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**Saving Power to Conserve Your Reputation?  
The effectiveness of private versus public information**

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University of California, Los Angeles**

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# **Saving Power to Conserve Your Reputation?**

## **The effectiveness of private versus public information**

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**Abstract**

**April 2012**

Environmental damage is often an unseen byproduct of other activities. Disclosing environmental impact privately to consumers can reduce the costs and/or increase the moral benefits of conservation behaviors, while publicly disclosing such information can provide an additional motivation for conservation - cultivating a green reputation. In a unique field experiment, we test the efficacy of private and public information on electricity conservation. Private information was given through real-time feedback and social norms over usage, and public information was given through a publicly visible conservation rating. While private information alone was ineffective, public information motivated a 20 percent reduction in electricity consumption.

JEL codes: Q2, Q4, Q5, D03.

Keywords: conservation behavior, conspicuous consumption, image motivation, electricity, energy efficiency, signaling, public information.

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# 1 INTRODUCTION

Environmental damage is often an unseen byproduct of other activities, with both consumers and those around them unable to gauge the impacts of their actions. Policies that correct this information asymmetry have the potential to encourage environmentally friendly behavior by consumers. Such information policies are becoming increasingly prevalent: eco-labels, which intend to reduce the information asymmetry between producers and consumers (Crespi & Marette, 2005; Leire & Thidell, 2005), have expanded from a mere dozen worldwide in the 1990s to more than 430 programs today.<sup>3</sup> Improved feedback over water, electricity and gas usage, which aims to better inform consumers about the impacts of their actions (Fischer, 2008), has resulted in the mass rollout of smart energy meters, with 76 million already installed worldwide.<sup>4</sup> Mandatory and voluntary corporate disclosure systems are increasingly being used to replace or augment government regulation (Khanna, 2001; Delmas et al., 2009), with common examples including the Toxics Release Inventory, lead paint disclosures, drinking water quality notices, and the international Environmental Management Standard ISO 14001 (Delmas & Montes-Sancho, 2011). Yet despite the popularity of information policies, we still have little understanding of their effectiveness.

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<sup>3</sup> [www.ecolabelindex.com](http://www.ecolabelindex.com)

<sup>4</sup> [www.pge.com/smartmeter](http://www.pge.com/smartmeter)

In this paper we evaluate the effectiveness of two different information policies in inducing electricity conservation. Electricity usage is a useful vehicle for assessing the impact of information treatments because it is generally invisible to both consumers and those around them. In the United States, most residential and commercial electricity users receive no information over their electricity usage apart from their monthly bills, which do not disaggregate across time periods or sources of usage. Understanding the potential mechanisms to induce energy conservation is an essential part of addressing climate change, since more than one quarter of all U.S. carbon dioxide emissions stem from electricity generation for commercial and residential customers (EIA 2010; EPA 2010).<sup>5</sup> Recent studies estimate that residential energy consumption could be reduced by 22 to 30 percent within the next five to eight years purely through behavioral changes (Gardner & Stern, 2008; Laitner et al., 2009). Thus information policies, which can change the costs and benefits of conservation, have the potential to become a major driver of behavioral change.

One potentially powerful informational tool is the provision of detailed feedback to consumers over their own energy usage. Such information can allow consumers to better understand the costs of their actions, leading to improved energy usage decisions (Fischer, 2008). Feedback can also indicate individual usage relative to comparable users (Schultz et al., 2007; Ayers et al., 2009; Alcott, 2011). This can create a social norm over electricity usage that increases the moral cost of not conserving (Levitt & List, 2007). Surveys of the existing feedback literature report savings in the range of 4 to 12 percent, with the highest savings

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<sup>5</sup> This is not surprising considering that residents of the United States spend more than 90 percent of their lives in buildings (Evans & McCoy, 1998).

coming from real-time feedback (Abrahamse et al., 2005; Darby, 2006; Ehrhardt-Martinez et al., 2010). However, not all results are this positive, and many studies have found no statistically significant reduction (Allen & Janda, 2006; Klos et al., 2008; Kihm et al., 2010), increased usage (Sexton et al., 1987; Sulyma et al., 2008) and heterogeneous responses (Van Houwelingen & Van Raaij, 1989; Brandon & Lewis, 1999; Parker et al., 2006; Costa and Kahn, 2010). Moreover many of these studies suffer from methodological difficulties in that they involve small samples (e.g. Allen & Janda, 2006; Parker et al., 2006) or short time periods (e.g. Peterson et al., 2007).

Individual feedback can be termed *private information* in that it is privately disclosed information about an agent's own (relative) energy use or environmental impact. We introduce a behavioral innovation – public information - and evaluate its efficacy relative to private information in a unique field experiment in the residence halls of the University of California, Los Angeles (UCLA). *Public information* is information about a specific agent's behavioral impact that is publicly disclosed, allowing environmentally friendly behaviors to act as a signal of “green” virtue. These reputational benefits can motivate conservation amongst consumers. Since both private and public information are non-pecuniary behavioral interventions, testing their efficacy in an environment devoid of complicating pecuniary motivations is ideal. Thus students in residence halls, who do not pay electricity bills, are the perfect subjects for such an experiment. In a nine-month long experiment, participants were given private information in the form of real-time feedback and social norms over their room's energy usage. A subset of participants also had their energy usage made public in the form of posters that described their room as being an above/below average energy conserver. We found that private information alone was not sufficient to motivate statistically significant energy savings in our sample.

However, when we combined private information with public information, we induced an average energy saving of 20 percent, with the majority of saving coming from high energy users. When public information was removed, conservation behavior continued to persist, even three months later, indicating habit formation. This is the first study to use public information to induce conservation behavior amongst individuals.

In a world where electricity is a small component of household expenditure<sup>6</sup> and price increases are politically difficult to implement, behavioral “nudges” are a necessary tool to induce energy conservation. The heterogeneity of consumers means that a one-size-fits-all solution is unlikely to be successful, and hence behavioral scientists need a varied toolkit that appeals to a variety of motivations. Compared to other policies such as pecuniary incentives, information policies are a relatively inexpensive way to encourage conservation, especially in this age of mass information and telecommunication technology. We show that public information, or “conspicuous conservation”, can be an effective and valuable part of this toolkit. Public information is particularly useful in that it can motivate conservation behavior among all consumers, *including* those who are not intrinsically motivated to conserve energy.

This paper is organized as follows. In section 2 we provide a conceptual framework and testable hypotheses. In section 3 we discuss the experiment location and technology, as well as the experimental design. In section 4 we describe how we implemented the private and public information treatments for the experiment, as well as recruitment and randomization strategies.

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<sup>6</sup> 2.8 percent of 2009 household expenditure for the United States as a whole, and 2.2 percent for the Western United States (Consumer Expenditure Survey online tables).

In section 5 we examine the experiment results, with a discussion of heterogeneous treatment effects and persistence. In section 6 we discuss the empirical results and bring in some qualitative evidence from entry and exit surveys to support them, before our concluding discussion in section 7.

## 2 INFORMATION AND MOTIVATION

This section develops behavioral hypotheses on the impact of public and private information on conservation behavior. A simple formalized model is presented in Appendix F.

Scholars have identified three main types of motivations to conserve (Benabou & Tirole, 2006): intrinsic motivation, extrinsic motivation and reputation or image motivation. *Intrinsic motivations* consist of both warm-glow and pure altruism (Ariely et al., 2009). Pure altruism is motivated only by an interest in the welfare of others, whereas warm-glow altruism is motivated by a boost in self-esteem associated with improving the welfare of others (Andreoni, 1990). *Extrinsic motivations* usually entail pecuniary rewards, although some non-pecuniary rewards have been used to motivate conservation in terms of energy conservation competitions (Peterson et al., 2007) and personal goal setting (Van Houwelingen & Van Raaij, 1989).<sup>7</sup> *Reputation motivation* differs from extrinsic motivations as it occurs when visibly prosocial actions act as a signal of virtue, creating a positive reputation. In this paper, we focus on intrinsic and reputation motivations because of the relatively low extrinsic rewards currently associated with energy

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<sup>7</sup> Peterson et al. (2007) induced dramatic savings of 30 percent in dormitory energy competition (with real-time feedback at the dormitory level). However this was over a short duration and it is not clear how sustainable this conservation behavior would be in the long run.



conservation at the residential level. We argue that private information can be an effective conservation tool for individuals with intrinsic motivations while public information can motivate individuals beyond their intrinsic motivations by appealing to their desire for social approval.

Private information can either consist of procedural information or social norms.

Procedural information, such as giving customers more detailed feedback over their *own* energy use, provides “know-how” and can reduce the cost of conservation activities (Schultz, 2002). For example, real-time information over fuel economy can show drivers exactly which aspects of their driving style uses the most gas, thereby allowing them to conserve fuel far more easily than before. According to psychologists, more information results in learning about potential behavior and therefore enables individuals to perceive alternative actions (Stern, 1992). Changes in behavior can occur when a person is aware of an issue, thinks his or her actions can influence it, and feels capable of engaging in such action (Fischer, 2008). Under such preconditions, detailed feedback on how to perform conservation activities, and on the outcomes of these activities, can facilitate conservation behavior (Fischer, 2008). It is therefore conceivable that learning about the impacts of energy usage can lower barriers to conservation action.

Information about social norms, such as information about *aggregate* energy usage by others, can increase the moral benefit from engaging in conservation. Social norms influence warm-glow altruism by changing perceptions of what behaviors are immoral, antisocial, or at odds with one’s own identity, thereby increasing the moral cost (or moral benefit) of an action (Levitt & List, 2007). For example, people may feel more guilty about not recycling when they are informed that all of their neighbors do so, compared to when they are informed that none do.

Empirical work by psychologists and political scientists has shown social norms to be effective at inducing conservation behavior in a number of settings, including: recycling (Schultz, 1999), towel re-use (Goldstein, Cialdini, & Griskevicius, 2008), litter reduction (Cialdini, Reno, & Kallgren, 1990), water conservation (Ferraro & Price, 2012) and energy conservation, which was discussed previously.

In conclusion, by decreasing the costs of conservation, or increasing the moral benefit, private information about detailed energy use or aggregate energy usage by others will lead to an increase in the level of conservation. We therefore hypothesize the following:

*Hypothesis 1: The level of conservation will increase when private information is provided.*

Public information will make conservation behavior visible to others, thereby influencing how others perceive the individual. Individuals wishing to obtain a socially desirable reputation for conservation may now have an additional motivation to conserve – reputation. This may increase the level of conservation relative to when conservation activities were unobservable.

Psychologists find that a prosocial reputation is valuable, allowing consumers to obtain a number of non-market goods such as trust (Barclay, 2004), friends, allies, romantic partners (Griskevicius et al., 2007; Miller, 2009) and leadership positions (Hardy & Van Vugt, 2006). Prosocial reputation has been shown to be a significant motivator for charitable donations (Ariely et al., 2009), volunteer firefighting (Carpenter & Knowles, 2008), blood donation (Lacetera & Macis, 2009), solar panel purchases (Lessem & Vaughn, 2011; Dastrup et al., 2012) and hypothetical green purchases (Griskevicius et al., 2010). In the corporate world, Jin and Leslie (2003) found that mandatory hygiene cards positively affected restaurant quality and

health outcomes, while Delmas et al. (2009) found that mandatory disclosure over utility electricity generation mixes resulted in an increase in cleaner fuels. Reputational motivation is unleashed through public information and has not yet been used as a mechanism to induce individual energy conservation behavior.

