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Nonprice incentives and energy conservation

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In the electricity sector, energy conservation through technological and behavioral change is estimated to have a savings potential of 123 million metric tons of carbon per year, which represents 20% of US household direct emissions in the United States. In this article, we investigate the effectiveness of nonprice information strategies to motivate conservation behavior. We introduce environment and health-based messaging as a behavioral strategy to reduce energy use in the home and promote energy conservation. In a randomized controlled trial with real-time appliance-level energy metering, we find that environment and health-based information strategies, which communicate the environmental and public health externalities of electricity production, such as pounds of pollutants, childhood asthma, and cancer, outperform monetary savings information to drive behavioral change in the home. Environment and health-based information treatments motivated 8% energy savings versus control and were particularly effective on families with children, who achieved up to 19% energy savings. Our results are based on a panel of 3.4 million hourly appliance-level kilowatt–hour observations for 118 residences over 8 mo. We discuss the relative impacts of both cost-savings information and environmental health messaging strategies with residential consumers.

energy conservation | decision making | health information disclosure | environmental behavior | randomized controlled trials

In the electricity sector, energy conservation through technological and behavioral change is estimated to have a savings potential of 123 million metric tons of carbon per year, which represents 20% of US household direct emissions (1). Although some scholars contend that improvements in energy-generation technologies offer the greatest potential for carbon emission reductions (2), others argue that household-level behavioral changes can also produce significant and immediate emission reductions (1). In residential electricity markets, however, promoting conservation through behavior change is particularly challenging. Traditional economic incentives for household energy conservation are typically small and subject to problems of inattention or imperfect information, which economists often classify as information or market failures (3–7). Tailored information strategies could solve problems of imperfect information in markets—by disclosing the unobserved costs of individual consumption decisions to consumers (8). However, because electricity demand is relatively price inelastic (9), nonprice information strategies using normative, intrinsic, or social motivations might prove effective alternatives (10, 11). In this article, we compare the effectiveness of environmental and health information disclosures on residential energy consumption to more traditional cost-based information strategies.

Public environmental and health damages from energy generation, which include premature mortality and morbidity (such as cancer, chronic bronchitis, asthma, and other respiratory diseases), have not traditionally been the focus of energy conservation policies. However, decades of research on environment and health effects of air pollution have shown electricity generation to be one of the most important sources of pollution and with recognized impacts on global health such as childhood asthma and cancer. Since the 1990s, prospective cohort studies, time-series studies, and rigorous epidemiological data have provided strong causal evidence of the associated health effects of ambient air pollution (12). These include both "somatic effects"—for example, those occurring in the persons exposed—along with "genetic effects"—those occurring in at-risk populations (12). Global health damages are by far the most prominent externalities, primarily due to air pollution from coal and natural gas, which constitute a majority of the current energy system. Health damage estimates already exceed \$120 billion in 2005 US dollars (13), with electricity price structures that do not necessarily reflect these costs.

Health Externalities: A Missing Link in Consumer Choice

The link between individual electricity use and the resulting impacts on human health (via energy-related industrial emissions) remains elusive for most consumers. Household electricity use is typically "invisible," meaning consumers have limited information about the external effects of their individual electricity consumption. In this article, we investigate whether information about the environmental health effects of energy consumption could impact conservation behavior.

Behavioral theory suggests that disclosing environment and health-based externalities to consumers can be effective at shifting conservation preferences and reducing the perceived costs and/or moral benefits of individual consumption (14). Prior literature also points to important differences in the effectiveness of environmental cues, according to the type of information provided and the context in which the information is communicated (15–17). In the context of energy consumption, we argue that policies that correct information asymmetries between individual consumption and pollution externalities can encourage conservation by reframing and creating new mental accounts on the perceived costs and benefits of household actions to conserve

Significance

We investigate the effectiveness of nonprice incentives to motivate conservation behavior. We test whether tailored information about environmental and health damages produces behavior change in the residential electricity sector. In a randomized controlled trial with real-time appliance-level energy metering over 8 mo, we find that environment and health-based information strategies outperform monetary savings information to drive energy conservation. Environment and health-based messages, which communicate the environmental and public health externalities of electricity production—such as pounds of pollutants, childhood asthma, and cancer—motivated 8% energy savings versus control. This strategy was particularly effective on families with children, who achieved 19% energy savings. However, we do not study the persistence of these behavioral changes after the conclusion of the study.

Author contributions: O.I.A. and M.A.D. designed research, performed research, contributed new reagents/analytic tools, analyzed data, and wrote the paper.

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energy. In pursuing tailored information disclosures related to environment and health externalities, we examine whether moral norms and moral choice can affect how individual consumption decisions are made and subsequently evaluated by consumers.

There is a rich literature on the importance of moral payoffs and moral norms on household consumption decisions. Research in psychology (18–23), economics (24–27), marketing (28–30), sociology (31–34), philosophy (35, 36), and neuroscience (37, 38) has shown that normative strategies can motivate human behavior in the interests of the long-term benefits of the social group rather than the short-term, self-interested behavior of one person. Learning that one's marginal consumption imposes social costs on others can lead to different moral sensitivities to external health damages. However, moral sensitivity to reducing harm in others is to be distinguished from purely altruistic motivations such as in philanthropy or charitable giving, as the benefits of individual conservation actions bestow not only social benefits onto others but also private benefits on the individual (i.e., lower costs, reduced pollution, cleaner air, etc.).

We consider two psychology-based mechanisms: The first is amplification of prosocial conservation preferences that is motivated by a need to reduce harm on others (or activate behavior that aids others); the second is amplification of private benefits from reduced marginal consumption, which also provide private benefits to the individual (e.g., fewer emissions leading to known health damages). This amplification strategy serves dual purposes and could apply equally to populations with greater sensitivities to the greater good and to those households who also stand to gain from cleaner air and the reduction of health externalities, which could represent a broad segment of the population. Particular examples of such study subjects could be urban communities and, in particular, affected populations such as the elderly or families with children. Targeting urban communities and families with children, we test the effectiveness of environment/health-related social messaging on household energy conservation in a real market setting.

Experimental Evidence

A large number of energy conservation studies have been conducted using various information strategies to reduce energy use (10, 39–45). These studies provide users with energy-saving tips, historical individual use, real-time energy use, and peer use, including social comparisons. Despite a growing body of literature on nonprice strategies with tailored information campaigns, researchers have not yet tested the effectiveness of consumer information disclosures based on environment and health externalities (45). Therefore, the empirical evidence of moralized consumer choice using environmental health cues remains as yet largely undetermined. Expanding the ensemble of large-scale behavioral strategies, we present experimental field evidence with residential electricity customers in a major US city. We demonstrate that nonprice-based environment and health messaging can have substantial and economically meaningful reductions in demand at the household level. Our central contribution is to test the role of information disclosure about environment and health damages as a new class of nonprice strategies for household energy conservation.

Measuring Conservation Behavior

In the energy conservation context, prior field studies have been limited in their ability to measure high frequency behavior and to provide residents with timely feedback about their electricity use. Prior studies often use data obtained from long or infrequent residential billing cycles, indirectly using energy modeling techniques or self-reported surveys about intentions to conserve. More generally, the lack of appliance-level energy metering data in US households and businesses has been a long-standing problem for modeling and understanding consumer behavior in residential and commercial buildings (46). In the current study, new technology developments allow us to observe kilowatt–hour (kWh) electricity behavior in real time, at the appliance level (47). A kWh is the most common unit of electricity used by electric utilities in residential and commercial billing.

Behavioral experiments in energy research are now transitioning from small-scale laboratory experiments to large-scale field studies (48–50), with randomized controlled trials (RCTs) emerging as a powerful approach for policy evaluation of information treatments. RCTs enhance the credibility of findings by modeling actual consumer behavior at scale and, under realistic settings, often in contrast to controlled laboratory studies. However, RCTs are usually more costly to conduct versus nonexperimental observational studies. This is because archival data are often cheaper per unit of observation, so it is possible to have more observations for the same unit cost over a broader setting or population than might be available in a RCT, particularly in cases when there are limits to sampling, measurement error, or treatment imbalance. For a discussion of strengths and limitations of RCT, see refs. 51 and 52. Sound inference comes from triangulating multiple sources of evidence. This is why we combine RCTs with survey data, not only to provide richer evidence of the effects of a treatment before and after an intervention but also as a way to optimize the treatment itself. In the current study, we conduct a high-frequency, high time-resolution RCT study at a multiple-building, family apartment residential field site. We observe consumer behavioral responses to information treatments in real time with appliance-level metering capabilities not previously available. We integrate a behavioral science-based consumer messaging strategy, which connects the causal chain between energy use and associated environment and health consequences at the individual household level.

