Behavioral responses to real-time individual energy usage information: A large scale experiment

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Magali Delmas
Institute of the Environment
Anderson School of Management
University of California—Los Angeles
delmas@ioe.ucla.edu

William Kaiser
Department of Engineering
University of California—Los Angeles
kaiser@ee.ucla.edu

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Disclaimer

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ABSTRACT

Electricity generation accounts for over 40 percent of the carbon dioxide emitted by the United States. ENGAGE investigates how real time appliance level energy usage information provided through advanced metering technology can induce conservation behavior. ENGAGE leverages a large asset of advanced residential energy monitoring technology deployed in 120 apartments in Los Angeles. ENGAGE systems frame energy feedback to optimize motivations to reduce energy use by recognizing that the impact of electricity use on the environment, on health, or on the community are often 'invisible' to consumers. We experiment with different message formats to identify best practices and optimal messaging. Specifically we compare the effectiveness of messages based on the environmental or health benefits associated with conservation to more conventional messages focused on the pecuniary savings associated with conservation. Our results, based on a panel of 440,059 hourly observations for 118 residences over 8 months show that health-based messages, which communicate the public health externalities of electricity production, outperform monetary savings information as a driver of behavioral change in the home. Participants who received messages emphasizing air pollution and health impacts associated with energy use reduced their consumption by 6% over the experimental period as compared to the control group. Health messaging was particularly effective on families with children, who achieved up to 19.8% savings. No significant conservation was found for participants who received messages informing them about monetary savings. Our research advances our knowledge of effective non-price incentives for energy conservation.

2 EXECUTIVE SUMMARY

Background

Residential and commercial buildings collectively account for over two-thirds of electricity usage and about a quarter of carbon emissions (EPA 2010, EIA 2010). The large impact of building energy usage is not surprising considering that residents of the United States spend more than 90 percent of their lives indoors (Evans and McCoy, 1998). Recent studies estimate that behavioral changes can reduce residential energy consumption between 22 and 30 percent over the next 5 to 8 years (Laitner et al, 2009; Gardner & Stern, 2008). One potentially major behavioral innovation aims to provide more detailed feedback to consumers about their energy usage, both in the private and public spheres. While currently most U.S. residential electricity consumers receive low resolution feedback through a monthly bill, the massive deployment of more than 65 million digital electricity meters by 2015 (Edison Foundation, 2011), will allow utilities to provide a wealth of new information to more than half of the nation's electricity accounts, unlocking new conservation potential. However, this substantial upgrade to smart meter technology (representing $16 to $32 billion in investment) is not countered by an equally sound understanding of the conservation behavior opportunities associated with these new technologies. This study investigates how real time appliance level energy usage information provided through advanced metering technology can induce conservation behavior.

Methods

At University Village, a graduate student housing community in Los Angeles, we outfitted 120 family apartments with wireless energy metering technology. We measured electricity use data in real-time 24 hours a day at the appliance level[1]. University Village is an ideal location for a study of this nature. First, the apartments are standardized and have the same appliances so that there are no differences in energy efficiency or size in the housing stock. Except for variations in size and floor plan, apartments are more or less standardized with the same included appliances and amenities. After controlling for environmental variables, this consistency promotes the validity of experimental effects of energy use as resulting from individual behaviors and lifestyles, not differences in apartment features. Second, the residents are renters and pay their electricity bills, so we can observe conservation behavior rather than investment in more efficient appliances. Third, the residents have adequate control of their environment (lights, thermostats, plug load, fridge, dishwasher and other appliances) to meaningfully engage in conservation. Fourth, on a per capita electricity basis, University Village residents are representative of the State of California multi-family renter populations. While the residents consist of single and married graduate college students, who are younger and more educated than the U.S. population, they represent the next generation of homeowners who are used to working with mobile electronic devices and increasingly rely on electronic communications in their daily lives.

One group of apartments was given detailed energy use feedback along with information about monetary savings. Another group was given feedback with an environment and health message about emissions and air quality impacts such as childhood asthma and cancer. A third group

[1] Data was updated every 30 seconds.

served as a statistical control following a six-month baseline period and random assignment. Statistical methods were used that compared the effectiveness of the detailed energy feedback on energy consumption for the treatment groups compared to the control group. The specifications consider treatment status along with other factors that may influence energy consumption such as household characteristics, apartment characteristics, environmental ideology, and weather.

Results

We estimate conservatively, an overall treatment effect of a 6% reduction in energy usage with environment and health messaging over the entire experimental period—after controlling for observed household characteristics, occupancy, weather, time trends, and environmentalist ideology. This was particularly effective on families with children, achieving up to 19.8% savings relative to the control group. On average, participants who only received information about potential monetary savings did not significantly alter their energy consumption. Our research advances our knowledge of effective non-price incentives for energy conservation. While non-price behavioral strategies can be viable alternatives to new capital projects by promoting peak load shifting and conservation, they can also be implemented immediately, at scale and at relatively low cost. Behavioral strategies enabled through information technologies can be an effective component of sustainable development pathways and do not require long lead times typical of new capital investments in energy generation, distribution and storage.

Conclusions

This study developed advanced technology-enabled information strategies to encourage energy conservation behavior in residential buildings. It makes use of a real world energy behavior laboratory that supports rigorous testing of behavioral science based strategies. We outfitted 120 family apartments with wireless energy metering technology that allowed us to provide the study participants with real time, appliance level information about their energy usage. Residents were then randomized into a control group or one of two treatment groups that received information about potential monetary savings or about the environmental and health consequences of their energy consumption. Participants who received messages emphasizing air pollution and health impacts associated with energy use reduced their consumption by 6.0% over the experimental monitoring period versus the control group. Using published price elasticities for California, this conservation effect on the treated is equivalent to a long-run electricity price increase of 15.4% or a 60-day short-run price increase between 23 and 45%. Families with children were much more responsive to the environment and health messaging achieving energy savings of up to 19.8%. Information about monetary savings was ineffective in engaging study participants to reduce their energy consumption.

3 INTRODUCTION

Background

This study developed advanced technology-enabled information strategies to encourage energy conservation behavior in residential buildings. It makes use of a real world energy behavior laboratory that supports rigorous testing of behavioral science based strategies. The sophisticated experimental setting enables highly detailed energy use measurement and feedback, where major end usage categories (e.g., plug load, lighting, heating & cooling, and appliances) are measured in real-time and communicated to consumers. This research expands our understanding of how users respond to technology-enabled energy usage information to save energy. Testing behavioral responses to different types of energy use information also enhances the theoretical understanding of how information can trigger behavior changes and enable new habit formation.

Residential and commercial buildings collectively account for over two-thirds of electricity usage and about a quarter of carbon emissions (EPA 2010, EIA 2010). The large impact of building energy usage is not surprising considering that residents of the United States spend more than 90 percent of their lives indoors (Evans and McCoy, 1998). Recent studies estimate that behavioral changes can reduce residential energy consumption between 22 and 30 percent over the next 5 to 8 years (Laitner et al, 2009; Gardner & Stern, 2008). One potentially major behavioral innovation aims to provide more detailed feedback to consumers about their energy usage, both in the private and public spheres. While currently most U.S. residential electricity consumers receive low resolution feedback through a monthly bill, the massive deployment of more than 65 million digital electricity meters by 2015 (Edison Foundation, 2011), will allow utilities to provide a wealth of new information to more than half of the nation's electricity accounts, unlocking new conservation potential. However, this substantial upgrade to smart meter technology (representing $16 to $32 billion in investment) is not countered by an equally sound understanding of the opportunities for conservation behavior associated with these new technologies.

The present study addresses the questions of how users make sense of smart meter technology and how it can be applied to generate energy conservation behavior. Smart meter technology enables more, better, and immediate information – a commonly proposed remedy to counter wasteful energy use patterns (Van Houwelingen & Van Raaij, 1989). ENGAGE systems frame energy feedback to optimize motivations to reduce energy use by recognizing that the impact of electricity use on the environment, on health, or on the community are often 'invisible' to consumers. The project experiments with different message formats to identify best practices and optimal messaging. Specifically we compare the effectiveness of messages based on the environmental or health benefits associated with conservation to more conventional messages focused on the pecuniary savings associated with conservation. Our research advances our knowledge of effective non-price incentives for energy conservation.

Energy usage feedback to consumers can take on many forms. The information can differ in granularity and resolution. Granularity refers to the level of feedback. For example, feedback can be given at the building level, room level, or device/appliance level. Resolution refers to the frequency of feedback, which can be provided on a monthly basis, daily or continuous basis. The most common time resolution for consumers occurs via monthly billing cycles. In this investigation, we enable very high feedback granularity and resolution, which enables consumers to access real-time information and social comparisons on a continuous basis. In addition to these two dimensions, feedback can differ widely in terms of the actual content presented and the means of conveying this content such as through a website or a paper bill. Content can be presented in terms of monetary impacts or alternatively, greenhouse gases or some aspect of energy use. This information can be shown graphically over time, or summarized; it can compare current usage with historical usage, peer usage, or potential usage. It can be displayed on a designated device, through a webpage, e-mailed, sent in the mail, hung on a doorknob, or accessed via a mobile device. Because of the variety of feedback methods and because of the diversity of the consumer base, we still know relatively little about how to best provide information to influence energy conservation.

