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Why does real-time information reduce energy consumption?

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Abstract

A number of studies have estimated *how much* energy conservation is achieved by providing households with real-time information on energy use via in-home displays. However, none of these studies tell us *why* real-time information changes energy-use behavior. We explore the causal mechanisms through which real-time information affects energy consumption by conducting a randomized-control trial with residential households. The experiment disentangles two competing mechanisms: (i) learning about the energy consumption of various activities, the "learning effect", versus (ii) having a constant reminder of energy use, the "saliency effect". We have two main results. First, we find a statistically significant treatment effect from receiving real-time information. Second, we find that learning plays a more prominent role than saliency in driving energy conservation. This finding supports the use of energy conservation programs that target consumer knowledge regarding energy use.

Keywords: energy efficiency; energy conservation; real-time information; experiment

JEL Codes: D03; D12; Q41; Q48

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1. Introduction

Reducing energy use is now a major policy goal in most developed and many developing countries. In-home displays (IHDs) have received increasing attention as an effective tool to encourage energy conservation. IHDs are designed to give electricity consumers detailed, real-time information about electricity use and cost. A number of studies have estimated *how much* energy conservation is achieved by providing households with IHDs (as opposed to monthly electricity bills, which provide information about aggregate usage and charges). However, none of these studies tell us *why* IHDs change energy-use behavior. In other words, what are the *causal mechanisms* through which these devices are working? Is it because the devices update consumers' beliefs about how much power different appliances use? Is it because IHDs make energy use more salient as residents are constantly reminded of their energy consumption? While the first hypothesis implies the presence of a "learning effect," the second hypothesis implies the presence of a "saliency effect".

This paper represents an initial attempt to disentangle the mechanisms through which real-time information affects energy consumption behavior by conducting a field experiment. The goal is to push the research agenda on real-time information beyond reduced-form questions of "Does the device have any effect?" towards a deeper structural understanding of "Why is this device affecting behavior?" This may have critical policy implications. For example, if learning about the energy consumption of various household devices is the reason why real-time information induces energy conservation, then this advocates for a particular suite of energy efficiency policies (e.g., educational outreach, labeling electronic appliances with their energy consumption, etc.). On the other hand, if the real benefit of having IHDs is as a constant "nudge" or reminder, then this suggests a very different set of energy efficiency policies (e.g., finding the best medium and timing to remind consumers about their energy consumption). Furthermore, understanding why IHDs work in a real field setting should help in the design of future IHDs.

In this paper, we present the results of a randomized-control experiment with 65 residential households in the same condominium complex in a large US city. In the experiment, we randomly assign households into one control and two treatment groups. After installing data-collecting devices for each household, the control group has their energy consumption monitored but does not receive an IHD during the experimental period. The two treatment groups have data-collecting devices installed, and then receive IHDs but with one critical difference. The "Saliency" treatment group has access to their IHDs for the entire duration of the experiment, while the "Learning" treatment group loses access to their IHDs in the last month of the experimental period. By comparing how electricity use changes over time and across the three groups, we are able to (i) estimate the amount of electricity conservation attributable to IHDs, and (ii) disentangle whether learning about energy use is sufficient to sustain energy conservation or whether having a constant reminder of energy use is necessary for energy conservation.

Although our sample size is small, our simple experimental design illustrates lessons that are extremely relevant to the rollout of IHDs. In line with previous studies, we observe an average reduction in electricity consumption between 0 and 11%, depending on the time of day. This effect gets weaker over time (again in line with previous studies) and the reductions appear to be driven primarily by learning and not by saliency effects. The rest of this paper is organized as follows: Section 2 provides a brief literature review, Section 3 explains the conceptual framework, Section 4 presents the experimental design, Section 5 summarizes our main findings and Section 6 concludes.

2. Literature Review

Many studies have used experiments to better understand energy conservation programs (see Abrahamse et al. (2005) for a review). An obvious method to achieve energy conservation is to provide economic incentives to reduce energy consumption (Winett et al., 1978; Midden et al., 1983; Petersen et al., 2007; Mizobuchi and Takeuchi, 2012). A number of empirical studies have estimated how detailed information on power use can contribute to energy conservation (Sexton et al., 1989; Wood and Newborough, 2003; Delmas et al., 2013). Building on Sexton et al. (1989), Matsukawa (2004) measured the effect of information (provided by a continuous-display, electricity-use monitoring device) on residential electricity demand in a field experiment with 319 randomly selected households. Subjects were randomly assigned to either a control or treatment group. Only the treatment group members had free provision and installation of monitors. Results demonstrated that monitor usage contributed to a modest reduction in electricity consumption. In terms of possible causes for the small effect, the author argues that subjects might have found the monitors difficult to operate and that updates in electricity use were not frequent enough (subjects received hourly not real-time information).

Faruqui, Sergici and Sharif (2010) review a number of pilot programs worldwide that focus on the energy-conservation impacts of IHDs as well as alternative electricity rate structures. Among the programs that tested the effect of IHDs on electricity consumption (where the test period ranged from three months to two and a half years), the average reduction in energy use was 7%, and the largest reduction observed was 13%. Fischer (2008) reviews a number of studies on IHDs, most of which have been published in the psychology literature. IHDs tend to achieve energy conservation gains between 5 and 12%. Houde et al. (2013) find average reductions of 5.7% but this effect only lasts for four weeks. The common theme in the literature is that in-home displays encourage people to reduce their energy consumption by 5-10%.

As Gillingham et al. (2009) explain, the literature on energy efficiency has debated the existence and extent of the "energy efficiency gap," i.e., a "significant difference between observed levels of energy efficiency and some notion of optimal energy use" (p.602). Consumers' lack of information about energy efficiency and "behavioral failures"—systematic biases in consumer decision making that lead to underinvestment in energy efficiency (or energy overuse)—are the identified factors behind the energy efficiency gap. Consumers often lack sufficient information about how much energy different appliances use and how much they cost to run.[1] Even when information is available, processing detailed information about the energy prices of each appliance and figuring out optimal electricity use would be challenging and costly for consumers. As for behavioral failures, bounded rationality (cognitive constraints in processing information to optimize consumers' energy use) and heuristic decision-making (i.e., non-optimal decision making that reduces the cognitive burden of decision making) have been discussed in the literature as reasons for the energy efficiency gap. All of these hypotheses could

[1] Newell and Siikamaki (2013) examine the effect of energy conservation labeling when households purchase electronic devices. They found that information on the device's costs had more of an effect than information on energy use in kWh or carbon emissions.

explain why energy over-use may result when residents have access to only aggregate, monthly electricity use data. Introducing IHDs may enable consumers to make more optimal energy use decisions; a common assumption in the literature is that optimal energy use implies less energy use, i.e., behavioral biases are unidirectional. There is some evidence to support this assumption: a recent study (Attari et al., 2010) of an internet-based survey finds that people tend to underestimate the energy used by household appliances (e.g., air conditioners) and the amount of energy savings from efficiency-enhancing activities (e.g., switching to high-efficiency light bulbs).