Our sample consists of Los Angeles Department of Water and Power (LADWP) customers who pay their electricity bills, and our experimental results represent outcomes of real-life consumption decisions in their natural settings. Our field experimental site, University Village, is a large family housing community in Los Angeles with 1,102 units. On a per capita electricity basis, University Village residents are typical of California multifamily renter populations (*SI Appendix*, Table S9) and are only slightly below the national average (due to the milder climate in the State of California). (For more information on the characteristics of our sample, please see *SI Appendix*.) 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 US population but are typical of users of information devices. Our target population represents the next generation of homeowners who are used to working with mobile electronic devices and increasingly rely on electronic communications in their consumption habits. Thus, our experimental results are indicative of how future residential electricity consumers can respond to high-frequency information, especially as electric utilities begin using smart metering data with information and communication technologies.

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 mo. We also conducted the analysis at higher frequency toward the limit of the technology (metering and data processing) at 1/30 Hz—for example, one reading every 30 s—to evaluate the optimal span of inference. Our optimal unit of observation in this study is hourly, which balances several competing requirements and considerations, not the least of which are the span of decision making for conservation behavior, the technical capabilities of the metering equipment, the precision of the estimates, computational burdens, and other practical considerations. We provided treated households with high-resolution information about costs (weekly cost estimates as opposed to monthly billing) or environmental and health impacts (weekly emissions and listing of particular health consequences; e.g., childhood asthma and cancer). Informational messages were delivered via a specialized, consumer-friendly website with monitored page views and analytics and weekly accessible emails by personal computer and portable electronic devices (*SI Appendix*, Fig. S1). Information feedback was specific to each consumer. Once randomly assigned to receive either cost savings or environment- and health-related information, households could not cross over between treatments. Building on previous literature and to provide all treated households with a reference point for their consumption, we compared our participants to the top 10% most energy efficient-similar neighbors in the complex. (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 LADWP electric rate schedules for residential customers. LADWP is the nation's largest public utility. Equivalent non–base-load emissions were calculated using emission factors from the Emissions & Generation Resource Integrated Database maintained by the US Environmental Protection Agency.) After a 6-mo baseline monitoring period, the treatment period was ~100 d, which is the typical duration of an information campaign during peak summer or winter months. Our treatment period is also greater than 60% of comparable studies from 1975 to 2012 (45).

Results and Discussion

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 8.2% over the 100-d experimental monitoring period versus control (Fig. 1 and *SI Appendix*, Table S4, column 1). These net energy savings, which invoke considerations of health damages as a psychological mechanism, are at the high end of prior nonprice strategies using social comparisons (39, 40). To give a practical sense for what these savings mean for a typical two-bedroom family apartment, an 8% conservation effect would be equivalent to plugging out a laptop computer for an additional 87 h/wk, plugging out a flat-screen TV for an additional 36 h/wk, or turning off one standard 60-W light bulb for an additional 72 h/wk. [For these equivalencies, we used nameplate wattages for typical household consumer appliances compiled by the US Department of Energy (available at http://energy.gov/energysaver/articles/estimating-appliance-and-home-electronic-energy-use).] Using published price elasticities for California (53, 54), this conservation effect on the treated is equivalent to a long-run electricity price increase of 20.5% or a 60-d short-run price increase between 30% and 60%. Consistent with our predictions, health and environment messaging was particularly effective on families with children, who collectively achieved up to 19% energy savings (Fig. 1) in our target population. Our results are robust to various estimation procedures and specifications. [We estimate treatment effects by difference-in-differences panel regression. The full set of statistical controls for observable characteristics include hourly weather controls (e.g. heating and cooling degree hours), time fixed effects, apartment size, and occupancy characteristics, including a proxy for household environmental leaning. Any unobserved characteristics common to the community are captured in the control group monitoring. Supporting materials and methods and further robustness checks are available in *SI Appendix*.] In particular, our results are robust to sampling frequency, and we do not rely on our panel's high time dimension to achieve statistical significance (*SI Appendix*, Table S12). Although we expect some attenuation of these effects across larger study populations, we demonstrate the behavioral principle of using health damages and moralized consumer choice as a promising behavioral strategy for residential energy consumption. By contrast, 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 (materials and methods are available in *SI Appendix*). This result of conservation in one group and no net conservation in another leads us to seek a deeper understanding of the underlying heterogeneity and individual behaviors driving household actions.

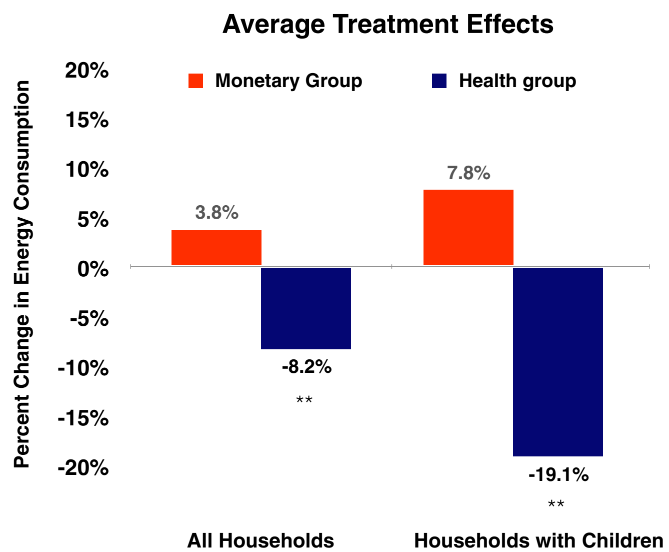

Fig. 1. Effects of informational messages on study households (n = 490,994 hourly kWh observations, 118 apartments by random assignment into treatment and control groups). Mean treatment effects are reported versus control households before and after treatment following a 6-mo baseline monitoring period. The cost savings information group shows no significant conservation behavior after the 100-d treatment period. The health group shows significant conservation behavior of 8.2% energy savings (significant at $^{**}P < 0.05$) after the 100-d experimental period. Health-related information treatments are particularly effective on families with children, achieving 19% energy savings relative to control (significant at $^{**}P < 0.05$). All panel regression estimates include statistical controls for household characteristics (apartment size, apartment layout, and building floor), occupancy (number of persons living in the household), hourly weather controls (e.g., heating and cooling degree hours), time fixed effects, and environmentalist ideology (head of household reports being an active member of an environmental organization). Materials and methods are available in *SI Appendix*.

The lack of a significant conservation effect with cost savings information, which might initially be a surprising result, is consistent with over 35 y of experimental evidence in the behavioral literature in energy conservation (45). Although cost savings has historically been an important economic incentive for household energy conservation, in practice the actual realizable dollar savings for most US 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 two-bedroom family apartment with an average consumption was US$5.40 to US$6.60/mo in direct kWh charges, which is roughly equivalent to a fast food combo meal or two gallons of fortified whole milk, based on the consumer price index average price data. [The consumer price index average price data, published by the Bureau of Labor Statistics, provides monthly data on prices paid by urban consumers for a representative basket of goods and services (available at www.bls.gov/cpi/).] On an annual basis, the savings estimate for the current multifamily residential housing complex, which is at the mid-range of national per capita electricity consumption (55), is a modest \$65 to \$80/y. These energy savings in dollar terms, although small relative to the US household budget, are realistic for most US households, suggesting that information about small monetary savings, especially over longer time horizons (weeks to months), may not sufficiently motivate household behavioral change and may be heavily discounted by consumers or subject to energy rebounds. Gneezy et al. (56) provide other examples on when and why monetary incentives do not work to modify behavior. Further work is needed to understand the thresholds that prompt informed consumers to change behavior, to disentangle the level of the incentive from incentive type.

