INFORMATION FEEDBACK FROM IN-HOME DISPLAYS AND SALIENCE EFFECTS: EVIDENCE FROM RESIDENTIAL ELECTRICITY CONSUMPTION

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ABSTRACT

This paper focuses on the policy interventions that correct for consumption biases associated with inattention and limited capacity by providing real-time information feedback via an in-home display (IHD) to households. Real-time information feedback provided via an IHD is expected to decrease the difference between the optimal and actual levels of electricity demand by increasing households' attention. The empirical evidence offered by this paper indicates that the effects of the cumulative usage of IHDs on residential electricity consumption depend on the pre-experiment level of electricity consumption. While the cumulative usage of IHDs reduced the electricity consumption of "energy-using" households, it raised that of "energy-saving" households whose electricity consumption had been relatively modest before the experiment.

JEL Classification: D12, D83, C93, Q41

Keywords: In-home displays, Real-time information feedback, Limited information-processing capacity, Inattention, Energy conservation, Boomerang effects.

1. INTRODUCTION

This article focuses on the policy interventions that correct for consumption biases associated with inattention and limited capacity by providing real-time information feedback via an in-home display (IHD) to households. Real-time information feedback provided via an IHD is expected to decrease the difference between the optimal and actual levels of electricity demand by increasing households' attention.

Because of learning over time, the repetition of attention may improve households' capacity to process information about electricity usage.

I investigate how information acquisition affects households' consumption of electricity, which has not been explicitly analyzed in the empirical literature on the effects of real-time information feedback (Sexton et al., 1989; Matsukawa, 2004; Abrahamse et al., 2005; Darby, 2006; Houde et al., 2013; Attari et al., 2014; Jessoe and Rapson, 2014; Lynham et al., 2016). The previous literature focuses on the presence of real-time information feedback, but not on how much information households obtain from the feedback. Information acquisition produces a more precise mapping of how consumption alternatives affect outcomes in the decision-making process (Simon, 1955; Gabaix et al., 2006). Information acquisition is crucial for estimating the effects of real-time information feedback, because inattention and limited information-processing capacity depend on how much households acquire available information. All else being equal, the more information households acquire, the more attention and capacity they achieve.

I measure the effects of information acquisition on households' usage of electricity using hourly data on whether households used IHDs in a randomized field experiment. This experiment corresponds to a "framed field experiment," which typically uses experimental participants from the market of interest and incorporate important elements within the context of the naturally occurring environment with respect to the commodity, task, stakes, and information set of the subjects (List and Price, 2013). The households could consult a graph of their half-hourly electricity consumption in real time on a tablet display at any time during the experiment. Electronic devices installed on the premises automatically recorded whether households

used IHDs each hour during the experiment. It is difficult to ensure that households using many electric appliances with different consumption levels attain a satisfactory level of electricity consumption. Access to the electricity information in the graph enables households to raise their attention and information-processing capacity. The welfare impact of the policy intervention that provides households with IHDs depends on how much information households acquire by using their IHDs and could be measured as the incremental benefit reaped from the choice of a more satisfactory level of electricity consumption.

The estimation results of a simultaneous equation model with discrete choice of hourly IHD usage and continuous hourly consumption of electricity of 501 households over 36 days in the experiment provide evidence on the effects of real-time information feedback over time. While the cumulative usage of IHDs reduced hourly electricity consumption of "energy-using" households whose electricity consumption before the experiment had been far higher than other households, it raised that of "energy-saving" households whose pre-experiment electricity consumption was relatively modest. The empirical evidence in this article provides an important policy implication: providing households with IHDs could adversely affect their energy conservation. This may occur because a "boomerang effect" raised electricity usage of well-informed households whose electricity saving had exceeded the optimal saving before obtaining information about their actual usage (Schultz et al., 2007; Ayres, Raseman, and Shih, 2009). The article thus contrasts with the earlier finding on IHDs' energy-saving effects on household electricity consumption (Sexton et al., 1989; Matsukawa, 2004; Abrahamse et al., 2005; Darby, 2006; Houde et al., 2013; Attari et al., 2014; Lynham et al., 2016).

