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Information strategies for energy conservation: A field experiment in India☆

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ABSTRACT

Little is known about the effectiveness of information strategies on energy conservation in developing countries. In this study, we conduct a field experiment in an apartment complex in India to test how information about electricity usage impacts the electricity consumption of urban middle class households. Our results, based on fifteen-minute electricity readings over an academic year, show that non-monetary messages that framed electricity consumption in terms of environmental and health impacts were more effective than messages emphasizing the monetary savings of reducing electricity consumption. Households in the environmental/health group accessed the online energy-monitoring dashboard more frequently and reduced their electricity usage by 18.4% relative to the control group. Households in the monetary group did not significantly alter their usage. These results about revealed preferences are contrasted with stated preferences disclosed in a survey of urban Indians who describe money, not health, as the main motivation for energy conservation. Our findings have important implications for the development non-monetary strategies for energy conservation in developing countries.

1. Introduction

Strategies that provide information about the environmental impact of activities are increasingly seen as an effective way to encourage conservation behavior (Evans et al., 2009). The environmental impact of everyday activities is often invisible to consumers who cannot gauge the impact of their actions. Information strategies that aim to correct this information asymmetry are increasingly common (Foulon et al., 2002; Kennedy et al., 1994). These include mercury and air pollution advisories (Cutter and Neidell, 2009; Shimshack and Ward, 2010; Shimshack et al., 2007; Zivin and Neidell, 2009); mandatory and voluntary corporate disclosure (Bennear and Olmstead, 2008; Delmas et al., 2010; Evans et al., 2009; Khanna, 2001; Konar and Cohen, 1997; Lyon and Maxwell, 2007; Powers et al., 2011) and ecolabels (Hallstein and Villas-Boas, 2013; Teisl et al., 2002). Such strategies are based on the principle that more and better information about the environmental impact of activities will encourage consumers to conserve.

Electricity conservation has been an especially active context for the deployment of information strategies. Electricity and heat generation accounts for over 40% of greenhouse gases across the world (International Energy Agency, 2014) and effective conservation programs could contribute to significant environmental improvements. A large number of energy conservation experiments have been conducted using various information strategies to reduce energy use (Allcott, 2011; Allcott and Rogers, 2014; Asensio and Delmas, 2015; Delmas and Lessem, 2014; Jessoe and Rapson, 2014). These include providing users with energy saving tips, historical individual usage, real time energy usage, peer usage, etc. Meta-analyses of these field experiments find these strategies to be effective for conservation

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(Delmas et al., 2013), although effectiveness varies with the type of message provided.

However, until very recently (McRae, 2015; Pellerano et al. 2015), there have been no field experiments in developing countries that focus on information strategies for energy conservation behavior. Indeed, a recent meta-analysis based on 156 field trials published in peer-reviewed journals from 1975 to 2012 found that 100% of the studies were conducted in developed countries, mostly Europe and the United States (Delmas et al., 2013). Developing countries differ in many characteristics from developed countries, including income and education levels, and information technology infrastructure, and it is unclear how energy information strategies would perform in such contexts. For example, conducting field experiments in developing countries could allow researchers to provide meaningful monetary gains and losses with the same amount that would be considered trivial in developed countries (Harrison and List, 2004; Kachelmeier and Shehata, 1992; Slonim and Roth, 1998).[1] At the same time, the demographic stratification of developing countries is changing rapidly, with an increase share of middle classes with higher income levels. For example, the middle class population of India is estimated at 267 million individuals and to double to 547 million individuals by 2026.[2] We still know little about the attitudes of these middle class households towards energy conservation and how to best engage them in conservation behavior (Mawdsley, 2004). Some have described middle classes as particularly responsive to environmental issues because they have inherited a culture of conservation due to scarcity of resources (Vyas, 2012). Others have suggested that middle class exhibit a lack of concern about the public good because they are swept into the global frenzy of consumption (Gidwani and Reddy, 2011). So it is unclear how middle class households in developing countries will engage with information about energy conservation and act on it.

Since the majority of the growth in energy demand over the next few decades will come from the developing world (Wolfram et al., 2012), and because of the rapid growth of middle class households, identifying cost-effective strategies for promoting energy conservation behavior for the middle class in these countries could have a profound impact on greenhouse gas emissions.

In this study, we contribute to the energy conservation behavior literature by conducting a field experiment on electricity conservation behavior in urban India. In recent years, India has emerged as one of the fastest growing economies of the world, entailing an equally rapid increase in energy consumption (Balachandra et al., 2010). The estimated electricity consumption in India was of 882,592 GWh in 2013, showing an annual growth rate of 9% since 2006 (Government of India, 2015). India's consumption of energy is now the fourth largest in the world, behind China, the U.S and Russia (IEA, 2012). Although the Indian economy is gradually becoming more energy efficient, India is still among the least energy efficient countries in the world (Balachandra et al., 2010).

Most importantly, electricity generation is a major source of air pollution in India (Guttikunda et al., 2013), since 66% of the electricity generation is derived from coal power plants (Guttikunda and Jawahar, 2014).[3] The pollution from these plants resulted in an estimated 80,000–115,000 premature deaths and >20 million asthma cases from exposure to total particulate matter (PM) 2.5 pollution (Guttikunda and Jawahar, 2014). Because of the significant health impact of electricity generation in India, we decided to conduct a randomized field experiment to test how motivations on the health impact of energy use motivate consumers to conserve electricity as compared to more conventional monetary motivations to conserve.

Buildings in India account for >30% (264,778 GWh) of overall energy consumption and residential building are responsible for 93% (246,243 GWh) of building energy consumption (Batra et al., 2013; CEA, 2012). Indian residential energy use is expected to increase by around 65–75% in 2050 compared to 2005 (Van Ruijven et al., 2011). The urban population constitutes about a third of the total population and a major share of the residential energy consumption (Chaturvedi et al., 2014). Studying middle class urban households is particularly important because research shows that the impact of urbanization on emissions is more pronounced in the middle-income group than in the other income groups (Poumanyvong and Kaneko, 2010). We therefore focus our research on identifying the most effective information strategies for energy conservation behavior in the residential sector for urban middle class households.

We replicated the methodology used in a randomized field experiment conducted in the U.S. by Asensio and Delmas (2015, 2016). We provided real-time, smart metering energy feedback to 19 Indian households over an academic year, to test the effectiveness of two different messaging strategies based either on the environmental and health impacts of electricity consumption, or on the monetary savings of reducing electricity consumption. While our sample size was relatively small, our advanced energy metering system enabled us to collect high frequency data with the statistical power necessary to detect changes in energy consumption behaviors. This aspect of our energy metering system is remarkable as low technology electricity infrastructure as often been the main barrier to conduct energy information experiments in developing countries. Indeed, in India, electrification rates are low, and the electricity grid frequently fails to provide a reliable supply of power when people need it (Urpelainen, 2014).

Furthermore, our system allowed us to identify participants' level of engagement with the treatment messages. Namely how many times participants actually read the messages we sent them and how many times they visited their personalized electricity usage dashboard. This feature allows us to assess the effect of the actual treatment, specifically when people access their energy feedback information, rather than just measuring the effect of the intent to treat, that is to say sending the email or making the information available on the dashboard. This contrasts with previous energy conservation messaging strategies that relied mostly on "*intent to treat*" study designs (Schultz et al., 2007; Allcott, 2011). This method also allows us to measure the link between engagement with the information and conservation behavior.

Our results show that non-monetary messages that framed electricity consumption in terms of environmental and health impacts were more effective than monetary messages that framed electricity consumption in terms of financial savings. Households in the environmental/health treatment group were more engaged with their electricity feedback, and reduced their electricity usage by 18.4% relative to the control group, while households in the monetary group did not make significant changes in their usage throughout the 12 weeks of the experiment relative to the control group. These revealed preferences provide stark contrast to the stated preferences disclosed in a survey of 1820 residents of urban India, in which survey participants identified monetary savings, not health protection, as their main motivation for energy conservation.