Initiatives to induce energy conservation behavior have mainly focused on providing information about energy saving strategies or about the potential cost savings associated with reduction of electricity usage (e.g., Burgess and Nye, 2008; Faruqui, Sergici, and Sharif, 2010). However, research suggests that traditional methods based purely on cost savings information and economic incentives might not be sufficient to encourage conservation (Abrahamse & Steg, 2005; Fischer, 2008). Although behavioral adjustments to energy usage can collectively add up to large reductions, individual financial savings are often small. Indeed electricity makes up a relatively small portion of household spending, averaging only 2.9 percent of 2010 household expenditure for the United States (Bureau of Labor Statistics, 2011).

To tackle the challenge of motivating conservation when price signals fail, we developed alternative methods for bringing about energy conservation, focusing on non-price motivations. Research on the influence of psychological aspects (Katzev & Johnson, 1983; Stern, 1992), motivation (McCalley & Midden, 2002), and social norms on conservation behavior (Schultz et al., 2007; Goldstein et al., 2008; Nolan et al. 2008) has begun to shed light on intervention factors beyond information that may drive conservation behavior. This research has been taken up by electric utilities (e.g., Duke Energy) and consulting firms (e.g., Opower, described in Alcott, 2011), providing practical evidence that non-price motivations can be a powerful driver of conservation.

We build on this research tradition by developing and testing how non-price strategies can trigger conservation behavior. In this research, we contend that feedback messages focused on pro-social and pro-self benefits of conserving have the potential to induce energy conservation behavior. Pro-social benefits include benefits for one's community or for society as a whole rather than the individual himself while pro-self benefits profit the participant directly, for example by benefiting health or improving how the participant is perceived by society (e.g., Fisher et al., 2008; White & Peloza, 2009). This study builds on this research by providing and testing the effectiveness of messages to consumers about the negative environmental and health externalities of their actual electricity consumption.

Previous Work - Understanding Levers for Energy Conservation Behavior

The failure to engage in energy efficiency can be characterized as a market failure: individuals lack the relevant information or knowledge to engage in energy saving behaviors (DeYoung, 2000; Hungerford and Volk, 1990; Schultz, 2002) and acquiring such information is costly. Therefore detailed and immediate feedback is a frequently proposed solution to remedy to counter wasteful energy use patterns (van Houwelingen and van Raaij, 1989).

We first describe how information about individual energy usage such as historical feedback, and real time feedback as well as information on saving approaches might facilitate conservation behavior. While these strategies aim at reducing the cost of acquiring information, they do not touch on the potential motivations that might trigger conservation. We then describe the potential effectiveness of information strategies based on social norms and pecuniary incentives.

Energy feedback. Feedback can be described as “the mechanism that directs attention to a specific goal” (McCalley 2006), making attempts to achieve this goal more likely in a hierarchy of goals. The most common form of feedback informs participants about their own energy usage, often drawing comparisons to the past (e.g., Nielsen, 1993, Winett et al., 1979). Research has shown that most individuals have low awareness about their energy usage or its impacts (Attari et al, 2010; Kempton and Montgomery, 1982; Read et al., 1994). Being reminded of energy usage periodically may help trigger conservation activities, by making energy usage more salient. In addition, learning about one’s own electricity use may increase the sense of relevance of taking action to conserve. If individuals perceive their own impact as negligible, they might not behave in a prosocial manner (Larrick and Soll, 2008). Consequently, making an individual more aware of their own energy usage may contribute to conservation.

Information on problem solving strategies. Another set of information strategies provide participants with energy savings tips (e.g., Schultz et al. 2007, Slavin et al. 1981) or conduct home energy audits (e.g., Nielsen 1993; Winett et al. 1982). Both of these information strategies involve teaching consumers about new behaviors that will lower their energy consumption.

The implicit assumption behind the use of information strategies to reduce energy usage is that these strategies will result in a higher level of knowledge and therefore enable participants to change their behavior (van Dam et al., 2010; Ouyang and Hokao, 2009). According to norm activation theory, changes in behavior occur when a person is aware of an issue and thinks he can influence it (Fischer, 2008; Schwartz, 1977; Vining and Ebreo, 2002). These preconditions to taking action may be enhanced if the person receives additional information on how to perform certain activities and on the outcomes of these activities. With regard to energy conservation behavior, it is conceivable that learning about the impacts of energy usage and receiving conservation tips will lower the barrier to actions. Energy savings tips and audits are likely to contribute to both awareness and perceived behavioral control. Providing such information in an easily accessible manner lowers the cost of information on conservation strategies for the consumer.

Conservation strategies based on energy feedback and information increase individual awareness of the problem and of the possibilities to influence the problem. Once individuals have this information, they will weigh motives versus the cost of actions. The following information strategies frame the message to motivate behavior by focusing on pecuniary incentives or social norms.

Pecuniary strategies. Pecuniary strategies represent another set of strategies commonly used in conservation behavior studies. Lowered energy use results in immediate financial benefits to a household, provided the household pays its own electricity bill. Individuals should be expected to take up energy conservation as long as the benefits of doing so are larger than the costs. Researchers have pointed out the importance of financial incentives and price signals for conserving energy (Hutton and McNeill, 1981).

Many energy conservation experiments inform participants about the financial expenses and/or savings potential associated with their energy usage (e.g., Bittle, et al. 1979; Wilhite and Ling 1995). Some studies include actual price incentives. These may take the form of rewards or rebate payments (e.g., Slavin et al. 1981), where participants receive a monetary payment for achieving certain energy savings goals. Other studies change the price of electricity (e.g., Sexton et al., 1987), raising for example the price per kWh or introducing rate schedules that change with the time of day or demand levels.

Two recent meta-analysis studies found strong effects of price signals on the timing of electricity consumption (Faruqui and Sergici 2010, Newsham and Bowker, 2010), demonstrating that price signals affect behavior. Furthermore, several studies have shown that electricity demand responds to prices, although price-elasticity can be low in the short-term (for an overview see Branch, 1993; Gillingham et al., 2009).

However, other studies indicate that pecuniary incentives might be counterproductive for energy conservation because they might crowd out more altruistic or prosocial motivations (Benamou and Tirole, 2005; Bowles, 2008). Furthermore, pecuniary strategies might not be effective if the monetary incentives are negligible. Potential savings from conservation as well as price incentives used in the experiments are often small, in order to bear some relation to the actual price of electricity. For instance, a study by Hayes and Cone (1977) provided a $3 weekly rebate payments for up to a 20% reduction in energy use. In experiments using time of day pricing or critical peak pricing[2], price differences can be more substantial (e.g. 1:9 ratio used by Aigner and Lillard (1984), as well as Sexton et al. (1987)).

The power of norms. Comparative feedback provides comparisons to others (e.g., Alcott, 2011; Kantola et al., 1984; Schultz et al., 2007) and can also be called a motivational strategy, or nudge. Such strategies send non-price signals to participants that activate intrinsic and extrinsic motivation. Besides comparative feedback, motivational strategies also include the use of competitions (e.g., McMakin et al., 2002) and goal-setting (e.g., Katzev and Johnson, 1984) where participants are assigned or select non-binding goals over a defined period of time.

Recognizing the importance of social and psychological aspects, a number of studies on energy use behavior have made use of comparative feedback (Alcott, 2011; Schultz et al., 2007). These studies illuminate other motivations for changing energy use behavior. In particular, the theory of normative conduct points to the importance of social norms in guiding conservation behavior. Norms influence behavior by giving cues as to what is appropriate and desirable. The effectiveness of social norms in bringing about conservation behavior is empirically supported by several studies. For example, Hopper and Nielsen (1991) find that recruiting neighbors to encourage and remind others in their community about recycling significantly increased recycling behavior. In an experiment presenting participants with the choice between a conventional, and a green, but inferior product, participants were more likely to choose the green product if their choices were publicly visible (Griskevicius et al. 2010). Similarly, Nolan et al. (2008) find that comparing individuals to the average energy user was more effective than other strategies at reducing energy usage. Overall, behavioral approaches predict that comparative

[2] In time of day pricing, prices follow a daily schedule, rising during high demand times. In critical peak pricing, prices are only raised on days with high load forecasts.

feedback strategies making use of social norms will be effective in bringing about changes in behavior.

Much of the previous work suffers from methodological problems. They involve small samples, short time periods, and low level of granularity (i.e. providing overall electricity usage without appliance level information). A surprisingly large number of studies do not have control groups or do not take baseline measurements prior to reporting changes in consumption. Additionally, many studies also do not account for the impacts of weather characteristics over time or demographics, jeopardizing the reliability of estimates. The estimation methods themselves could also be improved, by adopting more rigorous statistical approaches for time series analysis that can include de-seasonalizing trends in the data or employing difference-in-difference estimation.

Our research contributes three important elements to this body of research that previous studies have been unable to implement. First, this study provides consumers with detailed real-time feedback about their energy usage at the appliance level. This is a vast improvement over previous studies that are limited to aggregated energy consumption information that is presented in a monthly statement provided by the utilities company. Second, this study designs treatment groups that are given factual information about their potential monetary savings and environmental and health impacts of their energy usage compared to their most energy efficient neighbors. Third, this study uses an experimental design that measures actual responses to energy usage feedback compared to stated preferences toward energy conservation and hypothetical responses. Lastly, we use rigorous statistical approaches time series analysis and a number of controls for household characteristics.