The rest of this article proceeds as follows. Section 2 explains the design of the experiment on IHD provision and the evidence on the randomization of the experiment. Section 3 presents a simultaneous equation model with discrete choice of hourly IHD usage and continuous hourly consumption of electricity. Section 4 describes the hourly data obtained from the experiment and discusses stylized facts on information acquisition and electricity consumption. Section 5 presents the estimation results of the model, and the policy implications of the empirical findings. Section 6 concludes this article. The appendix provides additional information on the experiment and estimation results.

2. EXPERIMENTAL DESIGN

In summer 2012, the Keihanna Eco-City Next-Generation Energy and Social Systems Demonstration Project Promotion Council (hereafter, referred to as the Keihanna Eco-City Promotion Council) conducted an experiment in which households in a southern area of Kyoto, Japan, were assigned to either control or treatment groups. The experiment was implemented on weekdays during July 23 to September 13 in 2012 (36 days). An IHD was provided free of charge to households assigned to the treatment group. The control group households did not have IHDs. The area's climate during experimentation was hot and humid, the maximum ambient temperature often exceeding 30 degrees Celsius as shown in Figure A.1 in the Appendix.

2.1 IHDs and Information Provision

The households in the treatment could see a graph of their half-hourly electricity consumption in real time on a tablet display at any time during the experiment. The information feedback about the half-hourly usage of electricity in this article is closer to that provided in real-time usage than the feedback technologies employed in previous field experiments (Sexton et al., 1989; Matsukawa, 2004). However, the interval of information feedback in this article is a little longer than the 10-minute interval in Houde et al. (2013) and the 15-minute interval in Jessoe and Rapson (2014).

Figure 1 illustrates an example of the graph in the tablet display: each bar indicates the half-hourly electricity consumption on July 25, and the solid line with dots indicates the electricity consumption on the day before. The latest information on the half-hourly consumption of electricity indicates 0.27 kilowatt-hours (kWh), which is displayed in the middle of the graph in Figure 1. The peak period is indicated by the shaded areas. The peak period was from 1 PM to 4 PM in summer. A comparison of electricity consumption between one day and a day in the previous week could be made by touching the area labeled “Comparison with previous week” in the tablet display.

The use of IHDs is defined by whether each household accessed to the graph illustrated in Figure 1 each hour. The hourly access to an IHD was recorded whenever each household accessed to a graph in Figure 1 by operating the IHD. Although households could see other information items through IHDs such as the amount of electronic points associated with electricity consumption during peak hours (discussed later in Section 2.2), their access to these information items was not included in the use of IHDs.

The data on the half-hourly consumption of electricity were updated in real time by an electronic device installed in each household. Households could acquire information about which appliances were most frequently used by viewing the real-time usage of electricity in the IHDs without incurring information acquisition costs. Prior to the first experiment, engineers of the Keihanna Eco-City Promotion Council visited each household to ensure that the tablet display worked properly and that the household could use it fully.