Our findings illustrate the advantage of field experimental techniques to reveal conservation behavior and the potential for non-monetary information strategies for encouraging energy conservation behavior in developing countries.

2. Motivations for energy conservation

The failure to engage in energy efficiency has been characterized as a market failure associated with imperfect information: individuals lack the relevant information or knowledge to engage in energy saving

[1] See Duflo (2005) and Banerjee and Duflo (2009) for a review of field experiments in development economics.

[2] National Council of Applied Economic Research (NCAER) https://www.cgdev.org/doc/2013_MiddleClassIndia_TechnicalNote_CGDNote.pdf.

[3] Industry-wise estimates of consumption of coal shows that during 2013–14 electricity generating units consumed 427.23 MT of coal (Government of India, 2015).

behaviors (Golove and Eto, 1996; Brown, 2001; Gillingham et al., 2009) and acquiring such information is costly. One potentially effective informational tool is the provision of frequent feedback to consumers regarding their energy usage. Such information can allow consumers to better understand when and how they are using electricity, and help them improve energy usage decisions (Fischer, 2008). Being reminded of energy usage periodically may also help trigger conservation activities by making energy usage more salient.

Conservation strategies based on energy feedback and information increase individual awareness of the issues and of the possibilities to influence the problem. However, they do not automatically lead to energy conservation behavior. Once individuals have this information, they weigh the benefits versus the cost of their actions before deciding to engage in conservation. Information strategies can focus on different types of motivations of behavior, such as for example pecuniary motivations or moral payoffs. Yet, it is unclear which strategies are more effective depending on the context in which they are implemented. Furthermore, bounded rationality suggests that consumers are rational but face cognitive constraints in processing information that lead to deviations from rationality in certain circumstances (Gillingham et al., 2009; Yoeli et al. 2017). Thus the need to investigate the effectiveness of different information framing for energy conservation.

2.1. Pecuniary strategies

Pecuniary strategies represent a set of strategies commonly used in conservation behavior studies. Lowered energy use results in financial benefits to households that pay their own electricity bills. Individuals should be expected to take up energy conservation as long as the benefits of doing so are larger than the costs.

Many energy conservation experiments inform participants about the financial expenses and/or savings potential associated with their energy usage (see Delmas et al., 2013 for a review). Some studies found strong effects of price signals on the timing of electricity consumption (Faruqui et al., 2010; Newsham and Bowker, 2010), or total energy consumption (Gillingham et al., 2009; Ito et al., 2015), demonstrating that price signals affect behavior. However, other studies indicate that pecuniary incentives might be counterproductive for energy conservation because they might crowd out more altruistic or prosocial motivations (Bénabou and Tirole, 2006; Bowles, 2008). Furthermore, pecuniary strategies might not be effective if the monetary incentives are small. The literature is therefore divided on the effectiveness of pecuniary strategies for energy conservation.

2.2. Moral payoffs

There is a rich literature on the importance of moral payoffs and social norms on household consumption decisions. Research 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 the individual (Nolan et al., 2008).

Learning that one's marginal consumption imposes social costs on others can lead to different *moral sensitivities* to the health impact on others. Research suggests that disclosing environment and health-based externalities to consumers can be effective at shifting conservation preferences by increasing the perceived moral benefits of conservation (Thaler and Sunstein, 2008). However, health motivations differ from purely moral motivations since conservation provide not only health benefits to others, but also potential health benefits to the individual taking the conservation action.

Asensio and Delmas (2015, 2016) studied the effectiveness of monetary savings and environmental and health messaging strategies on energy conservation behavior in the U.S. They conducted a randomized controlled trial in 118 apartments in Los Angeles over 8 months and found that 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. They did not find any significant impact on energy conservation of a message on monetary savings. However, it is unclear how such information strategies would work when implemented in a developing country. For example, because monetary gains in developing countries might be a more salient motivation than in developed countries, we might expect framing based on monetary savings to be a more effective strategy (Harrison and List, 2004).

Indeed, cultural attitudes toward energy conservation might differ in developing countries from those in developed countries and lead to different responses to information. In India, for example, some have argued that people living in urban areas have a culture of 'deep conservation', where conservation is a learned habit due to scarcity of resources (Shrinivasan et al., 2013), and that the potential for conservation has already been tapped. This is in contrast to conservation attitudes observed in developed countries (Brounen et al., 2013). In order to explore attitudes towards energy conservation in India, a door-to-door survey of 1820 residents of urban India was conducted in 2013 (Batra et al., 2013).[4] The goal of this survey was to better understand the motivations to conserve energy as well as opinions about the use of information technologies for conservation. Middle- and high-income households in urban India were chosen as the focus population because they have access to electricity and own multiple types of appliances, allowing for various conservation strategies.[5]

Among other things, each participant was asked how often they engage in specific energy conservation behaviors as well as their motivations for engaging in those behaviors. The most common action to conserve electricity was unplugging appliances, with 86% of respondents stating they always or often engage in this behavior. This was followed by turning off the air conditioner (81%), buying energy efficient appliances (80%), turning off lights (67%), and changing appliance settings (55%).

We were particularly interested in the motivations for taking specific actions to reduce electricity consumption. The responses from this survey are summarized in Table 1. Health was among the least common motivation for almost every energy conservation behavior. Overall, for respondents that always or often engage in energy conservation behaviors, 84% cited saving money as a motivation and 43% cited habits. Only 9% of respondents cited the health of themselves or their family as a motivating factor for engaging in energy conservation.[6] For example, regarding unplugging appliances, as shown in Table 1, out of the households who unplug appliances always or often, 70% said they do so to save money, whereas 29% did so out of habit. Only 0.6% of these households unplugged their appliances because of health concerns.[7]

The relatively low percentage of respondents who indicated health as a motivation for energy conservation was quite surprising since energy production in India is a major cause of air pollution. This might indicate a lack of understanding of the link between energy use, the generation of electricity, and its associated air pollution. Most studies tend to show low awareness of the health impact of air pollution and

[4] Survey instrument available upon request from the authors.

[5] The average household represented in the survey has three adults, one child, and a 52 year old head of household. Approximately 56% of survey respondents were male, 71% had a bachelor's degree or higher, and 71% were married with a median annual income between 0.5 and 1 million Rupees. The surveyed population was comparable of the urban population of Delhi based on the 2012 Delhi census. See http://censusindia.gov.in/ Indeed, 98% of Delhi population is urban. On average, a Delhi urban household has 3.8 adult household members and 1.7 bedrooms. In the survey the number of adult household members is similar with 3.3 although of bedrooms is 2.6 and therefore slightly lower.

[6] This was calculated as the number of respondents that cited each motivation divided by the number of respondents that engage in any energy conservation behavior always or often.

[7] Table AI in the appendix compares the motivations for the survey responds that are most similar to our study's population. Even when the sample is reduced to respondents that have a bachelor's degree or higher, are in a household with two or three adults, and have income below five lakhs per year, money is the most frequently cited motivation for engaging in conservation behavior.

Table 1
Summary of energy conservation behaviors and motivations of 1820 respondents in urban Delhi.