Overall, our research seeks to identify and test novel methods for generating energy savings. It targets psychological motivations to bring about more sustainable energy use behavior. We use high-granularity, high frequency feedback combined with tailored behavioral science messages to empirically determine the most effective behavioral approaches to induce changes in energy use behavior.

4 MATERIALS AND METHODS

At a residential housing community in Los Angeles, we outfitted 120 family apartments with wireless energy metering technology. We measured electricity use data in real-time 24 hours a day at the appliance level. One group of apartments was given detailed energy use feedback along with information about monetary savings. Another group was given feedback with an environment and health message about emissions and air quality impacts such as childhood asthma. A third group served as a statistical control following a six-month baseline period and random assignment. The randomized control trial was conducted from October 2011 to July 2012 and weekly treatment messages were sent to participants. Figure 1 shows screen shots of the website and weekly e-mails shown to participants. No financial transfers or monetary rewards were offered for participation.

Field Site

Our field experiment site, University Village is a graduate student housing community for married students, domestic partners, many of whom have children, as well as single parents. It comprises two sites with roughly 1,100 one-, two-, and three-bedroom apartment units. Each apartment is equipped with heating and cooling systems and a full kitchen including refrigerator, microwave, stove, dishwasher, and garbage disposal. Residents pay their own electricity bills and thus have a built-in financial incentive to conserve electricity as opposed to undergraduate students and other graduate students living in residence halls and other student housing complexes where the utility costs are factored into a single housing bill.

Except for variations in size and floor plan, apartments are standardized with the same included appliances and amenities. After controlling for environmental variables, this consistency promotes the validity of experimental effects of energy use as resulting from individual behaviors and lifestyles, not differences in apartment features. Furthermore, circuits in University Village are fairly standardized with some minor variations. For example, the heating and cooling system is usually powered four circuits but sometimes three circuits, the refrigerator and microwave are always each on dedicated circuits, etc. This allowed us to design a hardware installation kit that would accommodate all of the circuit breaker panels without any hardware reconfiguration.

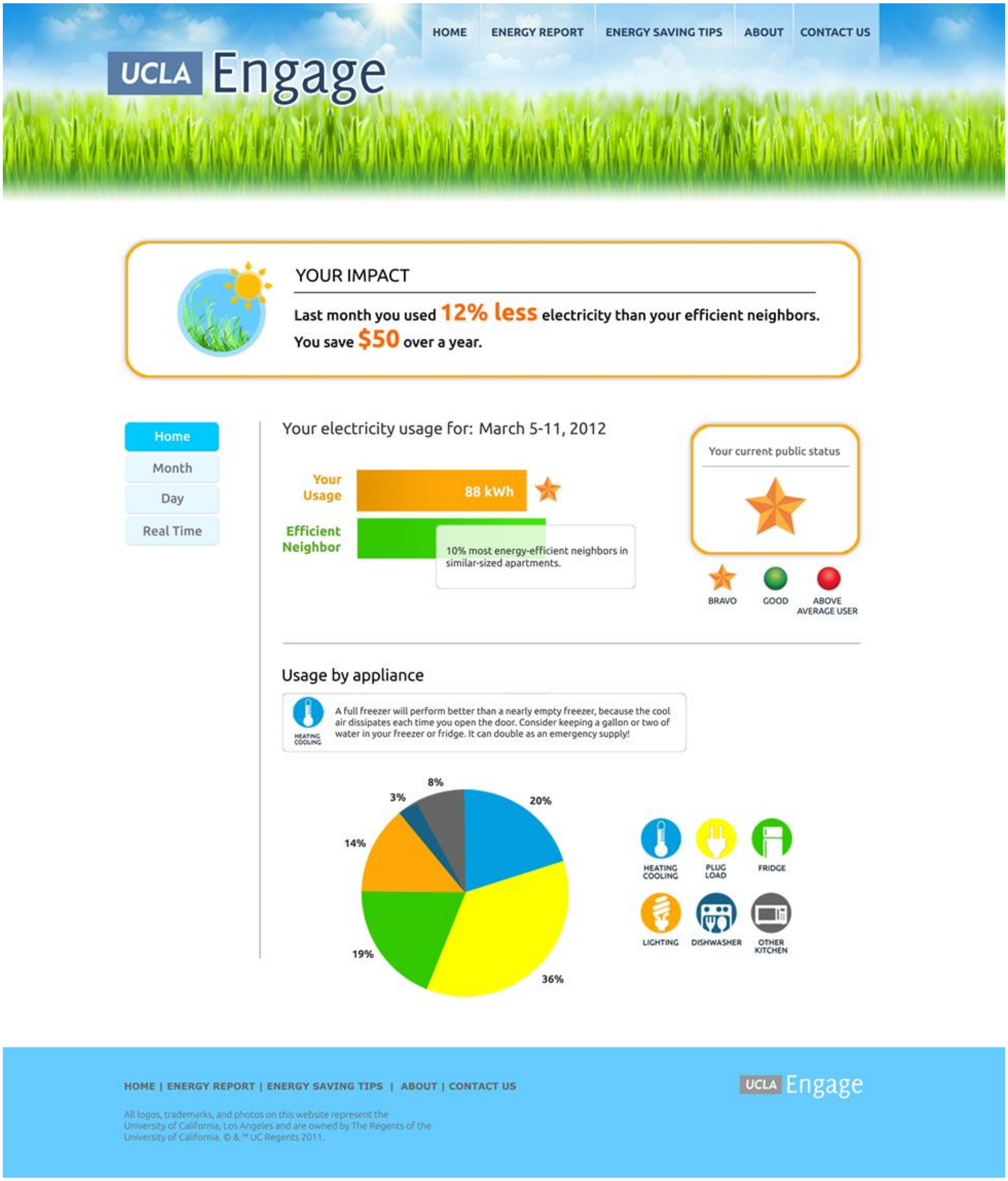
Population

University Village, is a large family housing community in Los Angeles located in proximity to public transportation, local businesses, parks and schools. On a per capita electricity basis, University Village residents are representative of general Los Angeles Department of Water and Power (LADWP) and State 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 participants consist of single and married graduate college students, who are younger and more educated than the U.S. population, but are representative of the next generation of users of information devices and are early adopters of smart metering technologies. They represent the next generation of homeowners who are used to working with mobile electronic devices and increasingly rely on electronic communications in their daily lives. Because political leaning or ideology can impact energy use attitudes and behaviors, we include statistical controls for household environmentalist ideology to estimate treatment effects conservatively and to account for the possibility that greener households might have more proclivities toward conservation. 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.

Recruitment

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 2011-2012 academic year. To meet all Institutional Review Board (IRB) ethics requirements regarding research with human subjects, participation was strictly voluntary and no personally identifiable information (PII) 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. Participant selection was then randomized. While households could at any point withdraw their consent to participate, new entry and dropouts among member households in the study were negligible for the entire duration of the experiment.

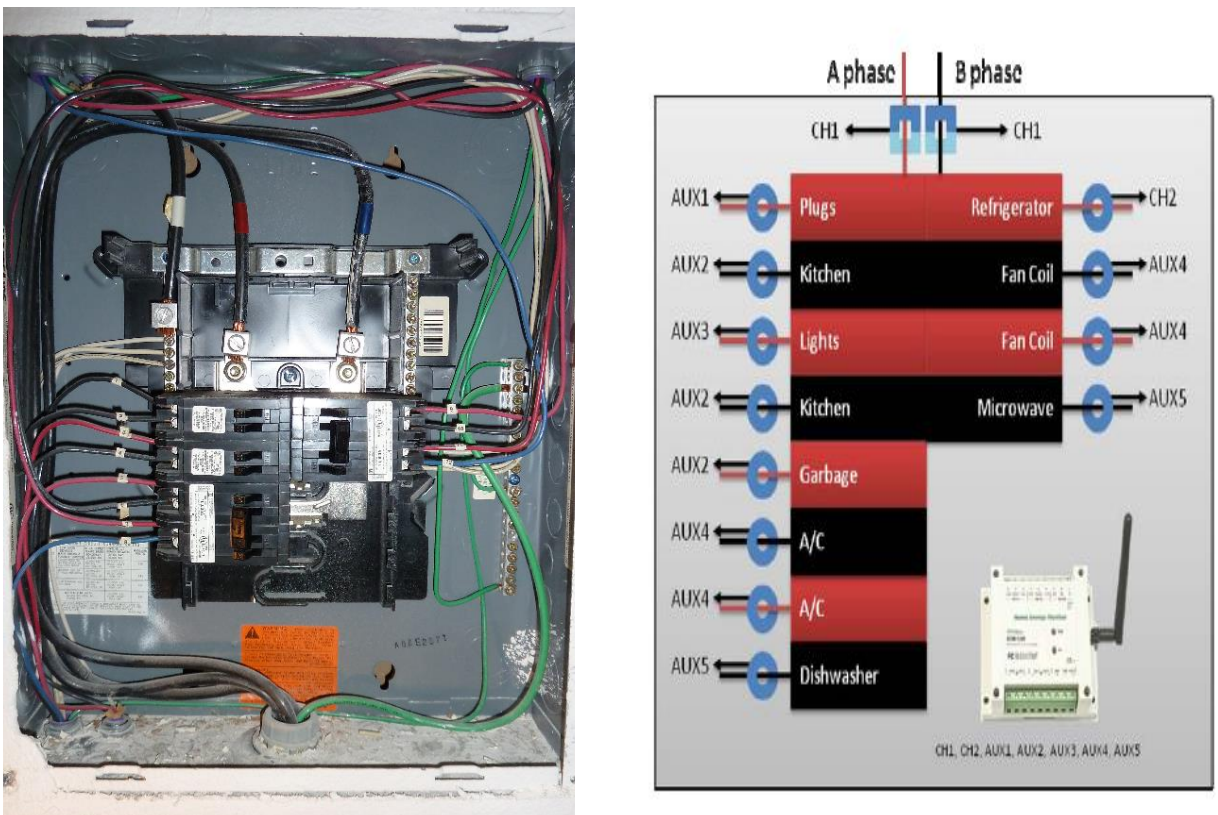
Figure 1: Sample Online Interface for Energy Use Feedback and Messaging