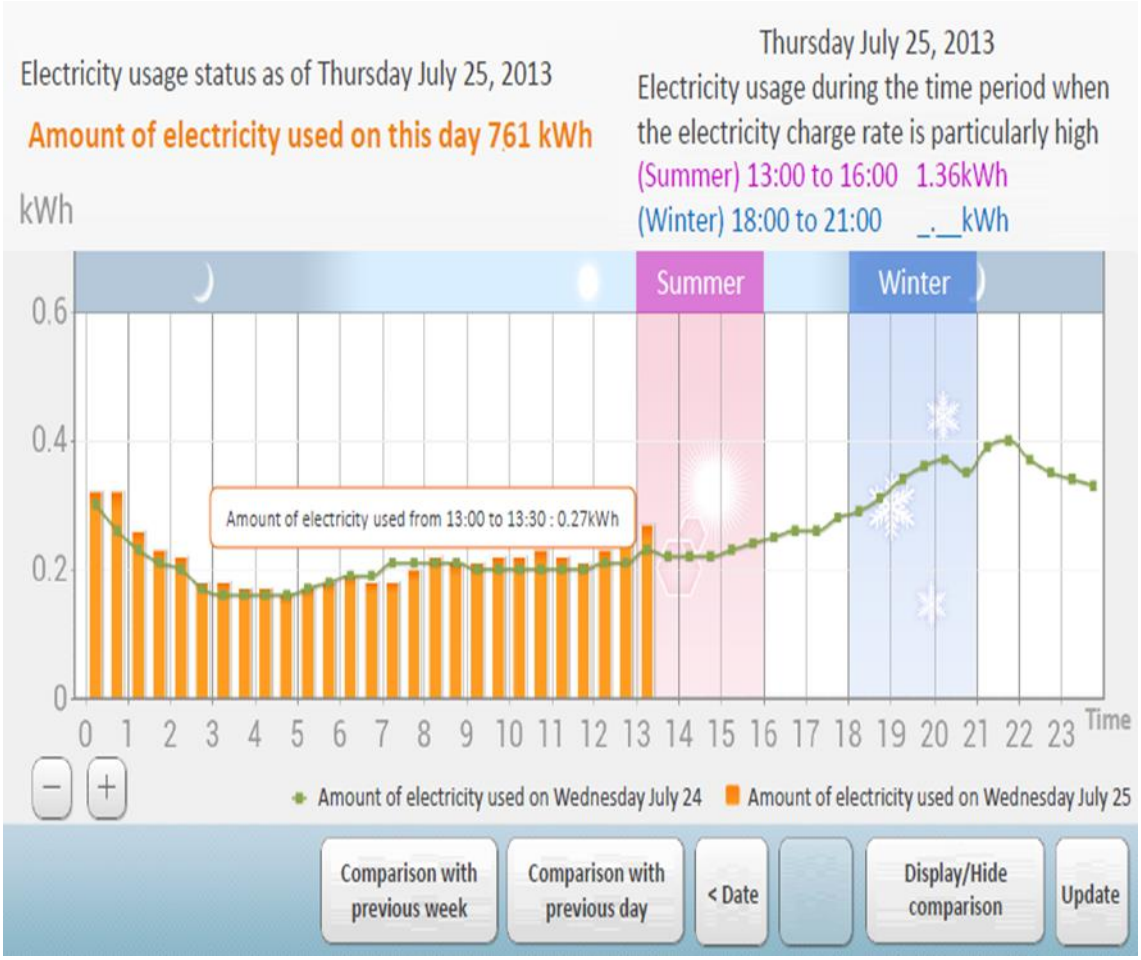

Figure 1. Graph of the Half-Hourly Electricity Consumption of a Household in a Tablet Display

Source: Mitsubishi Heavy Industries, Ltd.

2.2 Pecuniary Incentives for Electricity Saving during Peak Hours

In addition to the IHDs, a policy intervention using pecuniary incentives for reducing electricity usage during peak hours was applied to the treatment group. Before the experiment, all households in the treatment group received money-convertible electronic points worth 70 US dollars (1 US dollar = 100 yen). The initial amount of the electronic points corresponded to approximately 70% of the monthly average electricity expenditure per Japanese household in 2012 (EDMC, 2014). During the experiment, the more electricity households used during peak hours (i.e., from 1 PM to 4 PM on weekdays), the more points they lost. The lost points are computed as the product of two items: the unit electricity price (cents per kWh) and electricity consumption during peak hours. Thus, households that saved more electricity during peak hours would receive more electronic points as a pecuniary reward for saving electricity at the end of the experiment. If households lost all the points in the middle of the experiment, they had been excluded from the experiment. In fact, there has been no household that lost all the points until the end of the experiment.