Action	Motivation										
	Money	Habit	Necessity	Health	Future generations	Environmental friendly	Trends	Ethical/moral	Cultural	Other	No response
Unplug appliances	70.42	29.19	6.72	0.58	3.27	8.9	0.26	2.3	0.26	4.99	0.77
	(1100)	(456)	(105)	(9)	(51)	(139)	(4)	(36)	(4)	(78)	(12)
Buy energy efficient appliances	61.58	10.57	9.81	0.90	6.91	21.08	4.01	1.73	0.14	4.91	0.90
	(891)	(153)	(142)	(13)	(100)	(305)	(58)	(25)	(2)	(71)	(13)
Turn off AC	65.94	22.75	12.06	0.07	3.61	11.44	0.41	2.32	0.14	4.84	1.23
	(968)	(334)	(177)	(1)	(53)	(168)	(6)	(34)	(2)	(71)	(18)
Turn off lights	60.3	23.31	10.3	2.39	3.87	13.1	0.82	2.39	0.16	7.58	1.65
	(732)	(283)	(125)	(29)	(47)	(159)	(10)	(29)	(2)	(92)	(20)
Change appliance settings	38.71	18.55	10.38	11.49	2.62	14.21	2.32	3.23	0.3	13.81	2.82
	(384)	(184)	(103)	(114)	(26)	(141)	(23)	(32)	(3)	(137)	(28)

Notes: This table summarizes the motivations for taking energy conservation behaviors for the respondents that said they take action always or often. Respondents were able to list more than one motivation. The number of respondents in each category is listed in parentheses.

low understanding of how electricity is generated (Dunlap et al., 1993; Bickerstaff, 2004; Lee et al., 2015). Although existing studies tend to be focused on North America, Europe and Japan. One survey of 1724 respondents in India showed that while 78% were quite aware of the air pollution in their locality, very few respondents could identify the cause of air pollution (Mukherjee, 1993).

Based on the motivations from the survey, we would expect that information about monetary savings would be more effective to drive conservation behavior than information about health benefits since monetary motivations were cited more often than health motivations. However, research shows that there is often a gap between intentions and behavior (Nolan et al., 2008). Thus this importance of conducting a field experiment.

3. Methodology

While the survey is useful to gather information about energy conservation attitudes, it is limited in its ability to assess real conservation behavior. In order to test the effectiveness of monetary and non-monetary information strategies on electricity conservation behavior in India, we conducted a randomized controlled field experiment in a modern faculty apartment building located at the Indraprastha Institute of Information Technology (IIIT-D) in New Delhi.[8]

Our data includes 375,805 fifteen-minute electricity readings from 19 households over an academic year. Our field experiment, while small in size, takes advantage of two randomized treatment groups and a control group, high-frequency electricity data, detailed personalized electricity feedback, and knowledge of each participant's engagement with their electricity consumption feedback. This experimental design allowed us to test the impact of information strategies on energy conservation as well as the impact engagement with energy usage information has on conservation.

In one treatment, households received energy feedback messages describing the additional cost of their energy consumption in comparison to their most efficient neighbors. In the other treatment, households received feedback about their consumption in the metric of reduced air pollution emissions rather than as dollar costs to the household. That is, one group received information about how energy efficiency was serving their self-interest, and the other about how energy efficiency was contributing to the common good of reduced air pollution. The control group didn't receive energy feedback messages.

3.1. Field site and recruitment

Our field site has several important characteristics that facilitated the implementation of the experiment. First, all residents pay their own electricity bills, our experimental results therefore represent outcomes of real-life consumptions decisions in their natural settings. Second, apartments are standardized across the building with the same size and layout. This helps to control for differences in infrastructure to isolate energy use behavior. Third, our experimental design required the installation of an energy monitoring system that could record and process electricity usage, as well as distribute this information to participants on a web-based dashboard. Choosing a modern faculty housing complex on the IIIT-D campus ensured that 1) the infrastructure was in place that allowed the monitoring system to be installed, 2) there was an engineer on site that could immediately troubleshoot any issues with the system, and 3) the study participants would have internet access in their apartments and have the opportunity to view and interact with the treatment messages.

The apartment building was built in 2012 and consists of 28 individual faculty apartment units. In summer 2013, we sent an email to the faculty members in these apartments to describe the experiment and provided a link for each household to complete the consent process and entry survey.[9] Of the 28 households that were contacted, 19 (68%) agreed to participate in the study. To test for differences in average electricity consumption for the participants and non-participants, electricity consumption data were collected for all apartments in the complex; no statistically significant differences were found for the participating and non-participating households (P-value = 0.86).

Each apartment has three bedrooms and three bathrooms and is approximately 1700 square feet.[10] While individual appliances present in each apartment are not directly observable, the typical apartment includes multiple room-level air conditioners, a refrigerator, water heater, microwave, lights, fans, a television, and a computer. At the beginning of the study, each of the 19 participating households completed a brief survey that asked for basic household demographic information. Summary statistics for these demographics are presented in Table 2. Of the 19 households in the sample, 31.6% have children. The typical apartment has two adults with approximately 84% having a male head of household. While not shown in Table 2, the average household income for all of the participants is approximately 125,000–170,000 Rupees per month and their average monthly electric bill is approximately 1551 Rupees per month.[11] We recognize that our participating households are more educated and have higher income levels than the average household in India. While the sample may not be representative of the

[8] IIIT-D was established in 2008 and offers undergraduate and graduate degrees in computer science and engineering and electronics and communications engineering.

[9] This study was approved by the University Institutional Review Board (IRB): UCLA IRB#11-000669.

[10] The only exception is the director's apartment which is twice as large as the typical apartment. This apartment is made up of one unit on the 10th floor and the unit directly above on the 11th floor.

[11] At current exchange rates (January 6, 2016), this is equal to an income of $22,425–$30,498 (http://www.bloomberg.com/markets/currencies/). According to the World Bank, the purchasing power parity conversion factor between the United States and India is 0.3.

Table 2
Summary statistics.

Variable	Mean	Std. dev.	Min	Max
Has children	0.316	0.465	0	1
# of adults	1.947	0.759	1	4
Male	0.842	0.365	0	1
Daily kWh	8.940	10.285	0.000	104.360

Notes: This table shows summary statistics for the 19 households that participated in the study.

broader population of India, they are typical of urban households in India that could have smart metering technology installed in their homes.

When comparing these households to the sample in the survey of urban residents of New Delhi, we find that the average number of adults living in the household is slightly lower with 2 adults as compared to 3 in the survey, and that the number of bedroom is similar with 3 bedrooms in both cases. When we limit the survey responses to a more comparable sample of highly educated people living in apartments, we find that the responses regarding the importance of money versus health as a driver for conservation remains the same as with the main survey sample. That is to say, monetary motivations dominate, while health is seldom mentioned. In Appendix Table AI, we report the survey results for respondents with a bachelor's degree or higher, who live in a household with two or three adults, and have an income below five lakhs per year. The results show that for all conservation behaviors, money is cited as the main driver for above 60% of the respondents while health is about 1% or less. These results are not significantly different from those of the full sample.

Results based on the intake survey of our participating households, showed that only a minority of the participants thought their community was energy conscious (37%), but a majority believed it was possible to conserve energy (58%). This is important since if individuals perceive they can't have a significant impact on energy consumption, they might not behave in a pro-social manner (Larrick and Soll, 2008). In addition they exhibited slightly more pro-environmental attitudes than US households participating in Asensio and Delmas (2015, 2016). Our participants were more likely to agree with the statements that "when humans interfere with nature it often produces disastrous consequences" and "plants and animals have as much right as human to exist."

3.2. Experimental design

To test the effectiveness of our information messaging strategy on energy conservation, we followed the study design used in Asensio and Delmas (2015, 2016). Each participating household was randomly assigned to one of the two treatment groups or to the control group.

Both treatment groups had access to an online dashboard that displayed thirty-second, daily, weekly, and monthly electricity data. The electricity consumption of the control group was observed but this group did not receive any information about their electricity consumption.

The data presented on the dashboard included electricity consumption data for the past month, week, and day as well as real-time readings that would update every thirty seconds. Lastly, electricity consumption for the 20% most efficient apartments was calculated and presented on each apartment's dashboard as a benchmark for energy efficiency.[12] The dashboard can be seen in Fig. 1 and was accessible to the participants any time. In addition, personalized weekly emails were sent to each household in the treatment groups and summarized their past week's electricity consumption with a link to their personal energy dashboard.