Yates and Aronson (1983) found that consumers attach disproportionate weight to more psychologically vivid and observable factors, often called the saliency effect. Fischer (2008) reviews IHD projects that vary the frequency with which consumers receive information about electricity use; she finds that more frequent feedback results in larger energy savings. This is suggestive of a saliency effect but could also be explained by learning. There has been little work to distinguish whether one hypothesis is more plausible than another. Dietz (2010) argues that "many [policies] to promote household energy efficiency are not based on an understanding of how residents think about and make decisions regarding energy efficiency." As Gillingham et al. (2009) note, "the empirical literature testing behavioral failures specifically in the context of energy decision making is very limited." In the context of energy conservation, the mechanisms through which consumers reduce energy use when real-time information is provided have not been explored experimentally.[2] This paper is a first step in that exploration.

[2] In a recent experimental paper, Jessoe and Rapson (2014) explore how households with IHDs respond to electricity price changes relative to households without. Households with IHDs are more responsive to price changes and survey evidence suggests that this is due to learning and not saliency. The focus of Jessoe and Rapson (2014) is on differential price responses and not on why IHDs change behavior. Our experimental design is unique in that we

3. A Model of Energy Use with Learning and Salience

Gillingham et al. (2009) list prospect theory, bounded rationality, and heuristic decision making as the three primary behavioral models applied in the context of energy efficiency. The following model incorporates bounded rationality to try to explain why real-time information might induce energy conservation. In particular, the model describes residential energy users' decisions when there are costs to collecting information about energy use and to implementing energy efficiency improvements. This framework allows us to highlight the role of saliency and learning as mechanisms through which real-time information influences household energy conservation.

3.1. Assumptions

For simplicity, we take a household as a single decision maker who makes energy-use decisions for T rounds over a typical utility billing period (say a month). Let $x_t \geq 0$ be the household's consumption of "energy services" in round t. Let $y \geq 0$ be the consumption of the numeraire over a month. The household faces a flat energy charge of $p > 0$ per unit, and allocates its given monthly income $I > 0$ over the consumption of "energy" $e_t \geq 0$, $t = 1,2,\ldots,T$ and the numeraire.[3] Energy service x_t and the purchase of energy e_t have the following relationship:

observe behavior after IHDs are removed. Reassuringly, both studies suggest that learning is more important than saliency.

[3] We abstract away from the block rate structure typically observed with utility pricing.

$$e_t = \beta_t x_t,$$

where $\beta_t > 0$ represents the units of energy that the household requires to realize a unit of energy service.

Though T could be large (it includes the sum of the number of times each appliance is turned on and off), for simplicity let $T = 2$. The household's utility u is a function of its consumption of energy services and the numeraire:

$$u(x_1, x_2, y) = v(x_1) + v(x_2) + y \quad \text{for all } (x_1, x_2, y) \geq 0\,.$$

The specification of a quasilinear utility function allows us to abstract away from the income effect on energy service consumption.[4] We assume no discounting within a billing period. Let $v(x) = \frac{x^{1-\gamma}}{1-\gamma}$, with $\gamma = 2$ for a concrete illustration.[5] If the household is informed of the relationship between x_t and e_t, then the household's utility-maximizing problem over a billing period is given by:

$$\max_{x \geq 0, y} v(x_1) + v(x_2) + y$$

$$\text{subject to} \quad p(e_1 + e_2) + y \leq I, \quad e_t = \beta_t x_t, \quad t = 1,2.$$

[4] In a recent empirical study on the residential electricity demand in California, Reiss and White (2005), the estimated income elasticity ranged between -0.01 and +0.02. The authors argue that "the income effects are mostly statistically insignificant and negligible as a practical matter."
[5] Existing estimates of the price elasticity of residential electricity consumption (i.e., $1/\gamma$) fall below 1; see, for example, Espey and Espey (2004) and Fell et al. (forthcoming).

With $v(x_t) = -x_t^{-1}$, the demand for energy services is given by $x_t^*(p) = \left(\frac{1}{p\beta_t}\right)^{\frac{1}{2}}$ while the demand for energy is $e_t^*(p) = \left(\frac{\beta_t}{p}\right)^{\frac{1}{2}}$: the demand for energy is increasing in the energy requirement parameter β_t. The maximized value satisfies:

$$u^* \equiv \left(\frac{1}{p\beta_1}\right)^{\frac{1}{2}} + \left(\frac{1}{p\beta_2}\right)^{\frac{1}{2}} + I - (p\beta_1)^{\frac{1}{2}} - (p\beta_2)^{\frac{1}{2}}.$$

Suppose now that the household is not informed of the value of β_t. As argued in the literature (e.g., Simon 1956, Gillingham et al. 2009), we assume that it is costly for the household to (i) collect information about β_t and then (ii) attempt to improve energy efficiency by applying β_t to the utility maximization problem. Let C_I be the cost of identifying β_t, and C_P be the cost of processing the information for utility maximization. While C_I would include the opportunity cost of going over the monthly energy bill in detail and conducting research to check the power usage of each appliance in the house, C_P would include the cognitive cost of remembering this information and using it to implement an optimal energy use plan.

Suppose that, without knowing the values of β_t, the household uses β_h units of energy to derive a unit of energy services in each round. We assume $\beta_h > \beta_t$ for all t: the household consumes more units of energy to derive a unit of energy services. Furthermore, in the absence of real-time information (i.e., every round in the model's context) about the energy requirement, it is assumed that the requirement parameter is the same across rounds. The uninformed household without information acquisition then solves:

$$\max_{x \geq 0, y} v(x_1) + v(x_2) + y$$

$$\text{subject to } pe + y \leq I,\ e = \beta_h(x_1 + x_2).$$

The demand for energy satisfies $e_t^0(p) = \left(\frac{\beta_h}{p}\right)^{\frac{1}{2}}$, which is larger than $e_t^*(p)$ in all rounds given any price level. The maximized value is given by:

$$u^0 \equiv 2\left(\frac{1}{p\beta_h}\right)^{\frac{1}{2}} + I - 2(p\beta_h)^{\frac{1}{2}}.$$

Note that $u^* - u^0 \geq 0$. The household will not acquire information and implement energy conservation if the gains are smaller than the cost: $u^* - u^0 < C_I + C_P$.

3.2. Learning and saliency

When real-time information is given free of charge, the household does not have to pay for C_I to realize the values of β_t, and can now realize energy efficiency if $u^* - u^0 > C_P$. Furthermore, the cognitive cost required to remember information and how to use it is lowered from C_P to $C_{P'}$, so energy efficiency is realized if $u^* - u^0 > C_{P'}$. The process of learning allows the household to continue to optimize consumption when access to real-time information is terminated. After being exposed to real-time information (and losing access to it), the cost of information acquisition becomes smaller, with $C_{I'} < C_I$. In addition, $C_{P'}$ returns to C_P. Let $\alpha \in [0,1]$ represent the extent (or productivity) of learning. Assume the household's energy requirement after the learning process is:

$$\beta_t(\alpha) \equiv \alpha\beta_t + (1-\alpha)\beta_h.$$

When $\alpha = 1$, learning allows the household to implement the energy savings in the case of full information, whereas with $\alpha = 0$, learning is not effective. Let

$$u^L(\alpha) \equiv \left(\frac{1}{p\beta_1(\alpha)}\right)^{\frac{1}{2}} + \left(\frac{1}{p\beta_2(\alpha)}\right)^{\frac{1}{2}} + I - (p\beta_1(\alpha))^{\frac{1}{2}} - (p\beta_2(\alpha))^{\frac{1}{2}}$$

be the maximum value after learning with productivity α. The household makes use of learning and conserves energy if $u^L(\alpha) - C_{I'} - C_P > u^0$. The higher the learning productivity α and the lower the cost of collecting information under learning $C_{I'}$, the more likely this inequality holds.