By engaging in conspicuous prosocial behavior, consumers signal that they are pro-socially minded (rather than pro-self). If energy usage is made visible to the public, consumers may be motivated to conserve energy to gather the benefits of a “green” reputation (Griskevicius et al., 2010). We therefore hypothesize the following:

*Hypothesis 2: The level of conservation will increase when public information is provided.*

Both of these hypotheses describe an average treatment effect of public and private information. However, the effectiveness of both information treatments may vary with individual levels of intrinsic motivation and current energy usage.

First, the provision of private information might result in larger behavior changes by those individuals with higher levels of intrinsic motivation. The intuition behind this comes from examining the costs of conservation. Since each additional unit of conservation will be more difficult to attain than the previous unit (exhausting low hanging fruit), the marginal costs of conservation will increase with the level of conservation. Thus an individual who is already engaged in considerable amounts of green activity, will have a higher marginal conservation cost than an individual who is not engaged. The introduction of new procedural knowledge will proportionally reduce the cost of all conservation activities. Since the marginal cost of conservation is higher for those who are conserving more, any proportionate reduction in

conservation costs, will lead to a greater absolute decrease in marginal conservation costs. This in turn will lead to a larger increase in conservation activities.

Second, social norms could cause heterogeneous responses depending on whether individuals are outperforming or underperforming relative to the norm. Schultz et al. (2007) showed that social norms could cause a boomerang effect, with below average energy users increasing usage and converging to the norm. This only held for descriptive social norms, which describe what behavior is commonly enacted in a given situation and include information over aggregate behavior (Cialdini, Reno & Kallgren, 1990). The boomerang effect occurs because while the moral benefit of conservation will increase for those agents who are underperforming relative to the norm, the opposite may occur for those who are outperforming the norm. These individuals will therefore be less motivated to conserve and will increase usage.

Third, individuals might only increase their participation in this activity when doing so has a positive effect on society's assessment of them. Reputation functions by acting as a signal of virtue. Conservation levels should only increase in response to public information if the marginal change to reputation from increasing the level of a prosocial activity is greater than zero. If increasing the level of the prosocial activity will have no beneficial effect on the reputation of an individual, then making that activity public information should have no effect on it. For example, if person x always recycles in her own home, putting person x on a publicly visible reality TV show, like Big Brother, will not motivate person x to recycle more. Therefore individuals will be more likely to participate in conservation if this improves how they are perceived by other members of society.

We were able to test these hypotheses over aggregate and heterogeneous behaviors using uniquely generated experimental data. The experimental design and context is described in the next section.

### 3 METHODOLOGY

#### 3.1 Experimental Design

We installed real-time electricity meters in 66 residence hall rooms on the UCLA campus for one academic year (September 2010 to May 2011). Residence halls are an ideal location for a study of this nature. Firstly, the dormitory rooms are standardized so that there are no differences in energy efficiency or size in the housing stock. Secondly, students do not pay electricity bills, so there are no price effects to confound with our behavioral interventions. This is particularly relevant for reputation motivations, since pecuniary rewards (like saving money on your energy bill) can dilute the green signal given by conservation actions. Finally the students had adequate control of their environment (lights, thermostats, plug load, windows) to meaningfully engage in conservation.

Table 1 below outlines the basic experimental design. Participating rooms were randomly split into three different groups, which we designate: *control*, *dashboard* and *poster*. Initially, the baseline usage of all three groups was recorded over a 6 week period. During this period electricity usage was monitored by the experimenters, but the participants were given no information about their electricity usage. Following this was a 5 week period, during which the *dashboard* and *poster* groups were both exposed to the private information treatment, with the

*control* group continuing to receive no information. Private information took the form of real-time feedback delivered through an online energy usage dashboard and weekly emails. Each room had its own customized dashboard.

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[Insert Table 1 about here]

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The public information treatment, which lasted 7 weeks, involved exposing the *poster* group to both public and private information, while the *dashboard* group continued to receive only private information. Public information took the form of posters and emails, which publicly rated rooms as above or below average energy conservers. Those participants who now had their energy usage in the public realm could cultivate (or preserve) a “green” reputation by conserving energy.

In the final stage of the experiment we tested whether the new behaviors inspired by the experimental interventions resulted in habits that persisted even in the absence of these stimuli. A habit is formed when a task is repeated to the point where it becomes mechanical and enacted without awareness of circumstances (Beach & Mitchell, 1978; Aarts et al., 1997; de Vries et al., 2011). To test for persistence of treatment effects, we removed public information as a motivational instrument and observed whether conservation behavior persisted in its absence.

### **3.2 Location and Technology**

The experiment took place in three residence halls on the UCLA campus. All three buildings were built at the same time, opening their doors in 2005/2006, and are variations on a

common design. Rooms are standardized across the buildings, which are located within a few hundred feet of each other. Each occupant has a bed, desk and wardrobe. All rooms are equipped with a programmable thermostat, operable window and florescent overhead light. Shared rooms have an additional florescent hall light. Bathrooms are shared between rooms and were not monitored by the experiment.

The electricity infrastructure of the UCLA residence halls made energy monitoring at the room level impossible given existing technology. Like most commercial buildings, including dormitories, office blocks and schools, wiring is done at the building level, rather than at the room level, making room level feedback impossible. To overcome this problem, new technology was developed that allowed for the rapid retrofit of the rooms selected for the experiment. The new technology involved augmenting off-the-shelf plug point energy meters (which measure plug load) with sensing technologies to measure light usage and heating/cooling; and radios to wirelessly communicate with an internet-enabled gateway. This equipment was installed during the summer vacation, so that students moved into a new room complete with electricity monitoring equipment. Additional information over the technology used and room installations can be found in Appendix C.

## **4 EXPERIMENT IMPLEMENTATION**

### **4.1 Private and Public Information Treatments**

Private information was given to participants through a custom built web interface which we called the UCLA ENGAGE dashboard, as well as weekly email reports. The dashboard gave

users real-time information over their room's current electricity usage, as well as historical and social usage comparisons and a running average of electricity usage by source. An example of the ENGAGE dashboard can be seen in Figure 1, below:

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[Insert Figure 1 about here]

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The private information given in the dashboard and emails could potentially teach participants about when and how they were using electricity, lowering the cost of conservation (Fischer, 2008). In addition the dashboard and emails enhanced social norms towards conservation with visual comparisons between a participant's energy usage and that of similar rooms. This descriptive social norm should increase the moral benefits of conservation for above average users, increasing intrinsic motivation. It is also possible that the descriptive norm reduced conservation costs by benchmarking attainable conservation levels. Since social norms were built into the dashboard, we cannot separately identify the effects of feedback and social norms and have grouped them collectively under the label private information. dashboard access was tracked using Google Analytics.<sup>8</sup> More information on the dashboard as well a sample of the weekly email can be found in Appendix A.

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<sup>8</sup> Tracking took place at the room level. To facilitate ease of access to the dashboard, there were no logins. Rather each room had its own unique coded dashboard address. No identifying information was placed on the dashboard ensuring privacy. By tracking hits to the address, we can see how often rooms access the dashboard and which pages they were looking at (weekly, which was the default, daily or three hour). We cannot differentiate between roommates, since they have the same dashboard address.



Participants in the public information treatment were publicly rated as being above or below average energy conservers.<sup>9</sup> This relative rating system was used to protect the privacy of participants and prevent contamination of the control group with electricity usage information. Ratings were made public with large, prominently displayed posters, posted on each floor occupied by rooms participating in the public information treatment. The posters were placed on notice boards opposite the elevator, ensuring that all students on that floor would pass it several times a day. Ratings were determined on a weekly basis, where the weeks corresponded to the commonly known calendar weeks of the academic quarter. If a room used less electricity for the week than similar rooms (“an above average energy conserver”) it was given a green sticker for the week. If the room used more electricity (“a below average energy conserver”) it was given a red sticker for the week. The language on the poster was explicitly chosen to reflect positive behaviors – energy conservers as opposed to energy users.

Since the *poster* group only comprised one third of the entire group, it was possible for all rooms in the treatment to conserve energy and be awarded green stickers. This was made clear to the students through several emails as well as a note on the poster. To increase publicity and exposure, a copy of the poster was also emailed to each participant in the experiment (treatment and control). The public information treatment made the previously invisible prosocial action of conservation publicly visible. This created an additional motivation for participants to conserve – maintaining or creating a green reputation.

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<sup>9</sup> While the term ‘average’ was used for simplicity of exposition, rooms were actually rated as being above or below the median for their room type. Rooms were split into two types: single or shared. The use of the median and classification system were explained to students in the notes to the poster.

## 4.2 Experiment Recruitment

Several recruitment emails were sent to the 2,318 future residents of the three target residence halls. These were met with a high response rate, with 496 students completing an entry survey, of whom, 327 volunteered for the experiment (22 and 14 percent of the target population respectively). The final group of 102 experiment participants (from 66 rooms) was randomly selected from the group of volunteers, subject to room allocation constraints.

Table 2 below compares the randomly chosen experiment participants to the target residence hall population. Room allocation constraints led to us oversampling both single rooms (as opposed to shared rooms) and incoming students ( $\Pr(T < T) < 0.001$  in both cases). Incoming students may care more about creating a good/green reputation than older more established students. This could potentially bias the public information treatment effect upwards. Alternatively, incoming students may have fewer community ties and less reason to invest in a green reputation, biasing the treatment effect of public information downward. We have no *a priori* reason to believe that single rooms will be more or less affected by either treatment.

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[Insert Table 2 about here]

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The entry survey asked respondents about their energy usage habits, their beliefs about energy and the environment, as well as their beliefs about energy usage from different sources. We used the survey to construct an environmental and altruism factor, using questions from the New Ecological Paradigm (NEP) Scale (Dunlap et al., 2000) and Altruism Scale (Schwartz, 1977), respectively (see Appendix E for more information on the ideology factors). Although we

cannot compare participants' attitudes with the general population, we can compare them with those students who completed the survey, but did not volunteer to participate. We find that experiment participants are significantly more altruistic and environmentally friendly ( $\Pr(T < T) < 0.001$  in both cases). Self-selection along these criteria can potentially bias the effect of private information upward, since the effect of private information will increase with intrinsic motivation (see Hypothesis 1). However, since we do not find any significant effect of private information, this is not a concern. Neither is sample selection along environmental criteria a concern for public information. The effectiveness of public information does not depend on an individual's own green ideology, but rather on the greenness of those around her. So for example, while driving a Prius may earn you the respect of your peers in Berkeley, California, it is unlikely to do the same in Lubbock, Texas, regardless of your personal ideology.<sup>10</sup> This raises questions about the external validity of our experiment. These questions are correct in the narrow sense that a purely green signal may not work in non-green areas, but are less of a concern when we consider that a broad range of reputational signals exist, which may be deployed in accordance with the values of the local community.

### **4.3 Randomization into Treatments**

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<sup>10</sup> Alternatively, we could imagine that those who are identifying themselves as being green are in fact very brown in their private behavior. As such, they would be more motivated than browns to conserve by public information, since it exposes their private hypocrisy. Such behavior is at odds with the existing literature as well as our baseline period regressions, where environmentalists' behavior is consistent with their actions (see Clarke et al., 2003; Kotchen & Moore, 2007, Kahn & Vaughn, 2009). We evaluate this empirically by interacting public information with an environmentalism scale and find that environmentalists care less about reputation (see Table 7 regressions v and vi).