System Design

University Village uses a 208/120 volt 3-phase electrical service. Each apartment receives two legs of this system, which we will refer to as phase A and phase B. Each apartment at University Village each has its own electrical distribution panel through which power is routed to various loads (Figure 2). Many of these loads are powered by dedicated circuits. For example, circuits that power the heating and cooling system are dedicated to the heating and cooling system; recessed lights in the kitchen and bathrooms are powered by dedicated lighting circuits; the refrigerator is powered by a single dedicated circuit. Thus, we can conveniently measure electricity consumption from a centralized point in the apartment and with high granularity as determined by the circuit configuration in the panel.

Figure 2: Panel Layout and Installation



Our ability to disaggregate is limited at the plug level. As the wall plugs for the apartment tend to be powered by one or two circuits, we can only measure the load at these circuits and are not able to directly isolate power consumption for individual plug-in devices. While there are techniques for inferring individual device power consumption from aggregated signals, we have not yet explored their effectiveness in our system.

Although circuit types were fairly consistent, there was a strong lack of consistency in circuit configurations. For example, the refrigerator might be the first circuit on phase A in one apartment while in another apartment it might be the fifth circuit on phase B. During building construction and installation of the electrical infrastructure, variation in design across apartment units resulted in these inconsistencies in electrical wiring. This inconsistency in configuration created a challenge for categorization of circuits. Even though each panel contained a circuit key with labels for each circuit, as is standard practice, even the labels did not adhere to a consistent dictionary. Sometimes these labels even proved to be incorrect. We thus had to record each circuit configuration and store it in the database for use in appliance load calculations. Sometimes when energy calculations produced an unreasonable result, we needed to return to the unit to test the circuit and determine if the circuit was incorrectly labeled.

Many commercially available options exist for monitoring electricity use in circuit breaker panels and other measurement points. These range from platforms for building management system (BMS) integration to home metering kits for enthusiasts. However, many of these solutions measure only total energy consumption or are otherwise very expensive. Few provide high-granularity, appliance level information at low cost. Furthermore, the data signals may not be readily available but rather only summary statistics are available.

Our system uses a commercially-available, off-the-shelf (COTS) wireless energy metering device, the Brultech ECM-1240 that we adapted to our requirements. The Brultech ECM-1240 is a consumer-level, multi-channel, single-phase, wireless energy metering device designed for installation in circuit breaker panels. It measures power using a voltage transformer to step down voltage for digital measurement and current transducers to measure the current on each circuit in the panel. Because the electrical service uses two phases and the meters are only single phase, two meters are required to fully instrument the panel.

The microcontroller unit (MCU) in the energy meter converts the voltage and current measurements to accumulated energy measurements. These energy measurements are analogous to the dials on utility meters that display energy consumption. The data packets broadcast by the energy meters at 1 Hz are received by our gateway and parsed to obtain the values for each measurement channel.

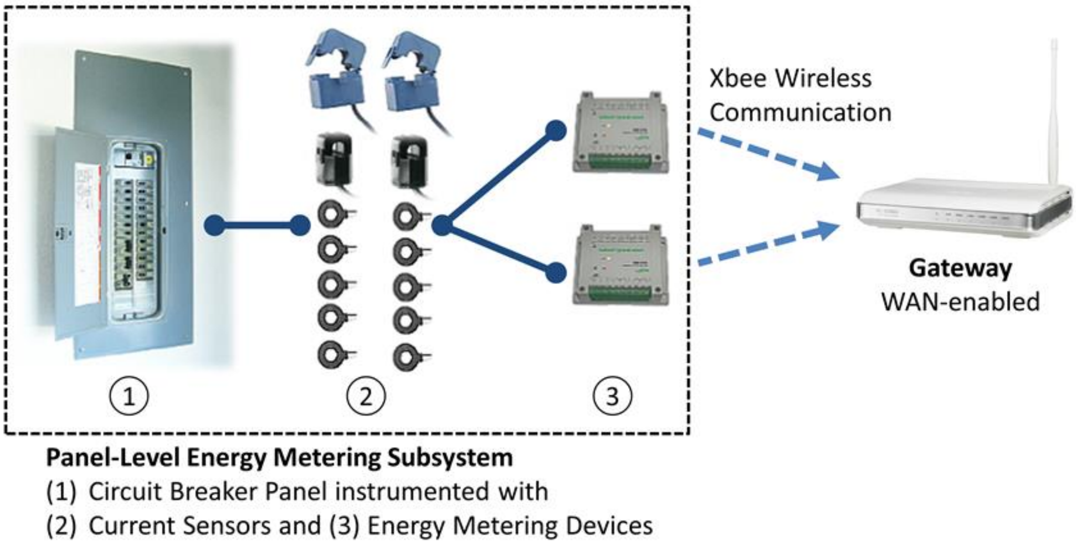
Our gateway is a modified wireless router using an open source firmware and adapted with an XBee receiver radio. The software program on the gateway, known as a daemon, continuously monitors incoming data packets and performs preprocessing before uploading measurements to our server. The daemon keeps track of the first and last data packets it receives, specifically the energy measurements E_0 and E_n and their timestamps t_0 and t_n. At the end of the 30-second interval, we compute the average power for the interval as

$$\bar{P} = \frac{E_n - E_0}{t_n - t_0}$$

With every packet uploaded from the gateway, we also upload both the window t_n-t_0 and a count of the number of packets received from each meter. The window information is used to correct for packet loss. Sometimes, due to packet loss, the interval for which we have received measurements from the meters is less than the 30 second upload window. In this case, we impute the average power for the rest of the interval.

On the server, measurements from each meter for each apartment are merged and labeled according to the stored circuit configurations. Further processing abstracts the 1/30 Hz measurements into hourly measurements to allow more direct computation of metrics such as daily, weekly, and monthly energy usage as well as group level comparisons. The energy metering system is shown in Figure 3.

Figure 3: Instrumentation and Information Flow



Treatment Messages

Information treatments received by households contain: (i) a neighbor comparison, which provides a reference point for their household consumption and (ii) a stated impact, either in terms of potential cost savings or public environmental and health externalities. The specific treatment messages are listed in Table 1. Neighbor comparisons are standardized in the following form: "Last week, you used ___% more/less electricity than your efficient neighbors…." This type of language provides households with a reference point for their energy consumption and is commonly referred to as comparative feedback or social norms. Neighbor comparisons in the energy conservation context have gained broad use in (i) small-scale lab or field studies, typically in applied behavioral psychology, building-science and engineering, and (ii) utility-scale energy conservation pilot projects, typically in economics and related fields. Impacts described were presented to households in numerical and scientifically verifiable terms.

Unlike many lab studies where numerical impacts may be the subject of manipulation, we provided households with factual evidence-based numbers that depend on their weekly consumption. Equivalent cost savings were calculated using household-level consumption data and the published LADWP electric rate schedules for residential customers. 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. Treatment messages were also pre-tested in a series of questionnaires for clarity, comprehension and stated

Table 1: Treatment Messages.

Group	Treatment Message
Monetary Savings Group	"Last week, you used 66% more/less electricity than your efficient neighbors. In one year, this will cost you (you are saving) $34 dollars extra."*
Health Group	"Last week, you used 66% more/less electricity than your efficient neighbors. You are adding/avoiding 610 pounds of air pollutants which contribute to health impacts such as childhood asthma and cancer."*
Control Group	None.

* 'Efficient neighbor' in this context means households in the top 10^{th} percentile of household weekly average kWh consumption (lowest users of electricity) for similar size apartments in the community.