Heterogeneous Effects on Households. Although average treatment effects vary for households with and without children (Fig. 1), we also investigated whether heterogeneous effects could be uncovered for different household use patterns. Heterogeneous responses to information treatments are well known in the behavioral literature on energy conservation. Using cross-sectional quantile regression, we evaluated the distributional impact of informational messages on treated households (Fig. 2 and *SI Appendix*, Table S8). We find that health and environment messaging produced statistically significant conservation effects in all but the lowest decile of household electricity use (e.g., households who are already the most energy efficient). Weekly cost savings messages, on the other hand, led to increased electricity use relative to control (Fig. 2). These deviations from mean treatment effects and positive splurging behaviors were particularly striking among families with children (Fig. 1) and the highest deciles of household electricity use (Fig. 2), whereas in contrast to health-based messages, monetary savings information was ineffective for the most energy-intensive households. To further understand what changes in behavior may be driving

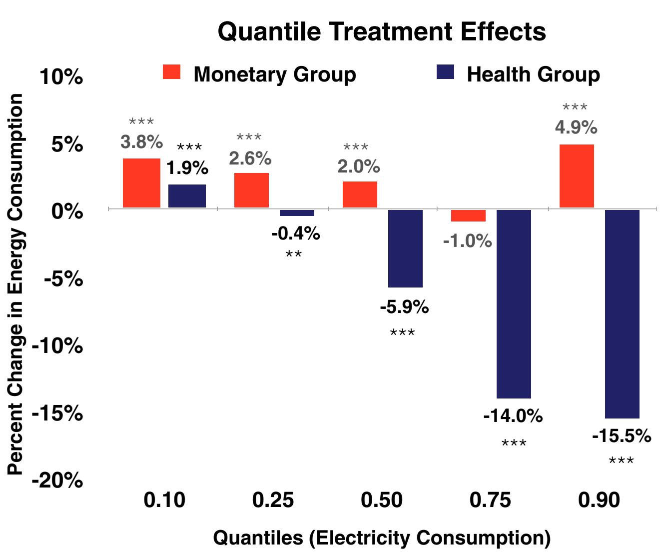

Fig. 2. Quantile treatment effects on the treated (n = 490,994 hourly kWh observations, 118 apartments). We observe significant conservation effects in the health treatment group across all quantiles of electricity use, except for the lowest decile (most energy efficient observations). By contrast, by the end of the experiment, we observe no significant conservation effect with the monetary savings group and observe splurging behavior, particularly among the highest use quantiles. Significance levels are as follows: ***P < 0.01, **P < 0.05, *P < 0.1.

these results, we evaluated the experimental treatment effects by appliance and by time of day.

Appliance-Level Behavior. The average electricity consumption across all households is 0.3157 kWh/h or ~230.4 kWh/mo across one-, two-, and three-bedroom units ranging from 595 to 1,035 square feet. Because we have separately metered appliances, we can further decompose the appliance-level consumption. In Fig. 3, we provide the breakdown of the appliance-level readings for all apartments in the study. 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%). The results shown in Fig. 3 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. By the current state of technology, there is no centralized appliance-level metering capability in US homes or residential electricity markets (46). This study is one of the first, to our knowledge, to have experimentally measured appliance-level data in a large energy study.

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. Estimates from the most recent Residential Energy Consumption Survey suggest that 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 (55). 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 multifamily households, and only 19% in our multifamily residential field site (Fig. 3). Although 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 residential apartments at our field site (Fig. 3).

For households randomly assigned to receive health messages, energy conservation occurs primarily through plug load and lighting behavioral changes (*SI Appendix*, Table S5). Whereas our environment and health strategy was most effective in reducing plug load, we observe markedly different appliance behavior with the monetary savings strategy. For households randomly assigned to receive cost savings information, we identify conservation effects at the appliance level only in lighting (*SI Appendix*, Table S5). However, as lighting is only a minor share of total household energy consumption (15%), any observed behavioral changes in lighting conservation are not enough to overcome observed splurging behavior in other consumption categories such as heating and cooling, resulting in no net conservation with monetary savings information by the end of the experiment, and in some cases increasing electricity use relative to control. This empirical result of conservation in one or more appliances (e.g., lighting) but no net conservation in the household aggregate energy use motivates further research into dynamic responses to information treatments and habit formation. Results from our focus group indicated that people were unclear on how to operate the refrigerator controls, for example, and we observed an 8% increase in refrigerator use (*SI Appendix*, Table S5), which could be an opportunity for manufacturers to improve designs. The recent work of Attari et al. highlights the importance of consumer perception and cognitive ability on the effectiveness of environmental cues (17, 57). One could ask the obvious question: Why should health-based information lead to different observed appliance-level behaviors? One explanation for this empirical result is that health-based strategies lead morally sensitized consumers to be more cognizant of household energy uses that might be perceived as "wasteful" sources of electricity—for instance, unused lights, phantom loads, or

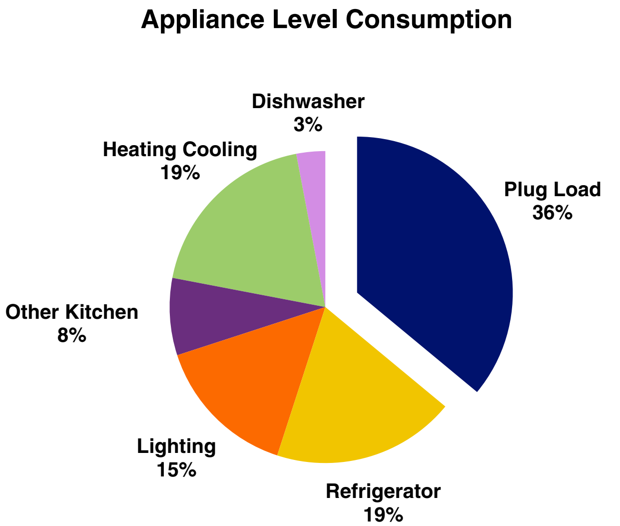

Fig. 3. Appliance-level electricity measurements (n = 490,994 hourly kWh observations, 118 apartments). Plug load is the largest share of household electricity use. The average kWh consumption is 230.4 kWh/mo across one-, two-, and three-bedroom units ranging from 595 to 1,035 square feet. Appliance-level data for multifamily residences in this study are among the first field demonstrations of comprehensive appliance-level metering capabilities not previously available. Results above represent a weighted average of all household electricity uses obtained by direct measurement and are not based on engineering estimates by modeling.

standby power sources. Consistent with this hypothesis, in post-study participant interviews, the most commonly reported behavioral changes in the health information group were turning off unused lights, unplugging electronics, and charging devices when not in use. Our metering technology has opened the possibility to study behavioral phenomena at very high resolution.

Implications for Load Shifting. We also decompose the appliance-level treatment effects by time of day to evaluate implications of our information treatments on possible load-shifting behavior. Load shifting of household electricity use from peak hours to off-peak hours is desirable for electric utilities to manage system power loads and reduce the risk of blackouts, brownouts, or overvoltages on the grid. For households randomly assigned to environment and health messages, we observe daily conservation effects, versus control households, beginning from about 12:00 AM (midnight) through 12:00 PM (noon). In-treatment energy savings persist overnight and during peak morning demand hours (*SI Appendix*, Table S6), where a local peak load period occurs for the community at ~9:00 AM (*SI Appendix*, Fig. S3). These changes in electric consumption patterns via appliance-level reductions in plug load and lighting behavior, particularly during morning peak hours, offers some evidence for habituation within treatment. Conservation treatment effects for our environment and heath group are also maintained overnight, consistent with our evidence of plug load conservation, suggesting both load-shifting behavior and conservation. By contrast, we find limited evidence of any load-shifting behavior with cost savings information treatments by the end of the experiment.

The Attitude–Behavior Gap. In the conservation literature, there is often a dichotomy between what people say they do and what they actually do (58). This so-called attitude–behavior gap is uniquely revealed in this field setting. Before the study, we conducted a stated preference 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 decision making in an actual market setting, only our nonmonetary, 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 hypothetical bias. 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 (11, 14, 56). The idea that a nonmonetary, information strategy centered on environment and health could produce energy conservation without a significant change in existing economic incentives advances our understanding of the range of large-scale behavioral science-based interventions that can be carefully applied at scale. Energy conservation strategies can be guided not only by traditional economic incentives such as rebates and price-based incentives but also by nonprice-based consumer disclosures concerning environmental and health damages not necessarily reflected in prices for electricity services.

Our study shows that nonprice incentives can effectively induce energy conservation, but it is not without limitations. First, our experiment provides both novel and repeated information to participants, making it difficult to separate the effect of learning from salience. Our participants acknowledged learning about appliance-level use and indicated that the appliance-level information was the most useful piece of information provided on the website. Most of them conveyed that they were surprised by how much or little electricity-specific appliances were being used. In addition, the information provided on the dashboard was updated in real time, and participants received weekly emails. Further research should seek to disentangle the effect of learning about the energy use of different appliances from the saliency of the information we provided, which reminded them repetitively about their energy consumption. This raises the important question of how often should people be reminded about their electricity use to form energy conservation habits. Our exit survey indicates that the combination of weekly emails with the possibility to access real-time data on a website was sufficient in our setting. Further research is needed to understand energy use habit-forming behavior with repeated information provision. Second, we report behavioral outcomes within the 100-d treatment period but do not study the persistence of these household behavior changes after the conclusion of the experiment. We therefore do not know whether energy conservation persisted after the end of the experiment. However, the results from the exit survey indicate that some actions undertaken during the experiment could have potential lasting effects on energy consumption. Indeed, the majority of the participants described that they achieved reduced energy use by unplugging electronics, changing the power savings settings of their computer or other electronics, or programming different temperature settings on their thermostat. This is important because it suggests that the savings resulting from these changes could persist even without taking further action.