Randomly selected households were assigned into one of the two treatment messages as displayed in Table 3. Households that were assigned to the monetary group were provided their actual electricity consumption in kWh along with information about much money they would spend over one year compared to their most efficient neighbor (₹7/kWh). Another group of households received energy use feedback with tailored information about the environmental health consequences of their consumption. Along with their actual electricity consumption in kWh, these households were told how many additional kilograms (kg) of pollutants were emitted (0.753 kg/kWh) as a result of their electricity consumption compared to their most efficient neighbor.[13] The messaging included a comparison to their most efficient neighbors, and therefore used descriptive norms. They were also told that these pollutants are known to contribute to health effects such as childhood asthma and cancer. As an example, of what the participants saw, we present below a message for each treatment that uses the same amount of electricity usage.

Monetary message: "Last week you used **20% more** electricity than your **efficient neighbors**. You spend **₹1820** more over one year."

Environment/health message: "Last week you used **20% more** electricity than your **efficient neighbors**. Over one year, you are **adding 195 kg** of pollutants which contribute to health impacts such as **childhood asthma and cancer**."

With the exception of the treatment messages, the dashboards for the health and financial groups were identical. This ensured that the average treatment effects that were estimated were a function of the treatment message and not of the availability of detailed historical electricity data.

One concern might be that some of the households in the control group might be aware of the experiment and that they behavior might be impacted by this knowledge. Although this is a possibility, it is unclear how this information would impact the behavior of the control group since they had no information about their electricity usage. In other words, they did not know whether they were above or below average users in the complex. If households in the control group did take measures to reduce their electricity during the experiment, then this would reduce the magnitude of our results, and therefore would indicate that our results are conservative.

Summary statistics for the treatment and control groups are presented in Table 4. Observable household characteristics are balanced across the treatment groups, but differences do exist in pre-treatment electricity consumption. Household fixed effects are included in the regressions below to control for any time-invariant differences between the treatment and control groups.

3.3. Technology

As is shown in Fig. 2, each apartment in this faculty complex was equipped with an energy metering system that allowed high-frequency electricity readings to be recorded every thirty seconds and stored on a server. Building on the system described in Chen et al. (2015), a script was written to automatically process the data as it was received by the server and then push the results to a personalized energy web dashboard for each apartment.

High-frequency electricity data was collected for each of the 19 participating households from August 1, 2013 to May 12, 2014. The data collection period corresponds to the academic year.[14] The baseline period lasted about 6 months. On February 18, 2014, participants in the two treatment groups received the first email with the treatment messages and were provided access to their personal energy dashboard. The treatment period lasted about 3 months.

[12] Since there was variation in occupancy across apartments, energy consumption was scaled by the number of occupants in each household and the top 20th percentile was estimated. The "efficient" number that was shown on each participant's dashboard was the value for the top 20th percentile multiplied by the number of occupants in each household's apartment.

[13] See Table VI of Cropper et al. (2012) and Table VIII of CEA (2011). The average emissions factor was based on PM 2.5, SO_2, NO_x and CO_2 emissions.

[14] The base line period of August 1, 2013 through February 17, 2014 is 201 days. The treatment period from February 18, 2014 through May 12, 2014 is 84 days.

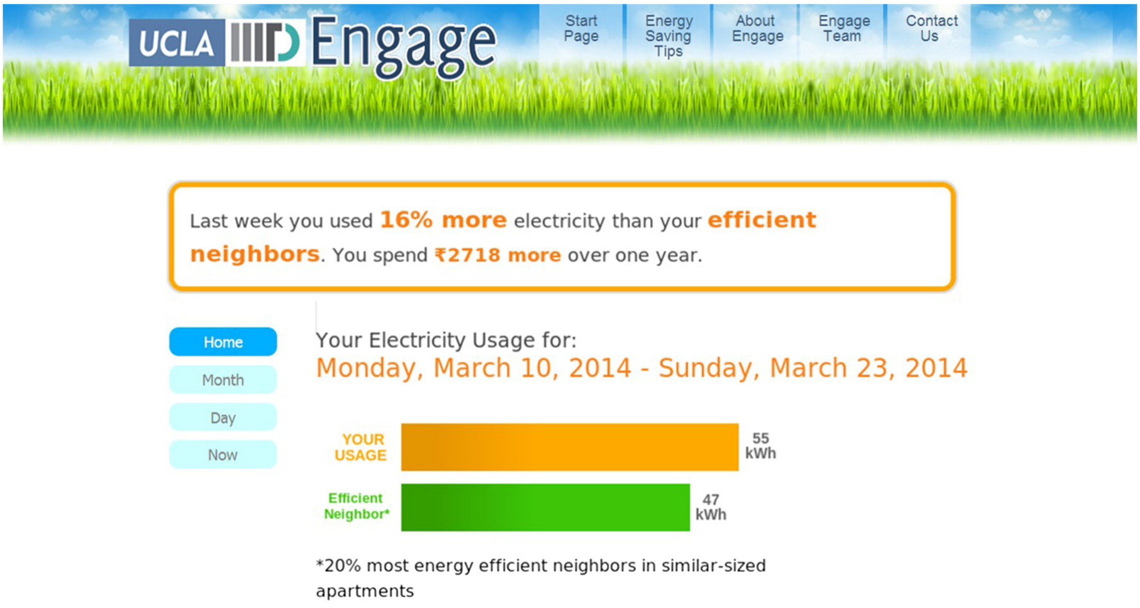

Fig. 1. Energy dashboard.

Table 3
Treatment messages.

Group	Treatment message
Financial group	"Last week, you used x% more/less electricity than your efficient neighbors. You spend/save ₹y more over one year."*
Health group	"Last week, you used x% more/less electricity than your efficient neighbors. You are adding/avoiding y kg of air pollutants which contribute to health impacts such as childhood asthma and cancer."*
Control group	None.

Notes: 'Efficient neighbors' in this context means households in the top 20th percentile of household weekly average kWh consumption (households with the lowest electricity use) for similar size apartments in the community.

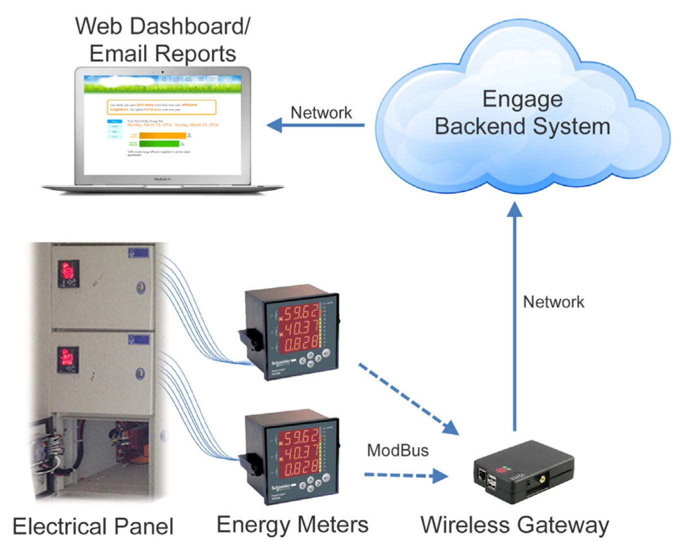

Fig. 2. Data flow.