Randomization into the three treatment groups took place at the room level and was undertaken before the experiment began. We limited the public information treatment to only take place over half of the residence hall floors. These ‘public information eligible’ floors were randomly chosen. This was to increase possible peer effects and reduce the experimenter’s effort costs involved in updating posters every week. The sample was then stratified by gender and room type (single or shared), to ensure that these groups were evenly split across treatments.

Regressing energy usage during the baseline period on dummies for the treatment groups and each of the randomization strata, we find that randomization was successful, with no significant differences found between the three groups for heating/cooling, lighting plug load or overall. These results can be seen in Appendix D, Table 9.

## **5 EXPERIMENT RESULTS**

### **5.1 Baseline Usage**

Table 3 shows that the average electricity usage over the entire period was 7.8 kWh per day. On a per capita basis this amounts to 198 kWh per month, which is comparable to the 2008 California monthly per capita *household* average of 210 kWh per household resident (US EIA, 2010). The majority of energy usage in all periods comes from heating and cooling, although there is substantial variation across rooms, with some rooms pumping the heater/AC all day, and others using it sparingly or not at all. Energy usage is lowest during the milder fall and spring seasons, which correspond with the baseline and persistence periods respectively.

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[Insert Table 3 about here]

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Using the baseline period, where no one received any form of information, we can examine what factors influence energy usage. Since not all participants completed the entry survey, this investigation is limited to a sub-sample of 55 rooms.<sup>11</sup> The results of this analysis are presented in Table 4. Interestingly we can see that environmentalists (those with a higher score on the environmental factor) use substantially less heating and cooling than their peers (the difference between the most and least environmental participants would be almost 100 percent of the baseline period mean). Surprisingly, single rooms used significantly more heating/cooling (about 45 percent of the baseline mean) than shared rooms, although they do use less lights and plug load (although this is not statistically significant).

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[Insert Table 4 about here]

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## 5.2 Main Results

After 6 weeks of baseline monitoring, the private information treatment began with both the *dashboard* and *poster* groups receiving real-time feedback over their energy usage through the UCLA ENGAGE dashboard. After 5 weeks of private information, participants in the *poster* group were informed about the upcoming public information treatment. The public information

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<sup>11</sup> In shared rooms, room level values are calculated by averaging those of the inhabitants.

treatment lasted for seven weeks, and ended two weeks early due to technical problems.<sup>12</sup> In all of the following analysis, we exclude data from university holidays and exam weeks yielding a total of 156 observation days taken over a 9 month period.

We ran the following econometric specification to test the effectiveness of public and private information:

$$\text{Usage}_{it} = \beta_0 + B_{1i}*(\text{room FE}) + B_2*(\text{weather}_t) + B_3*(\text{time}_t) + B_4*\text{private info}_{it} + B_5*\text{public info}_{it} + \varepsilon_{it}$$

Where  $i$  is room and  $t$  is day. Treatments are designated by dummy variables in the periods that the treatments are operational. A significantly negative coefficient on the private info dummy would indicate that private information did induce conservation, validating Hypothesis 1; while a significantly negative coefficient on the public info dummy would signify that public information did induce energy savings, validating Hypothesis 2.

To remove any baseline differences between rooms we include a room level fixed effect. We account for changes in weather across time by including heating and cooling degree days, which measures the potential need for heating or cooling with respect to a baseline temperature.<sup>13</sup> We interact these degree days with a dummy for female, since research on thermal comfort has found that women are more sensitive to temperature changes than men (Parsons, 2002; Karjalainen, 2007). Changes in usage patterns across time are captured by the

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<sup>12</sup> The intended treatment time was 9 weeks.

<sup>13</sup> We approximate heating and cooling degree days as the number of degrees the daily maximum is above, or the daily minimum is below 65 degrees Fahrenheit, respectively. Daily temperature data was collected from an on campus weather station (with special thanks to James Murakami for providing this data).

inclusion of a cubic of a daily time trend, weekly fixed effects, and day of the week fixed effects. The cubic time trend is intended to non-parametrically measure long term patterns, such as the slow adoption of electronics (or unpacking) after moving in to a new residence hall room. Weekly fixed effects on the other hand capture short-term time trends. These weeks correspond to the academic calendar and will capture common events such as midterm week or a public holiday. Finally, day of the week fixed effects capture habitual behavior like spending less time in rooms over weekends. To account for the non-asymptotic nature of our sample size and possible error clustering at the room level, we bootstrap all standard errors (Bertrand et al., 2004).

The public information treatment is additive to the private information treatment, meaning that participants receiving public information, continued to receive private information. The marginal effect of public information is identified since there was a period when participants in the public information treatment group (the poster group) received private information only. Our estimation results, with usage broken down by source, are shown in Table 5 below.

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[Insert Table 5 about here]

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The effects of private information on total energy usage are negative, but not statistically significant. There is a statistically significant effect of private information on overhead light usage, which was reduced by 78 watt hours a day. This is equivalent to turning off the main room light for 80 minutes a day, or represents a 20 percent reduction in light usage from the

private information period average.<sup>14</sup> Light usage during this period constituted less than 5 percent of total energy usage. This focus by minimally motivated participants on light usage is similar to those found in our pilot study and Peterson et al. (2007). This can possibly be explained by habits/ideas ingrained during childhood. In our entry survey nearly 90 percent of respondents agreed with the statement that “While growing up, I was told repeatedly to turn off the lights when leaving a room.” When asked about a similar statement for heating/cooling behavior, only 40 percent of respondents agreed with it. Apart from the effect of lighting, we find little support for Hypothesis 1 that private information can induce conservation. This failure could occur because participants do not view or understand the dashboard, or because descriptive norms cause a boomerang effect, resulting in convergence to the norm. This is investigated further in Section 6.3.

Public information by contrast, had a very large and statistically significant effect on total energy usage. Participants placed in the public information treatment reduced their heating/cooling by 25 percent of the period average. Plug load and lighting were also reduced by 7 and 5 percent respectively, although these reductions were not statistically significant. This amounted to a total reduction of 1,500 watt hours or 20 percent of the period average. This result is robust to alternative specifications such as random effects with individual level controls and daily fixed effects models (not shown). These results support Hypothesis 2, which conjectured that public information would induce conservation.

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<sup>14</sup> We obtain similar results when restricting our analysis to the baseline and private information periods only (not shown).



## 5.3 Private Information

### *Dashboard Views*

Private information yielded no significant average treatment effect. This could be because the intention to treat did not translate into actual treatment received. A successfully administered treatment under private information would have involved a participant: a) receiving information, b) finding that this information was useful and c) using it to update prior misconceptions.

Using Google Analytics, we were able to track which rooms viewed the ENGAGE dashboard and when. Of the 43 rooms which were given access to the dashboard, 39 viewed it at least once, with the median number of views being 7 and several rooms viewing it almost every day.<sup>15</sup> Since more than 90 percent of rooms viewed the dashboard (and non-viewers may still have seen the email reports), it seems reasonable to conclude that participants did receive the information.

The next question is whether the participants' prior knowledge about their energy usage was correct, with the information treatment then providing no new information. Figure 2 contrasts actual energy usage by source from the baseline period, with the energy usage that participants predicted for an *average room* during the entry survey.<sup>16</sup>

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<sup>15</sup> The four rooms who never viewed the webpage were equally split between the *private* and *public information* groups. Similarly, Allen & Janda (2006) found that half of their sample never touched their real-time energy meters despite having requested them.

<sup>16</sup> This was to ensure that we captured respondents' perceptions of energy usage rather than their own idiosyncratic energy usage behavior.

Figure 2 clearly shows that respondents completely overestimated how much of their energy usage was constituted by lighting, and completely underestimated how much was constituted by heating and cooling (this also occurred in our pilot study). Compared to respondent estimates of roughly equal usage, experiment participants used on average 15 times more electricity for heating and cooling than overhead lighting during the baseline period. This result of roughly one third per usage source is unlikely to be due to default bias, since the question was structured such that respondents had to move a sliding cursor for each energy source from zero to their desired setting in order to proceed.<sup>17</sup> Attari et al. (2010) found similar results in a national survey, with survey respondents underestimating “*energy use and savings by a factor of 2.8 on average, with small overestimates for low-energy activities and large underestimates for high-energy activities.*” These results indicate that there is ample room for private information to correct erroneous beliefs and thereby lower the cost of conservation actions.

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[Insert Figure 2 about here]

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To evaluate whether participants learned anything from the private information treatment, we included an interaction between private information and cumulative dashboard views in our treatment regressions. By looking at a cumulative count of dashboard views over time, we are

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<sup>17</sup> It may however be the result of the 1/n bias witnessed in portfolio allocations, in which allocations are evenly split between n options (Benartzi & Thaler, 2007).

able see whether a marginal view of the dashboard continued to add value.<sup>18</sup> A negative marginal effect would imply that participants are learning over time. This is investigated in Table 6, specifications *i* and *ii*.

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[Insert Table 6 about here]

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None of the interactions above are significant, but given our sample size, the point estimates are suggestive. Equation *i* shows that the effect of cumulative dashboard views on energy usage is negative, with each additional view of the dashboard decreasing daily energy usage by about 40 watt hours. Since dashboard views are more likely to be undertaken by those who are most interested in conservation<sup>19</sup>, equation *ii* accounts for selection bias by including the total number of dashboard views at period end (interacted with private information). Despite the obvious correlation between these terms, the coefficient on cumulative dashboard views retains its magnitude. These results suggest that for those motivated to view the dashboard, marginal views do matter and that some sort of learning process is taking place over time.

An alternative approach to investigating whether private information effectively lowered the costs of conservation is to examine whether additional motivation could induce conservation in its absence. We cannot test this with the public information treatment since it was always

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<sup>18</sup> Excluding views in week 1, in which many rooms viewed the webpage an inordinate number of times, causing massive outliers.

<sup>19</sup> This turns out to not be true. None of our attitudinal measures had any predictive value for total dashboard views.

accompanied by private information in our experiment. Fortunately another form of motivation was supplied to all three treatment groups allowing us to separately identify the effects of motivation with and without the presence of private information. Additional motivation was supplied in the form of an inter-dormitory energy conservation competition that took place during part of the reputation period. Non-pecuniary rewards such as energy competitions have been shown to be significant motivators of energy conservation (Van Houwelingen & Van Raaij, 1989; Peterson et al., 2007).

The competition was at the building level and nobody apart from the ENGAGE participants had any type of feedback over usage. As part of the competition, residents could sign an energy conservation pledge. Almost 40 percent of the experiment rooms signed the pledge. Table 6, equation *iii*, shows that those who pledged to conserve energy, but were not given private information, failed to conserve any more energy than the rest of the group. On the other hand, those who pledged and were given private information succeeded in reducing their energy consumption by 15 percent of the private information period average. While the results are not statistically significant, the point estimates do suggest that private information does reduce the cost of conservation and is a necessary component of any other motivational mechanism.

### ***Convergence to Norm***

An alternative explanation for private information's low average treatment effect could be a "boomerang effect" caused by descriptive social norms. The dashboard and email reports created a descriptive social norm by informing participants about whether they were using more or less electricity than other users. It is possible that this information weakened the norm towards

conservation for below average energy users, whilst strengthening it for those who used more than average. This would cause convergence to the norm and a zero average treatment effect.

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[Insert Table 7 about here]

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We investigate this in Table 7, equation *i*, and find that the below median users *decreased* their usage in reaction to private information, while there is no effect on above median users.<sup>20</sup> While not statistically significant, these point estimates suggest that instead of a boomerang effect with below average users increasing their usage, we see the opposite with these participants further decreasing their energy consumption!<sup>21</sup> This seemingly paradoxical result can be explained by examining the interaction between ideology and usage.