Policy Implications. The relationship between electricity use and impacts on the environment and global health remains an elusive concept for many consumers. The generation of fine particulate air pollution and its effects on health are usually removed from ordinary daily consumer decision making. This low consumer awareness stands in contrast to strides in our scientific understanding. We show that providing consumers specific, tailored, and scientifically verifiable information about the associated environmental and health effects of their electricity consumption can influence and motivate behavioral decision making about daily electricity use. More generally, this research advances our understanding of the effectiveness of information-based policies for conservation based on the principle that making information about the external damages of activities more salient to consumers can encourage conservation through household behavioral changes (59, 60). It has been argued that given the relative price inelastic behavior of electricity consumers in both the United States and the European Union, public policies to encourage energy conservation will require more than increases in electricity retail prices (9). Consumer information strategies can inform environmental policy about conservation efforts and can be used particularly where price-based strategies may not be politically feasible or effective. We argue that behavioral strategies in household electricity markets can be complements rather than substitutes for regulatory or price-based solutions. 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. Although nonprice 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 (11). 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.

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SUPPORTING INFORMATION

Materials and Methods

We outfitted 118 family apartments with wireless energy metering technology at a residential housing community in Los Angeles. We measured electricity use data in real-time 24 hours a day at the appliance level. The randomized controlled trial was conducted from October 2011 to July 2012 and weekly treatment messages were sent to participants. The first group of apartments was given detailed energy use feedback along with information about monetary savings. The second group was given feedback with a health message about emissions and its air quality impacts such as childhood asthma. The third group served as a statistical control following a six-month baseline period and random assignment. Fig. S1 shows screen shots of the website shown to participants and Fig. S2 shows a time series of the community consumption. No financial transfers or monetary rewards were offered for participation.

Field Site. Our field experimental site, University Village, is a large residential community located in proximity to public transportation, local businesses, parks and schools. It is a multiple building, family apartment/condo-style housing complex with 1,102 units. The community spans two census block groups serviced by the Los Angeles Department of Water and Power (LADWP), the nation's largest public utility. Although the facilities are owned and operated by the University of California, the University does not subsidize living costs for the community and offers market-based rental rates. All utilities are paid by the tenant, including electricity. While apartments vary in size and layout, all units are furnished with a common set of appliances—a refrigerator, gas stove, dishwasher, and microwave oven. This allows for standardization in the housing capital stock. We monitor direct electricity usage in each of the participant households.

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 of electricity use, either in terms of potential cost savings or public health externalities. The specific treatment messages are listed in Table S1. Neighbor comparisons are standardized in the following form: "Last week, you used ___% more/less electricity than your efficient neighbors" Neighbor comparisons in the energy conservation context have gained broad use in (i) small-scale lab or field studies, typically in applied social psychology, building-science and engineering, and (ii) utility-scale 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 and based on LADWP electricity fuel mix. Treatment messages were also pre-tested in a series of questionnaires for clarity, comprehension and stated willingness-to-save energy with independent populations.

Participant Recruitment. Households were recruited to participate in the study. In order to prevent biases in recruitment selection, no direct environmental messaging was used. 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. Among the 1,102 households at University Village, 226 households volunteered to participate and another 88 households in our entry survey chose not to participate. This equals a participation rate of 20%. We randomly selected 118 participating households from these 226 volunteers. The participating households in our experiment represent 10.7% of the population at University Village. Household assignment into treatment and control groups was then randomized.

While households could at any point withdraw their consent to participate, no households dropped from the study for the entire duration of the experiment.

We tested for potential differences between the population of households at our field site and our sample of volunteer participants. We compared the monthly electricity meter readings of the entire population of University Village to those of our participants as well as other characteristics such as the size of the apartment, the number of occupants, the apartment floor and the location of the apartment in the complex. As shown in Table S2, there are no significant differences between participating and non-participating households. This analysis is based on electricity meter readings for 12 months prior to the start of the experiment.

Empirical Strategy. We modeled the household behavioral outcomes as a 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 proxy for household environmental leaning and seasonal variables including weather and time trends. Table S7 lists descriptive statistics for all variables in this study. To estimate the treatment effects on the study population, we use an analytical approach by difference-in-differences (DD). We define "treatment" to mean weekly updating informational messages about household energy use defined previously. Treatments are exhaustive and mutually exclusive, meaning each household receives only one randomly assigned treatment. Once assigned, there is no crossover between treatments. A control group is also monitored alongside the treatment groups, but receives no information other than their standard utility bill.

Identification. In keeping with our identification strategy, we define treatment dummies denoting treatment *group* and event *time* status. Let $\widehat{T}_i$ 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 (i.e., post-treatment period), and 0 during the baseline period (i.e., pre-treatment period). Let $\mathbb{E}[\cdot]$ denote the expectations operator. The behavioral response function y_j for household *j* is allowed to be heterogeneous at the household level. Conditioning on observables, we define the average treatment effect on the treated (ATET) as:

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

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

Treatment is identified when the group-time interaction $\{(\widehat{T}_i = 1) \times (P = 1)\}$ equals 1 over all feasible treatments $\{i = 1, 2\}$ (i.e., monetary savings or health). The ATET in Equation 1.1 is the population average difference in the *control group* $\widehat{T}_i = 0$ before and after treatment minus the population average difference in the *treated group* $\widehat{T}_i = 1$ before and after treatment. We condition on household level covariates, X. Any common unobservable characteristics are also captured in the control group.

Dependent Variable. Our dependent variable and behavioral response measure is the total kilowatt-hour (kWh) electric power consumption. A kilowatt-hour (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 (including the microwave and kitchen outlets). These six appliance categories 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. We normalize our dependent variable by dividing by the average post-treatment control group consumption, and multiplying by 100, allowing us to interpret our regression coefficients directly as percentages versus control group. We do not use logs as monotonic transformations of the hourly kWh measurements since appliance-level electricity loads in the range $[0, \mathrm{R}^+)$ can frequently be equal or close to zero, for example, when the dishwasher or other appliance is off. For other examples of this normalization approach with electricity metering data, see (1). The distribution of dependent variables is shown in Table S3.

Independent Variables. The variables of interest are the treatment group indicators, observable household characteristics, and seasonal controls including weather and time trends. *Household occupancy* includes the number of adults (ranging from 0 to 3), and number of children (ranging from 0 to 4). *Apartment size* indicates the number of bedrooms in the unit, ranging from 1 to 3 bedrooms. *Building floor* captures apartment elevation, ranging from 1 to 3, where 1st floor indicates ground level. *Floor plan* captures differences in apartment layout, measured in nominal square footage. Because political leaning or ideology can significantly impact energy use attitudes and behaviors (2-4), we include statistical controls for household environmentalist ideology to account for the fact that greener participating households might have more proclivities toward conservation. To this end, *member environmental organization* is a proxy variable which captures a fixed measure of household environmentalist ideology or orientation. It is equal to 1 if the head of household reports being an active member of an environmental non-governmental organization (NGO), and 0 otherwise.

Seasonality and Time Trends. Electricity demand (in kWh per unit time) exhibits seasonal fluctuations and serial correlation that depends 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), 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 $\mathbf{\Psi}_t = [\Psi_t^H, \Psi_t^C]$ where:

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

$$\Psi_t^C = \max\left\{0,\ \sum_{h=1}^{24}\left(\theta_{out} - \theta_b\right)\right\} \quad \text{cooling degree hours} \tag{1.2}$$

As shown in Equation 1.2, the larger the indoor heating or cooling requirement, the larger the distance between the measured mean hourly outside temperature θ_{out} and a given base temperature θ_b. By U.S. convention, the indoor base temperature θ_b is defined as 65˚F (18.3˚C) (5). 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. By rigorously specifying heating and cooling degree hours, we mitigate issues of seasonality and serial correlation in the disturbances of the regression model and address some methodological limitations previously identified in the literature (6).