Table 2: Treatment Messages Used in Pre-testing

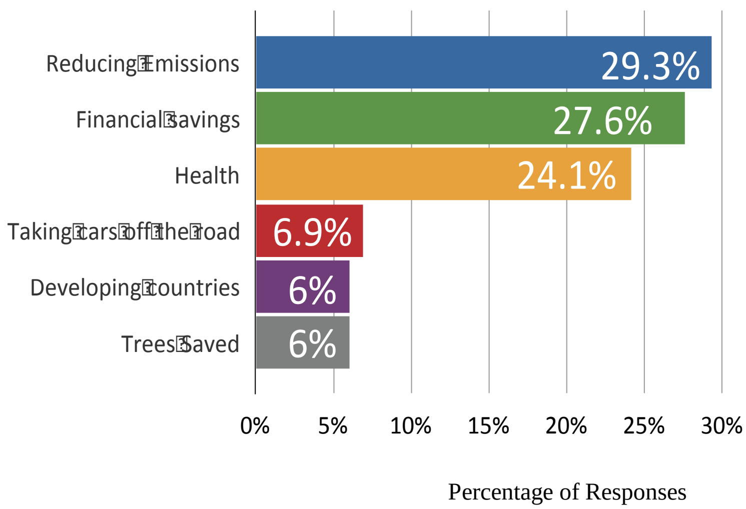
Financial	"Last month you used 66% more electricity than your efficient neighbors. In one year, this will cost you $34 dollars extra."
Health	"Last month you used 66% more electricity than your efficient neighbors. You are adding 610 pounds of air pollutants which contribute to health impacts such as childhood asthma and cancer."
Trees	"Last month you used 66% more electricity than your efficient neighbors. Over a year, your extra emissions are equivalent to removing 7 trees from your community."
Cars	"Last month you used 66% more electricity than your efficient neighbors. Over a year, this is equivalent to adding 1 car to the road."
Emissions	"Last month you used 66% more electricity than your efficient neighbors. Over a year, this is an additional 609 pounds of CO_2 emissions from a coal-fired power plant."
Developing Country	"Last month you used 66% more electricity than your efficient neighbors. Over a year, the extra energy would be enough to provide power to 3 Kenyan citizens."

willingness-to-save energy with independent populations. The messages that were used in pre-testing are shown in Table 2.

It is interesting to point out that of the categories chosen to relate energy consumption to its negative externalities, respondents most often reported reducing emissions as the primary reason they would reduce energy use. The ranking of these categories is shown in Figure 4.

Figure 4: Potential Categories to be used to Induce Energy Conservation

"For which of the following would you be MOST willing to reduce energy use? [CHOOSE ONE]



Empirical Strategy

We model the household behavioral outcomes as time series of electricity consumption, before and after the start of information treatments. Our general empirical strategy consists of panel regressions of total and appliance-level electricity loads on a series of treatment group indicators and important statistical controls, namely, household and occupancy characteristics, a measure of household environmental ideology and seasonal variables such as weather and time trends. To estimate the treatment effects on the study population, we use an analytical approach by difference-in-differences (DID). Difference-in-differences is also referred to as 'before-after' designs in the statistical literature. In keeping with our identification strategy, we define various indicator variables denoting treatment group and event time status. Let $\hat{T}_i$ be the binary treatment group indicator, equal to 1 if household is a member of treated group i and 0 otherwise. Let P be the binary post-treatment indicator, equal to 1 after the start of information treatments (e.g. post-treatment period), and 0 during the baseline period (e.g. pre-treatment period). Let $\mathbb{E}[\cdot]$ denote the expectations operator. Conditioning on observable covariates, the average treatment effect on the treated (ATET) is:

$$\tau^{DID} \equiv \left[\mathbb{E}[y_j \mid X, \hat{T}_i = 1, P = 1] - \mathbb{E}[y_j \mid X, \hat{T}_i = 0, P = 1] \right] \text{ (post-treatment period)}$$

$$-\left[\mathbb{E}[y_j \mid X, \hat{T}_i = 1, P = 0] - \mathbb{E}[y_j \mid X, \hat{T}_i = 0, P = 0] \right] \text{ (pre-treatment period)} \quad (1.1)$$

Treatment status occurs exclusively when the group-time interaction $\{(\hat{T}_i = 1) \times (P = 1)\}$ equals 1 over $\{i = 1, 2\}$ and does not occur under any other possible combinations of our group and event time indicator variables. In Equation 1.1, the ATET is the population average difference in the control group ($\hat{T}_i = 0$) subtracted from the population average difference in the treated group ($\hat{T}_i = 1$) over time during pre- and post- treatment. This analytical procedure helps remove estimation bias or confounding associated with any common unobserved trends or heterogeneity in the data, which might be unrelated to the intervention (Athey and Imbens 2006).

Dependent Variable

Our dependent variable and behavioral response measure is the total kilowatt-hour (kWh) electric power consumption. A kWh is the most common unit of electricity used by electric utilities in commercial and residential billing. We aggregate real-time electricity measurements into hourly observations. Our total kWh signal for each household is further decomposed into one of six major appliance categories. By direct measurement, the appliance-level kWh consumption categories are: (i) lighting, (ii) heating and cooling, (iii) plug load, (iv) refrigerator, (v) dishwasher, and (vi) other kitchen (meaning the microwave and kitchen outlets). These six appliance categories, as we define, make up the complete circuit breaker distribution for all electricity uses in the household. We note that this level of granularity in kWh measurement is unique to our installed metering technology and wireless sensor network.

Independent Variables

The variables of interest are the treatment group indicators as defined above, household characteristics, and seasonal controls including weather and time trends. Household and occupancy characteristics include statistical controls for total occupancy, e.g., the number of adults, and number of children living in the household. Apartment size indicates the number of bedrooms in the apartment, ranging from 1 to 3 bedrooms. Building floor captures apartment elevation, also ranging from 1 to 3, where 1st floor indicates ground level. Floor plan captures differences in apartment layout, measured in nominal square footage. Member environmental organization is a common proxy variable which captures a fixed measure of household environmentalist ideology or orientation. It is a dummy variable equal to 1 if the head of household reports being an active member of an environmental non-governmental organization (NGO), and 0 otherwise. These apartment characteristics represent time-invariant fixed effects for behavioral modeling. We also specify important seasonal variables and time trends.

Seasonality and Time Trends

Electricity demand (in kWh per unit time) exhibits seasonal fluctuations 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 from the Santa Monica Municipal Airport weather station, as maintained by the National Climatic Data Center (NCDC). Outside dry bulb temperatures were recorded hourly at the Santa Monica Municipal Airport weather station, located less than 1 mile from the study site. Archival access was provided by the National Oceanic and Atmospheric Administration (NOAA's) Quality Controlled Local Climatological Data (QCLCD) product, which contains hourly, daily and monthly summaries of outside weather conditions for the specific station. Mean degree-hours are a fundamental measure in building energy management that expresses the magnitude of expected heating or cooling load at a given location. 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 weather vector is $\Upsilon_t = [\Upsilon_t^H, \Upsilon_t^C]$ where:

$$\Upsilon_t^H = \max\left\{0,\ \sum_{h=1}^{24}\left(q_b - q_{out}\right)\right\} \quad \text{heating degree hours}$$

$$\Upsilon_t^C = \max\left\{0,\ \sum_{h=1}^{24}\left(q_{out} - q_b\right)\right\} \quad \text{cooling degree hours} \qquad (1.2)$$

As shown in 1.2, the larger the indoor heating or cooling requirement, the larger the distance between the measured mean hourly outside temperature q_{out} and a given base temperature q_b. By U.S. convention, the indoor base temperature q_b is defined as 65˚F (18.3˚C) (Day and Karyannis, 1998). When outside temperatures rise above the given indoor 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, differential effects of heating and cooling load on electricity consumption are decomposed in a meaningful way over a 24-hour period. In addition to seasonal degree-hours, we also specify time dummies to capture common time trends (or cycles) in the data and any calendar shocks on consumption. By rigorously specifying seasonal variables in our behavioral model, we directly address potential confounding factors such as serial correlation in the disturbances of the regression model.

Econometric Model

The main econometric specification for household *j*, in treatment group *i*, at time *t*, is

$$E_{jit} = \alpha P_i + \tau(P_i \cdot \widehat{T}_i) + \mathbf{H}_j + \mathbf{\Psi}_t + \gamma_t + \varepsilon_{jt} \qquad (1.3)$$

The dependent variable, E_{jit}, represents hourly panel observations of total and appliance-level electricity loads. Our main coefficient of interest, $\hat{t}$, indicates the average treatment effect on the treated and the coefficient $\hat{a}$ indicates the post-treatment effect on the population. $\mathbf{H}_j$ is the vector of household covariates and Υ_t is the weather vector. We include time dummies, g_t which specify hour-by-day, day-by-week and week-by-month dummies that capture common time trends and any calendar shocks on consumption. Time dummies offer a convenient and robust control for community-wide effects in short or high frequency panels. The residual error is captured in e_{jt}. We normalize our dependent variable by dividing by the average post-treatment control group consumption, $\mathbb{E}[y_j \mid X, \widehat{T}_i = 0, P = 1)]$, and multiplying by 100, allowing us to interpret our coefficients directly as percentages.[3]

We model the electricity use in Equation 1.3 by difference-in-differences using a feasible generalized least squares (GLS) estimator. While we will not review the theory regarding GLS or weighting least squares estimators here, we note that GLS panel estimation is feasible because the panel's time dimension is larger than the cross-sectional dimension of N households, a characteristic of our high time-resolution data set. While also more computationally intensive, GLS panel estimation offers the advantage of being less sensitive to outliers in the data (a common feature of residential electricity data) while being robust to heteroskedasticity and cross-sectional correlation in the error structure. We mitigate the effects of serial correlation—a common source of estimation bias in difference-in-differences models (Bertrand *et.al.* 2004) by fully specifying important seasonal variables with autoregressive components on consumption and clustering the standard errors at the household level.

