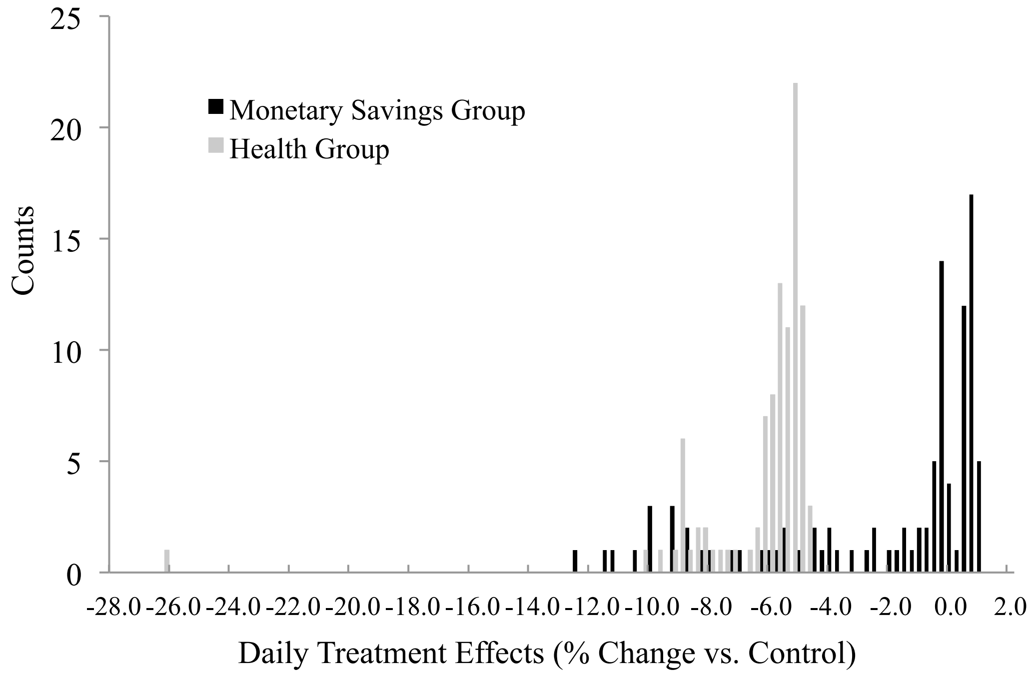
$$H\{P[y_j^{\Re}(t_0)\,|\,X]\} \text{ (control group)}$$

$$= [0,1] \cap \left[\{P[y_j^{\Re}(t_0)\,|\,X, \xi_j = (t_0)] - (p_1 + p_2)\} / (1 - p_1 - p_2),\ P[y_j^{\Re}(t_0)\,|\,X / (p_1 + p_2)] \right] \qquad (6)$$

Appendix 3 Participant Engagement

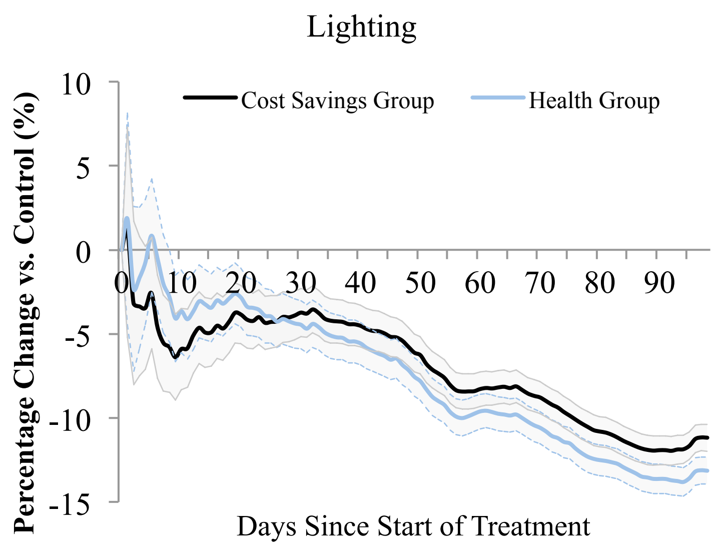


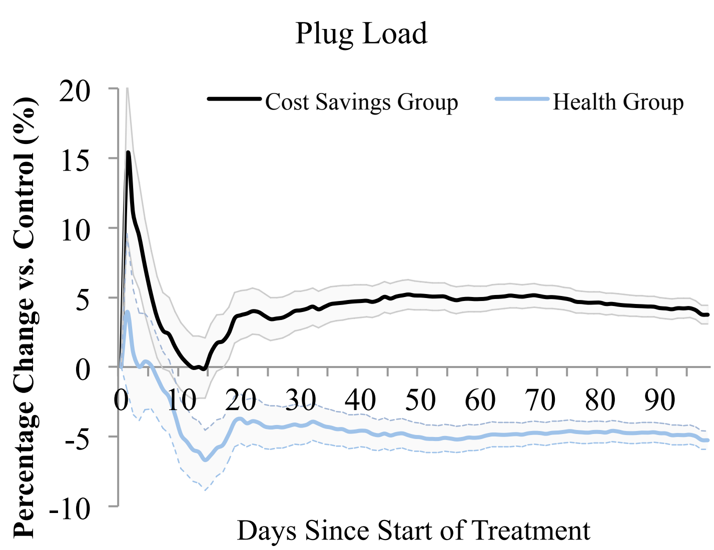
Appendix 4. Distribution of Daily Treatment Effects