This data was used to calculate electricity consumption over fifteen- and thirty-minute intervals as well as hourly and daily electricity readings. Even though the study site was able to provide electricity reliably, there were still several instances when the metering system failed to record electricity data. If the metering system failed to record data at non-random times, or non-randomly across treatments, there is a concern that the average treatment effects could be biased. This problem was mitigated by calculating electricity usage as the difference in cumulative energy consumption at two points in time, not by aggregating the thirty second readings. This ensured that electricity consumption can be accurately estimated even when there are periodic disruptions with the metering system. For example, electricity consumption for a fifteen-minute window for a specific apartment was calculated as $E_{it} - E_{it-15}$ where E is cumulative energy for apartment i. Calculating electricity consumption using this method ensured that electricity consumption can be accurately estimated even if there is a network failure between time periods t and $t - 15$.[15]

There were also several instances where data were missing for longer intervals so that electricity usage could not be estimated reliably using the method described above. As long as the data were missing randomly, unbiased average treatment effects can still be estimated. The patterns of missing data were investigated by calculating the share of missing observations for each hour of the day, and for each day of the week. Missing data appears to be randomly distributed across

Table 4
Summary statistics by treatment group.

Group	Number	Floor	Children	Adults	Male	Daily kWh
Control	7	5.857	0.286	1.714	0.857	7.667
		(1.864)	(0.488)	(0.488)	(0.378)	(10.973)
Financial	6	5	0.333	2.167	0.833	6.008
		(2.966)	(0.516)	(0.983)	(0.408)	(5.872)
Health	6	5.667	0.333	2	0.833	14.45
		(3.141)	(0.516)	(0.894)	(0.408)	(12.045)
P-value		0.84	0.98	0.60	0.99	0.00

Notes: There are no statistically significant differences across treatment in floor, children, adults, or male. Statistically significant differences do exist in pre-treatment energy consumption. Fixed effects will be included in the regressions that follow to account for unobserved heterogeneity at the apartment level.

[15] If the cumulative electricity readings were missing at the end of a specific time period, the last recorded value for that period was used. For example, if the cumulative electricity reading was missing at 15 min past the hour but available at 12 min past the hour, the reading at 12 min past the hour was used. While this introduces a small amount of measurement error, over 99% of the fifteen-minute electricity readings covered a time period of exactly 15 min.

Table 5
Pre- and post-treatment daily kWh usage by treatment status.

Group	Pre-treatment	Post-treatment	P-value
Control	7.667 (10.973)	6.711 (8.329)	0.069
Financial	6.008 (5.872)	5.736 (6.639)	0.438
Health	14.45 (12.045)	12.08 (10.712)	0.000

Notes: Standard deviations are reported in parentheses. The P-value is from a test for equality of pre- and post-treatment means.

Table 6
Estimated treatment effects.

Variables	(1)	(2)	(3)	(4)
	ln(15 min kWh)	ln(30 min kWh)	ln(hourly kWh)	ln(daily kWh)
Average daily temp				−6.41e−05 (0.00281)
Hourly temperature	0.000704 (0.000766)	0.000117 (0.000989)	−0.00119 (0.00125)	
Post treatment	−0.556*** (0.0221)	−0.502*** (0.0304)	−0.399*** (0.0428)	−0.409*** (0.121)
Financial × post	−0.0197 (0.0185)	−0.0445* (0.0258)	−0.0607 (0.0369)	0.0394 (0.140)
Health × post	−0.184*** (0.0205)	−0.151*** (0.0289)	−0.121*** (0.0424)	−0.113 (0.127)
Constant	−2.420*** (0.0670)	−1.604*** (0.0863)	−0.787*** (0.110)	2.322*** (0.292)
Household fixed effects	Yes	Yes	Yes	Yes
Observations	375,805	199,379	103,704	4802

Notes: Day of the week fixed effects and a cubic time trend are included in each of the specifications above. Hour of day fixed effects are included in columns 2–4.
Standard errors in parentheses.
*** P < 0.01.
** P < 0.05
* P < 0.1

days of the week. With the exception of 1–3 a.m., missing data also appears to be distributed randomly throughout the day. During 1–3 a.m., there are significantly fewer missing observations compared to all other hours. As a robustness test, the share of missing values for each apartment-day-hour was calculated and included in regression Eq. (1) described below.

One concern might be that some households were away for long time periods during the experiment and thus had a lower consumption, or that some households could have replaced one or more appliances with some that are more energy efficient. We asked for these possibilities in the exit survey and respondents told us that they were present most of the time during the experimental period, which took place during the academic year.

The final sample included 375,805 fifteen-minute observations to be used in the analysis. The data is available at Delmas (2017). The average household used approximately 8.94 kWh of electricity per day (272 kWh/month) which is slightly below the household average of 374 kWh/month in Delhi shown in Tewathia (2014). Since the apartments in the study area are relatively new compared to the rest of Delhi, the lower level of electricity consumption is not surprising. As shown in Table 5, pre- and post-treatment electricity consumption is significantly different for the health group ($P < 0.001$). There is also a slight decrease in consumption for the control group ($P < 0.1$) but no significant difference for the monetary group.

3.4. Econometric specification

Data was collected for over 9 months for each of the 19 households in the sample. Since the number of time periods is significantly greater than the number of households, treatment effects can be estimated using an efficient generalized least squares estimation (Cameron and Trivedi, 2010). The long panel characteristics of our data allows individual household effects to be accounted for using apartment-specific fixed effects and a more robust model of the error term than what is typically used.[16] The following difference-in-differences specification is estimated:

$$Y_{it} = \beta_1 \mathrm{post}_t + \beta_2 \mathrm{financial}_i * \mathrm{post}_t + \beta_3 \mathrm{health}_i * \mathrm{post}_t + \beta_4 \mathrm{temp}_t + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the log of electricity usage for apartment i at time t. We observe electricity usage at the daily, hourly, thirty-minute, or fifteen-minute intervals and provide the results for all these different time intervals. $Post_t$ is a dummy variable equal to one for all observations after treatment messages started, and $health_i$ and $financial_i$ are dummy variables indicating which treatment group to which each household was assigned. α_i represents household-specific fixed effects that account for any time-invariant household specific effects, and γ_t includes a cubic time trend as well as day-of-week and hour-of-day dummy variables.[17] ε_{it} is the error term and accounts for auto-correlated errors within household.[18] Additionally, the standard errors are corrected for heteroskedasticity. If both of the hypotheses discussed above are correct, $\beta_2 < 0$ and $\beta_3 = 0$. We also run robustness tests with additional specifications as described after the main results.

In what follows, the average treatment effect refers to the β_2 and β_3 coefficients in Eq. (1) above. Since a difference-in-differences specification is used, the average treatment effects measure the difference in electricity usage for the treatment group pre-and post-treatment minus the difference in electricity usage for the control group pre- and post-treatment. More formally, the average treatment effect is approximately $[Y_{T,Post} - Y_{T,Pre} - (Y_{C,Post} - Y_{C,Pre})]$ where Y measures average electricity usage for the treatment and control groups pre- and post-treatment. A negative average treatment effect would indicate that the reduction in electricity usage for the treatment group is larger than any reduction in electricity usage for the control group. That is, the average treatment effects that are discussed below measure energy savings relative to the control group.[19]

4. Results

4.1. Main specification

Results from the primary specification in Eq. (1) are shown in Table 6. Column 1 of Table 6 uses fifteen-minute electricity readings as the dependent variable, which is similar to the reading frequency available with most modern electricity smart meters. As such, this frequency

[16] For example, Allcott and Rogers (2014) and Jessoe and Rapson (2014) include household fixed effects but only cluster standard errors at the household level to account for within-household correlation of electricity consumption. The long panel nature of our dataset allows for household fixed effects and for the errors to be correlated within household, follows a household-specific auto-regressive process, and allows for heteroscedasticity.

[17] Hour-of-day dummy variables are not included in the daily electricity regressions. A cubic time trend was used to capture long-term changes in electricity consumption that may be impacted by seasonal changes. Additional specification was estimated with week-of-the-year dummy variables instead of a cubic time trend to allow for a more flexible non-linear effect. The results are robust to this specification and provided in Table AII.