5 RESULTS

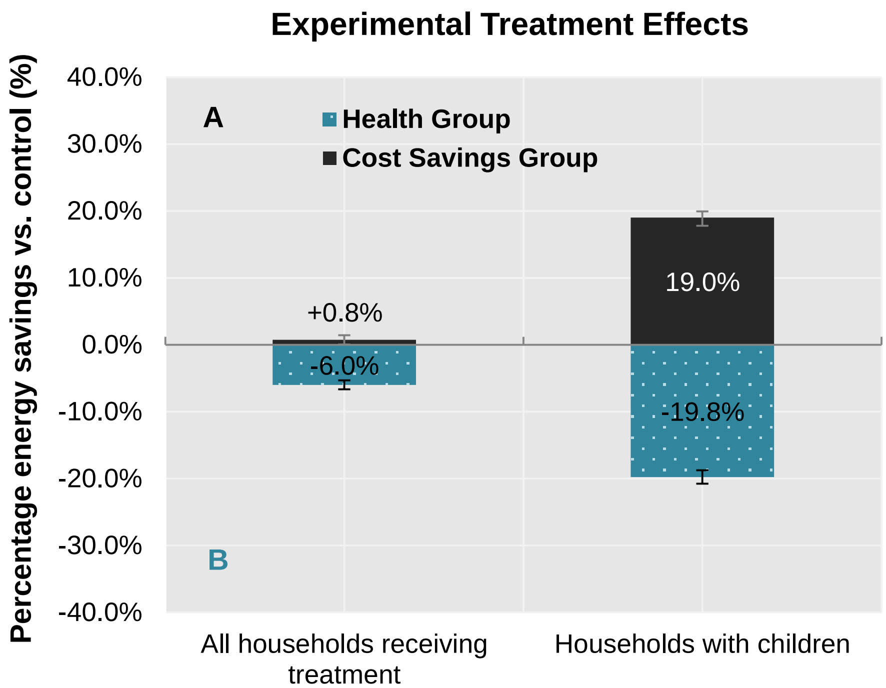
Building an intelligent, wireless sensor network, we gave consumers real-time access to detailed, appliance-level information about their home electricity consumption. Our results are based on a panel of 440,059 hourly kWh observations (or 3.43 million underlying appliance level kWh observations) for 118 residences over a time span of 8 months. Informational messages were delivered via a specialized, consumer-friendly website with monitored page views and weekly accessible e-mails by personal computer and portable electronic devices (Figure 1). Information feedback was specific to each consumer. In order to present residential energy consumption in context, we compared our participants to the top 10% most energy efficient similar neighbors to build on prior literature and provide treated households with a reference point for their consumption[4]. We find that health and environment messages, which communicate the public health externalities of electricity production such as childhood asthma and cancer, outperform monetary savings information as a driver of behavioral change in the home. Participants who received messages emphasizing air pollution and health impacts associated with energy use reduced their consumption by 6.0% over the experimental monitoring period versus control (Figure 5). The largest reductions were found in households with children who achieved up to 19.8% energy savings (Figure 5). Participants who received messages informing them about monetary savings did not produce significant conservation by the end of the experimental period, net of all statistical controls[5].

[3] We do not use logs as monotonic transformations of the hourly kWh measurements since appliance-level electricity loads belonging to $[0,\mathbb{R}^{+})$ can frequently be equal or close to zero, for example, when the dishwasher or other appliance is off. See Alcott (2011) for other examples of this approach with electricity metering data.

[4] Households were provided with factual evidence-based numbers that depended on their weekly kWh electricity consumption. Equivalent cost savings were calculated using household consumption data and the published Los Angeles Department of Water and Power (LADWP) electric rate schedules for residential customers. LADWP is the nation's largest public utility. Equivalent non-baseload emissions were calculated using emission factors from the Emissions & Generation Resource Integrated Database (eGRID) database maintained by the U.S. EPA

[5] We estimate treatment effects with a before-after statistical design by difference-in-differences panel regression. The full set of statistical controls for observable characteristics include weather controls as heating and cooling

Figure 5: Effects of informational Messages on Study Households

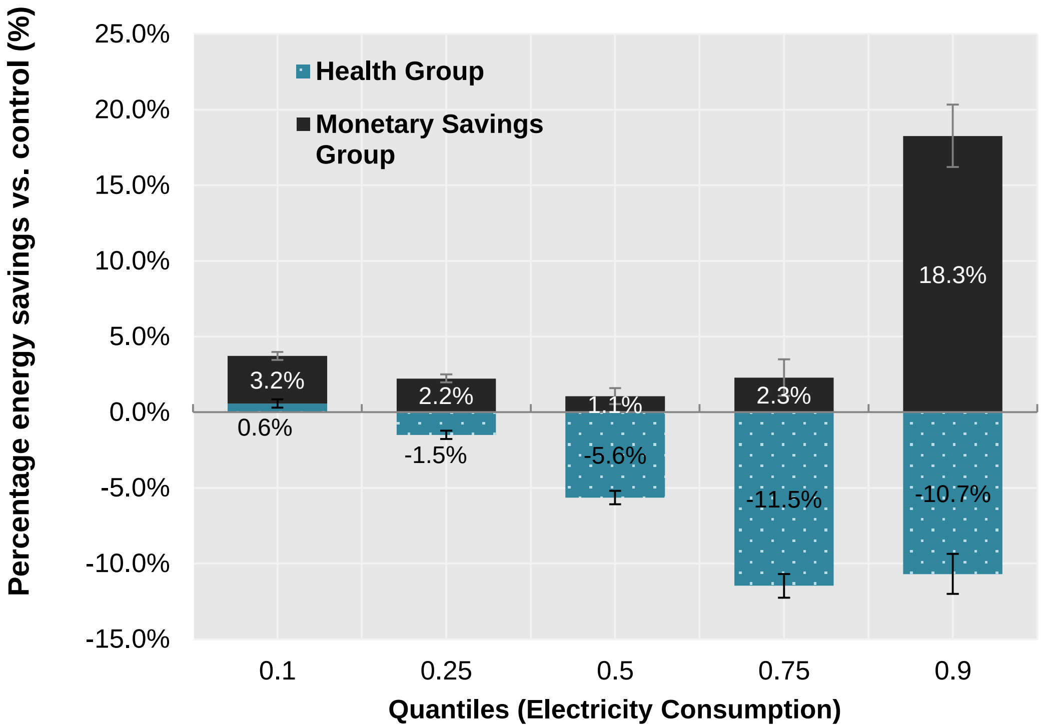


Quantile Treatment Effects

Using quantile regression, we evaluated the distributional impact of informational messages on treated households for both low and high users of electricity. We find that environment and health messaging produced statistically significant conservation effects in all but the lowest decile of households (who are already the most energy efficient households). Cost savings messages, on the other hand, led to increased electricity use relative to control (Figure 6). This defiance to treatment result was particularly striking among families with children (Figure 5) and the highest deciles of electricity use, where monetary savings information was ineffective for the most energy-intensive households (Figure 6). The lack of a significant conservation effect with cost savings information, which might initially be a surprising result, is consistent with over 35 years of experimental evidence in the behavioral conservation literature (Delmas et al. 2013). While cost savings has historically been an important incentive for household energy conservation, in practice the actual realizable dollar savings for most U.S. households compared with the top 10% most energy efficient similar neighbors is typically small. In the current experiment, for example, household cost savings potential for a 2–bedroom family apartment was $5.40 to $ 6.60 USD per month, which is roughly equivalent to 2 gallons of fortified whole

degree hours, time fixed effects, apartment size and household occupancy characteristics, including a proxy for household environmentalist ideology. Any common unobserved characteristics are captured in the control group.

Figure 6: Quantile Treatment Effects (QTE)



milk, based on the consumer price index (CPI) average price data.[6] On an annual basis, these savings for the current multi-family residential housing complex, which is at the mid-range of national per capita electricity consumption (EIA 2009), is a modest $65 to $80 dollars per year. These energy savings in dollar terms, while small relative to the U.S. household budget, are realistic for most U.S. households, suggesting that information about small monetary savings, especially over longer time horizons (weeks to months) may not sufficiently motivate household behavioral change.