### ***Environmental Ideology and Conservation***

In our baseline period regressions we found that environmentalists used significantly less electricity (see Table 4) than non-environmentalists. We conjectured that these participants, who had greater levels of intrinsic motivation, would be more responsive to private information than their browner counterparts. We test this in Table 7, regressions *iii* and *iv*, by interacting private information with an environmental and altruism factor, respectively. Although not statistically significant, the point estimates indicate that greener, more altruistic participants are more responsive to private information, with those in the top decile of environmentalism and altruism

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<sup>20</sup> The net effect of private information + private information \* above median user is zero.

<sup>21</sup> Similarly, Ferraro and Price (2011) also found no evidence of a boomerang effect from descriptive norms.

reducing usage by 1,000 and 1,600 watt hours respectively, while those in the bottom decile did not conserve.

## **Public Information**

### *Large Energy Users and Conservation*

The results on who conserves under public information are strikingly different from that of private information. Table 7, equation *ii*, which interacts above median baseline usage with the public information treatment, shows that the entire effect of public information is coming through those participants who were above average electricity users in the baseline period. These large users reduce their electricity usage by about 20 percent compared to the average usage for other large users during this period. Due to the binary nature of the reputation mechanism, only those participants who were rated as below average conservors could improve their reputation. Those participants who already rated above average conservors could not gain any further reputational benefits by conserving more. The results above confirm that public information is only effective in inducing conservation when the marginal change to reputation from conservation is positive.

This is a powerful result since these above average energy users were the least intrinsically motivated to conserve in the first place, and were unaffected by the provision of private information. Public information successfully motivated them to conserve out of a desire to obtain the benefits of a “green” reputation, rather than any intrinsic motivation. Equations *iv* and *vi* reiterate this point, showing that there is no significant and negative interaction between ideology and the public information treatment.

### ***Persistence and Habit Formation***

The public information treatment induced large behavioral change with above median users reducing their energy usage by 20 percent. But did this motivational mechanism inspire unsustainable actions that would end with the treatment, or were new and lasting habits formed? Behavioral decision theorists view habits as a rational response to frequently occurring tasks, since they allow individuals to forego having to undertake the entire decision process each time that the task occurs. A habit is formed when a task is repeated to the point where it becomes mechanical and enacted without awareness. Habitual behaviors may be the result of an earlier, more reasoned decision, but may be non-optimal given changing circumstances (Beach & Mitchell, 1978; Aarts et al., 1997; de Vries et al., 2011). Thus we may expect that the withdrawal of public information is not a disruptive/salient enough event that participants will re-optimize their habitual behaviors.

To evaluate this, we ended the public information treatment while continuing to supply participants in both the *dashboard and* poster groups with private information over their energy usage. The persistence period lasted for 10 weeks after the public information treatment ended. Treatment effects have been shown to wane significantly over similar time periods in other conservation experiments (Nolan et al., 2008; Allcott, 2010; Ferraro & Price, 2012). Due to technical problems, exams and spring break, we only examine the last 5 weeks of this period. This later time period, plus the disruption of examinations and a vacation period, ensure that we are catching lasting habits. We run the same specification as the main regression, but extend the time period to include the persistence period. We also add in an extra term called persistence,

which is a dummy for being in the *poster* group, but no longer receiving the public information treatment.

$$\text{Usage}_{it} = \beta_0 + B_{1i} * (\text{room FE}) + B_2 * (\text{weather}_t) + B_3 * (\text{time}_t) + B_4 * \text{feedback}_{it} + B_5 * \text{reputation}_{it} + B_6 * \text{persistence}_{it} + \varepsilon_{it}$$

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[Insert Table 8 about here]

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Table 8 shows that the effects of persistence are significant and large. In fact the magnitude is seemingly larger than that of the public information treatment, but is actually statistically indistinguishable. This holds for total usage, as well as usage by all three constituent sources (although the effect on plug load and light use is again statistically insignificant). In a separate regression we find that the persistence effect is operating completely through above median users, as with public information (regression not shown).

## 6 DISCUSSION OF RESULTS

In our empirical analysis we found no effect of private information on conservation behavior, while public information induced a reduction in electricity use of 20 percent. Given the cost of supplying private information and its current popularity in the realm of energy conservation, it is worth examining the interplay between private and public information in more detail. Looking at the marginal effect of viewing the ENGAGE dashboard it does appear that learning takes place, with each additional view of the dashboard increasing conservation in the private information treatment. Interestingly, none of our attitudinal measures have any predictive



powers for dashboard views (including the environmental and altruism factors). When we looked at the efficacy of motivation with and without private information, we found that motivation in the form of a conservation pledge was insufficient by itself, signifying that private information is probably necessary, but not sufficient in inducing significant energy conservation. More interestingly, the large behavioral change induced by public information, was not accompanied by an increase in dashboard views. This can be seen in Figure 3, which shows that there is no difference in frequency of views between the *dashboard* and *poster* groups, even with the introduction of the public information treatment.<sup>22</sup>

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[Insert Figure 3 about here]

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This gives a very complex story of conservation behavior. Participants in the *poster* group reacted to public information by reducing heating/cooling, without acquiring new information. This implies that participants in the *dashboard* group must have been also been aware of the efficacy of reducing heating/cooling. Yet their main conservation action was turning off lights. This illustrates the importance of focusing on the costs and motivators of conservation – without proper motivation, even informed consumers can make poor decisions.

This analysis is supported by qualitative data gathered during focus groups and exit surveys at the conclusion of the experiment. Students in both the *dashboard* and *poster* groups

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<sup>22</sup> Regression analysis on the probability of viewing the dashboard in a given week (not shown) confirms these results.

remarked on being astonished at how much of their energy usage came from heating and cooling. Nonetheless, private information only helped those students who were already motivated to conserve. By way of example, one student in the *dashboard* group said, *“I feel that having access to my power usage made me more aware and considerate of the amount of power I used.”* While for those students who were not intrinsically motivated, private information just wasn’t enough: *“The amount of energy that I consume compared to other rooms wasn't a great enough incentive to cut back.”*

This reaction stood in stark contrast to that of participants in the *poster* group, where reaction to the public information treatment (poster) was far less equivocal:

- *“Once the poster got up, it became serious...”*
- *“I liked the poster, it made us want to get green dots.”*
- *“We want to make it green because red looks bad.”*
- *“I thought the posters were pretty crucial to the whole process. It gets everyone else involved.”*
- *“We did not want to attract attention because we were red.”*
- *“I turned off all the lights and wear a lot of sweaters so I could get a green dot.”*
- *“When I got a green dot, I received high 5.”*

Our experiment did not allow us to investigate the finer points of reputation as a mechanism, such as whether people were really seeking status or avoiding shame. Some of the comments shown above do seem to indicate the latter, although shaming is at odds with the incredible amount of positive comments we received about the public information treatment. Not only did we not receive a single negative comment or complaint about the posters, but some

students even reported missing having the posters up. Further research on this topic would be beneficial, particularly with regard to asymmetric responses between the two mechanisms.

Another potential motivational mechanism that could explain the strong result of public information is competitiveness between participants. This seems unlikely since participants were given their relative usage in the private information treatment. If they merely desired to “beat” other participants, they would have reduced consumption in the private information treatment. If they only started competing in the public information treatment, then it is because they wanted to acquire a reputation for being a better energy conserver than others. Moreover, in all of the surveys and focus groups, the word competition was only mentioned once.

Our study is the first to show that public information can effectively induce conservation, but it is not without limitations. Firstly, our experiment population is somewhat younger and lives in a more environmentally aware community than most U.S. residents. This may bias the effects of public information upwards, as the marginal reputational benefit of conservation may be higher for our sample than the rest of the U.S. population. However, since public information can potentially work with a number of different reputational signals, which can be chosen to reflect the values of the underlying population, sample selection may be less of a concern. Secondly, we have no monetary rewards in our experiment. In practice, monetary rewards such as a reduced electricity bill may dilute the reputational signal of conservation, since agents may be perceived as conserving purely to save money. However, if agents do not mentally place conservation efforts in the pecuniary realm (since saving money on bills is not an explicit incentive), financial rewards may operate alongside reputation, boosting the effectiveness of public information. Finally, our public information mechanism did not encourage further

conservation by environmentalists, since it only provided positive marginal reputational benefits to those large electricity users who were not already conserving. Future mechanisms should incorporate levels that encourage all consumers to conserve. These limitations provide ample opportunity for future research by changing both the experiment context and public information mechanism.

## **7 CONCLUSION**

Private information such as real-time feedback over energy usage allows consumers to be better informed and hence make better decisions. But without sufficient motivation, consumers will not incur the costs of gathering, interpreting and utilizing this information. Public information can motivate consumers to engage in green behaviors so that they obtain the benefits of a green reputation. Psychologists have shown that a reputation for being pro-social (as opposed to pro-self) can lead to a number of rewards such as mates, leadership opportunity and friends. By making previously unobservable pro-social behavior such as energy conservation visible, consumers have an additional motivation to engage in such a behavior, that of a socially beneficial reputation.

In a unique experiment we fitted out residence hall rooms at UCLA with real-time energy metering equipment and provided a number of these rooms with real-time feedback about individual and aggregate electricity usage. We found that those participants receiving private information in the form of feedback and social norms were only minimally motivated to conserve, and thus there was no significant effect of private information on energy conservation. By making energy usage public for a subset of participants, we were able to engage reputational

motivations for conservation and induced a 20 percent reduction in energy usage among above median electricity users. Moreover, after two months of the public information treatment, these previously large energy users had formed substantially better energy usage habits, which persisted until the experiment ended three months later.

In a world of heterogeneous consumers, social scientists need a number of tools in their behavioral toolbox to appeal to a variety of motivations. Compared to other policies, such as pecuniary incentives, information policies are a relatively inexpensive way to encourage conservation, especially in this age of mass information and telecommunication technology. Public information in particular has a potentially important role to play since it can motivate both those who are *and* those who are not ideologically green to conserve.

Public information has already become a valuable tool in encouraging corporations to behave in a more environmentally friendly manner (see for example Delmas, et al. 2009), but it has also been abused in this environment with firms engaging in “green-washing”, by reporting only selective information in voluntary disclosure programs (Lyon & Kim, 2011). This is a particularly salient issue for the implementation of any consumer-orientated public information program. Consumers are unlikely to find any sort of mandatory public disclosure program palatable, while any voluntary public information policies may lead to adverse self-selection into only those programs that reflect current behaviors in a good light. To overcome this, any voluntary program needs to be designed in such a way so as to ensure a positive marginal reputational benefit to conservation for targeted consumers, encouraging both participation and conservation. For example, the reputation mechanism can combine absolute measures with changes from baseline, to reward both those beginning and those continuing to conserve.

Credible public information mechanisms can be employed in a variety of creative ways to encourage consumers to conserve: from car window displays showing fuel efficiency; to social media applications that show the environmental impact of your shopping cart. Intelligently designed public information mechanisms can encourage conservation, while allowing people to communicate their greenness to the world.