The unit electricity price of 40, 60, or 80 cents per kWh was applied to electricity consumption during peak hours on the days when the regional demand for electricity is likely to almost reach the available capacity for electricity supply. These days are often referred to as “critical peak days.” In the experiment, a limited number of weekdays were designated as critical peak days and were called on a day-ahead basis. On weekdays not designated as critical peak days, a price of 20 cents per kWh was applied to electricity consumption during the peak hours. The experiment’s maximum electricity price of 80 cents per kWh is a little more than three times the average

electricity price of 25 cents per kWh for typical Japanese households. This price difference is smaller than that in the literature on critical peak pricing (Wolak, 2011; Faruqui, Sergici and Akaba, 2014; Fenrick et al., 2014; Jessoe and Rapson, 2014).

There were five critical peak days for each price in the experiment. As shown in Table A.1 in the Appendix, the price applied did not depend on ambient temperature. The unit electricity price of 20 cents per kWh was applied to peak usage on weekdays except for critical peak days. Households in the treatment group had been informed of the maximum number of critical peak days before the experiment began. These households were informed of the electricity price at approximately 8 PM the day before each critical peak day by e-mail to their cellular phones and personal computers and on the tablet display during the experiment. A post-experiment survey indicates that almost all households used their cellular phones, personal computers, or tablet displays to confirm which price would be applied to electricity consumption.

2.3 Sample Construction and Tests for Randomization

To solicit household participation in the treatment group, the Keihanna Eco-City Promotion Council sent a letter to all households in Kyotanabe City, Kizugawa City, and Seika Town, located in the south of Kyoto, Japan, in January 2012. In the letter, the Council asked these households three questions: whether they had any interest in the experiment, whether they had any access to the Internet, and whether they owned an onsite generation facility, such as a roof-top photovoltaic. Of 39,166 households in the experimental site, 1,649 (4.2%) replied and showed a willingness to participate in the experiment. After eliminating households without access to the Internet, those with onsite generation facilities, and the students living alone, the Council randomly selected

500 households and assigned them to the treatment group in February 2012. Of the 500 households asked to participate in the treatment group, 375 (75.0%) had agreed to join the experiment by the end of March 2012, and smart meters that measured half-hourly electricity consumption were installed free of charge at their homes by the end of June, 2012. The rest refused to participate in the experiment.

Apart from the treatment group, 126 control group subjects were randomly selected from approximately 3,000 households living in the experimental site with a smart meter and owning no facility for onsite generation. Unfortunately, no data on the compliance rate of the control group are available. Because of a difference in the process used to select households in the treatment and control groups, the compliance rate of the control group may have been different from that of the treatment group and selectivity in compliance may have occurred in the experiment.

Two statistical tests for randomization are conducted to examine whether there had been any difference between the control group and the treatment group before the experiment began. First, electricity consumption prior to the experiment is regressed on a dummy variable for the treatment group (Delmas and Lessem, 2014). The daily-average data on household consumption in June 2012 were obtained from the Keihanna Eco-City Promotion Council. The daily-average electricity consumption in June 2012 is regressed on the treatment dummy. Because of one missing observation, the number of households in the treatment group is 374 for the data on electricity consumption in June 2012. Table 1 indicates that the dummy variable was not statistically significant even at the 10% level and F statistic was insignificant. These results support experimental randomness.

Table 1. Regression of electricity consumption before the experiment

Variables	Coefficients
Dummy for the Treatment group (1 = yes)	–0.463 (0.732)
Constant	12.356*** (0.658)
Adjusted *R*-squared	0.000
F statistic	0.477 (*p*-value = 0.490)
Number of observations	500

Notes: The dependent variable is daily average consumption of electricity in June 2012. Observations include the control and treatment groups. White's robust standard errors are employed. Standard errors are in parentheses. Because of a missing observation on electricity consumption in June 2012, the number of households decreased from 501 to 500.