The above conceptual framework reveals that whether the learning or saliency effect prevails depends on each household's characteristics regarding energy efficiency decisions: the costs of information acquisition $(C_I, C_{I'})$, the cost of information processing $(C_P, C_{P'})$ and the extent of learning (α). If α is large and $C_{I'}$ is small enough, then the household would continue conserving energy after losing access to real-time information (because of learning). If $C_{P'}$ is close enough to C_P, then the household would continue conserving energy, because saliency is not that important. However, if $C_{I\prime}$ is close to C_I and α is small (it's hard to acquire information and learning is weak), then households will return to their old habits after losing their IHDs. Likewise, if $C_{P\prime}$ is small, households with IHDs will continue to have lower levels of electricity use relative to those who had them removed, even if learning is strong.

4. Experimental Design

4.1 Hypothesis Tests

This research aims to identify the *mechanisms* through which real-time information reduces energy consumption. The experiment consists of three periods: Periods 0, 1, and 2, each lasting for about 30 days. Electricity measurement (and recording) devices are installed in all apartments at the beginning of Period 0. Period 0 is the baseline period with no IHDs for all groups. Our experimental design has one control and two treatment groups: the control group has no real-time information about their energy consumption during the experimental period (just their usual monthly bill), whereas the households of the two treatment groups receive IHDs (i.e., real-time information) at the beginning of Period 1. Period 1, which lasts for about 30 days, should be enough time for any learning to occur in the treatment groups. At the beginning of Period 2, IHDs are then removed from the Learning treatment group, while the other treatment group, the Saliency treatment group, continues to have IHDs for the duration of Period 2. Energy consumption information for all groups is still being recorded in each period by the recording devices, not the IHDs.

This experimental design allows us to identify the primary effect of receiving real-time information. Since there is existing evidence of people reducing their energy consumption if they receive real-time information, our first testable hypothesis is the following:

Hypothesis 1: Real-time information reduces residential households' energy consumption.

[L1+S+RL1+L2<0]

We will test this hypothesis by comparing the control group and the treatment groups' electricity use before and after receiving the devices, i.e., Period 0 compared to Periods 1 and 2 (see Table 1). The econometric model we use follows the preferred specification in Houde et al. (2013), who ran a very similar experiment using the same devices. Next, we move to identify why people reduce their energy consumption. To test this deeper question, we examine behavior over three experimental periods (Table 1). Our second testable hypothesis is the following:

Hypothesis 2: Real-time information induces energy savings by causing households to learn more about their individual energy use. [L1+RL1+L2<0]

In order to test Hypothesis 2, we will examine if the Learning group's electricity consumption in Period 2 is the same as the control group's electricity consumption in Period 2 (if RL1<0 then this implies that L1+RL1+L2<0). If there is a difference between the control group and the learning treatment group, then the difference comes from behavior changes induced by the IHDs that persist once the IHDs have been removed. We have labeled this the remaining learning effect (RL1) but this may also be due to the formation of good habits. We will use results from an exit survey to determine whether RL1 is due to learning or habit formation. In particular, we test if households in the Learning group are still just as informed as the Saliency group about the energy consumption of various appliances, even though households in the Learning group have not had access to an IHD for a month. However, if RL1=0, then this indicates no remaining learning effect. Our third testable hypothesis is the following:

Hypothesis 3: Real-time information induces energy savings by making energy use more salient. [S<0]

In Period 2, the households who belong to the Learning group do not have IHDs, which means they do not receive any real-time information. That is, they are not constantly reminded of their electricity consumption by the IHD. In order to test Hypothesis 3, we will examine if the Learning group's electricity consumption in Period 2 is equal to the Saliency group's electricity consumption in Period 2. If there is no difference, Hypothesis 3 is rejected (L2+S=0 in Table 1). That is, saliency does not matter for reducing energy consumption and, furthermore, there is no learning effect in Period 2.[6]

4.2 Experiment procedure

In order to conduct the proposed field experiment, we recruited households at a condominium complex to voluntarily participate in the experiment. In order to give the residents incentives to participate in the experiment, the residents were notified in advance that they would be able to keep the installed IHDs free of charge after the end of the experiment. Eventually, 65 households voluntarily participated in the experiment. Unfortunately, the devices only recorded accurate data over the entire experimental period in 58 out of the 65 households.[7] In terms of housing units, they are all fairly homogeneous: virtually all units have an identical, 2-bedroom

[6] Note that, based on the existing literature and our theoretical setup, we are assuming that the learning and saliency effects are negative (<0), i.e., they reduce energy consumption if they have any effect.
[7] One subject in the saliency treatment group moved out during the experiment – around the end of Period 1 - so we only use this household for the testing of Hypothesis 1.

floor plan, identical room designs, electricity circuits, and lighting structures. All households have the same basic appliances: oven, refrigerator, water heater, etc. Based on survey responses, we found that almost all households have a TV set and desktop computer. Households pay their electricity bills by themselves. As stated earlier, we randomly assigned households to three groups: one control and two treatments.

Table 2 summarizes the description of our subject households based on survey responses. The average age in a household was 33.53, and each household had an average of 2.69 people (including 0.86 children). In each household, there were 1.48 income earners on average. Each household was occupied approximately 16.19 hours per day on weekdays and 17.79 hours per day on weekends. There were no statistically significant differences between treatment groups in terms of these important determinants of energy use. There may, of course, be unobserved differences between households so all of our regression models include household fixed effects.

We used two main devices for this experiment: an electricity measurement device and an IHD. The electricity measurement device was installed in each unit's circuit breaker panel at the beginning of the experiment, and we also conducted an initial survey at this point. After we confirmed that the recording devices were working well, we distributed IHDs to the two treatment groups. IHDs provide users with real-time information about their energy consumption (in both kWh and in dollars).[8] The IHD is portable, so that households using it can easily walk around, switch various devices on and off, and identify how much electricity various devices

[8] The IHD we used is marketed as the "TED 5000" by The Energy Detective (http://www.theenergydetective.com/).

consume.[9] Overall, the experiment lasted for approximately 90 days, depending on the exact date of measurement device installation and final debriefing. There was minimal temperature, climatic or precipitation changes over this three month period.

5. Analysis and Results

First of all, we summarize the average electricity consumption by group and by period. Figure 1 presents average consumption per hour (normalized so that each treatment group consumes 1 unit in Period 0). In the control group, the average hourly consumption increases from Period 0 to Period 1, and then decreases from Period 1 to Period 2. In the Learning and the Saliency groups, average consumption decreases noticeably in Period 1. Consumption continues to decrease from Period 1 to Period 2 but only slightly for the Saliency group. Overall, both treatment groups reduce their consumption from Period 0 to Period 2 (8% for Learning and 4% for Saliency).