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**Table 1: Experimental Design**

| <b>Baseline</b><br>(6 weeks) | <b>Private</b><br><b>Information</b><br>(5 weeks) | <b>Public</b><br><b>Information</b><br>(7 weeks) | <b>Persistence</b><br>(5 weeks) | <b># of rooms</b> |
|------------------------------|---|--|---------------------------------|-------------------|
|                              | Control   | Control  | Control                         | 23                |
|                              | Private<br>Information                            | Private<br>Information                           | Private<br>Information          | 22                |
|                              | Private<br>Information                            | Private + Public<br>Information                  | Private<br>Information          | 21                |

**Table 2: Summary Statistics for Experiment Participants**

|                              | <b>Experiment Participants</b> |              |            |            | <b>Population</b> |              |
|------------------------------|--------------------------------|--------------|------------|------------|-------------------|--------------|
|                              | <b>mean</b>                    | <b>sd</b>    | <b>min</b> | <b>max</b> | <b>mean</b>       | <b>sd</b>    |
| <b>Age</b>                   | 18.50                          | <i>1.167</i> | 17.00      | 24.00      | 20.090            | <i>1.362</i> |
| <b>Year of Study</b>         | 1.48                           | <i>0.941</i> | 1.00       | 4.00       | 1.790             | <i>0.959</i> |
| <b>Female</b>                | 0.48                           |              |            |            | 0.530             |              |
| <b>Single room</b>           | 0.71                           |              |            |            | 0.38              |              |
| <b>Environmental Factor*</b> | 0.52                           | <i>0.217</i> | 0.04       | 0.92       |                   |              |
| <b>Altruism Factor*</b>      | 0.55                           | <i>0.248</i> | 0.00       | 0.92       |                   |              |
| <b>Member Enviro. Org.*</b>  | 0.12                           |              |            |            |                   |              |
| <b>Observations</b>          | 102 individuals (*77)          |              |            |            | 2318 individuals  |              |

**Table 3: Summary of Electricity Usage at the Room Level<sup>23</sup>**

|                            | <b>Total Usage (Daily Wh)</b> |                  |            |            |
|----------------------------|-------------------------------|------------------|------------|------------|
|                            | <b>Mean</b>                   | <b>Std. Dev.</b> | <b>Min</b> | <b>Max</b> |
| <b>Entire Period</b>       | 7834.19                       | 4645.93          | 1362.06    | 20836.94   |
| <b>Baseline Period</b>     | 6160.69                       | 4485.23          | 519.02     | 20972.34   |
| <b>Private Info Period</b> | 9440.91                       | 5953.02          | 1601.70    | 26987.78   |
| <b>Public Info Period</b>  | 8027.09                       | 5425.02          | 1450.84    | 26462.03   |
| <b>Persistence Period</b>  | 7499.34                       | 5339.63          | 687.92     | 21677.60   |

|                        | <b>Baseline Usage by Source (Daily Wh)</b> |                  |            |            |
|------------------------|--|------------------|------------|------------|
|                        | <b>Mean</b>                                | <b>Std. Dev.</b> | <b>Min</b> | <b>Max</b> |
| <b>Lights</b>          | 288.37                                     | 164.80           | 0.00       | 673.61     |
| <b>Heating/Cooling</b> | 4433.37                                    | 4298.17          | 0.00       | 20165.35   |
| <b>Plugload</b>        | 1438.95                                    | 1184.11          | 93.82      | 6336.00    |

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<sup>23</sup> There are 66 rooms in the baseline period, 65 in the public and private information periods and 62 in the persistence period. Attrition is due to student room changes.

**Table 4: Room Level Regression on Baseline Usage**

|  | <b>Total Usage</b>         | <b>Heating/<br/>cooling</b> | <b>Overhead<br/>Light</b> | <b>Plugload</b>       |
|--|----------------------------|-----------------------------|---------------------------|-----------------------|
| <b>Female</b>  | -1,155.393<br>(1,191.295)  | -779.824<br>(1,140.997)     | -91.465*<br>(48.647)      | -276.634<br>(252.255) |
| <b>Age</b>   | -35.690<br>(686.667)       | -378.962<br>(573.087)       | -44.267<br>(32.735)       | 392.903*<br>(236.998) |
| <b>Year of Study</b>                                       | -75.823<br>(670.274)       | -129.976<br>(631.560)       | 60.703**<br>(29.732)      | -18.962<br>(169.413)  |
| <b>Environmental Factor</b><br>(0.04 < Env. Factor < 0.92) | -5,248.328*<br>(3,018.645) | -5,486.787*<br>(2,958.568)  | 135.806<br>(99.505)       | 119.065<br>(569.348)  |
| <b>Altruism Factor</b><br>(0 < Altruism Factor < 0.92)     | 1,953.077<br>(2,725.658)   | 2,593.734<br>(2,561.553)    | -56.074<br>(99.565)       | -539.914<br>(506.736) |
| <b>Member of Enviro Org.</b>                               | -518.500<br>(1,226.459)    | -230.534<br>(1,151.134)     | -23.876<br>(54.841)       | -267.277<br>(409.090) |
| <b>Single Room</b>   | 1,955.991<br>(1,351.889)   | 2,561.988**<br>(1,191.548)  | -141.073**<br>(60.628)    | -477.056<br>(354.920) |
| <b>Observations</b>  | 1879                       | 1879                        | 1879                      | 1879                  |
| <b>Number of rooms</b>                                     | 55                         | 55                          | 55                        | 55                    |
| <b>Mean for baseline period</b>                            | 5929.241                   | 4231.889                    | 291.6913                  | 1405.661              |

Robust standard errors are reported in parentheses and are clustered at the room level. One, two and three asterisks indicate significance at the  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$  level, respectively. Variables not reported: heating and cooling degree days, heating and cooling degree days\*female, residence hall dummies, day of the week fixed effects, week fixed effects, constant and cubic time trend.

**Table 5: Basic Treatment Effects**

|  | <b>Total Usage</b>          | <b>Heating/<br/>Cooling</b>  | <b>Light</b>          | <b>Plugload</b>       |
|--|-----------------------------|------------------------------|-----------------------|-----------------------|
| <b>Private Information</b>               | -441.692<br>(1,142.924)     | -361.578<br>(892.152)        | -78.391*<br>(45.810)  | -1.723<br>(216.695)   |
| <b>Public Information</b>                | -1,504.371**<br>(626.157)   | -1,330.889**<br>(650.205)    | -24.221<br>(26.033)   | -149.261<br>(166.929) |
| <b>Heating degree days</b>               | 96.945**<br>(48.439)        | 92.534*<br>(47.735)          | 2.502**<br>(1.239)    | 1.909<br>(4.734)      |
| <b>Cooling degree days</b>               | 121.808***<br>(40.218)      | 122.161***<br>(43.503)       | 0.801<br>(1.139)      | -1.154<br>(2.688)     |
| <b>Heating degree days *female</b>       | 76.181<br>(68.736)          | 64.929<br>(66.659)           | 0.910<br>(1.750)      | 10.342<br>(9.697)     |
| <b>Cooling degree days*female</b>        | 42.242<br>(58.360)          | 38.245<br>(70.537)           | -1.769<br>(1.633)     | 5.767<br>(5.145)      |
| <b>Constant</b>                          | 12,933.362**<br>(5,977.318) | 13,517.838***<br>(5,046.575) | -253.565<br>(333.154) | -330.908<br>(808.722) |
| <b>Observations</b>                      | 7120                        | 7120                         | 7120                  | 7120                  |
| <b>Number of rooms</b>                   | 66                          | 66                           | 66                    | 66                    |
| <b>R-squared</b>                         | 0.11                        | 0.08                         | 0.11                  | 0.19                  |
| <b>Mean for entire regression period</b> | 7772.045                    | 5443.149                     | 372.3732              | 1956.523              |

Bootstrapped standard errors are reported in parentheses and are clustered at the room level. One, two and three asterisks indicate significance at the  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$  level, respectively. Variables not reported: day of the week fixed effects, week fixed effects and cubic time trend.



**Table 6: Effects of Cumulative Dashboard Views and Access to the Dashboard**

|  | <b>Learning</b>    |                    | <b>Information</b> |
|--|--------------------|--------------------|--------------------|
|  | <b>i</b>           | <b>ii</b>          | <b>iii</b>         |
| <b>Private Information</b>   | -251.9<br>(934.9)  | -129.5<br>(1055)   | -341.6<br>(1002)   |
| <b>Public Information</b>  | -1453**<br>(661.2) | -1533**<br>(736.1) | -1419**<br>(611.1) |
| <b>Private Info*Cumulative Dashboard Views</b><br>(0 ≤ Cum. Views ≤ 74)* | -38.40<br>(34.38)  | -24.15<br>(37.41)  |                    |
| <b>Private Info*Total Dashboard Views</b><br>(0 ≤ Total Views ≤ 172)     |                    | -7.657<br>(10.65)  |                    |
| <b>Pledged Energy Competition</b>  |                    |                    | 321.5<br>(718.8)   |
| <b>Private Info*Pledged Energy Competition</b>                           |                    |                    | -1125<br>(881.2)   |
| <b>Observations</b>  | 7120               | 7120               | 7120               |
| <b>Number of id</b>  | 66                 | 66                 | 66                 |
| <b>R-squared</b>   | 0.109              | 0.109              | 0.108              |

All measurements are at the room level and are in Watt Hours per day.

Bootstrapped standard errors are reported in parentheses and are clustered at the room level. One, two and three asterisks indicate significance at the  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$  level, respectively.

Variables not reported: day of the week fixed effects, week fixed effects and cubic time trend. day of the week fixed effects, week fixed effects and cubic time trend, heating and cooling degree days, heating and cooling degree days interacted with female, constant.

**Table 6: Heterogeneous Treatment Effects – User Type and Ideology**

|   | User Type          |                    | Ideology           |                    |                  |                   |
|---|--------------------|--------------------|--------------------|--------------------|------------------|-------------------|
|   | i                  | ii                 | iii                | iv                 | v                | vi                |
| <b>Private Information</b>  | -1120<br>(938.1)   | -453.6<br>(1132)   | 583.8<br>(1584)    | 1277<br>(1900)     | -336.0<br>(1072) | -354.6<br>(995.2) |
| <b>Public Information</b>   | -1590**<br>(626.4) | 37.34<br>(812.5)   | -1392**<br>(666.1) | -1352**<br>(609.1) | -1862<br>(1132)  | -2029*<br>(1172)  |
| <b>Private Info*Above Median User</b>                                   | 1242<br>(1208)     |                    |                    |                    |                  |                   |
| <b>Public Info*Above Median User</b>                                    |                    | -2330**<br>(998.9) |                    |                    |                  |                   |
| <b>Private Info*Environmental Factor</b><br>(0.04 < Env. Factor < 0.92) |                    |                    | -1775<br>(2601)    |                    |                  |                   |
| <b>Private Info*Altruism Factor</b><br>(0 < Altruism Factor < 0.92)     |                    |                    |                    | -2747<br>(2974)    |                  |                   |
| <b>Public Info*Enviromental Factor</b><br>(0.04 < Env. Factor < 0.92)   |                    |                    |                    |                    | 994.1<br>(2368)  |                   |
| <b>Public Info*Altruism Factor</b><br>(0 < Altruism Factor < 0.92)      |                    |                    |                    |                    |                  | 1227<br>(1680)    |
| <b>Observations</b>   | 7120               | 7120               | 7120               | 7120               | 7120             | 7120              |
| <b>Number of rooms</b>  | 66                 | 66                 | 66                 | 66                 | 66               | 66                |
| <b>R-squared</b>  | 0.109              | 0.111              | 0.108              | 0.108              | 0.109            | 0.108             |

Bootstrapped standard errors are reported in parentheses and are clustered at the room level. One, two and three asterisks indicate significance at the  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$  level, respectively. Variables not reported: day of the week fixed effects, week fixed effects and cubic time trend. day of the week fixed effects, week fixed effects and cubic time trend, heating and cooling degree days, heating and cooling degree days interacted with female, constant.