Econometric Model. The basic econometric specification for household *j*, in treatment group *i*, at time *t*, is

$$E_{jit} = \alpha P_i + \tau(P_i \cdot T_i) + \mathbf{H}_j + \mathbf{\Psi}_t + \gamma_t + c + \varepsilon_{jt} \tag{1.3}$$

The dependent variable, E_{jit}, represents hourly panel observations of total and appliance-level electricity loads. Our main coefficient of interest, $\hat{\tau}$, indicates the *average treatment effect on the treated* and the coefficient $\hat{\alpha}$ indicates the *post-treatment on the population*. $\mathbf{H}_j$ is the vector of household covariates and Ψ_t is the weather vector. We include degree hours of the study period and day of the week time dummies to control for common time trends. Time dummies offer a convenient and robust control for community-wide effects. The regression constant is denoted by *c* and the residual error is captured in ε_{jt}. We mitigate the effects of serial correlation—a common source of estimation bias in difference-in-differences models (7) by fully specifying important seasonal weather variables on consumption and clustering the standard errors at the household level. Our standard errors 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 have been standardized across the community. This provides for more precise behavioral estimates than are otherwise available in comparable studies with monthly residential billing data. Second, we control for the impact of seasonality and time-varying characteristics on consumption by use of degree hours, which offers a finer resolution controls for weather variability than typical approaches that use heating and cooling degree-days, or that have no weather controls at all (6). 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. We estimate treatment effects in Equation 1.3 conservatively by difference-in-differences using the standard feasible generalized least squares estimator (FGLS), $\hat{\beta}_{GLS} = (\mathbf{X}\hat{\Omega}^{-1}\mathbf{X})^{-1}\mathbf{X}'\hat{\Omega}^{-1}\mathbf{y}$ (8). 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. In the next section, we also present alternative results and show robustness checks using OLS.

Baseline Characteristics. Table S10 shows descriptive statistics for both treated and control households during the 6-month baseline period. As shown in Table S10, the covariates and electricity consumption are reasonably balanced between treated and control households. In particular, the average electricity consumption is statistically indistinguishable between groups along with other important household fixed effects. The last column in Table S10 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. One exception is the variable representing membership of an environmental organization, which is significant at the 10 percent level. We note that households who report membership in an environmental organization represent a very minor share (~8%) of households in the study. In separate results, we computed the effect of belonging to an environmental organization as a proxy for green behavior. These results show no significant interaction with either treatment (results available from the authors upon request). This indicates that environmentalist households are not driving the study's main results.

Robustness checks. Table S11 shows the ATE specifications using OLS. Table S11 lists results of standard protocols with robust standard errors clustered at the household level, starting with a simple comparison between treatment and control groups and subsequently adding covariates. Column I shows a simple comparison between treatment and control groups in the post-period, without adjustment for the covariates. We obtain a -9.9% point estimate of the treatment effect in the health treatment group, and no significant conservation result in the cost savings group. We then add covariates to reduce standard errors. Specifications II to V present the estimates with covariates, which are robust to different configurations of fixed effects and controls. In Column V in Table S11, we include heating and cooling degree hours in addition to hourly fixed effects. As described above, degree hours capture both the magnitude and direction of heating and cooling loads on electricity consumption due to outside weather variation. We note that our use of degree-hour bins instead of hourly dummies leads to more conservative estimates of the treatment effects -8.2% treatment effect (Table S11, column V) versus -9.8% (Table S11, column IV). Here we confirm why usage of rigorous degree hours might be preferable to usage of time dummies alone.

We carefully considered the impact of a large effective sample size for this case given a fixed N and large T dimension across households. The issue of autocorrelation, cross-sectional correlation and finding appropriate controls has been in the household energy consumption literature for some time (9). As robustness checks on our estimates, we considered both a range of sampling intervals and clustering options in order to distinguish statistically trivial from substantively important treatment effects. First, we compared results based on different frequencies. Second, we evaluated some of the pitfalls of panel data analysis identified in Bertrand, Duflo, and Mullainathan (7), particularly autocorrelation variance estimation. Third, we implemented multi-way clustering as described by Cameron, Gelbach and Miller (10) and Thompson (11) to account for dependence in both group and time dimensions.

In order to check for the potential effects of large sample size on our estimates, Table S12 shows OLS estimates at various sampling frequencies. To do this, we re-sampled our electricity time series at monthly, weekly, daily, hourly, minute, and 30-second intervals. As expected, our clustered standard errors decrease as the sampling frequency increases, and we show that our ATE estimates are robust even at the lower-frequency sampling rate. While the precision of our estimates is improved by our panel's time dimension, we do not rely on high T to demonstrate statistical significance. As such, we differentiate statistically trivial from substantively important effects, particularly for the health group in which the ATE estimates range from 8-11%. We report the most conservative ATE estimates in this study.

Comments on External Validity. Our sample population consists of Los Angeles Department of Water and Power (LADWP) customers who pay their electricity bills. They are a California multi-family renter population with typical housing characteristics and demographics (age, income, household composition, per capita electricity usage, etc.). Our population has been described as one of five recognizable U.S. lifestyle consumers: young urban families –new baby, new car, smaller unit, newer appliances, fast food, frozen food, travel for commuting, shopping and visiting (12). Importantly, our participants are part of the information generation of consumers who regularly use Internet-based devices in their consumption habits.

Here we compare the housing characteristics of our multi-family renter community with broader populations. For example, 42.1% of housing units in Los Angeles County and 30.9% of housing units in California are in multi-unit housing structures, making the multi-unit housing communities meaningful to study (U.S. Census, 2014). More generally, there are 28.1 million multi-family housing units in the United States (Residential Energy Consumption Survey 2013, 2009 data) and 24.3 million of these housing units are renter occupied. According to data from the American Community Survey 2013, 52.7% of American housing units are renter-occupied. Among these renter-occupied households nationally, the average number of occupants was 2.84 persons, which falls very close to the average occupancy of 2.42 persons in our sample at University Village. We also note that 90% of all multi-family housing units in the United States are 1-, 2- and 3-bedroom units (Residential Energy Consumption Survey 2009), with the most common type being 2-bedrooms (there are 12.7 million 2-bedroom units in the U.S.). In our sample at University Village, all multi-family apartments are 1-,2- and 3-bedroom units, with 2-bedroom units being the most common type (N=101 households, 86% of all units in the study). In terms of square footage, the average size of multi-family homes in the U.S. (with 5 or more units) is 811 sq. ft. (Residential Energy Consumption Survey 2009). In our sample, the average sq. footage of multi-family homes at University Village is 835 (ranges from 595-1035 sq. ft.).

In terms of sample demographics, we also compared the age range of our sample participants to a broader population. For example, the median age in our sample of participants (heads of household) is 31 (ranges from 22 to 47); while the median age in California is 35.2 and in the U.S. is 37.2 (U.S. Census 2010). We note that persons aged 18 to 44, who are the most common age span of our sample participants, make up 38.7% of the entire population in California (14.4 MM people), and 36.5% of the U.S. population (112.8 MM people) based on Census data. In terms of their educational attainment status, our participants at University Village are more highly educated than the general U.S. population, having all received a bachelors degree or higher. We note however, that this is still a population of interest. Persons with a bachelor’s degree or higher (age 25+) represent about 1/3 of the population: 29.5% of the population in Los Angeles county, 30.5% of the population in California and 31.7% of the population in the U.S. as a whole (U.S. Census 2010).

Our sample population is also a fast growing demographic in the. Between 2003 and 2013, there has been a 28% increase in the population of males seeking advanced degrees and 52.2% increase in females seeking advanced degrees. Thus, while educational attainment status represents about 1/3 of the population in the U.S., our sample participants who are seeking advanced degrees, are also a growing demographic.

Our final demographic variable we consider is family income. Because income disclosure was voluntary, we had very few respondents (N=46, or 38% of population) who provided family income information. Among those participants who chose to disclose the information: the median annual household income for University Village participants is $50,000 to $74,000 (ranging from under 25,000 to 100,000 or more). By comparison, the median household income in the U.S. was $51,017 in 2012 (US Census 2014), which places our sample participants in the middle range of income in the U.S. Because our self-reported income data is a biased sample due to nonresponse, we report the average household income for the two nearest Census block groups. The average income for University Village block group 1 is $51,182 (U.S. Census 2010) and the average income for University Village block group 2 is $61,467 (U.S. Census 2010), which also places our sample in the mid-range of earners in the U.S.