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Second, experimental randomness is examined by a binary probit model for being assigned to the treatment (Houde et al., 2013). Table 2 presents the estimation results of the binary probit model, in which the dependent variable takes 1 if households were assigned to the treatment group and 0 otherwise. Daily-average electricity consumption in June 2012 and the dummy for the all-electric contract are employed as explanatory variables. The data on households' electricity contracts were obtained from the Keihanna Eco-City Promotion Council. No household changed electricity contracts during the experiment. The maximum likelihood estimates of the model indicate that no explanatory variable is statistically significant, and the likelihood ratio statistic is insignificant.

Table 2. Estimation Results of a Probit Model for Being Assigned to the Treatment Group

Variables	Coefficients	
Electricity usage in June, 2012 (kWh/day)	0.003	(0.011)
Dummy for all electric (1 = yes)	–0.236	(0.159)
Constant	0.704***	(0.129)
Likelihood ratio statistic	2.647	(*p*-value = 0.266)
Number of observations	500	

Notes: The dependent variable is equal to one if each household is assigned to the treatment group, and zero otherwise. Observations include the control and the treatment group. Standard errors are in parentheses. Because of a missing observation on electricity consumption in June 2012, the number of households decreased from 501 to 500.

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

The results of these statistical tests in Tables 1 and 2 provide evidence of randomization. In fact, as shown by Table A.2 in the Appendix, there had been no statistically significant difference in daily-average electricity consumption and in the ratio of households' all-electricity contracts between the control and treatment groups prior to the experiment. The evidence of randomization in Tables 1 and 2 implies that the average treatment effect on the treated can be estimated by the difference in the expected outcomes between the treated households and the untreated households (Wooldridge, 2002).

However, the estimates of the average treatment effect on the treated in this article may imply those of the average effect of the intention to be treated, because the treatment content was delivered by letters and it was not observed whether each household receiving the invitation letter but not participating in the experiment opened the letter (Hahn et al., 2016, p.10). Furthermore, because of "site selection bias" (Allcott, 2015), the response of households in the experiment to the treatment may

differ from that of the average household in the Kansai region where the experimental site is located. The site selection bias may arise because a survey on the Kansai region (population approximately 21 million as of October 1, 2014 [JSB, 2016]) indicates that households in the treatment group lived with more members than the average household, and were more likely to live in a relatively new detached house that was spacious and equipped with a larger number of air conditioners, as shown in Table A.3 in the Appendix.

3. THE MODEL

3.1 A Simultaneous Equation Model with Discrete Choice of IHD Usage and Continuous Consumption of Electricity

A basic assumption of this article is that households' biased beliefs about consumption cause their choice of consumption to deviate from their utility-maximizing consumption. Policy intervention that increases households' attention to their consumption through information provision enables households to lessen their deviation from optimal consumption. This assumption is in line with Grubb and Osborne (2015) and Allcott, Mullainathan and Taubinsky (2014). Given income and prices that are fully known to household i, the actual consumption of electricity at time t, denoted by $KWH_{i,t}$, and the decision to use an IHD at time t, denoted by $\delta_{i,t}$, are assumed to be described by the following simultaneous equation model:

$$\frac{KWH_{i,t}}{KWH^{*}_{i,t}} = (1 + S_{i,t-1} + \delta_{i,t})^{\lambda} \exp(\gamma_1 L_{i,t} + Y_{i,t}\,\zeta + e_{1,i,t}) \ , \qquad (1)$$

$$KWH^{*}_{i,t} = \exp(Z_{i,t}\,\tau), \qquad (2)$$

$$L_{i,t} = X_{2,i,t}\,\alpha_2 + \beta \log(1 + S_{i,t\text{-}1} + \delta_{i,t}) + \gamma_2 \log KWH_{i,t} + e_{2,i,t}\,, \qquad (3)$$

where

$\delta_{i,t} = 1$ if $L_{i,t} \geq 0$,

$\delta_{i,t} = 0$ if $L_{i,t} < 0$, and

$S_{i,t-1} \equiv \sum_{k=1}^{t-1} \delta_{i,k}$.