Energy saving behaviors could be very different at different times of the day. Therefore, we also consider average hourly consumption in kWh by each treatment group in each period at different times of the day. We focus on four time periods: morning (6-9am), daytime (10am-5pm), evening (6-9pm), and night (10pm-5am). Table 3 presents average electricity consumption for these four time periods across treatments and across experimental periods. Most of the interesting changes in behavior occur when people are at home so we focus on those time periods. We start with the morning, 6-9am (Figure 2). In the control group, the average

[9] The cost of using an IHD itself is extremely small ($0.08 per month), so we assume that there is no significant difference between the control and treatments groups due to having the IHD plugged in.

consumption decreases slightly from Period 0 to Period 1, and then increases from Period 1 to Period 2 to a higher level than Period 0. In the Learning group, the average consumption decreases noticeably from Period 0 to Period 1, then increases from Period 1 to Period 2, but is still lower than Period 0. In the Saliency group the trend is the same, the average consumption drops dramatically from Period 0 to Period 1, then rebounds from Period 1 to Period 2, but is still lower than Period 0.

Next, we look at 6-9pm (right hand side of Figure 2). In the control group, the average consumption increases from Period 0 to Period 1, and then decreases from Period 1 to Period 2, to end up lower than Period 0. In contrast, in the Learning group, the average consumption decreases from Period 0 to Period 1, and then decreases again from Period 1 to Period 2. In the Saliency group, the average consumption decreases from Period 0 to Period 1, and then decreases again from Period 1 to Period 2. Overall, both treatment groups reduce their consumption from Period 0 to Period 1, whereas the control group increases their consumption during this time frame. This suggests that the IHDs are having a stronger and more persistent effect on behaviors in the evening. This is perhaps due to households having more flexibility to change their behavior in the evening compared to the rush to get ready for work and school in the morning.

Figures 1 and 2 certainly suggest that the IHDs are having an effect on behavior. We now use formal regression analysis to empirically estimate the effect of having an IHD on electricity consumption. Table 4 presents the results from least squares regressions estimating the following model:

$$\log \text{Consumption}_{\text{i, t}} = \alpha + \beta \text{ HavingIHD}_{i,t} + \gamma_i + \eta_t + e_{i,t},$$

where $\log \text{Consumption}_{\text{i, t}}$ is the log of average hourly electricity usage on each day for household i and the dummy $\text{HavingIHD}_{i,t}$ takes the value 0 for those who do not have IHDs and the value 1 for those who have IHDs on that day. The other variables are household fixed effects (γ_i), day fixed effects (η_t) and a standard error term. This specification is the same as the most preferred specification in Houde et al. (2013). Because all subjects in our sample live in the same area, the weather variables used in Houde et al. (2013) are not considered here; the time fixed effect captures any weather differences across days. As for the time horizon, we consider all Periods and then just Periods 0 and 1. We estimate our main regression separately for the four different time periods during the day (6-9am, 10am-5pm, 6-9pm, and 10pm-5am) and for the whole day (12am-11pm). In Table 4, the coefficient on the IHD effect, β, is presented. It is negative and statistically significant for the 6-9am time period (all Experimental Periods and just Periods 0 & 1), and for the 6-9pm time period (all Experimental Periods). The rest of the coefficients are insignificant. These results are almost identical to those found in Houde et al. (2013): strong effects in the morning and evening but mixed results overall.

In addition to the model used by Houde et al. (2013), we can also estimate the IHD effect using a standard Difference-In-Differences (DID) model, and by dropping the household fixed effects. Tables 5 and 6 show the OLS results of estimating the following DID model:

$$\log \text{Consumption}_{\text{i, t}} = \alpha \text{ Treatment}_{i,t} + \gamma \text{ Period}_{i,t} + \beta \text{ Treatment}_{i,t} \text{*Period}_{i,t} + \eta_t + e_{i,t},$$

In Table 5, the dummy $\text{Treatment}_{i,t}$ takes the value 1 for those who belong to the two treatment groups, and the value 0 for those who belong to the control group. The dummy $\text{Period}_{i,t}$ takes the value 1 for Period 1, and the value 0 for Period 0. The interaction term $\text{Treatment}_{i,t}*\text{Period}_{i,t}$ takes the value 1 for those who belong to the two treatment groups and are in Period 1, and the value 0 otherwise. In the Table 6, the dummy $\text{Treatment}_{i,t}$ takes the value 1 for those who belong to the Saliency group, and the value 0 for those who belong to the control group. The dummy $\text{Period}_{i,t}$ takes the value 1 for Period 1 or 2, and the value 0 for Period 0. The interaction term $\text{Treatment}_{i,t}*\text{Period}_{i,t}$ takes the value 1 for those who belong to the Saliency group for Period 1 or 2, and the value 0 otherwise.

Finding 1: Receiving real-time information leads to energy conservation during peak load hours (6-9am and 6-9pm) but the overall daily effect is not statistically significant.

The interpretation of these results is as follows: through having the IHD, households with IHDs were able to adjust their consumption down during times of the day when they were at home and using a large amount of electricity. In contrast, the results of the 10pm-5am and the 10am-5pm measurements imply that subjects did not change (or might have even slightly increased) their consumption when they were out of the house or asleep. Therefore, we conclude that having an IHD has an effect on electricity usage in the morning and the evening. We also ran the above regressions without household fixed effects but including a suite of controls. Our main results are unchanged. The only controls that turn out to be statistically significant are the number of people in a household (which is positively correlated with energy consumption) and a dummy variable for having a water hear timer (which is negatively correlated with energy consumption).

One of the most striking findings in Houde et al. (2013) is that the effect of having an IHD declines rapidly over time. To estimate whether we also observe a “decreasing IHD effect”, we estimate the following model for our 6-9am and 6-9pm samples:

$$\log \text{Consumption}_{\mathrm{i,\,t}} = \alpha \; + \beta \text{ HavingIHD}_{i,t} + \delta \text{ Expday*HavingIHD}_{i,t} + \gamma_i + \eta_t + e_{i,t},$$

where the coefficients and variables have the same interpretation as before with Expday representing a daily time trend starting on the first day that households received an IHD. The results are presented in Table 7. We see that, just like Houde et al. (2013), the effect of the IHD in the morning is getting weaker over time. With each additional day, the reduction in energy use gets smaller and smaller. Interestingly, we also observe a time trend at 6-9pm but in the opposite direction: the effect of the IHD appears to get stronger over time. Both sets of results strongly suggest that there is a temporal component to the ways in which IHDs change behavior. The various effects gradually build up or fade away over time.

Next, we move to a deeper investigation. Based on the previous literature (Houde et al., 2013), we test for both constant learning (and saliency) effects and declining learning (and saliency) effects. Before trying to identify the causal mechanisms, we review our two hypotheses, the learning effect and the saliency effect. The learning hypothesis states that people reduce their energy usage when they receive real-time information due to better knowledge of how different devices consume electricity. The saliency hypothesis is that people reduce their energy usage due to being constantly reminded about their consumption.

We start by assuming that the learning and saliency effects are constant through time. The first panel of Table 8 shows the OLS results of estimating the following model:

$$\log \text{Consumption}_{\text{i, t}} = \alpha + \beta \, \text{RL1}_{i,t} + \gamma_i + \eta_t + e_{i,t}$$

where the dummy $\text{RL1}_{i,t}$ takes the value 1 for those who had an IHD in Period 1 and are currently in Period 2. We test the remaining learning effect in Period 2 (RL1) by comparing the control group with the Learning group in Period 0 and Period 2. Based on this test, there is no statistical evidence of a strong learning effect.