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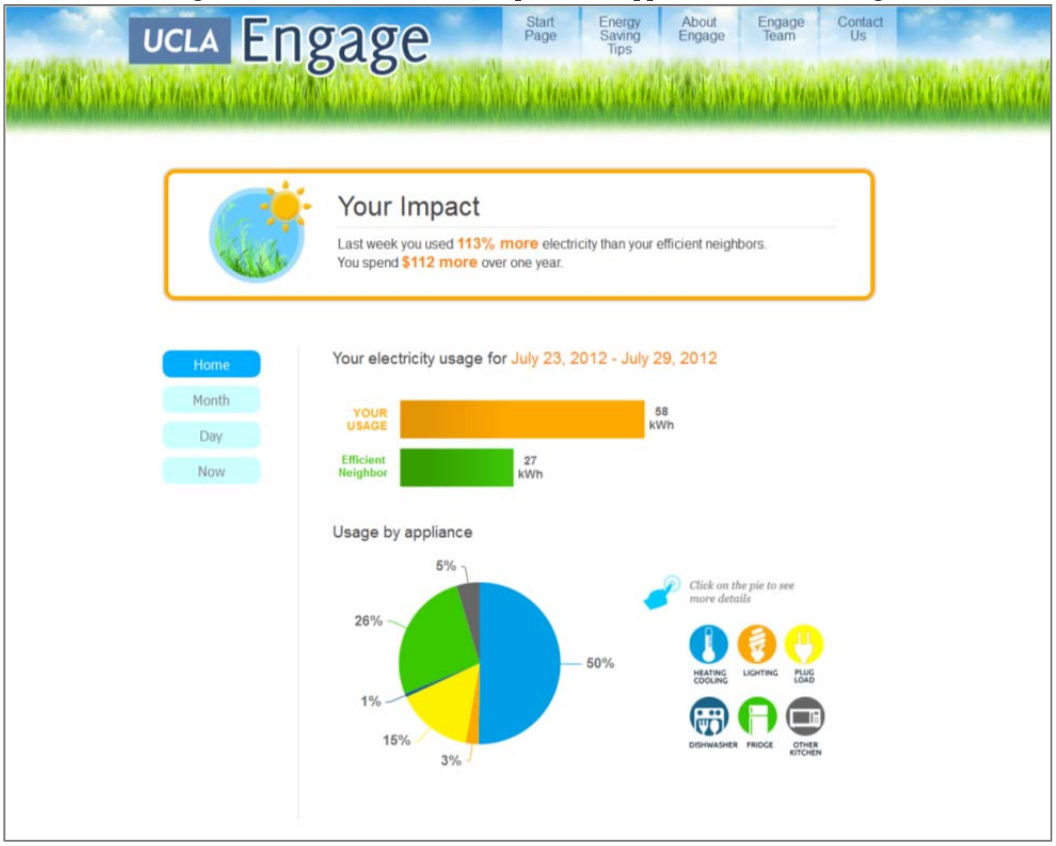
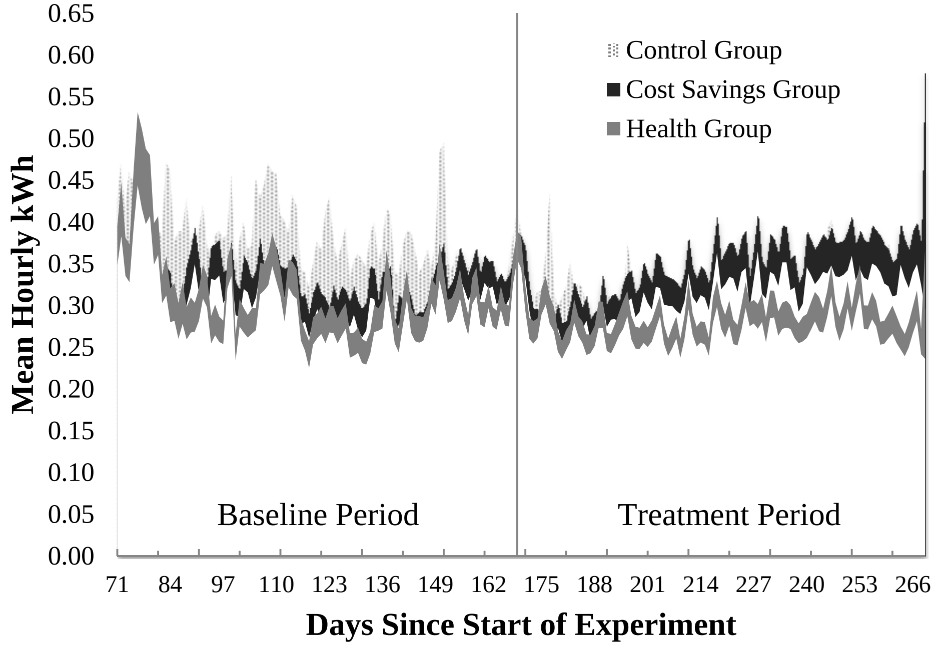
Fig. S1. Website Information Graphic with Appliance-Level Metering



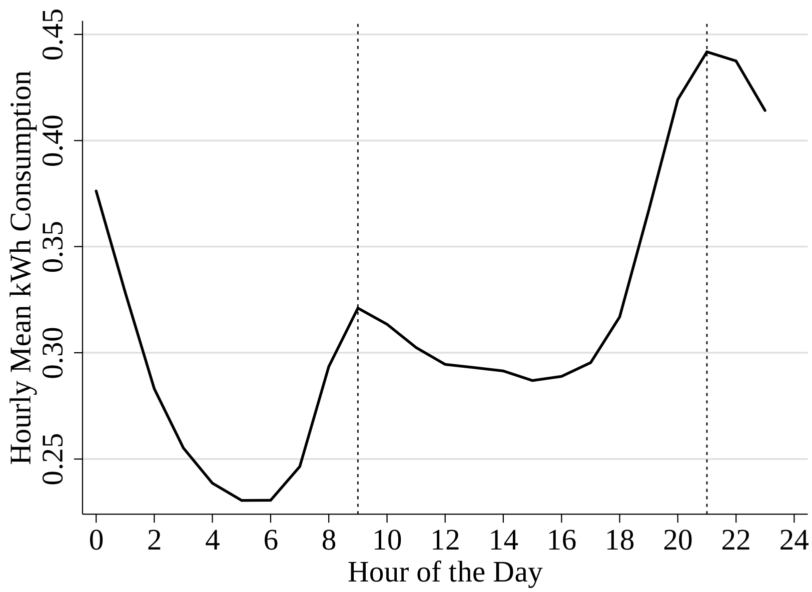
The weekly treatment message is highlighted in the rectangular box. Appliance-level feedback is shown as an interactive pie chart with clickable elements. Historical consumption information, including real-time feedback, is also accessible from the left pane of the website.

Fig. S2. Time Series of kWh Consumption by Group



During the baseline period, the mean hourly consumption is overlapping for all three groups. After treatment begins, the mean hourly consumption diverges for all three groups. Treatment effects are identified by difference-in-differences using a before-after-control-impact design.

Fig. S3. University Village Daily Load Profile



Peak daily consumption for the community occurs at 9:00am and 9:00pm

Table S1. 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 neighbors' in this context means households in the top 10^{th} percentile of household weekly average kWh consumption (households with the lowest electricity use) for similar size apartments in the community.

Table S2. Comparison of Participating versus Non-Participating Households at University Village (Meter Readings Data)

	Participating Households (S.D.)	**Non-Participating Households (S.D.)**	**Difference (S.D.)**	$Y_{in} - Y_{out}$ **(S.E.)**
Electricity Consumption §				
Average kWh per day	8.429	8.737	0.3070	-.0004
	(15.2)	(28.7)	(32.5)	(0.0004)
kWh per square foot	0.2007	0.2043	0.0036	.0833
	(0.339)	(0.479)	(0.587)	(0.198)
kWh per person	42.53	44.72	2.18	-0.0003
	(68.5)	(108.8)	(128.6)	(0.0009)
Square Footage	859.79	868.83	9.04	-0.0001
	(106.3)	(98.54)	(144.9)	(0.0002)
Number of bedrooms	1.97	1.97	-0.003	-0.0263
	(0.379)	(0.343)	(0.511)	(0.160)
Number of bathrooms	1.60	1.65	0.05	.0143
	(0.490)	(0.474)	(0.681)	(0.040)
Number of occupants	4.03	4.01	-0.02	-0.0107
	(0.566)	(0.512)	(0.763)	(0.126)
Building Floor	2.08	2.08	0.002	-0.0308
	(0.808)	(0.786)	(1.12)	(0.021)
Location in Complex	0.543	0.596	0.053	-0.041
(1 if Sawtelle, 0 if Sepulveda)	(0.498)	(0.491)	(0.699)	(0.040)
Number of Households	118	986	1,102	1,102
Number of Observations	5,533	46,184	51,718	51,718
F-test *p*-value	-	-	-	0.669

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

Table S3. Distributions of Dependent Variables (hourly kWh measurements)

Percentiles

Percentiles	Total	Heating Cooling	Lighting	Plug Load	Refrigerator	Dishwasher	Other Kitchen
1%	0.0044	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5%	0.0824	0.0007	0.0000	0.0075	0.0050	0.0000	0.0000
10%	0.1038	0.0029	0.0000	0.0160	0.0187	0.0000	0.0000
25%	0.1442	0.0083	0.0008	0.0337	0.0446	0.0000	0.0000
50%	0.2288	0.0156	0.0160	0.0616	0.0675	0.0000	0.0041
75%	0.4017	0.0239	0.0702	0.1197	0.0894	0.0060	0.0149
90%	0.6321	0.1807	0.1351	0.2200	0.1275	0.0134	0.0742
95%	0.8236	0.3704	0.1850	0.2941	0.1455	0.0487	0.1402
99%	1.3374	0.8098	0.3091	0.6311	0.1794	0.1167	0.3857
Mean	0.3157	0.0622	0.0471	0.1105	0.0701	0.0084	0.0277
Std. Dev.	0.2746	0.1622	0.0700	0.2739	0.0402	0.0297	0.1061
Observations	490,994	490,994	490,994	490,994	490,994	490,994	490,994