The optimal, utility-maximizing electricity consumption for household i at time t, denoted by $KWH^*_{i,t}$, is assumed to a function of $Z_{i,t}$, which denotes a vector of exogenous variables including income and prices. The effects of these variables are denoted by τ, a vector of parameters. The term $1 + S_{i,t\text{-}1} + \delta_{i,t}$ on the right-hand side of Eqs. (1) and (3) indicates how much information on electricity consumption household i has acquired until time t from the cumulative usage of an IHD over time. This term remains unity as long as households never use IHDs. An unobserved latent variable $L_{i,t}$ determines $\delta_{i,t}$ and is assumed to be a function of the natural log of actual electricity consumption, a vector of exogenous variables ($X_{2,i,t}$), the natural log of the term $1 + S_{i,t\text{-}1} + \delta_{i,t}$, and the error term $e_{2,i,t}$. The ratio of the actual to optimal electricity consumption is assumed to be a function of $L_{i,t}$, a vector of exogenous variables ($Y_{i,t}$), the term $1 + S_{i,t\text{-}1} + \delta_{i,t}$, and the error term $e_{1,i,t}$. α_2 and ζ are vectors of parameters, and β, γ_1, and γ_2 are parameters.

The effect of IHD use is indicated by parameter λ, which is positive if household i's biased beliefs about electricity consumption lead to under-consumption (i.e., $KWH_{i,t} < KWH^*_{i,t}$), and negative if they lead to over-consumption (i.e., $KWH_{i,t} > KWH^*_{i,t}$). If biased beliefs lead to under-consumption (over-consumption), then increasing attention through information acquisition raises (reduces) consumption (i.e., $\lambda > 0$ [$\lambda < 0$]). The

cumulative use of IHDs over time is expected to improve households' capacity to process information because households could learn about how to reduce the difference between actual and optimal consumption from their experience of adjusting consumption.

A simultaneous equation model with discrete choice of IHD usage and continuous consumption of electricity is assumed in Eqs. (1)–(3), because of a bilateral relationship between IHD use and electricity consumption. While households may use IHDs first and then determine their usage of electricity to achieve the targeted usage, they may determine electricity usage first and then check IHDs to see if they attain the targeted usage. For instance, other things being equal, households consuming more electricity because of owning the larger number of electric appliances may be more likely to check IHDs while those consuming less electricity because of being out of home longer may be less likely to check IHDs. Thus, for the effects of IHD use on electricity consumption to be identified, it is necessary to employ a simultaneous equation model with discrete choice of IHD usage and continuous consumption of electricity.

3.2 Econometric Specification

The effects of IHD usage on electricity consumption are estimated using a set of reduced-form equations of households' hourly choices of IHD use and electricity. After inserting Eq. (2) into Eq. (1), taking natural logs on both sides of Eq. (1) yields the following equation:

$$\log KWH_{i,t} = X_{1,i,t}\,\alpha_1 + \lambda \log(1 + S_{i,t\text{-}1} + \delta_{i,t}) + \gamma_1 L_{i,t} + e_{1,i,t} \quad , \qquad (4)$$

where a vector of exogenous variables, $X_{1,i,t}$, consists of $Y_{i,t}$ and $Z_{i,t}$ and α_1 is a vector of parameters. The error terms $e_{1,i,t}$ in Eq. (4) and $e_{2,i,t}$ in Eq. (3) are assumed to be jointly normally distributed, with mean vector zero and covariance matrix

$$\begin{bmatrix} \sigma_1^2 & \sigma_{1,2} \\ \sigma_{1,2} & \sigma_2^2 \end{bmatrix}.$$