The second panel of Table 8 shows the OLS results of estimating the following model:

$$\log \text{Consumption}_{\text{i, t}} = \alpha + \beta \, (\text{L2+S})_{i,t} + \gamma_i + \eta_t + e_{i,t}$$

where the dummy $(\text{L2+S})_{i,t}$ takes the value 1 for those who still have an IHD in Period 2. We test the existence of a saliency effect in Period 2 by comparing the learning group with the saliency group in Period 0 and Period 2. Based on this test, there is no strong evidence of a saliency effect, except during 6-9pm, where the effect is statistically significant at the 10% level.

The third panel of Table 8 shows the OLS results of estimating the following model:

$$\log \text{Consumption}_{\mathrm{i,\,t}} = \alpha \ + \beta_1 (\text{L1+S})_{i,t} + \beta_2 \text{RL1}_{i,t} + \beta_3 (\text{L2+S})_{i,t} + \gamma_i + \eta_t + e_{i,t}$$

where the dummy $(\text{L1+S})_{i,t}$ takes the value 1 for those who had an IHD in Period 1, and are currently in Period 1. The dummy $\text{RL1}_{i,t}$ takes the value 1 for those who had an IHD in Period 1, and are currently in Period 2, which is a common dummy variable for the treatment groups. The dummy $(\text{L2+S})_{i,t}$ takes the value 1 for those who had an IHD in Period 2, and are currently in Period 2. We test these effects by comparing all groups in Periods 0, 1 and 2. This confirms our early finding of a combined Learning and Saliency effect but doesn't provide any statistical evidence to disentangle between the two. Interestingly, the daily effect (i.e., averaging over all hours of the day) is now statistically significant at the 10% level, suggesting IHDs reduce overall consumption by 3.5% in the first month of use.

Finding 2: There is no strong time-invariant RL1 or (L2+S) effect.

So far, we have assumed time-invariant behavioral effects. However, such effects might decrease over time as was demonstrated in Houde et al. (2013) and our earlier analysis. In order to test whether learning and/or saliency effects exist but are declining over time, we conducted a series of regressions with time interactions. Table 9 summarizes the results. The model of the first panel of Table 9 is as follows:

$$\log \text{Consumption}_{\mathrm{i,t}} = \alpha \ + \beta \ \text{RL1}_{i,t} + \delta \ \text{Expday*RL1}_{i,t} + \gamma_i + \eta_t + e_{i,t}$$

where the dummy $\text{RL1}_{i,t}$ takes the value 1 for those who had an IHD in Period 1, and are in Period 2 on that day, and the value 0 otherwise. The $\text{Expday*RL1}_{i,t}$ is an interaction term, which interacts $\text{RL1}_{i,t}$ with a daily time trend. A positive coefficient on the interaction term indicates a declining learning effect. In Table 9, we find a large statistically significant effect for the 6-9am time period. Having exposure to the IHD in Period 1 reduces consumption by 17% but this effect declines 0.72 percentage points per day.

The second panel of Table 9 shows the OLS results of estimating the following model:

$$\log \text{Consumption}_{\text{i, t}} = \alpha + \beta\ (\text{L2+S})_{i,t} + \delta\ \text{Expday*(L2+S)}_{i,t} + \gamma_i + \eta_t + e_{i,t}$$

where the variables have the same interpretation as before. We are testing the existence of a saliency effect in Period 2 by comparing the learning group with the saliency group in Period 0 and Period 2. We don't observe a very strong effect, either in terms of magnitude or statistical significance. The third panel of Table 9 shows the OLS results of estimating the following model:

$$\begin{aligned}\log \text{Consumption}_{\text{i, t}} &= \alpha + \beta_1(\text{L1+S})_{i,t} + \delta_1(\text{L1+S})\text{*Expday}_{i,t} + \beta_2\text{RL1}_{i,t} + \ldots \\ &\ldots + \delta_2\text{RL1*Expday}_{i,t} + \beta_3(\text{L2+S})_{i,t} + \delta_3(\text{L2+S})\text{*Expday}_{i,t} + \gamma_i + \eta_t + e_{i,t}\end{aligned}$$

where the variables have the same interpretation as before. We test for these effects by comparing all groups in Periods 0, 1 and 2. We find all three effects ((L1+S), RL1 and (L2+S)) are statistically significant but the saliency effects in period 2 actually *increases* energy consumption. In summary, we find evidence for a learning effect that is decreasing over time. We fail to find strong support for the saliency hypothesis, especially after a few weeks of having the IHD. In fact, we find (L2+S)>0. Our results are therefore roughly consistent with RL1<0 but not S<0.

Finding 3: We observe a declining learning effect but no saliency effect.

As a further test of the learning effect, at the end of the experiment, we surveyed households about the electricity consumption of various devices. on each device. Figure 3 summarizes the results of the survey. Note that the Learning group households have not had access to an IHD for over a month at this point and control households have not received their IHD yet. The figure clearly demonstrates that households have learned something relative to the control group and there does not appear to be any differences between the beliefs of the Saliency group and the beliefs of the Learning group. For three out of the four devices, the Learning group is actually closer to the actual energy consumption compared to the Saliency group. Although this represents stated beliefs and not actual behavior, it strongly corroborates our earlier findings that the learning effect appears to be stronger than the saliency effect. Furthermore, one obvious confound in our experimental design is that we cannot strictly disentangle learning (updating beliefs) from habit formation (changing behavior and then sticking with it) but there is little support in our data for habit formation. As evidence of this, energy-saving behavior does not persist over time but accumulated knowledge does appear to persist.

6. Conclusion

Building on the existing literature that studies whether IHDs reduce residential electricity consumption, this paper explored the causal mechanisms behind the effect of receiving real-time information on electricity consumption. In particular, we attempted to disentangle whether the effect is because information enables households to learn about their energy consumption or if it is because in-home displays make energy-use salient by constantly reminding households of their energy consumption. The first main result of our randomized-control field experiment is that those who received real-time information about their electricity consumption reduced their consumption in the morning and the evening but not at other times of the day. Furthermore, the effect appears to diminish over time. These findings are almost identical to those in a very similar study (Houde et al., 2013). In addition, we also provide new evidence on the mechanism behind the energy-conservation effects of real-time information: we find support that this effect is driven by learning effects and not by saliency effects. This finding suggests that energy-conservation policies that target learning (e.g., educational outreach, labeling electronic appliances with their energy consumption) might be more cost-effective than the expensive process of installing devices that provide a constant reminder of energy use. Our study does not rule out the existence of saliency effects but they do not stand out. For example, the Saliency group does not have lower consumption in Period 2 and they do not outperform the Learning group on the exit survey.

To the extent that households in the condominium complex respond to IHDs differently from the average US household, a simple extrapolation of the findings from this study to wider contexts may be misleading. The sample size constrained the number of treatments that we could implement without making the size of each treatment group too small. Introducing further variations in the kinds of information that each target group receives would make for an interesting follow-up. One drawback to the current design is that we cannot strictly disentangle learning from habit formation but there is little support in our data for habit formation (for example, energy-saving behavior does not persist over time) but accumulated knowledge does appear to persist. We believe that disentangling such effects would provide further policy implications for how best to design information programs to enhance long-term energy conservation in an efficient manner.