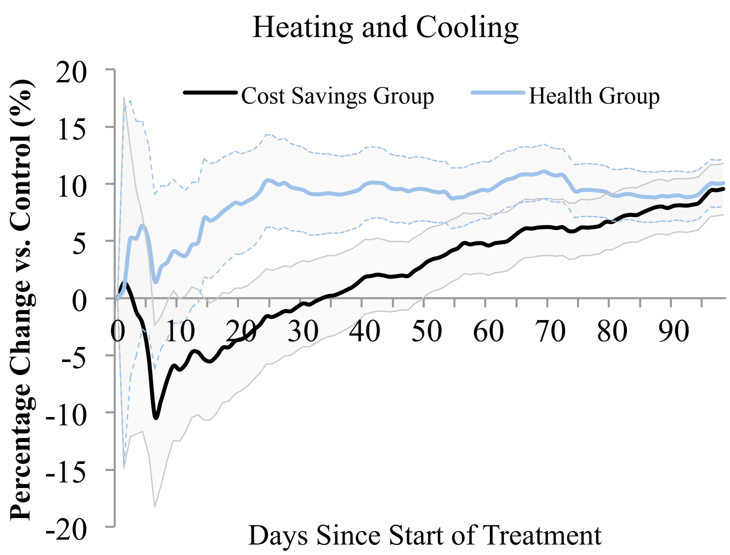


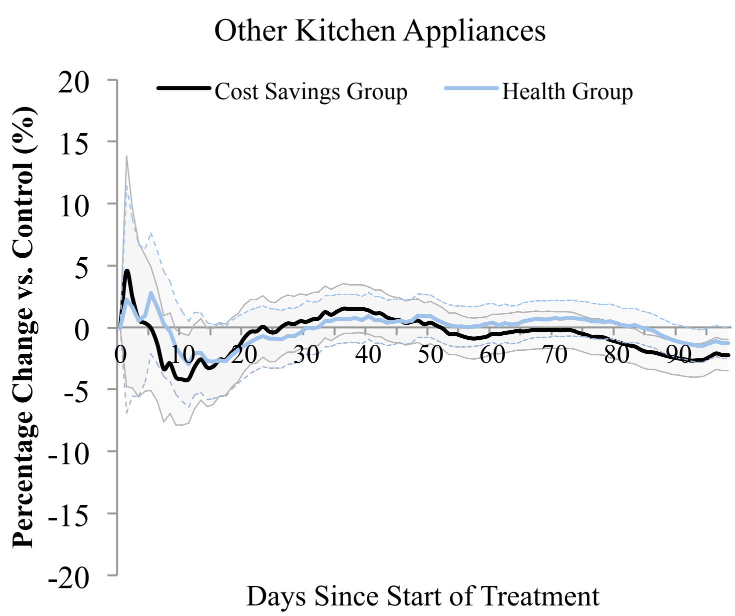
Appendix 5 Appliance Dynamics

Dynamic Treatment Effects at the appliance-level.






Heating and Cooling
Cost Savings Group
Health Group
Percentage Change vs. Control (%)
20
15
10
5
0
-5
-10
-15
-20
0
10
20
30
40
50
60
70
80
90
Days Since Start of Treatment


Other Kitchen Appliances
Cost Savings Group
Health Group
Percentage Change vs. Control (%)
20
15
10
5
0
-5
-10
-15
-20
0
10
20
30
40
50
60
70
80
90
Days Since Start of Treatment

Appendix 6 Website Analytics

A61. Engagement Metrics by Group

	Cost Savings Group					Health Group					
Variable	Obs.	Mean	St. Dev.	Min	Max	Obs.	Mean	St. Dev.	Min	Max	*p*-value
Daily Page Entrances	260	0.7	0.4	0	1	752	0.6	0.49	0	2	.001
Total Events	260	9.9	30.0	0	185	752	41.8	63.7	0	261	.000
Count of Sessions	260	7.4	16.6	1	131	752	10.4	16.7	1	121	.012
Time on Page (sec)	260	322.9	1,265.0	0	13,884	752	520.6	2,161.7	0	26,040	.163
Exit Rate	260	71.8	40.9	0	100	752	56.5	47.1	0	100	.000
Bounce Rate	260	22.2	41.4	0	100	752	17.4	37.5	0	100	.083

A62. Website Page Entrances by Day of Week

	Cost Savings Group			Health Group			
Day of Week	Panel Freq.	Percent %	Cum. %	Panel Freq.	Percent %	Cum. %	*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