[18] In the primary specification, each household's errors are assumed to follow a different AR(1) process. Because the number of time periods is large relative to the number of participants, we must specify a model for the serial correlation (Cameron and Trivedi, 2010). Additional specifications are estimated using fixed effects with standard errors clustered at the household level. The results are robust to this specification.

[19] It is possible to estimate a negative treatment effect when the treatment and control groups both increase electricity usage if the control group experiences an increase in electricity usage post treatment that is larger than an increase in electricity usage post treatment for the treatment group. Since Table 5 shows reductions in electricity consumption post treatment for all group, this possible result is not a concern.

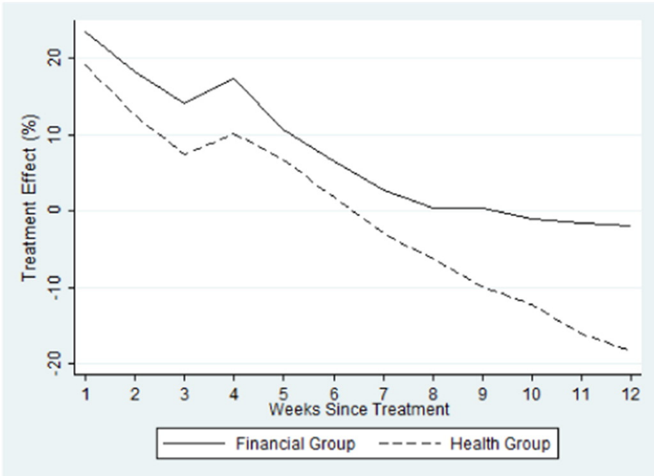

Fig. 3. Cumulative electricity conservation relative to the control group.

of electricity data is what would likely be used to estimate the impact of information strategies on energy conservation on a large scale. For example, Jessoe and Rapson (2014) uses fifteen-minute electricity smart meter data to measure the impact of real-time electricity pricing information. Using the fifteen-minute data as the dependent variable reveals a statistically significant average treatment effect of −18.4% for households in the health group and no statistically significant difference for households in the financial group.

In addition, to determine how sensitive the average treatment effects are to the frequency of data use, Eq. (1) was estimated using daily, hourly, and thirty-minute electricity readings as the dependent variable. Results that use thirty-minute electricity readings as the dependent variable are used in Column 2 and an average treatment effect of −15.1% is estimated for those in the health group. For the financial group, a marginally significant average treatment effect of −4.45% is estimated. In Column 3, hourly electricity readings are used as the dependent variable and an average treatment effect of −12.1% is estimated for those in the health group. An average treatment effect of −6.1% is estimated for households in the financial group, but this effect is not significant at conventional levels. In column 4, daily electricity readings are used as the dependent variable and the results show no significant average treatment effects for the health or financial groups. Given the relatively small number of participants in this study, it is not surprising that such low-frequency data are unable to detect any significant differences in the treatment groups.

Cumulative average treatment effects for the health and financial groups are shown in Fig. 3. Eq. (1) was estimated using all fifteen-minute energy readings (pre- and post-treatment) collected through the end of each seven-day period past treatment as the dependent variable to determine how energy conservation behavior evolves over time. The estimated β_2 and β_3 coefficients from Eq. (1) are shown in Fig. 3. In the early weeks of treatment, we find positive treatment effects for both treatment groups indicating that both treatment groups were saving less electricity post treatment relative to the control group. After approximately week six, electricity consumption for the financial group was not statistically different from the control group and this pattern continued throughout the remainder of the experiment. After week 12, or approximately six weeks of treatment, the estimated average treatment effects for the health group were negative and statistically significant indicating that electricity usage for the health group fell relative to the control group by the end of the study.[20]

In summary, the health and financial treatment messages had different effects on electricity savings. The health treatment messages led to statistically significant reduction in electricity usage relative to the control while the financial treatment messages were less effective in promoting energy conservation. Except for the marginally significant savings that were estimated using thirty-minute electricity data, on average, the financial treatment messages did not lead to a reduction in electricity usage relative to the control group.

Interviews with the participants after the study revealed that the savings in the health group were mostly a result of reduced heating and air condition and turning off lights and fans.[21] None of the households in the financial group who were interviewed indicated they took any actions to reduce their electricity consumption. Our results are therefore the opposite of what we hypothesized based on the motivations stated in the survey of urban Indians.

4.2. Treatment effects and participant engagement

The next set of results takes advantage of data on each household's engagement with the treatment messages and electricity dashboard to determine if the treatment effects depended on the level of engagement with the information provided. Engagement was measured two different ways. The first measured counts the number of weekly treatment emails that were opened, and the second counts the number of times each household viewed their personalized electricity dashboard. Summary statistics for the engagement variables are presented in Table 7. As shown in the top panel of Table 7, of the thirteen emails that were sent, the average participant in the health group opened ten emails with a standard deviation of 2.58, and the average participant in the financial group opened nine with a standard deviation of 5.43. For both groups, the most engaged participants in both groups opened all thirteen emails containing the treatment messages. The least engaged household in the health group opened just under half of the emails, but at least one participant in the financial group never viewed the treatment message. These summary statistics provide assurance that households in the health treatment group were exposed to the treatment messages, while it is possible that at least one member of the financial group never viewed the treatment messages.

The second measure of engagement indicates how many times each household viewed their personalized web-based electricity dashboard. Each dashboard had the embedded ability to track unique visits to the dashboard, the amount of time spent viewing the data, and which pages within the dashboard were viewed. Of these different measures, the number of sessions was determined to be the best measure of engagement with the dashboard.[22] This variable is summarized in the bottom panel of Table 7. The average household in the health group logged six unique sessions to their electricity dashboard with a standard deviation of seven sessions, while the average household in the financial group logged only two sessions with a standard deviation of two sessions. While both treatment groups had as least one household that never viewed the online dashboard, the most engaged household in the health group logged over three times as many sessions as the most engaged household in the financial group. A lack of engagement with the treatment messages and electricity data for this group could

[20] The cumulative electricity conservation relative to the control group at week 12 corresponds to the average treatment effects displayed in Table 6. Fig. A1 in the Appendix displays the confidence intervals for these results.

[21] After the end of the experiment, we conducted face to face interviews or email interviews with the participants. The questions posed during the interviews were open ended to gather information about the participants experience with the experiment, and the type of actions they took, if any, to reduce their energy consumption.

[22] Time spent viewing the dashboard appeared unreliable since some households tended to leave their browsers open for hours at a time one a single page. These households would be credited with being extremely engaged when it is likely they were not at the computer or were doing other tasks. The number of unique pages was also unreliable since households that switch between links sporadically could be credited for being extremely engaged. For example, someone that clicks back and forth between the monthly and weekly data 10 times within one minute would appear more engaged than someone who spends only a few minutes on the weekly and monthly data and then closes their browser.

Table 7
Summary statistics for engagement variables.

Group	Mean	Std. dev	Min	Max
Emails opened[a]				
Health	10.33	2.58	6	13
Financial	8.67	5.43	0	13
# of sessions[b]				
Health	6	7.16	0	16
Financial	1.83	1.94	0	5

[a] There were 13 emails sent to the participants between February 18, 2014 and May 12, 2014.
[b] A session is defined as a unique visit to the energy usage dashboard.

partially explain the insignificant average treatment effects for this group in Table 6.

The impact of engagement on energy conservation is estimated by interacting each household's level of engagement with the group-specific post-treatment interaction variable in Eq. (1). Table 8 provides the results with the number of emails opened as a measure of engagement.