**Table 7: Persistence of the Reputation Treatment**

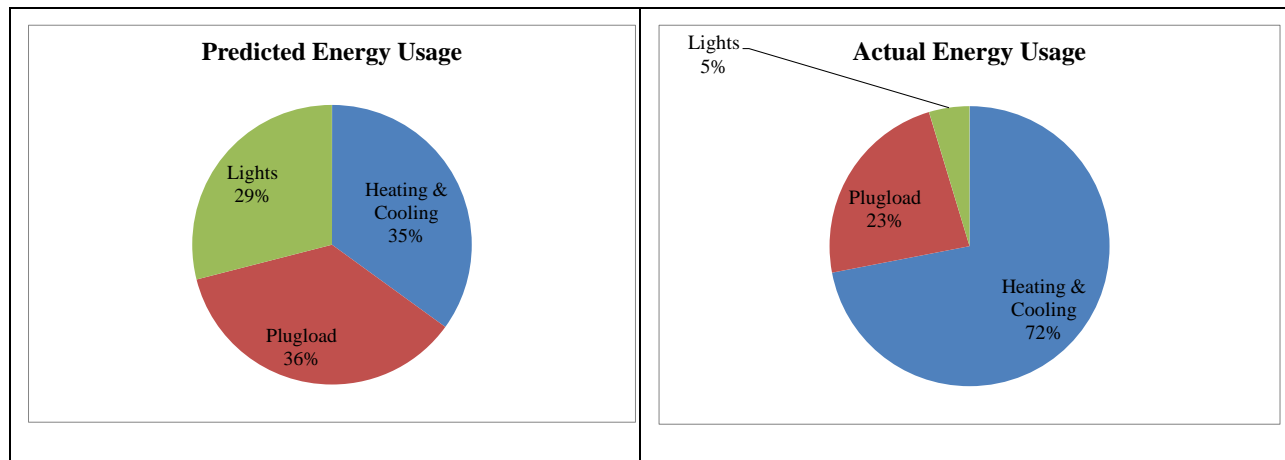
|  | <b>Total Usage</b>         | <b>Heating/<br/>Cooling</b> | <b>Light</b>         | <b>Plugload</b>           |
|--|----------------------------|-----------------------------|----------------------|---------------------------|
| <b>Private Information</b>               | -504.530<br>(977.654)      | -443.706<br>(876.920)       | -82.437*<br>(49.822) | 21.614<br>(228.022)       |
| <b>Public Information</b>                | -1,516.046**<br>(615.887)  | -1,338.582**<br>(582.851)   | -20.537<br>(23.818)  | -156.928<br>(166.748)     |
| <b>Persistence of Public Info</b>        | -1,921.633*<br>(1,131.868) | -1,764.047*<br>(990.326)    | -33.975<br>(40.681)  | -123.611<br>(199.500)     |
| <b>Heating degree days</b>               | 94.848**<br>(43.342)       | 94.151**<br>(45.459)        | 0.792<br>(1.304)     | -0.094<br>(4.546)         |
| <b>Cooling degree days</b>               | 139.166***<br>(34.450)     | 137.914***<br>(40.429)      | 0.279<br>(0.884)     | 0.973<br>(3.262)          |
| <b>Heating degree days *female</b>       | 62.581<br>(54.347)         | 51.248<br>(66.316)          | 0.747<br>(1.779)     | 10.586<br>(9.211)         |
| <b>Cooling degree days*female</b>        | 13.995<br>(49.870)         | 10.460<br>(61.591)          | -1.368<br>(1.324)    | 4.902<br>(5.362)          |
| <b>Constant</b>                          | 9,563.446<br>(7,036.841)   | 7,183.373<br>(7,241.615)    | 355.037<br>(371.799) | 2,025.044*<br>(1,204.147) |
| <b>Observations</b>                      | 8917                       | 8917                        | 8917                 | 8917                      |
| <b>Number of rooms</b>                   | 66                         | 66                          | 66                   | 66                        |
| <b>R-squared</b>                         | 0.09                       | 0.07                        | 0.09                 | 0.16                      |
| <b>Mean for entire regression period</b> | 7762.262                   | 5422.693                    | 371.0645             | 1968.504                  |

Bootstrapped standard errors are reported in parentheses and are clustered at the room level. One, two and three asterisks indicate significance at the  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$  level, respectively. Variables not reported: day of the week fixed effects, week fixed effects and cubic time trend.

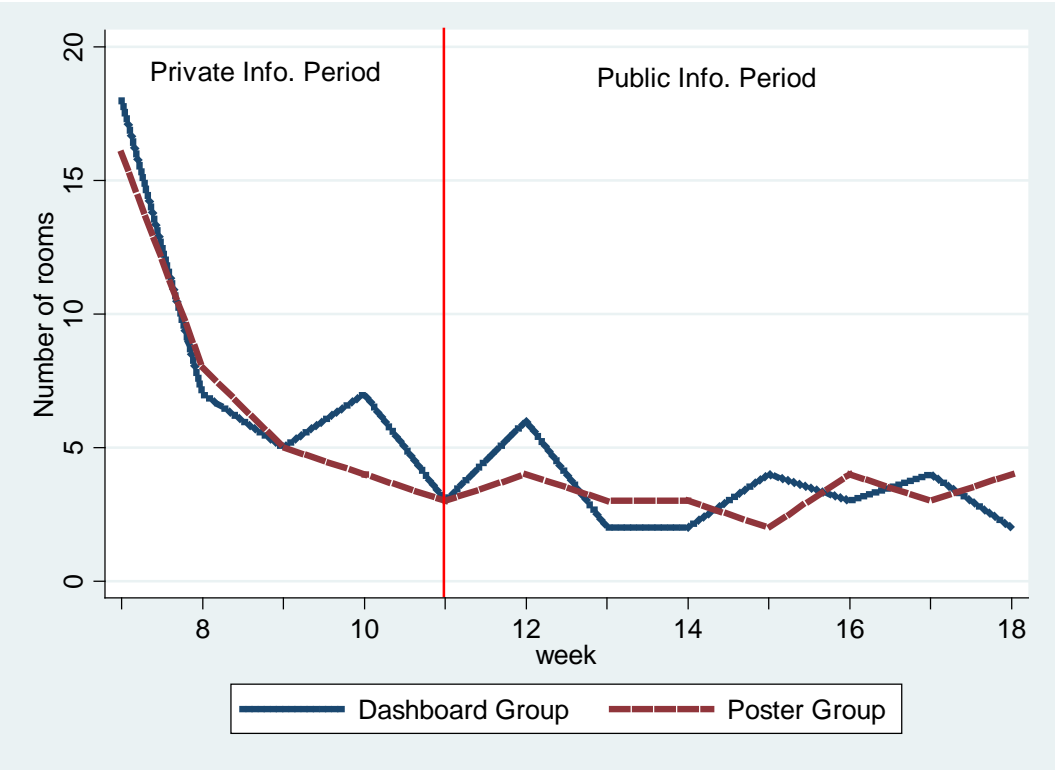
Figure 1: UCLA ENGAGE Dashboard (blocked labels inserted)



**Figure 2: Predicted versus Actual Energy Usage**



**Figure 3: Number of Rooms that Viewed the Dashboard by Experiment Week**



**Saving Power to Conserve Your Reputation?**  
**The effectiveness of private versus public information**

**APPENDIX**

## **Appendix A: Private Information**

Participants in the Private Information treatment were given access to a real-time online display and received weekly e-mails over their electricity usage. The online display, called the UCLA ENGAGE dashboard, was custom designed for the experiment. The dashboard gave users real-time information over their current electricity usage, historical and social usage comparisons, as well as a running average of electricity usage by source. Each room had its own individual dashboard display. An example of the dashboard can be seen in Figure 1 in the main paper.

The real time energy usage box was intended to allow users to dynamically investigate and learn about their energy usage through experimentation and observation. To make the current usage figure more easily understandable, we extrapolated this instantaneous usage into a daily total and contrasted this with a historical daily running average. This would allow users to contrast the effect of current actions with their past behavior (e.g. “Wow, if I turn on my new tanning bed all day, I use ten times more electricity per day than I normally do”).

The bar chart contrasted current usage with historical and social norms. This would provide appropriate benchmarks and allow for the analysis of long term trends. Within this chart, users are able to choose the level of resolution they view feedback at – over the last week, day or 3 hours. The weekly view shows usage by day for the past week. The daily views shows usage over the past 24 hours split into 6 hour blocks – morning, afternoon, evening and night time. The 3 hour view shows a line graph of usage over the past three hours (in two minute increments). Different levels of resolution allow for different types of analysis (e.g. “Wow, I use almost as much energy when I am outside my room in the morning as when I am home at night”). The historical comparisons are made with similar time periods (so for



example historical usage for Tuesday will be the running average for all previous Tuesdays), while the social comparisons are with rooms of a similar type (single or shared).

Energy usage by source is calculated as a running average to reflect long term trends rather than short term changes. This was intended to show students where their energy usage predominantly came from and thereby allow them to make informed decisions on how to conserve.

Above the main dashboard page, students had links to energy conservation tips and a carbon comparison that relates energy usage behaviors to other environmentally destructive behaviors that are more visible.

The weekly email sent to students (Figure 4) graphically showed their daily usage over the previous week. They were also told the average of their daily usage for the previous week and how this compared to the average usage of similar rooms. The email also had a room-specific link to the ENGAGE dashboard.

**Figure 4: Weekly Feedback Email to Students**

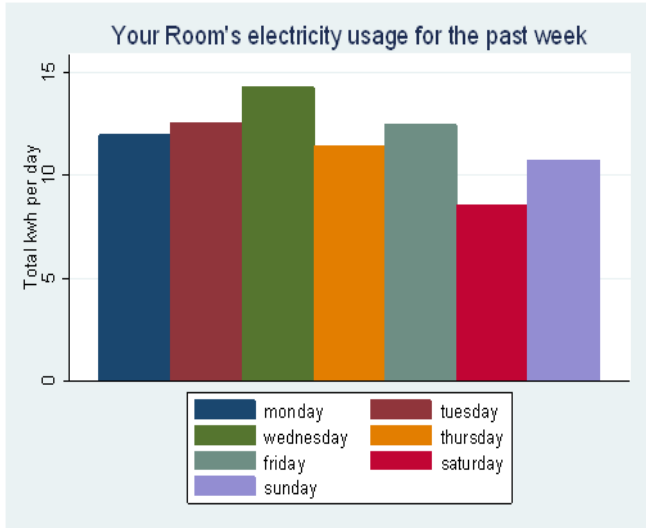
Dear Neil

Last week you used 10 kwh per day of electricity on average. This amount is **more than** that of the average 1 person room, which used an average of 6 kwh per day.