The condition $\beta + \lambda\gamma_2 = 0$ is a necessary and sufficient condition for the model of Eqs. (3) and (4) to be identified (Heckman, 1978, p.936). With the condition $\beta + \lambda\gamma_2 = 0$ imposed, equation system consisting of Eqs. (3) and (4) can be written in reduced form as

$$\log KWH_{i,t} = X_{1,i,t}\pi_{1,1} + X_{2,i,t}\pi_{1,2} + \pi_{1,3}\log(1 + S_{i,t\text{-}1} + \delta_{i,t}) + \varepsilon_{1,i,t}\,, \tag{5}$$

$$L_{i,t} = X_{1,i,t}\pi_{2,1} + X_{2,i,t}\pi_{2,2} + \varepsilon_{2,i,t}\,, \tag{6}$$

where

$\pi_{1,1} = \alpha_1/(1 - \gamma_1\gamma_2)$, $\pi_{2,2} = \alpha_2/(1 - \gamma_1\gamma_2)$, $\pi_{2,1} = \alpha_1\gamma_2/(1 - \gamma_1\gamma_2)$,

$\pi_{1,2} = \alpha_2\gamma_1/(1 - \gamma_1\gamma_2)$, $\pi_{1,3} = (\lambda + \gamma_1\beta)/(1 - \gamma_1\gamma_2)$,

$\varepsilon_{1,i,t} = (e_{1,i,t} + \gamma_1 e_{2,i,t})/(1 - \gamma_1\gamma_2)$, and $\varepsilon_{2,i,t} = (e_{2,i,t} + \gamma_2 e_{1,i,t})/(1 - \gamma_1\gamma_2)$.

Random variables $\varepsilon_{1,i,t}$ and $\varepsilon_{2,i,t}$ are assumed to be jointly normally distributed, with mean vector zero and covariance matrix

$$\begin{bmatrix} \omega_1^2 & \omega_{1,2} \\ \omega_{1,2} & 1 \end{bmatrix}.$$

Because the variable $\delta_{i,t}$ is endogenous and correlated with the error term $\varepsilon_{1,i,t}$, the estimates of Eq. (5) are biased. To correct for the endogeneity bias, a two-step estimation procedure proposed by Heckman (1978, p.938) is applied to the equation system consisting of Eqs. (5) and (6). First, the binary probit model specified by Eq. (6) is estimated. Then, using the parameter estimates of the binary probit model, the estimate of the inverse Mills ratio, denoted by $M_{i,t}$, is computed for the treatment group as

$$M_{i,t} = \frac{\phi(X_{1,i,t}\widehat{\pi_{2,1}} + X_{2,i,t}\widehat{\pi_{2,2}})}{\Phi(X_{1,i,t}\widehat{\pi_{2,1}} + X_{2,i,t}\widehat{\pi_{2,2}})} \qquad \text{if } \delta_{i,t} = 1,$$

$$M_{i,t} = \frac{-\phi(X_{1,i,t}\widehat{\pi_{2,1}} + X_{2,i,t}\widehat{\pi_{2,2}})}{[1 - \Phi(X_{1,i,t}\widehat{\pi_{2,1}} + X_{2,i,t}\widehat{\pi_{2,2}})]} \quad \text{if } \delta_{i,t} = 0, \tag{7}$$

where $\varphi(.)$ is the standard normal probability density function, $\Phi(.)$ is the corresponding cumulative function, and $\widehat{\pi_{m,n}}$ is the consistent estimate of $\pi_{m,n}$. By including the estimates of the inverse Mills ratio for the treatment group, Eq. (5) becomes:

$$\log KWH_{i,t} = X_{1,i,t}\pi_{1,1} + X_{2,i,t}\pi_{1,2} + \pi_{1,3}\log(1 + S_{i,t\text{-}1} + \delta_{i,t}) - \omega_{1,2}M_{i,t} + \varepsilon_{1,i,t}\,. \tag{8}$$