For the financial group, each additional email that is opened leads to an average treatment effect that is 1.05% larger (more electricity used relative to control) when the dependent variable is fifteen-minute electricity usage (column 1) and 0.69% larger when thirty-minute electricity readings are used as the dependent variable (column 2). For the health group, each additional email that is opened leads to additional savings relative to the control group of 4.67% when fifteen-minute electricity readings are used as the dependent variable (column 1) and 3.39% when thirty-minute electricity usage is used as the dependent variable (column 2). The engagement interaction variables are not statistically significant for either treatment group when daily and hourly electricity readings are used. While statistically significant differences do exist across the four frequencies of data used, the estimated differences in kWh savings are quite small. For example, multiplying the additional savings (relative to the control group) of 4.67% per email opened by the daily average kWh of 8.49 kWh/day results in a savings for the health group of only 0.40 kWh/day for each additional email that is opened.

Results using the number of unique sessions to the web-based electricity dashboard as a measure of engagement are presented in Table 9. When hourly data is used as the dependent variable (column 3), each additional session is associated with an average treatment effect that is 1.35% larger (more savings relative to the control group). Similar to the previous measure of engagement, this effect is also robust the frequency of data that is used. The smallest reduction relative to the control group of 1.30% per session is estimated using thirty-minute electricity readings as the dependent variable, and the largest effect of 1.55% is estimated using the fifteen-minute electricity readings as the dependent variable. Once again, no significant treatment effects are detected for either group when daily electricity readings are used. For the financial group, regardless of the frequency of data that is used, additional dashboard views have no significant effect on electricity consumption.

The estimated average treatment effects for different levels of engagement are presented in Table 10 for the health group. Using estimates from the specifications that use fifteen-minute electricity readings as the dependent variable and the number of emails opened as the measure of engagement, the average treatment effect evaluated at the mean number of emails opened −16.7%. Evaluating the average treatment effect at thirteen emails opened (the maximum) shows an average treatment effect of just over 30%. Similar average treatment effects are found when evaluating the "Health × Post × # of Sessions" variable at the mean and maximum number of sessions.

In summary, the effect of engagement on energy conservation was significantly different for the health and financial groups. Each additional email opened by members of the health group was associated with additional energy savings relative to the control group, while the opposite effect was found for the financial group. For the financial group, it is possible that each additional email revealed how small the monetary costs of additional electricity consumption was relative to the private benefits of their electricity consumption. This imbalance of costs and benefits would be more salient for households that viewed the treatment messages more frequently leading to the more engaged users consuming more electricity than the least engaged. For the health group, the private and external costs of additional electricity consumption would become more salient to households that viewed

Table 8
Estimated treatment effects with engagement (email).

Variables	(1)	(2)	(3)	(4)
	ln(15 min kWh)	ln(30 min kWh)	ln(hourly kWh)	ln(daily kWh)
Average daily temp				−3.73e−05
				(0.00281)
Hourly temperature	0.000602	5.36e−05	−0.00120	
	(0.000765)	(0.000989)	(0.00125)	
Post treatment	−0.558***	−0.503***	−0.398***	−0.409***
	(0.0221)	(0.0304)	(0.0428)	(0.121)
Financial × post	−0.113***	−0.107***	−0.135**	−0.0841
	(0.0305)	(0.0399)	(0.0576)	(0.224)
Financial × post × emails opened	0.0105***	0.00691**	0.00826*	0.0137
	(0.00273)	(0.00335)	(0.00489)	(0.0199)
Health × post	0.300***	0.193**	0.0331	−0.223
	(0.0734)	(0.0917)	(0.130)	(0.332)
Health × post × emails opened	−0.0467***	−0.0339***	−0.0162	0.0127
	(0.00680)	(0.00860)	(0.0129)	(0.0353)
Constant	−2.380***	−1.576***	−0.763***	2.357***
	(0.0674)	(0.0868)	(0.111)	(0.299)
Observations	375,805	199,379	103,704	4802
Household fixed effects	Yes	Yes	Yes	Yes
P-value[a] health	0	0	0	0.64
P-value[a] financial	0	0.03	0.06	0.76

Note: Standard errors in parentheses.
[a] P-value is from an F-test of joint significance for the treatment effect and engagement interaction terms. Day of the week fixed effects and a cubic time trend are included in each of the specifications above. Hour of day fixed effects are included in columns 2–4.
*** P < 0.01.
** P < 0.05.
* P < 0.1.

Table 9
Estimated treatment effects with engagement (dashboard visits).

Variables	(1)	(2)	(3)	(4)
	ln(15 min kWh)	ln(30 min kWh)	ln(hourly kWh)	ln(daily kWh)
Average daily temp				−3.35e−05
				(0.00281)
Hourly temperature	0.000614	5.25e−05	−0.00121	
	(0.000766)	(0.000989)	(0.00125)	
Post treatment	−0.558***	−0.503***	−0.400***	−0.404***
	(0.0221)	(0.0305)	(0.0429)	(0.121)
Financial × post	−0.0414*	−0.0391	−0.0486	−0.0546
	(0.0250)	(0.0333)	(0.0485)	(0.195)
Financial × post × # of sessions	0.0114	−0.00284	−0.00603	0.0524
	(0.00877)	(0.0112)	(0.0156)	(0.0764)
Health × post	−0.0758***	−0.0647*	−0.0518	−0.0657
	(0.0264)	(0.0358)	(0.0504)	(0.143)
Health × post × # of sessions	−0.0155***	−0.0130***	−0.0135**	−0.0118
	(0.00241)	(0.00320)	(0.00533)	(0.0165)
Constant	−2.404***	−1.598***	−0.787***	2.354***
	(0.0672)	(0.0866)	(0.111)	(0.296)
Observations	375,805	199,379	103,704	4802
Household fixed effects	Yes	Yes	Yes	Yes
P-value[a] health	0	0	0	0.53
P-value[a] financial	0.25	0.22	0.24	0.76

Notes: Day of the week fixed effects and a cubic time trend are included in each of the specifications above. Hour of day fixed effects are included in columns 2–4. Standard errors in parentheses.
[a] P-value is from an F-test of joint significance for the treatment effect and engagement interaction terms.
*** $P < 0.01$.
** $P < 0.05$.
* $P < 0.1$.

the treatment messages more frequently, leading to the most engaged participants to have the largest relative electricity savings.

Also, the estimates show that additional visits to the electricity dashboard had a smaller effect on electricity consumption than additional weekly emails being opened. For the health group, the marginal savings of an additional visit to the electricity dashboard ranged from 1.30 to 1.55%, while the marginal savings of viewing an additional email ranged from 1.88 to 4.67%. Since all the treatment information that was available on the dashboard was also contained in the weekly emails, the marginal savings of viewing the treatment message on the dashboard should be smaller for those who opened their emails. In addition, since there was a direct link to the electricity dashboard in the weekly email, most of the dashboard views come directly after being exposed to the treatment message in the emails.

4.3. Robustness tests

We conducted several robustness tests that are reported in the Appendix.

The first set of robustness tests using 15-minute electricity readings as the dependent variable is shown in Table AII. In each column, the more efficient GLS method with household fixed effects is used. For reference, column 1 presents the coefficients from Colum 1 in Table 6. In Column 2, week fixed effects are used instead of a cubic time trend to allow for a more flexible non-linear effect in energy usage across longer periods of time. The average treatment effect is slightly larger while the standard errors are slightly smaller. In column 3, day-of-the-week and hour-of-day fixed effects were omitted and the average treatment effect is slightly smaller. In column 4, we include the share of missing observations. The estimated average treatment effects remain robust.