References

Abrahamse, W., Steg, L., Vlek, C., & Rothengatter, T. (2005). A review of intervention studies aimed at household energy conservation. *Journal of environmental psychology*, *25*(3), 273-291.

Attari, S. Z., DeKay, M. L., Davidson, C. I., & de Bruin, W. B. (2010). Public perceptions of energy consumption and savings. *Proceedings of the National Academy of Sciences*, *107*(37), 16054-16059.

Delmas, M. A., Fischlein, M., & Asensio, O. I. (2013). Information strategies and energy conservation behavior: A meta-analysis of experimental studies from 1975 to 2012. *Energy Policy*, *61*, 729-739.

Dietz, T. (2010). Narrowing the US energy efficiency gap. *Proceedings of the National Academy of Sciences*, *107*(37), 16007-16008.

Espey, J. A., & Espey, M. (2004). Turning on the lights: a meta-analysis of residential electricity demand elasticities. *Journal of Agricultural and Applied Economics*, *36*(1), 65-82.

Faruqui, A., Sergici, S., & Sharif, A. (2010). The impact of informational feedback on energy consumption—A survey of the experimental evidence. *Energy*, *35*(4), 1598-1608.

Fell, H., Li, S., & Paul, A. (forthcoming). A New Approach to Estimate Residential Electricity

Demand Using Household Expenditure Data. *International Journal of Industrial Organization*.

Fischer, C. (2008). Feedback on household electricity consumption: a tool for saving energy?. *Energy Efficiency*, *1*(1), 79-104.

Gillingham, K., Newell, R. G., & Palmer, K. (2009). Energy Efficiency Economics and Policy. *Annual Review of Resource Economics*, *1*(1), 597-620.

Houde, S., Todd, A., Sudarshan, A., Flora, J. A., & Armel, K. C. (2013). Real-time Feedback and Electricity Consumption: A Field Experiment Assessing the Potential for Savings and Persistence. *Energy Journal*, *34*(1).

Jessoe, K., & Rapson, D. S. (2014). Knowledge is (Less) Power: Experimental Evidence from Residential Energy Use. *American Economic Review*, *104*(4), 1417-1438.

Matsukawa, I. (2004). The Effects of Information on Residential Demand for Electricity. *Energy Journal*, *25*(1).

Midden, C. J., Meter, J. F., Weenig, M. H., & Zieverink, H. J. (1983). Using feedback, reinforcement and information to reduce energy consumption in households: A field-experiment. *Journal of Economic Psychology*, *3*(1), 65-86.

Mizobuchi, K., & Takeuchi, K. (2012). Using Economic Incentives to Reduce Electricity

Consumption: A field Experiment in Matsuyama, Japan. *International Journal of Energy Economics and Policy*, *2*(4), 318-332.

Newell, R. G. & Siikamäki, J. V. (2013). Nudging Energy Efficiency Behavior: The Role of Information Labels. *National Bureau of Economic Research*.

Petersen, J. E., Shunturov, V., Janda, K., Platt, G., & Weinberger, K. (2007). Dormitory residents reduce electricity consumption when exposed to real-time visual feedback and incentives. *International Journal of Sustainability in Higher Education*, *8*(1), 16-33.

Reiss, P. C., & White, M. W. (2005). Household electricity demand, revisited. *Review of Economic Studies*, *72*(3), 853-883.

Sexton, R. J., Sexton, T. A., Wann, J. J. W., & Kling, C. L. (1989). The Conservation and Welfare Effects of Information in a Time-of-Day Pricing Experiment. *Land economics*, *65*(3).

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review*, *63*(2), 129.

Winett, R. A., Kagel, J. H., Battalio, R. C., & Winkler, R. C. (1978). Effects of monetary rebates, feedback, and information on residential electricity conservation. *Journal of Applied Psychology*, *63*(1), 73.

Wood, G., & Newborough, M. (2003). Dynamic energy-consumption indicators for domestic appliances: environment, behaviour and design. *Energy and Buildings*, *35*(8), 821-841.

Yates, S. M., & Aronson, E. (1983). A social psychological perspective on energy conservation in residential buildings. *American Psychologist*, *38*(4), 435.

Figures and Tables

Figure 1. Average electricity consumption by group and by period

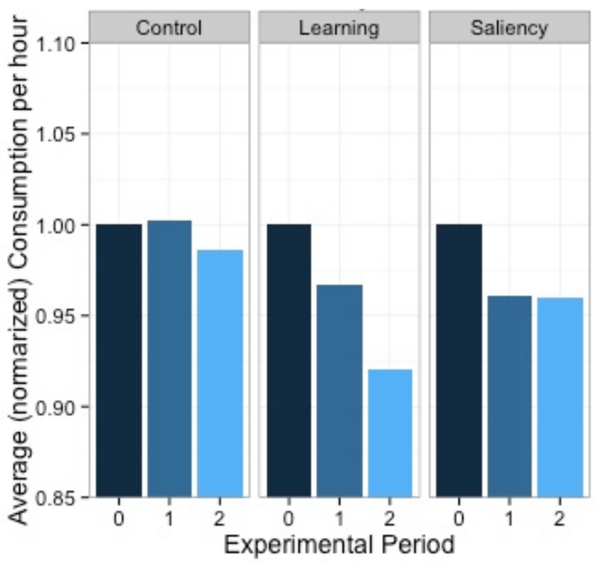


Figure 2. Average electricity consumption in the morning and in the evening

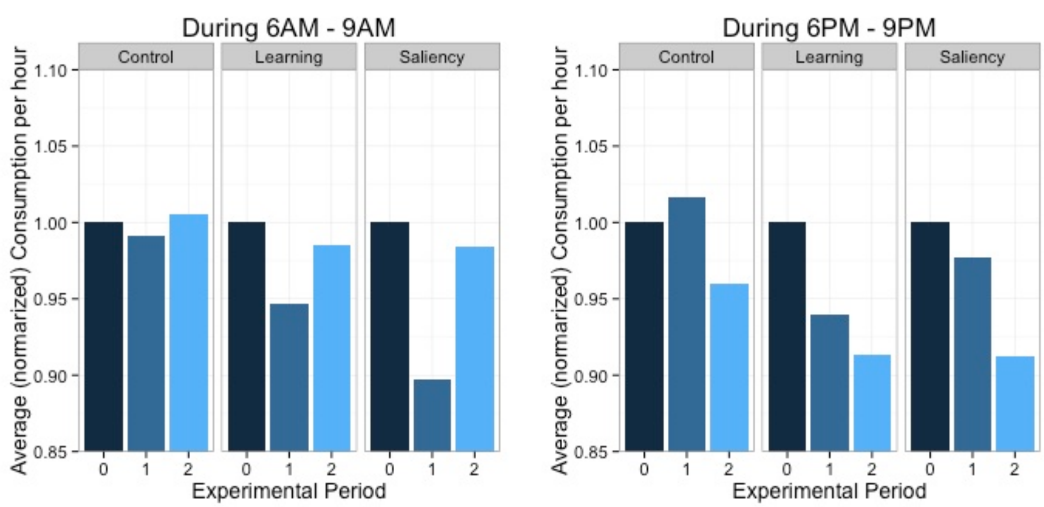
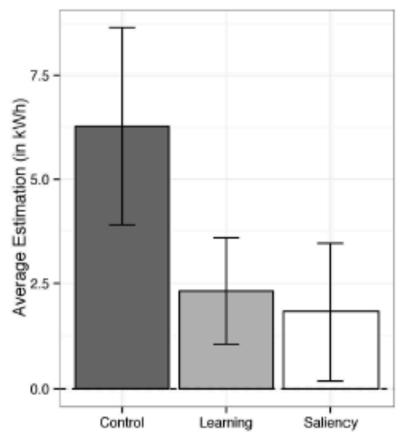
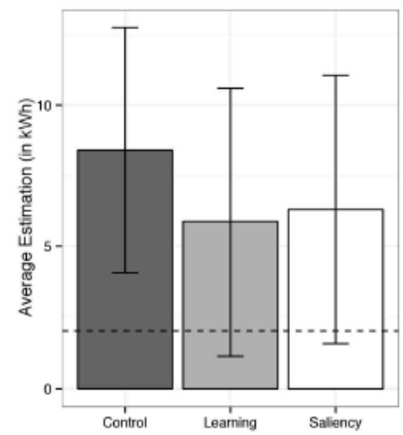