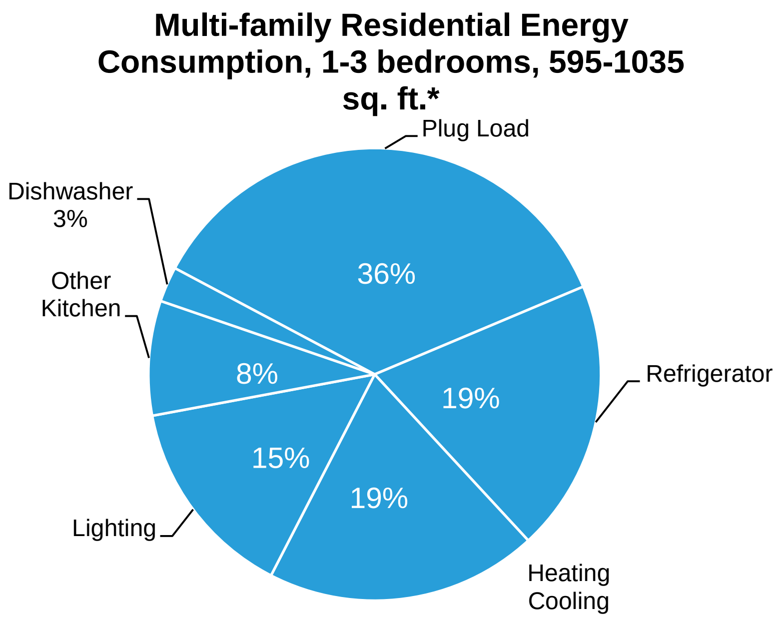
Appliance-Level Information

Because we have separately metered appliances, we can further decompose the appliance level consumption. The average electricity consumption across all households is 0.3157 kWh per hour or approximately 230.4 kWh per month across 1, 2 and 3 bedroom units ranging from 595 to 1035 square feet. For decades, heating and cooling (e.g. space conditioning) was considered to be the major source of household electricity use, based on national data from the Residential Energy Consumption Survey (RECS). Estimates from the most recent RECS survey suggest that

[6] The consumer price index (CPI) average price data, published by the Bureau of Labor Statistics (BLS) provides monthly data on prices paid by urban consumers for a representative basket of goods and services. (available at http://www.bls.gov/cpi/)

the share of residential electricity use for heating and cooling is declining nationally in the United States, down to 48% in 2009 from 58% in 1993 (EIA 2009). In California, due to the milder climate, the share of heating and cooling makes up a smaller fraction of energy use, (31%) across all single and multi-family households, and only 19% in our multi-family residential field site (Figure 7). While space heating and cooling is declining nationally, the share of energy use for appliances and electronics continues to rise. Consistent with these estimates, by direct measurement, we show that *plug load* is already the largest share (36%) of appliance-level electricity consumption for apartments at our field site (Figure 7). Major appliances (e.g. refrigerator, dishwasher), the plug load (e.g. charging devices, consumer electronics, etc.) and lighting make up a significant share of household direct energy use (73%). In future years, behavioral strategies that can target conservation through reductions in plug load, appliances, electronics and lighting will be increasingly important. We note that summary results shown in

Figure 7: Appliance-Level Electricity Measurements



** Includes all household electricity uses*

Figure 7 represent experimentally observed appliance-level electricity readings, and are not the result of survey estimates or modeling as in traditional approaches to obtain such data. Household appliance-level data is typically scarce, incomplete, and/or obtained indirectly. More generally, the lack of appliance-level energy metering data in U.S. households and businesses has been a long-standing problem for modeling consumer behavior in residential and commercial buildings (Hirst, 1980). By the current state of technology, there is no centralized appliance-level metering capability in U.S. homes or residential electricity markets. This study is one of the first field contributions of its kind to have experimentally measured appliance-level data in a large energy study.

Effects By Time of Day

We also decompose the appliance-level treatment effects by time of day. For households randomly assigned to environment and health messages, our results show significant conservation effects, versus control households, beginning about 12:00 noon. These energy savings persist in the afternoon during peak demand hours and throughout the evening, where peak load for the community occurs nightly at approximately 9:00pm (Figures 8 and 9). For our environment and health-messaging group, energy conservation occurs primarily through plug load and lighting behavioral changes. Consistent with post-study participant interviews, the most commonly reported changes in household behavior include turning off lights, unplugging electronics and charging devices when not in use. Conservation treatment effects for our environment and heath group are also maintained overnight, suggesting both load shifting behavior and conservation. Whereas our environment and health strategy was most effective in reducing plug load, lighting, and electricity use in kitchen outlets and other appliances, we observe different appliance behavior with the monetary savings strategy. For our cost savings information group, we identify conservation effects only in lighting, particularly during peak community hours. However, as lighting is only a minor share of total household energy consumption (15%), behavioral changes due to lighting conservation are not enough to overcome splurging behavior in other consumption categories, in particular, plug load and heating and cooling, resulting in no net conservation with monetary savings information by the end of the experiment. This empirical result of conservation in one or more appliances (e.g. lighting), but no net conservation in aggregate motivates further research into the persistence of household behaviors and dynamic behavioral responses to information treatments.

Figure 8: Energy Usage by Time of Day

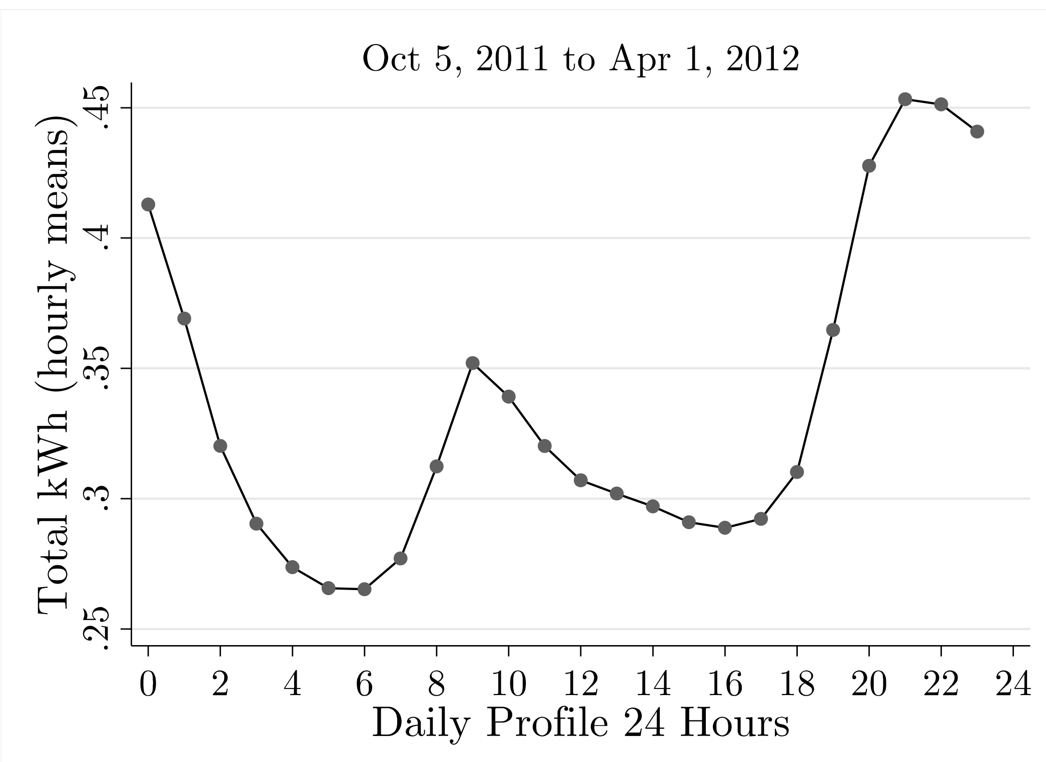
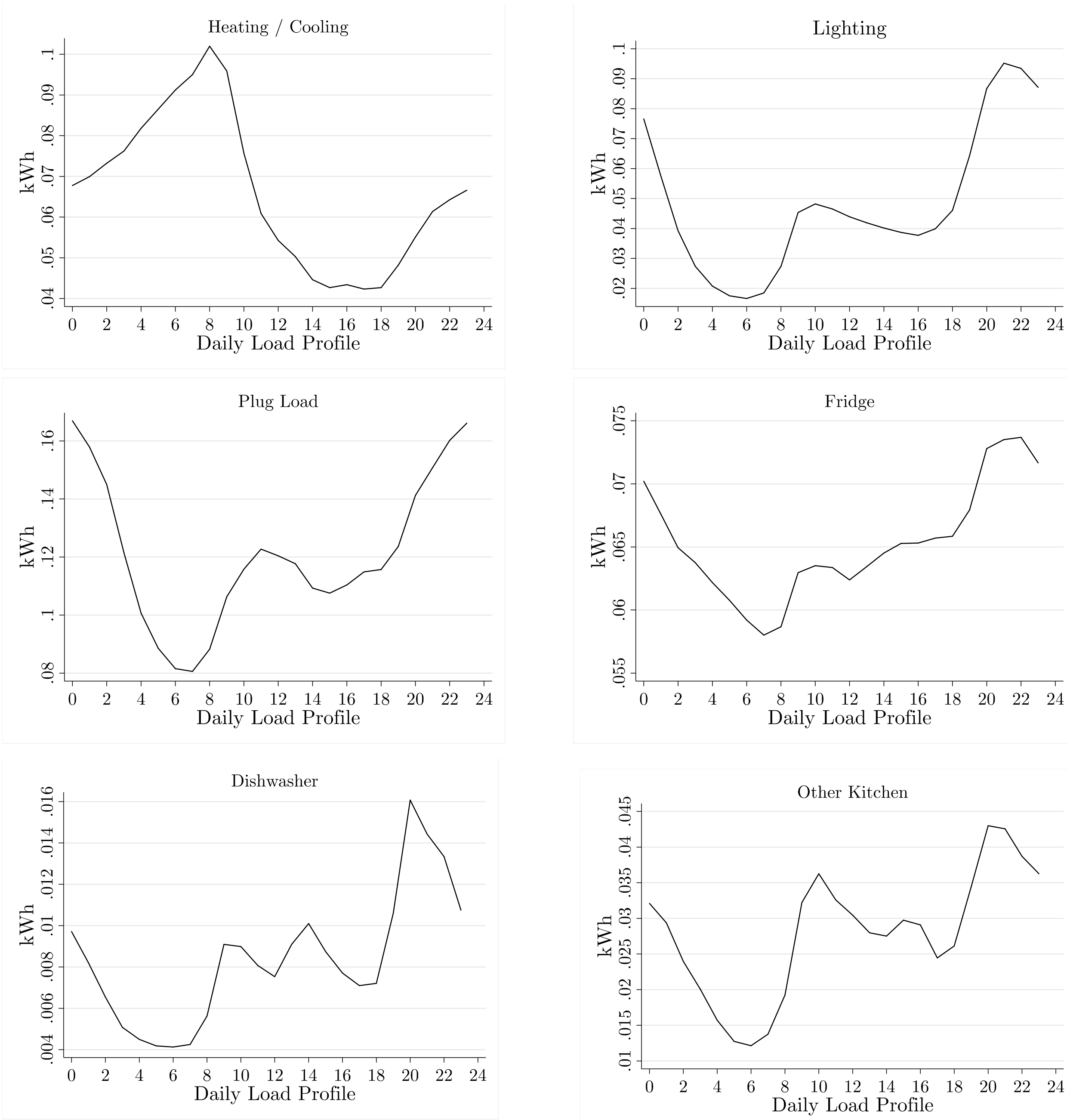