The second set of robustness test are shown in Table AIII and are estimated using fixed effects with clustered standard errors (not the more efficient GLS method) and 15-minute electricity readings as the dependent variable. In Column 1, the average treatment effect for the health group is −19.1% compared to −18.4% in Table 6 Column 1. In Column 2, we drop the apartment that never viewed the email messages containing the treatment information, and in Column 3 we dropped the participant that lived in an apartment that was made up of two regular apartments. In each specification, the average treatment effect remains robust and significant at the 10% level.[23] In Table AIV, we conduct the same robustness tests using fixed effects with clustered standard errors for the specifications that use the number of treatment emails opened as a measure of engagement. In each specification, the results are similar to the main specification in Table 8. The main difference is that opening emails is not always significant for the financial group. In Table AV, we conduct the same robustness tests using fixed effects with clustered standard errors for the specifications that use the number of dashboard visits as a measure of engagement. The results for the health group are similar to those reported in the main specification in Table 9. Nothing changed for the financial group since dashboard views were not significant in our main specification.

Table 10
Summary of treatment effects for the health group.

	15 minute	30 minute	Hourly	Daily
No interactions				
Average effect	−0.184	−0.1510	−0.1210	−0.1130
Interaction with # of emails opened				
Effect at min (6)	0.0198	−0.0104	−0.0641	−0.1468
Effect at mean (10)	−0.167	−0.146	−0.1289	−0.096
Effect at max (13)	−0.3071	−0.2477	−0.1775	−0.0579
Interaction with # of sessions				
Effect at min (0)	−0.0758	−0.0647	−0.0518	−0.0657
Effect at mean (6)	−0.1688	−0.1427	−0.1328	−0.1365
Effect at max (16)	−0.3238	−0.2727	−0.2678	−0.2545

Note: All treatment effects are in percentages.

[23] The results in Tables AIII and AIV are from a specification that includes household fixed effects and clusters the standard errors at the household level and not the more efficient GLS procedure that is used in the main tables. When the panel GLS method is used with household fixed effects, the treatment effects for the health group are significant at the 1% level when we drop the double apartment and when we drop the apartment that never viewed the treatment messages by email.

5. Discussion and conclusion

Individual feedback about a household's electricity consumption decisions has been used to promote energy conservation behavior for nearly forty years (Delmas et al., 2013), but has seldom been employed in developing countries. This study builds on this literature by conducting a residential electricity field experiment that investigates the impact of information strategies on electricity consumption decisions in India. There are three important lessons to be learned from this study. First, households who received frequent information that framed their electricity consumption in terms of health and environmental impacts experienced electricity savings relative to the control group, which was not provided additional information about their electricity usage beyond the electricity bill. Those who received information in terms of financial savings, or cost, did not experience electricity savings relative to the control group. This result was opposite of what we could have predicted based on the survey of energy conservation attitudes. On average, households that received the health/environmental messages reduced electricity consumption by 15–18%. We also found that conservation is short-lived when the curtailment benefits are framed as a monetary reward, and is more persistent when it is framed as an environment and health-based community concern.

These results are consistent with Asensio and Delmas (2015, 2016) electricity field experiment conducted in Los Angeles, where the households who received the health/environmental messages did reduce their electricity consumption by 8% as compared to the control group, and those who received the monetary messages did not differ significantly from the control group. They are also consistent with another experiment conducted in Germany, where an environmental framing lead to high intention for climate-friendly behavior while the monetary framing lead to no difference with the control group (Steinhorst et al., 2015). In addition, results from an experiment conducted in the US showed that some households reduced electricity usage in response to a decrease in electricity prices, thus providing evidence that other factors such as non-monetary considerations could play a larger role in energy conservation behavior than do energy prices (Jessoe et al., 2014).

Nevertheless, the insignificant results for the monetary group were somewhat surprising given that expenditures on electricity represent a larger share of income in India compared to the United States or Germany. However, when we interviewed our participants at the end of the experiment, households in the monetary group indicated that they did not consider monetary savings provided in the treatment messages when making their electricity consumption decisions. Based on the weekly treatment messages, the median household in the financial group saw a potential savings of 327 Rupees per month if they reduced their electricity consumption to the level of their efficient neighbor. This is enough to buy roughly two gallons of milk or just over one gallon of gasoline. Several said that the savings presented in the treatment messages were not sufficiently large to motivate them to conserve or that monetary savings was not something that motivated them to reduce their electricity consumption. Energy pricing in India has been kept relatively low to promote spread of electricity especially in rural areas. Such low prices might be a barrier to achieving energy efficiency. We started with the premise that the Indian context could be a setting were monetary gains and losses would make a larger fraction of the income than in the U.S. However, our results indicate that the monetary savings were insufficient to drive conservation in the context of our Indian urban participants.

This raises question on how different the context of the experiment was as compared to the U.S. context and whether our results can be generalized to the rest of the population of a developing community. Our participants were highly educated and represented higher income than the average Indian population. However, there were more typical of middle class urban households in New Delhi with access to information technologies. While our intake surveys showed some attitudinal differences regarding sustainability between Indian and US households, it is possible that motivations for energy conservation become more alike as differences in income and education between middle class in India and developed countries diminish. Further studies should evaluate how these motivations vary for different levels of income and education within developing countries.

Second, our findings about the effectiveness of health messages indicate the potential to use non-monetary messages for urban middle class households in developing countries. This is particularly important as this demographic is growing at a rapid pace. Every household from this group that was interviewed indicated that the treatment messages motivated them to take actions to reduce their electricity consumption. Our findings are contrasted with the motivations to conserve stated in the survey of Indian urban households. It might indicate a lack of knowledge about the link between energy use, air pollution and health. Indeed, while the field of air pollution and atmospheric science is gaining ground in India with a surge in the published research, much of the knowledge is widely scattered and not really shared with the population. While reviews in the past have provided scientific recommendations (Pant and Harrison, 2012) there has been no concerted effort towards addressing the various aspects of the air pollution (source to impacts), and providing a global summary as well as gaps in current knowledge to the public.

Third, this study is the first to show the importance of household's engagement with electricity consumption data to understand conservation behavior. While Asensio and Delmas (2015, 2016) described consumer engagement with the information provided, they didn't study how different levels of engagement impacted conservation behavior. Our analysis allows us to tease out the difference between those that were treated but did not look at the information and those that were treated and were engaged with the information by opening their emails or accessing the website. The results show that engagement with the information can have a positive or negative effect on energy conservation. Households that were more engaged with the health/environmental messages that reminded them of the negative consequences of their electricity consumption conserved more than households that were less engaged. Engagement had the opposite effect in the financial treatment group. Households that were more engaged with the monetary savings messages that reminded them of how small the savings were from reducing their consumption consumed more electricity than those that were less engaged. These results show that although it is important to design informational strategies that will engage consumers of electricity, the context of the messages should be well-planned to ensure that the information strategy does not have the opposite effect of the one anticipated and discourage energy conservation behaviors.

Fourth, we show a difference between what was stated in a survey about conservation motivations and the revealed behavior through the experiment. This difference puts in question the validity of self-report measures of pro-environmental behavior (Kormos and Gifford, 2014). Similar to the way hypothetical bias is mitigated in stated preference surveys by including a consequential coercive payment mechanism (Carson, 2012), the experimental results presented here are more reliable than stated motivations in a survey because our treatment strategy included realistic monetary rewards and health consequences for the participants (Harrison and List, 2004). Future research should focus on the difference in stated preferences towards energy conservation behavior and observed actions in both developed and developing countries. Since public awareness about effective conservation strategies and the health consequences of electricity generation will vary significantly across cultures, information campaigns could be an effective way to narrow the gap between stated and observed energy conservation behaviors.

Lastly, our study is not without limitations. In addition to the potential technical issues that were discussed above, our study includes a relatively small sample of households that lived in the faculty-housing complex. Despite this limitation, we were still able to precisely estimate changes in electricity consumption behavior because our metering technology recorded electricity data at a very high frequency. When hourly, thirty-minute, and fifteen-minute electricity readings were used, significant and robust average treatment effects were estimated, and the effects were estimated more precisely as higher frequency data were used. This result shows that future studies focusing on changes in electricity consumption behavior should rely on higher frequency electricity consumption data than monthly electric bills.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2017.09.004.

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