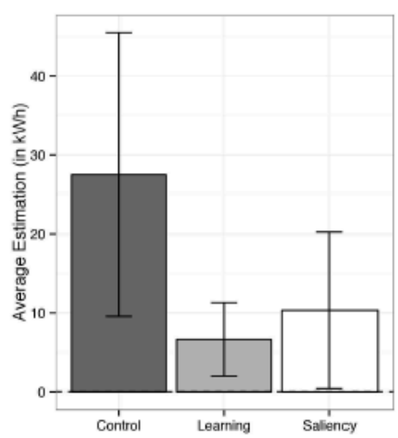
Figure 3. Survey Responses to the Question: How Much Energy Does This Device Consume?



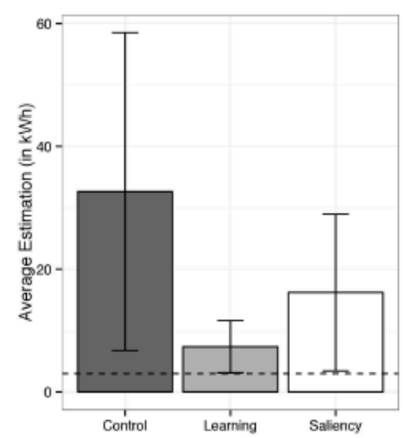
(a) Lamp



(b) Stovetop



(c) TVset



(d) Water-heater

Notes: Each column represents the mean survey response of how much each device consumes in terms of Kwh by treatment group. Bars represent estimated standard errors and the horizontal dashed lines represent how much each device actually consumes.

Table 1. Experimental Design and Potential Effects

Group	Period 0	Period 1	Period 2
Control	No Information (No effect)	No Information (No effect)	No Information (No effect)
Learning treatment	No Information (No effect)	Receive Information (L1 and S)	No Information (RL1)
Saliency treatment	No information (No effect)	Receive Information (L1 and S)	Receive Information (RL1, L2 and S)

Notes: "No Information" means that the residents in the corresponding group receive no information beyond their monthly electricity bills. "Receive information" means that they receive in-home displays, which provide additional real-time information. The potential treatment effects are in parentheses. "L1" means the learning effect occurring in Period 1, "S" means the saliency effect, "L2" means the learning effect occurring in Period 2, "RL1" means the remaining learning effect from Period 1.

Table 2. Characteristics of household participants

	Overall	Control	Learning	Saliency
Age of Each Household	33.53 (1.39)	35.51 (2.95)	31.68 (2.34)	33.58 (1.97)
# of People in Each Household	2.69 (0.15)	2.33 (0.25)	3.09 (0.30)	2.64 (0.22)
# of Children (under 18 years old)	0.86 (0.12)	0.60 (0.17)	1.27 (0.23)	0.68 (0.17)
# of Income Earners	1.48 (0.07)	1.40 (0.11)	1.41 (0.11)	1.64 (0.14)
Hours at Home on Weekdays	16.19 (0.51)	14.64 (0.89)	16.25 (0.91)	17.61 (0.80)
Hours at Home on Weekends	17.79 (0.54)	16.76 (1.04)	17.80 (0.97)	18.75 (0.76)
Observations	58	21	22	22

Notes: Standard errors in parentheses.

Table 3. Average Electricity Consumption (in kWh)

Treatment	Control			Learning			Saliency		
Period	0	1	2	0	1	2	0	1	2
Mean 6am-9am	0.585	0.580	0.588	0.500	0.473	0.492	0.619	0.556	0.610
s.e.	0.061	0.056	0.059	0.051	0.037	0.043	0.074	0.062	0.061
Mean 10am-5pm	0.401	0.404	0.390	0.385	0.389	0.342	0.401	0.404	0.391
s.e.	0.042	0.042	0.043	0.035	0.037	0.030	0.039	0.038	0.035
Mean 6pm-9pm	0.671	0.682	0.644	0.791	0.743	0.723	0.663	0.648	0.604
s.e.	0.074	0.072	0.071	0.093	0.084	0.082	0.066	0.051	0.044
Mean 10pm-5am	0.286	0.296	0.299	0.243	0.251	0.243	0.264	0.257	0.262
s.e.	0.032	0.032	0.035	0.025	0.021	0.021	0.022	0.018	0.020
Mean Daily (per hour)	0.442	0.443	0.437	0.432	0.418	0.398	0.438	0.421	0.420
s.e.	0.039	0.038	0.040	0.035	0.034	0.032	0.037	0.031	0.031
No. of Households	17	18	18	13	18	19	17	20	20

Table 4. IHD Regression Results

	(1)	(2)	(3)	(4)	(5)
Observations	6AM-9AM	10AM-5PM	6PM-9PM	10PM-5AM	12AM-11PM
All Periods	-.0461*	0.0116	-.0730**	0.0085	-0.0189
	(0.0278)	(0.0249)	(0.0301)	(0.0193)	(0.0145)
Periods 0 & 1	-.112***	0.0102	-0.0567	0.0131	-0.0254
	(0.0425)	(0.0372)	(0.0448)	(0.0289)	(0.0222)

Notes: Standard errors in parentheses, * $p < .10$, ** $p < .05$, *** $p < .01$. In the regressions, each model includes household and time fixed effects, and a constant.