Figure 9: Appliance Level Energy Usage by Time of Day



6 DISCUSSION

This research advances our knowledge of non-price information based strategies for energy conservation. Information-based policies for conservation can be used, particularly where price-based strategies may not be politically feasible or effective. More generally, energy conservation is desirable in the economy as an alternative to costly capital investments in new power generation, and can help delay managerial investment decisions for new generation capacity. While non-price behavioral strategies can be viable alternatives to new capital projects by promoting peak load shifting and conservation, they can also be implemented immediately, at scale and at relatively low cost. Behavioral strategies enabled through information technologies can be an effective component of sustainable development pathways and do not require long lead times typical of new capital investments in energy generation, distribution and storage.

Using non-monetary information treatments, we observe significant reductions in energy consumption by appliance (e.g. lighting, heating/cooling, plug load, etc.) and by time of day. Our environment and health based messaging strategy was more effective at sustaining favorable conservation outcomes versus the cost savings strategy. Environment and health messaging achieved a 6% reduction in energy usage overall, and a 19.8% reduction for respondents with children. Using price elasticities for California from Ito (2012) and Reiss and White (2005, 2008), this conservation effect on the treated is equivalent to a long-run electricity price increase of 15.4% or a 60-day short-run price increase of 23 to 45%. Empirical evidence from this randomized field experiment contributes the first known use of health-based conservation strategies with residential customers. We demonstrate environmental health messaging as a new class of non-price incentives for energy conservation. We also add to a growing experimental literature on the use of non-price interventions as cost-effective strategies for energy conservation.

In the conservation literature, there is often a dichotomy between what people say they do, and what they actually do. This so-called *attitude-behavior* gap is uniquely revealed in this field setting. Prior to the study, we conducted a stated preference (SP) survey asking independent, random samples of participants to choose messages that would be most likely to change their behavior and motivate conservation in the home. When pushed to state their energy preferences, we find that consumers do state a willingness to change behavior and that financial savings are at the top of their concerns. However, when faced with actual decision-making in the field, only our non-monetary, environment and health strategy produced a lasting conservation effect. This distance between what people say they would do and what they actually do is referred to as the "cheap talk" critique. As long argued by psychologists and behavioral economists, monetary savings, which by standard accounts should motivate rational decision making in the home, can often fail with ordinary consumers (Stern 1992). The idea that a non-monetary, information strategy centered on environment and health, could produce energy conservation without a significant change in economic incentives, advances our understanding of the range of effective large-scale behavioral interventions that can be carefully applied at scale.

Energy conservation strategies can be guided not only by traditional consumer incentives such as saving money, but also by non-price based consumer information about health and environmental effects not necessarily reflected in prices for electricity services. We argue that behavioral strategies in household electricity markets can be complements rather than substitutes for regulatory or price-based solutions. In the current discussion on climate policy and behavioral wedge strategy, it is therefore of great interest for researchers and policy makers to develop effective behavioral interventions that can transcend political ideology or environmentalist orientation.

7 SUMMARY AND CONCLUSIONS

This study developed advanced technology-enabled information strategies to encourage energy conservation behavior in residential buildings. It makes use of a real world energy behavior laboratory that supports rigorous testing of behavioral science based strategies. The sophisticated experimental setting enables highly detailed energy use measurement and feedback, where major end usage categories (e.g., plug load, lighting, heating & cooling, and appliances) are measured in real-time and communicated to consumers. This research expands our understanding of how users respond to technology-enabled energy usage information to save energy. Testing behavioral responses to different types of energy use information also enhances the theoretical understanding of how information can trigger behavior changes and enable new habit formation.

At a residential housing community in Los Angeles, we outfitted 120 family apartments with wireless energy metering technology. We measured electricity use data in real-time 24 hours a day at the appliance level. One group of apartments was given detailed energy use feedback along with information about monetary savings. Another group was given feedback with an environment and health message about emissions and air quality impacts such as childhood asthma. A third group served as a statistical control following a six-month baseline period and random assignment. The randomized control trial was conducted from October 2011 to July 2012 and weekly treatment messages were sent to participants.

Non-monetary information treatments resulted in significant reductions in energy consumption relative to the control group Our environment and health based messaging strategy led to a 6% reduction in energy usage overall, and a 19.8% reduction for families with children. While non-price behavioral strategies can be viable alternatives to new capital projects by promoting peak load shifting and conservation, they can also be implemented immediately, at scale and at relatively low cost. Behavioral strategies enabled through information technologies can be an effective component of sustainable development pathways and do not require long lead times typical of new capital investments in energy generation, distribution and storage.

Besides the contribution to social science theory, our research also advances practical knowledge about energy conservation behavior. We have developed a unique experimental setting, providing both real-time feedback and appliance level information. The high resolution of the information in our experiment allows for unique insights into how participants respond to non-price motivations to reduce energy use. The availability of such detailed information sets our experiment apart from previous research.

8 RECOMMENDATIONS

Despite decades of research on the health effects of air pollution, the link between individual electricity use and resulting impacts on human health (via energy-related industrial emissions) remains elusive for most consumers. Historically, the development of electricity services has not been guided by particular concern for associated health effects (Comar and Sagan, 1976; Brunekreef and Holgate, 2002). Environmental damage is often an unseen byproduct of other activities, with both consumers and those around them being unable to gauge the impacts of their actions. Disclosing environmental and health effects privately to consumers can reduce the perceived costs and/or moral benefits of household actions to conserve energy. Policies that correct this information asymmetry between individual electricity consumption and public health effects have the potential to encourage environmentally friendly outcomes by re-framing and creating new mental accounts on the perceived benefits and costs of household behavioral actions.

Information-based policies for conservation can be used, particularly where price-based strategies may not be politically feasible or effective. More generally, energy conservation is desirable in the economy as an alternative to costly capital investments in new power generation, and can help delay managerial investment decisions for new generation capacity. While non-price behavioral strategies can be viable alternatives to new capital projects by promoting peak load shifting and conservation, they can also be implemented immediately, at scale and at relatively low cost. Behavioral strategies enabled through information technologies can be an effective component of sustainable development pathways and do not require long lead times typical of new capital investments in energy generation, distribution and storage.

Future work should make use of the appliance level data that is measured in this study to design algorithms that gives consumers without appliance-level monitoring a more detailed analysis of their energy consumption. Since the equipment developed in this study provides real-time appliance level feedback, an appliances “energy usage signature” can be determined. Comparing the patterns in total energy usage with the appliance level feedback could allow utility companies to provide consumers with more detailed feedback about their energy usage without the need for any capital investment by the consumer.

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10 LIST OF PUBLICATIONS PRODUCED

Delmas, Magali A, Miriam Fischlein, and Omar I Asensio. "Information Strategies and Energy Conservation Behavior: A Meta-analysis of Experimental Studies from 1975 to 2012." *Energy Policy*, 2013: 729-739.

11 LIST OF ABBREVIATIONS

Description	**Abbreviation**
Average Treatment Effect On The Treated	ATET
Building Management System	BMS
Commercially-Available, Off-The-Shelf	COTS
Consumer Price Index	CPI
Difference-In-Differences	DID
Emissions & Generation Resource Integrated Database	eGRID
Generalized Least Squares	GLS
Institutional Review Board	IRB
Kilowatt-Hour	kWh
Los Angeles Department of Water and Power	LADWP
Microcontroller Unit	MCU
NATIONAL CLIMATIC DATA CENTER	NCDC
National Oceanic and Atmospheric Administration	NOAA
Non-Governmental Organization	NGO
Personally Identifiable Information	PII
Quality Controlled Local Climatological Data	QCLCD
Residential Energy Consumption Survey	RECS
Stated Preference	SP