Table S4. Heterogeneous Treatment Effects on Families with Children

Study Variables	(1) Total kWh	(2) Total kWh	(3) Total kWh
Experimental			
Post-Treat*Monetary Savings Group	**3.785**	**1.688**	**3.771**
	(4.391)	(5.221)	(4.391)
Post-Treat*Health Group	**-8.215****	**-8.206****	**-1.419**
	(4.120)	(4.119)	(4.862)
Post-Treat*Monetary Savings Group*Children=1 or more		**7.831**	
		(11.32)	
Post-Treat*Health Group*Children=1 or more			**-19.07****
			(8.998)
Monetary Savings Group	1.853	1.531	2.478
	(7.814)	(7.722)	(7.844)
Health Group	-1.383	-1.542	-0.844
	(8.033)	(8.022)	(8.053)
Household Characteristics			
Adults	4.003	3.705	3.400
	(8.556)	(8.419)	(8.557)
Children (1 or more)	17.91**	16.63**	21.42***
	(7.494)	(6.923)	(7.780)
Apartment Size (No. of bedrooms)	33.01*	32.44*	32.03*
	(16.95)	(16.96)	(17.06)
Floor Plan (Nominal square footage)	-0.0109	-0.00983	-0.00852
	(0.0612)	(0.0610)	(0.0613)
Building Floor	9.854***	9.732***	9.265***
	(3.400)	(3.384)	(3.426)
Ideology			
Member Environmental Organization	-7.222	-7.464	-8.908
	(9.076)	(8.937)	(8.884)
Hourly Weather Controls			
Heating Degree Hours	0.284	0.286	0.281
	(0.255)	(0.254)	(0.255)
Cooling Degree Hours	-0.811***	-0.809***	-0.813***
	(0.186)	(0.186)	(0.186)
Time Dummies			
Day-by-Week	Yes	Yes	Yes
Constant	12.94	14.59	13.83
	(33.75)	(33.45)	(33.48)
Observations	490,994	490,994	490,994
Number of Apartments	118	118	118
R^2	0.0437	0.0451	0.0454

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

Table S5. Treatment Effects by Appliance

Study Variables	(4) Heating Cooling	(5) Lighting	(6) Plug Load	(7) Refrigerator	(8) Dishwasher	(9) Other Kitchen
Experimental						
Post-Treat*Monetary Savings Group	**5.331***	**-11.46*****	**0.414**	**8.844*****	**3.260**	**0.987**
	(2.779)	(4.274)	(2.395)	(2.153)	(3.918)	(3.056)
Post-Treat*Health Group	**-2.567**	**-9.011*****	**-4.719****	**8.673*****	**-3.790**	**-1.370**
	(2.554)	(2.324)	(2.152)	(1.981)	(2.471)	(4.454)
Monetary Savings Group	3.248	-20.61	-81.42	18.37*	-16.68	-38.79
	(3.189)	(17.73)	(51.13)	(9.372)	(24.42)	(25.29)
Health Group	6.370**	-19.32	-87.15*	15.41*	-37.06*	-37.81
	(3.129)	(14.29)	(48.52)	(9.161)	(22.20)	(24.93)
Household Characteristics						
Adults	-0.839	-6.284	-2.518	16.83*	-11.89	16.16
	(3.165)	(16.27)	(18.95)	(10.13)	(14.45)	(17.74)
Children (1 or more)	3.982	0.650	-22.42	11.11*	-4.389	-1.703
	(2.909)	(14.67)	(27.07)	(6.722)	(14.02)	(14.67)
Apartment Size (No. of bedrooms)	3.792	53.26	-80.41	40.39***	28.58	39.46
	(6.700)	(43.85)	(56.84)	(14.94)	(29.88)	(28.09)
Floor Plan (Nominal square footage)	0.00887	-0.0676	0.226	-0.102*	0.00103	-0.105
	(0.0232)	(0.0958)	(0.231)	(0.0547)	(0.102)	(0.0975)
Building Floor	1.661	-8.622	-5.106	13.81***	5.492	3.162
	(1.553)	(8.345)	(22.40)	(4.016)	(8.502)	(8.908)
Ideology						
Member Environmental Organization	-6.223**	-10.97	-0.228	-3.647	-14.51	3.426
	(2.742)	(9.532)	(16.15)	(11.24)	(15.75)	(17.68)
Weather Controls						
Heating and Cooling Degree Hours	Yes	No	No	Yes	No	No
Time Dummies						
Hour-by-Day, Day-by-Week	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-10.08	128.5***	169.5	50.52*	67.38	95.00
	(12.59)	(41.70)	(141.8)	(30.67)	(53.80)	(68.10)
Observations	490,994	490,994	490,994	490,994	490,994	490,994
Number of Apartments	118	118	118	118	118	118
R^2	0.0163	0.145	0.0316	0.0964	0.0159	0.0124

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

Table S6. Treatment Effects by Time of Day

Study Variables	(10) Midnight - 3:00am	(11) 3:00-6:00am	(12) 6:00-9:00am	(13) 9:00-12:00pm	(14) 12:00-3:00pm	(15) 3:00-6:00pm	(16) 6:00-9:00pm	(17) 9:00-Midnight
Experimental								
Post-Treat*Monetary Savings Group	**-6.919**	**-0.351**	**4.434**	**1.965**	**8.999***	**15.46*****	**20.22*****	**5.346**
	(4.960)	(4.890)	(5.241)	(5.953)	(4.865)	(5.215)	(6.024)	(6.099)
Post-Treat*Health Group	**-17.51*****	**-12.01****	**-11.43***	**-10.13***	**-1.689**	**6.665**	**5.027**	**-5.725**
	(4.328)	(5.048)	(6.131)	(6.110)	(4.132)	(4.354)	(5.028)	(4.871)
Monetary Savings Group	2.845	-5.393	-2.503	2.788	2.180	0.467	2.420	5.663
	(9.320)	(8.854)	(8.023)	(9.561)	(9.127)	(9.267)	(10.12)	(10.34)
Health Group	-1.928	-0.428	5.402	-2.706	-3.751	-4.329	-3.850	-5.858
	(9.900)	(9.620)	(9.740)	(9.513)	(8.211)	(8.317)	(9.220)	(10.18)
Household Characteristics	2.845	-5.393	-2.503	2.788	2.180	0.467	2.420	5.663
Adults	3.251	-8.546	-9.369	-0.283	7.129	12.16	15.51	13.51
	(9.976)	(9.802)	(10.04)	(10.83)	(10.06)	(10.59)	(12.69)	(9.828)
Children	14.38*	10.79	15.81**	24.16***	18.79**	18.75**	21.73**	18.74*
	(7.690)	(6.931)	(6.373)	(9.312)	(9.292)	(9.383)	(10.32)	(9.836)
Apartment Size (No. of bedrooms)	28.36	28.26	38.97**	34.30	24.86	22.91	36.21	49.94**
	(19.41)	(17.44)	(16.59)	(20.93)	(20.01)	(20.36)	(22.79)	(20.15)
Floor Plan (Nominal square footage)	-0.0352	-0.0410	-0.0402	-0.00901	0.0143	0.0236	0.0222	-0.0177
	(0.0689)	(0.0605)	(0.0561)	(0.0697)	(0.0694)	(0.0727)	(0.0816)	(0.0782)
Building Floor	9.115**	6.130*	11.25***	8.551**	7.538*	8.820**	12.79***	14.81***
	(3.737)	(3.533)	(3.462)	(4.260)	(3.927)	(4.259)	(4.840)	(4.358)
Ideology								
Member Environmental Organization	-7.491	-4.355	-7.588	-4.960	-4.180	-2.367	-10.66	-15.94
	(9.676)	(9.151)	(9.098)	(10.14)	(9.862)	(11.07)	(12.95)	(10.92)
Hourly Weather Controls								
Heating Degree Hours	0.800***	1.251***	0.746***	1.258***	0.188	0.119	0.765**	0.579
	(0.290)	(0.269)	(0.269)	(0.241)	(0.219)	(0.219)	(0.356)	(0.395)
Cooling Degree Hours	2.662	-5.304***	3.932***	-0.245	-0.157	0.517**	-0.591	0.180
	(4.208)	(1.936)	(0.764)	(0.181)	(0.189)	(0.260)	(0.681)	(1.294)
Time Dummies								
Day-by-Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	48.54	49.73	25.34	9.612	-5.217	-23.34	-39.93	-2.685
	(38.41)	(36.16)	(34.22)	(38.02)	(37.89)	(41.02)	(45.58)	(41.68)
Observations	60,942	60,433	61,206	61,543	61,402	61,581	61,891	61,996
Number of Apartments	118	118	118	118	118	118	118	118
R^2	0.0404	0.0521	0.0762	0.0616	0.0558	0.0542	0.0567	0.0630