Table 5. DID Regression Results for Periods 0 & 1

	(1) 6-9AM	(2) 10AM-5PM	(3) 6-9PM	(4) 10PM-5AM	(5) Daily (per hour)
Treatment	-0.0102	-0.0189	0.122	-0.114	-0.0175
	(0.146)	(0.134)	(0.135)	(0.117)	(0.104)
Period	-0.0349	-0.0150	0.0954	0.117	0.0362
	(0.118)	(0.105)	(0.127)	(0.0804)	(0.0629)
Treat*Period	-0.108**	0.0111	-0.0667	-0.000214	-0.0294
	(0.0442)	(0.0388)	(0.0468)	(0.0301)	(0.0231)
Constant	-0.0884	-0.614***	-0.890***	-1.706***	-0.652***
	(0.519)	(0.184)	(0.161)	(0.357)	(0.104)
Observations	2,807	2,827	2,852	2,804	2,852
# households	56	56	56	56	56

Notes: Standard errors in parentheses, * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 6. DID Regression Results for All Experimental Periods

(Control and Saliency Groups)

	(1) 6-9AM	(2) 10AM-5PM	(3) 6-9PM	(4) 10PM-5AM	(5) Daily (per hour)
Treatment	0.0809	0.0312	0.0993	-0.0631	0.0168
	(0.179)	(0.133)	(0.157)	(0.121)	(0.129)
Period	-0.0478	0.0103	0.229	0.253***	0.0996
	(0.134)	(0.122)	(0.151)	(0.0924)	(0.0705)
Treat*Period	-0.0947**	-0.0271	-0.0724	-0.0212	-0.0451*
	(0.0457)	(0.0412)	(0.0508)	(0.0316)	(0.0237)
Constant	-0.105	-0.542***	-0.808***	-1.705***	-0.686***
	(0.505)	(0.205)	(0.185)	(0.349)	(0.116)
Observations	3,057	3,067	3,056	3,055	3,056
# households	38	38	38	38	38

Notes: Standard errors in parentheses, * p < .10, ** p < .05, *** p < .01.

Table 7. IHD Regression Results Interacted With a Time Trend

Observations		(1) 6AM-9AM	(3) 6PM-9PM
All periods	IHD	-0.104**	-0.0462
		(0.0427)	(0.0467)
	IHD*Expday	0.00173*	-0.000801
		(0.000963)	(0.00107)
Periods 0 &1	IHD	-0.108*	0.0321
		(0.0572)	(0.0608)
	IHD*Expday	-0.000269	-0.00506**
		(0.00219)	(0.00234)

Notes: Standard errors in parentheses, * p < .10, ** p < .05, *** p < .01. In the regressions, each model includes household and time fixed effects, and a constant.

Table 8. Constant Saliency and Learning Effects

Comparison: Group name (Period)		(1) 6-9AM	(2) 10AM-5PM	(3) 6-9PM	(4) 10PM-5AM	(5) Daily (per hour)
Control vs Learning	RL1	-0.0655	0.00161	0.0641	-0.0158	-0.002
(Period 0 and 2)		(0.0539)	(0.0473)	(0.0592)	(0.0392)	(0.0255)
	Constant	-0.286	-0.705***	-0.960***	-1.719***	-0.710***
		(0.481)	(0.16)	(0.137)	(0.35)	(0.059)
	Observations	1571	1579	1574	1571	1574
	R-squared	0.076	0.189	0.065	0.041	0.08
	Number of households	37	37	37	37	37
Learning vs Saliency	(L2+S)	0.0173	-0.0306	-0.1000*	0.00325	-0.0288
(Period 0 and 2)		(0.0496)	(0.0477)	(0.0544)	(0.0368)	(0.0245)
	Constant	-1.236***	-0.627***	-0.695***	-1.299***	-0.560***
		(0.12)	(0.188)	(0.133)	(0.0891)	(0.0601)
	Observations	1588	1594	1590	1590	1590
	R-squared	0.131	0.176	0.068	0.046	0.085
	Number of households	39	39	39	39	39
All groups (Period 0, 1 and 2)	(L1+S)	-0.126***	-0.00209	-0.0594	0.00288	-0.0354*
		(0.0408)	(0.0364)	(0.0438)	(0.0284)	(0.0211)
	RL1	-0.0623	-0.0198	0.0467	-0.00217	-0.00983
		(0.0487)	(0.0436)	(0.0527)	(0.0339)	(0.0254)
	(L2+S)	0.0345	0.0235	-0.0787*	0.0147	-0.000938
		(0.0387)	(0.0349)	(0.0425)	(0.0270)	(0.0204)
	Constant	-0.0921	-0.618***	-0.818***	-1.778***	-0.659***
		(0.491)	(0.147)	(0.117)	(0.342)	(0.0562)
	Observations	4,398	4,410	4,401	4,396	4,401
	R-squared	0.098	0.147	0.044	0.025	0.052
	Number of households	57	57	57	57	57

Notes: Standard errors in parentheses, * p < .10, ** p < .05, *** p < .01.

Table 9. Time-Varying Saliency and Learning Effects

Comparison: Group name (Period)		(1) 6-9AM	(2) 10AM-5PM	(3) 6-9PM	(4) 10PM-5AM	(5) Daily (per hour)
Control vs Learning (Period 0 and 2)	RL1	-0.170**	0.0326	0.0824	-0.0852	-0.0383
		(0.0754)	(0.0665)	(0.0839)	(0.0548)	(0.0361)
	RL1*Expday	0.00724**	-0.00217	-0.00131	0.00481*	0.00259
		(0.00366)	(0.00328)	(0.00423)	(0.00266)	(0.00182)
	Constant	-0.290	-0.704***	-0.960***	-1.722***	-0.710***
		(0.480)	(0.160)	(0.137)	(0.350)	(0.0590)
	Observations	1,571	1,579	1,574	1,571	1,574
	R-squared	0.079	0.189	0.065	0.043	0.081
	Number of households	37	37	37	37	37
Learning vs Saliency (Period 0 and 2)	(L2+S)	0.0999	-0.0503	-0.0927	0.0331	0.00662
		(0.0691)	(0.0668)	(0.0768)	(0.0512)	(0.0346)
	(L2+S)*Expday	-0.00556*	0.00135	-0.000498	-0.00201	-0.00243
		(0.00324)	(0.00319)	(0.00372)	(0.00239)	(0.00168)
	Constant	-1.236***	-0.627***	-0.695***	-1.299***	-0.560***
		(0.120)	(0.188)	(0.133)	(0.0891)	(0.0600)
	Observations	1,588	1,594	1,590	1,590	1,590
	R-squared	0.133	0.176	0.068	0.047	0.086
	Number of households	39	39	39	39	39
All groups (Period 0, 1 and 2)	(L1+S)	-0.116**	0.0254	0.0166	0.0235	0.00209
		(0.0551)	(0.0494)	(0.0597)	(0.0384)	(0.0287)
	(L1+S)*Expday	-0.000586	-0.00151	-0.00422*	-0.00118	-0.00209*
		(0.00207)	(0.00186)	(0.00225)	(0.00144)	(0.00109)
	RL1	-0.164**	0.0192	0.0452	-0.0770	-0.0488
		(0.0720)	(0.0648)	(0.0789)	(0.0501)	(0.0380)
	RL1*Expday	0.00702*	-0.00293	-0.000453	0.00505**	0.00251
		(0.00368)	(0.00335)	(0.00417)	(0.00255)	(0.00201)
	(L2+S)	0.122*	0.0102	-0.0591	0.0495	0.0413
		(0.0659)	(0.0595)	(0.0727)	(0.0458)	(0.0350)
	(L2+S)*Expday	-0.00607*	0.00107	-0.00111	-0.00241	-0.00286
		(0.00364)	(0.00333)	(0.00412)	(0.00253)	(0.00198)
	Constant	-0.0933	-0.618***	-0.818***	-1.779***	-0.659***
		(0.491)	(0.147)	(0.117)	(0.342)	(0.0561)
	Observations	4,398	4,410	4,401	4,396	4,401
	R-squared	0.099	0.147	0.045	0.026	0.053
	Number of id	57	57	57	57	57

Notes: Standard errors in parentheses, * p < .10, ** p < .05, *** p < .01.