To get real-time usage information as well as conservation tips **check out your *personalized Engage webpage*** at:

<http://eawins38.ee.ucla.edu/~energy/engage/room/code/7f8dc3e4>

The graph below shows your electricity usage for the past week.



| Day       | Total kWh per day |
|-----------|-------------------|
| Monday    | 12                |
| Tuesday   | 12.5              |
| Wednesday | 14                |
| Thursday  | 11.5              |
| Friday    | 12.5              |
| Saturday  | 8.5               |
| Sunday    | 10.5              |

Note: If you have a zero/near zero value for electricity usage, it probably means that your energy meter was no working correctly on this day. |

## Appendix B: Public information

**Figure 5: UCLA ENGAGE Energy Stars Poster**



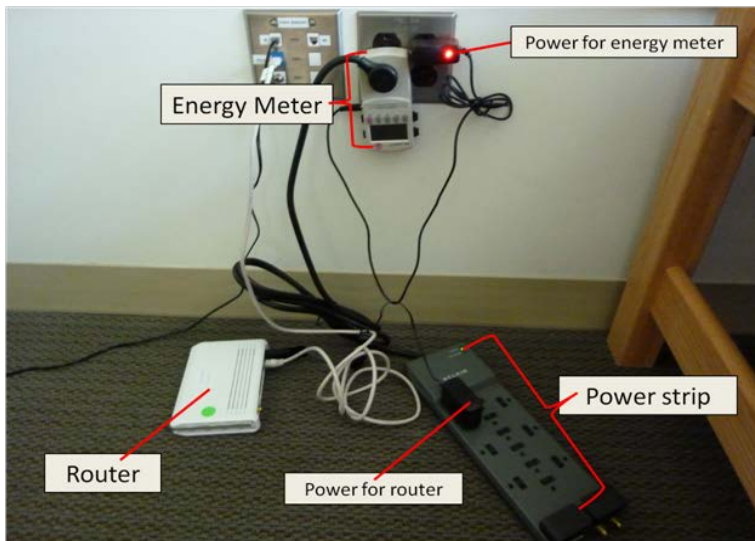
Students in the public information treatment were publicly rated as being above or below average energy conservers. Ratings were published on large, prominently displayed posters and through weekly emails to all experiment participants (including the control group). Rooms were rated on a weekly basis, where the weeks corresponded to the commonly known calendar weeks of the academic quarter. If a room used less electricity for the week than similar rooms (“an above average energy conserver”) it was given a green sticker for the week. If the room used more electricity (“a below average energy conserver”) it was given a red sticker for the week. The posters were placed on each floor occupied by rooms participating in the public information treatment and were posted on notice boards opposite the elevator, ensuring that all students on that floor would pass it several times a day (Figure 5). The language on the poster was explicitly chosen to reflect positive behaviors – energy conservers as opposed to energy users.

Since the public information treatment group only comprised one third of the entire group, it was possible for all rooms in the treatment to conserve energy and be awarded green stickers. This was made clear to the students through several emails as well as a note on the poster. To increase publicity and exposure a copy of the poster was also emailed to each participant in the experiment (all treatment and control groups). Due to privacy concerns, the poster only displayed room numbers, not occupant names.

## Appendix C: Technology and Equipment

A rapid retrofit energy metering system was custom designed for this project. The key objective was to be able to retrofit a furnished/partially furnished room quickly and unobtrusively. The system also had to be flexible enough to allow for a variety of room layouts and accommodate different end uses. To this end, each room was outfitted with two energy meters, a variety of sensors, a router and a number of power strips to plug their electronics into. The energy meters were connected to the wall outlet and

**Figure 6: Energy Metering Equipment**



measured plug load. All other wall outlets were taped over with security tape to prevent usage. Power strips, with enough capacity to more than cover the taped over outlets, were then plugged into the energy meters. Also connected to the energy meter were custom developed light and temperature sensors that would allow us to measure when lights and heating/cooling were turned on/off. Data from the sensors and energy meter was sent wirelessly to an internet gateway (router) every 10 seconds using a radio transmitter built into the energy meter. The gateway consisted of an internet connected router, custom adapted with hardware and software that allowed it to collect, process and aggregate data from each energy meter and sensor set. This data was then transmitted to a central data server at two minute intervals. A representative set of equipment can be seen in Figure 6.

The energy meter was constructed by augmenting the commercially available Kill-a-Watt electricity monitor with hardware enhancements that allowed for wireless data transmission and additional sensor channels. Wireless transmission was based on a popular open source modification called

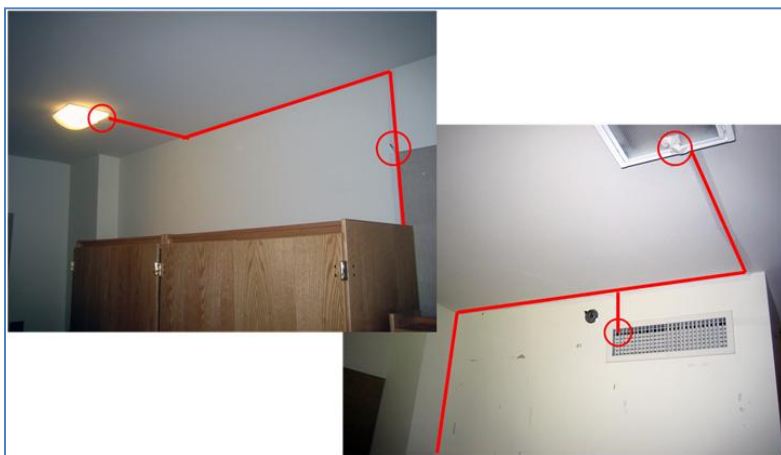
Tweet-a-watt. The Tweet-a-Watt integrates a small wireless transmitter (based on the Zigbee protocol) into the Kill-a-Watt with the intention of enabling the Kill-a-Watt to “tweet” energy usage data to Twitter, via an internet-connected PC acting as a receiver.

Additional sensor channels allowed for the incorporation of light and temperature sensors which measured overhead light usage and heating/cooling usage respectively. This was done by leveraging the additional analog input channels on the wireless transmitter and wiring these to custom physical connections on the Kill-a-Watt. The light and temperature sensors were custom developed using long

**Figure 7: Temperature and light sensors in an installed room**



**Figure 8: Temperature and light sensors in an installed room – highlighted**



lengths of cable and low-cost, commercially available photodiodes and temperature sensors. The light sensors were mounted directly on/in the housing of the overhead lights; thus allowing us to determine when the lights were on or off. One temperature sensor was placed directly at the heating/cooling vent and another was placed away from the vent to capture ambient temperature. An on-off status of the heating/cooling was determined by looking at temperature differences of the two sensors.

In order to make the system as unobtrusive as possible cables were routed along natural lines such as corners whenever possible. The cables were attached to the walls using painter’s tape that would be easy to handle to expedite the installation process. We chose to use white tape to match the wall color so the cables would be hidden and the equipment would blend in. In addition, tape was selected that would not leave residue or peel paint from the wall so that no further repair costs would be incurred by the installation.

Participants commented that after a while they stopped noticing the cables, while guests would often not notice them at all. Figure 7 shows a typical setup. The cables are difficult to see and thus are highlighted in Figure 8.

## Appendix D: Additional Tables

**Table 9:** Random effects regression of daily electricity usage by source to test randomness across the treatments in the baseline period.

|                                | <b>HVAC</b>              | <b>Plug</b>           | <b>Light</b>        | <b>Total</b>             |
|--------------------------------|--------------------------|-----------------------|---------------------|--------------------------|
| <b>Private Info Only Group</b> | 1,370.969<br>(1,156.347) | 420.753<br>(365.139)  | -32.878<br>(45.359) | 1,723.835<br>(1,151.216) |
| <b>Public Info Group</b>       | 469.453<br>(1,689.876)   | -225.329<br>(386.289) | -50.877<br>(48.463) | 181.978<br>(1,663.754)   |
| <b>strata1</b>                 | 253.770                  | -689.802              | -<br>209.282***     | -636.093                 |

|                        |             |             |            |             |
|------------------------|-------------|-------------|------------|-------------|
|                        | (1,766.687) | (631.715)   | (51.684)   | (1,907.022) |
| <b>strata2</b>         | 1,458.383   | 17.415      | -          | 1,231.028   |
|                        |             |             | 236.480*** |             |
|                        | (1,662.565) | (635.880)   | (41.389)   | (1,752.547) |
| <b>strata3</b>         | -878.346    | -846.546    | -          | -2,058.146  |
|                        |             |             | 236.491*** |             |
|                        | (1,926.735) | (603.978)   | (74.350)   | (2,136.197) |
| <b>strata4</b>         | 127.796     | -           | -          | -1,128.724  |
|                        |             | 1,012.009** | 243.396*** |             |
|                        | (1,407.052) | (513.417)   | (38.589)   | (1,571.345) |
| <b>strata5</b>         | -1,797.416  | -405.147    | -76.478    | -2,282.704  |
|                        | (1,656.015) | (582.208)   | (78.100)   | (1,901.976) |
| <b>strata6</b>         | -           | -840.397*   | -5.490     | -           |
|                        | 2,625.189*  |             |            | 3,467.035** |
|                        | *           |             |            |             |
|                        | (1,225.290) | (510.746)   | (125.155)  | (1,414.093) |
| <b>strata7</b>         | -           | -941.687    | -203.099** | -           |
|                        | 3,291.717*  |             |            | 4,439.352** |
|                        | *           |             |            | *           |
|                        | (1,465.653) | (625.297)   | (85.813)   | (1,672.599) |
| <b>Constant</b>        | 3,910.774*  | 1,897.264** | 498.822*** | 6,321.588** |
|                        | *           | *           |            | *           |
|                        | (1,566.083) | (509.006)   | (43.394)   | (1,727.971) |
| <b>Observations</b>    | 2207        | 2207        | 2207       | 2207        |
| <b>Number of rooms</b> | 65          | 65          | 65         | 65          |

The sample was stratified by gender, room type and floor/building. Robust standard errors are reported in parentheses and are clustered at the room level. One, two and three asterisks indicate significance at the  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$  level, respectively.

## Appendix E: Surveys and Factor Construction

An entry and an exit survey were taken, each with several different iterations. The initial entry survey was taken during the recruitment period to better understand underlying attitudes and knowledge about energy usage and the environment. The exit survey was taken at the conclusion of the experiment to learn about how participants perceived the equipment and treatments and how they reacted to them.

### *Entry Survey*



The entry survey was undertaken during the summer of 2010 as part of the recruitment process. Surveys were sent along with recruitment materials to the 2,318 future residents of the three target residence halls. The response rate was high with 496 students (22 percent of the target population) completing a survey. The entry survey asked respondents about their energy usage habits, their beliefs about energy and the environment, as well as their beliefs about energy usage from different sources.

In addition respondents were asked 5 questions from each of the New Ecological Paradigm (NEP) (Dunlap et al., 2000) and Altruism Scales (Schwartz 1977). These questions were jointly used to construct an environmental concern and altruism factor for each respondent. The particular subset of questions chosen from each scale was based on the previous surveys administered by the authors to similar populations. Both the NEP and altruism scale have been shown to be significant predictors of green behavior (eg. Clarke et al., 2003; Kotchen & Moore, 2007).