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

Table S7. Means, Standard Deviations, and Correlations

		Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Total kWh (normalized)	103.11	89.71	0.0	3489.1	1.00											
Experimental																	
(2)	Health Group	0.37	0.48	0.0	1.0	-0.06*	1.00										
(3)	Monetary Savings Group	0.38	0.49	0.0	1.0	0.02*	-0.61*	1.00									
(4)	Control Group	0.24	0.43	0.0	1.0	0.04*	-0.44*	-0.45*	1.00								
Household Characteristics																	
(5)	Number of Adults	1.93	0.29	1.0	3.0	-0.01*	-0.18*	0.12*	0.07*	1.00							
(6)	Number of Children	0.52	0.81	0.0	4.0	0.14*	-0.04*	-0.08*	0.13*	-0.10*	1.00						
(7)	Apartment Size (beds)	1.97	0.38	1.0	3.0	0.15*	-0.14*	0.04*	0.12*	-0.09*	0.30*	1.00					
(8)	Floor Plan (Nominal sq.ft.)	862.3	104.49	595	1035	0.14*	-0.14*	0.05*	0.10*	0.06*	0.20*	0.83*	1.00				
(9)	Building Floor	2.07	0.81	1.0	3.0	0.08*	0.04*	-0.13*	0.10*	0.07*	-0.05*	0.03*	0.05*	1.00			
Ideology																	
(10)	Member Env. Organization	0.09	0.28	0.0	1.0	-0.02*	0.00	0.10*	-0.11*	-0.15*	-0.01*	0.02*	-0.03*	-0.05*	1.00		
Weather Controls																	
(11)	Heating Degree Hours	7.15	5.76	0.0	26.0	0.03*	-0.01*	-0.01*	0.02*	0.00	0.00*	0.00	0.00	-0.01	-0.01	1.00	
(12)	Cooling Degree Hours	0.6	1.94	0.0	26.0	-0.02*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.39*	1.00

N = 440,059 panel observations (118 apartments)
** p <.05*

Table S8. Quantile Regression Estimates

	Quantiles				
Study Variables	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Experimental					
Post-Treat*Monetary Savings Group	**3.835*** **	**2.597*** **	**2.006*** **	**-1.031**	**4.912*** **
	(0.153)	(0.174)	(0.382)	(0.801)	(1.587)
Post-Treat*Health Group	**1.907*** **	**-0.428** **	**-5.898*** **	**-13.98*** **	**-15.52*** **
	(0.170)	(0.175)	(0.339)	(0.632)	(1.200)
Monetary Savings Group	-2.551***	-2.980***	-5.655***	-2.029***	18.34***
	(0.112)	(0.159)	(0.331)	(0.667)	(1.212)
Health Group	-3.137***	-2.574***	-5.780***	-6.069***	7.288***
	(0.174)	(0.117)	(0.268)	(0.541)	(0.978)
Household Characteristics					
Adults	-0.908***	0.622***	-5.351***	-2.349***	10.28***
	(0.174)	(0.141)	(0.563)	(0.760)	(1.598)
Children	4.465***	8.248***	20.37***	26.86***	32.90***
	(0.0942)	(0.139)	(0.256)	(0.595)	(0.920)
Apartment Size (No. of Bedrooms)	6.211***	11.92***	27.41***	40.44***	36.51***
	(0.353)	(0.289)	(0.511)	(0.941)	(1.231)
Floor Plan (Nominal square footage)	0.00368***	0.00481***	-0.0121***	-0.00597*	0.0626***
	(0.00124)	(0.000914)	(0.00166)	(0.00337)	(0.00439)
Building Floor	3.760***	4.814***	6.871***	10.16***	14.93***
	(0.0810)	(0.0748)	(0.125)	(0.226)	(0.343)
Ideology					
Member Environmental Organization	0.850***	-1.488***	-0.260	-6.505***	-23.09***
	(0.135)	(0.155)	(0.377)	(0.469)	(1.182)
Hourly Weather Controls					
Heating Degree Hours	-0.0523***	-0.0566***	-0.0626***	0.687***	1.642***
	(0.00894)	(0.00895)	(0.0196)	(0.0473)	(0.0763)
Cooling Degree Hours	-0.252***	-0.380***	-0.823***	-1.129***	-0.580***
	(0.0287)	(0.0231)	(0.0507)	(0.116)	(0.223)
Time Dummies					
Day-by-Week	Yes	Yes	Yes	Yes	Yes
Constant	13.65***	9.360***	28.95***	31.59***	-4.360
	(0.687)	(0.521)	(1.369)	(2.381)	(4.052)
Observations	490,994	490,994	490,994	490,994	490,994
Number of Apartments	118	118	118	118	118
Pseudo R-squared	.0119	.0199	.0337	.0403	.0397

Quantile treatment effects with bootstrap standard errors. *** p<0.01, ** p<0.05, * p<0.1

Table S9. Per Capita Residential Electricity Consumption

Region	2010 Population (in thousands)	Annualized kWh	kWh per capita
United States*	308,746	3,749,985 x 10^6	12,146
California*	37,254	250,384 x 10^6	6,721
LADWP*	1400	8017.65 x 10^6	5,726
University Village	0.518	2910.782	5,619

* Source: California Energy Commission data, 2010

Table S10. Comparison of Baseline Usage Characteristics Between Treated and Control Households

	Control Group (S.D.)	**Treatment Group 1: (S.D.)**	**Treatment Group 2: (S.D.)**	**Difference Treat 1- Control (S.D.)**	**Difference Treat 2 - Control (S.D.)**	$Y_0^T - Y_0^C$ **(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 S11. ATE Specifications, OLS (Hourly Sampling)

	I	II	III	IV	V
	Total kWh	Total kWh	Total kWh	Total kWh	Total kWh
Post-Treat*Cost Savings Group	**5.210**	**3.917**	**3.915**	**3.822**	**5.297**
	(5.019)	(4.966)	(4.968)	(4.972)	(4.533)
Post-Treat*Health Group	**-9.958****	**-9.694****	**-9.682****	**-9.833****	**-8.192***
	(4.656)	(4.648)	(4.647)	(4.652)	(4.306)
Treat Cost Savings	-7.302	2.801	2.797	2.902	2.238
	(8.488)	(7.303)	(7.303)	(7.298)	(7.382)
Treat Health Group	-8.469	-0.157	-0.173	-0.035	-0.795
	(8.870)	(8.085)	(8.086)	(8.090)	(8.060)
Degree-hour bins	No	No	No	No	Yes
Apartment fixed effects	No	Yes	Yes	Yes	Yes
Day x Week time dummies	No	No	Yes	Yes	Yes
Hour x Day time dummies	No	No	No	Yes	No
Observations	490,994	490,994	490,994	490,994	490,994
R^2	0.005	0.043	0.044	0.094	0.044
F-statistic	2.549	3.627	9.117	27.480	8.985
Number of households	118	118	118	118	118

Robust standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1
Sampling frequency: hourly kilowatt-hour electricity consumption.

Table S12. ATE Estimates at Various Sampling Frequencies, OLS

	I Monthly	II Weekly	III Daily	IV Hourly	V Minute	VI 30 sec
Post-Treat*Cost Savings Group	**5.669**	**4.111**	**3.914**	**2.962**	**2.961**	**2.972**
	(4.808)	(4.696)	(4.720)	(4.455)	(4.455)	(4.471)
Post-Treat*Health Group	**-8.673***	**-9.131****	**-9.474****	**-10.54****	**-10.54****	**-10.58****
	(4.409)	(4.376)	(4.429)	(4.177)	(4.176)	(4.191)
Treat Cost Savings	-0.314	0.4611	0.580	0.994	0.994	0.998
	(7.377)	(7.478)	(7.499)	(7.542)	(7.542)	(7.569)
Treat Health Group	-2.431	-2.186	-1.991	-1.523	-1.523	-1.529
	(7.85)	(7.859)	(7.879)	(7.864)	(7.864)	(7.892)
Apartment fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Degree-hour bins	Yes	Yes	Yes	Yes	Yes	Yes
Day by Week time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	855	3,320	21,437	490,994	26,718,555	53,437,110
R^2	0.003	0.023	0.023	0.048	0.024	0.024
F-statistic	3.176	4.319	11.30	12.93	12.93	12.93
Number of households	118	118	118	118	118	118

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