**Table 8: Environmental and Altruism Factor Questions**

| Item   | Cronbach's |      |       |         |       |       | item-rest corr. | factor loading |
|--|------------|------|-------|---------|-------|-------|-----------------|----------------|
|  | Alpha      | SD   | D     | Neither | A     | SA    |                 |                |
| <b>Environmental Scale</b>   |            |      |       |         |       |       |                 |                |
|  | 0.5665     |      |       |         |       |       |                 |                |
| When humans interfere with nature it often produces disastrous consequences                  |            | 2.1  | 9.37  | 21.99   | 49.33 | 17.21 | 0.3418          | 0.4554         |
| Plants and animals have as much right as humans to exist                                     |            | 1.91 | 5.54  | 10.13   | 37.86 | 44.55 | 0.3401          | 0.4596         |
| The earth is like a spaceship with limited resources   |            | 2.1  | 6.12  | 10.13   | 44.17 | 37.48 | 0.2956          | 0.3998         |
| The balance of nature is strong enough to cope with the impacts of modern industrial nations |            | 2.87 | 11.85 | 21.99   | 47.23 | 16.06 | 0.2962          | 0.3974         |
| Humans were meant to rule over nature  |            | 4.21 | 10.13 | 26.58   | 34.23 | 24.86 | 0.3572          | 0.476          |
| <b>Altruism Scale</b>  |            |      |       |         |       |       |                 |                |
|  | 0.5877     |      |       |         |       |       |                 |                |
| Contributions to community organizations rarely improve the lives of others                  |            | 1.74 | 3.88  | 10.08   | 53.68 | 30.62 | 0.2825          | 0.3473         |
| Many of society's problems are caused by selfish behavior                                    |            | 0.97 | 3.29  | 12.98   | 45.16 | 37.6  | 0.2559          | 0.3521         |
| It is my duty to help other people when they are unable to help themselves                   |            | 1.74 | 4.07  | 19.19   | 51.74 | 23.26 | 0.4541          | 0.6235         |
| My responsibility is to provide only for my family and myself                                |            | 2.13 | 6.2   | 17.83   | 55.43 | 18.41 | 0.3215          | 0.4179         |
| My personal actions can greatly improve the well-being of people I don't know                |            | 0.78 | 1.55  | 13.18   | 54.65 | 29.84 | 0.4259          | 0.5803         |

*All scores are rescaled so that strongly agree (SA) reflects a higher level of environmental consciousness or altruism. Scale runs Strongly Disagree, Disagree, Neither Agree or Disagree, Agree, Strongly Agree*

Table 10 shows each question that goes into a scale measure, along with the percent of each type of response. Cronbach's alpha shows the (aggregate) internal reliability (consistency) of the responses across questions. The alpha values for both factors are quite high indicating some common causality

underlying the responses. The item-rest correlation shows the internal consistency of a particular item within a scale. All items items are of similar consistency. This is not surprising given that the questions were handpicked based on previous surveys to similar populations.

The factors were normally distributed and supplementary regressions (not shown) seem to indicate that they are capturing altruistic and environmental attitudes. We found that the environmental factor was a significant predictor of membership in an environmental organization, while both factors were significant predictors of whether someone volunteered for the experiment.

The exit survey was targeted at experiment participants and asked about the efficacy of the various treatments (we compared this with just having the equipment for the control group) and what conservation methods they undertook. 58 of the 102 experiment participants completed the survey, accounting for 52 of the 66 experiment rooms. The exit survey was combined with a series of focus groups.

Figure 9 shows self-reported one-off behavior changes. These are changes the equipment or technology that only need to be undertaken once in order to be effective. The only notable difference between groups is that participants in both the Public and Private Information treatment groups were more likely to change their laptop power settings than the control group, although this result was not statistically significant.

### **Figure 9: Self-reported One-Off Energy Use Changes**

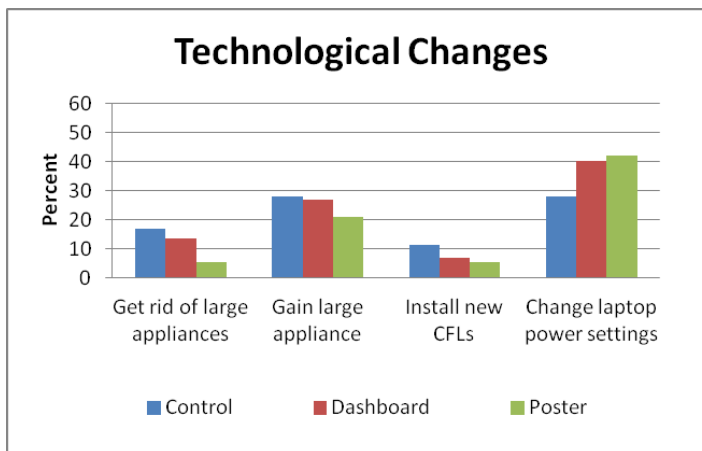
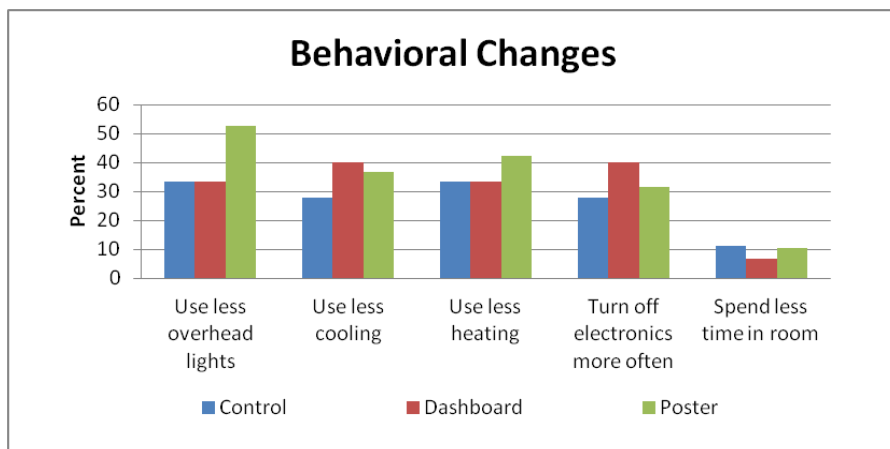


Figure 10 shows similar results for behavioral changes, these actions need to be conducted on a regular and ongoing basis in order to be effective. Notably participants in the *poster* group were more likely to reduce their lighting and heating than participants in the *dashboard* and *control* groups. However, only lighting was statistically significant ( $\Pr(T < t) = 0.0544$ ). If we think of energy conservation as a combination of different strategies, then participants in the Public Information group were more likely to engage in at least 3 or more strategies ( $\Pr(T < t) = 0.0401$ ), where 2 strategies is the median.

**Figure 10: Self-Reported Changes to Frequent Energy Use Behaviors**



## Appendix F: Model

In this section we formalize the interaction between information, motivation and costs with a simple model that allows us to develop testable behavioral hypotheses. To this end we build on Benabou and Tirole's (2006) model of prosocial behavior. In this framework, an individual's incentives to engage in prosocial behavior, such as performing conservation action  $a$ , is divided into three basic motivations, intrinsic ( $nv_a$ ), extrinsic ( $yv_y$ ) and reputation,  $R(a, y)$ . Formally an agent's utility is:

$$U(a) = (nv_a + yv_y)a + R(a, y) - C(a, k, \theta) \quad (1)$$

Where  $v_a$  is an agent's own ideology and  $n$  is the perceived saliency of the set of social norms that pertain to a particular action. In contrast to Levitt and List (2007), who model social norms as increasing the moral cost of undertaking an anti-social action, we model social norms as increasing the moral benefits of acting prosocially. Thus a greater value of  $n$  is associated with a stronger norm for conservation. We allow the effect of social norms to vary positively with own ideology by interacting the social norm with personal ideology in accordance with the empirical results obtained by Costa and Kahn (2010). Extrinsic motivations are a combination of the monetary reward,  $y$ , and its valuation by the agent,  $v_y$ . The cost of behaving prosocially  $C(a, k, \theta)$  depends on an individual's procedural knowledge,  $k$ , and cost shifter,  $\theta$ . We will initially assume that the state of procedural knowledge,  $k$ , is constant across individuals. Personal ideology ( $v_a, v_y$ ) is determined by an independent draw from a bivariate normal distribution, while costs  $C(a, k, \theta) = \theta k^{-1} \frac{a^2}{2}$ .

The provision of private information to an agent can influence behavior by increasing procedural knowledge,  $k$ , strengthening the social norm,  $n$ , or both. Increasing knowledge will decrease the cost of conservation, whereas strengthening the social norm will amplify intrinsic motivation.

Reputation,  $R(a, y)$ , depends on whether conservation actions are public information or not ( $I : x \rightarrow \{0,1\}$ ), the degree to which agents care about their reputation,  $\gamma$  (which we assume is constant across all agents), and the expectation that others have of their (unobservable) attitudes ( $nv_a$ ), based on their observable behavior and rewards, hence:

$$R(a, y) = I(x)\gamma E(nv_a | a, y) \quad (2)$$

Substituting in the cost and reputation terms and taking the first order condition to determine the optimal level of the prosocial action  $a$ , we are left with

$$a^* = \frac{1}{\theta k^{-1}} [nv_a + yv_y + r(a, y)] \quad (3)$$

where  $r(a, y) = I(x)\gamma \frac{dE(nv_a | a, y)}{da}$  is the marginal reputational return to a change in the level of the prosocial activity.

Following Benabou and Tirole (2006) we are able to solve for the optimal level of conservation using standard results from the normal distribution and the fact that the level of  $a$  informs us about the agent's intentions. This yields the optimal level of the conservation activity  $a^*$ , such that:

$$a^* = \frac{nv_a + yv_y}{\theta} k + \gamma \mathcal{I}(x) \rho \text{ where } \rho = \frac{\sigma_{nv_a, nv_a + yv_y}}{\sigma_{nv_a + yv_y}^2} \quad (4)$$

To solve for this conditional expectation, we can follow Benabou and Tirole in exploiting the fact that the level of  $a$  tells us something about an agent's intentions. Since  $v_a$  and  $v_y$

are jointly distributed and  $y$  is exogenously given, we have

$$E[nv_a | a, y] = E[nv_a | a\theta k^{-1} - R(a, y)] = E[nv_a | nv_a + yv_y]$$

Following on standard results for the normal distribution<sup>24</sup> we have

$$E[nv_a | nv_a + yv_y] = \overline{nv_a} + \rho(nv_a + yv_y - \overline{nv_a} - \overline{yv_y})$$

where

$$E[nv_a | nv_a + yv_y] = \overline{nv_a} + \rho(a\theta k^{-1} - \gamma \mathcal{I}(x) \frac{dE(nv_a | a, y)}{da} - \overline{nv_a} - \overline{yv_y})$$

$\rho = \frac{\sigma_{nv_a, nv_a + yv_y}}{\sigma_{nv_a + yv_y}^2}$ . We can then substitute in the first order condition, yielding

Taking the derivative with respect to  $a$  gives us a linear differential equation

$$\frac{dE(nv_a | a, y)}{da} - \rho\theta k^{-1} + \rho\gamma \mathcal{I}(x) \frac{d^2 E(nv_a | a, y)}{da^2} = 0, \text{ which has the general solution}$$

---

<sup>24</sup>If  $(x_1, x_2) \sim N(\nu_1, \nu_2; \begin{matrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{matrix})$  then  $E(x_1 | x_2) = \overline{\nu_1} + \frac{\sigma_{12}}{\sigma_2^2}(x_2 - \nu_2)$

$$\frac{dE(nv_a | a, y)}{da} = \rho\theta k^{-1} + \xi e^{\frac{-a}{\rho\mathcal{I}(x)}}$$

Where  $\xi$  is the constant of integration. Benabou and Tirole show that an interior solution exists only in the case where  $\xi = 0$ .

We can then substitute this marginal value of reputation into equation 3 of the main text. This yields the optimal level of the prosocial activity  $a$  to be:

$$a^* = \frac{nv_a + yv_y}{\theta} k + \mathcal{I}(x)\rho$$