The hourly electricity consumption model in Eq. (8) is estimated at the second step. The estimates of Eq. (8) are consistent, because the term $\omega_{1,2}M_{i,t}$ corrects for the endogeneity bias associated with the possible correlation between $\delta_{i,t}$ and $\varepsilon_{1,i,t}$. The

consistent estimate of parameter λ is obtained directly from the estimate of $\pi_{1,3}$ in Eq. (8), using $\pi_{1,3} = (\lambda + \gamma_1\beta)/(1 - \gamma_1\gamma_2)$ and the condition $\beta + \lambda\gamma_2 = 0$. Note that neither γ_1 nor γ_2 could be identified, because it is difficult to determine whether each exogenous variable belongs to $X_{1,i,t}$ or $X_{2,i,t}$.

The learning effects of IHD usage may differ across households. The heterogeneity of IHD effects across households, if any, may be relevant to electricity consumption prior to the experiment. To examine whether the learning effects of IHD usage depend on electricity consumption prior to the experiment, the parameter λ in Eq. (1) is assumed to be a linear function of the pre-experiment level of electricity consumption:

$$\frac{KWH_{i,t}}{KWH^*_{i,t}} = (1 + S_{i,t-1} + \delta_{i,t})^{\lambda_0+\lambda_1\log(KWH\_6_i)}\exp(\gamma_1 L_{i,t} + Y_{i,t}\,\zeta + e_{1,i,t}), \quad (9)$$

where KWH_6_i denotes household i's daily-average electricity consumption in June 2012. With the condition $\beta + [\lambda_0 + \lambda_1\log(KWH\_6_i)]\gamma_2 = 0$ imposed for each household, the model for hourly electricity consumption can be written as

$$\log KWH_{i,t} = X_{1,i,t}\pi_{1,1} + X_{2,i,t}\pi_{1,2} + [\pi^0_{1,3} + \pi^1_{1,3}\log(KWH\_6_i)]\log(1 + S_{i,t\text{-}1} + \delta_{i,t}) - \omega_{1,2}M_{i,t} + \varepsilon_{1,i,t}\,. \quad (10)$$

The consistent estimate of parameters λ_0 and λ_1 are obtained directly from the estimates of $\pi^0_{1,3}$ and $\pi^1_{1,3}$ in Eq. (12), using $\pi^0_{1,3} + \pi^1_{1,3}\log(KWH\_6_i) = [\lambda_0 + \lambda_1\log(KWH\_6_i) + \gamma_1\beta]/(1 - \gamma_1\gamma_2)$ and the condition $\beta + [\lambda_0 + \lambda_1\log(KWH\_6_i)]\gamma_2 = 0$.

A fixed effects model is used to estimate the binary probit model of hourly IHD use in Eq. (6) and the hourly electricity consumption model in Eq. (10), because of the lack of data on demographic and housing characteristics, income, and appliance ownership. Specifically, the following models are estimated:

$$L_{i,t} = \xi_i + \sum_{k=2}^{24} a_k^L HOUR_{k,t} + \sum_{k=2}^{36} b_k^L DATE_{k,t} + \sum_{k=1}^{4} c_k^L D_{k,i,t} + \varepsilon_{2,i,t}, \quad (11)$$

$$\log KWH_{i,t} = \nu_i + \sum_{k=2}^{24} a_k^W HOUR_{k,t} + \sum_{k=2}^{36} b_k^W DATE_{k,t} + \sum_{k=1}^{4} c_k^W D_{k,i,t}$$
$$+ [\pi_{1,3}^0 + \pi_{1,3}^1 \log(KWH\_6i)] \quad \log\left(1 + S_{i,t-1} + \delta_{i,t}\right) - \omega_{1,2} M_{i,t} + \varepsilon_{1,i,t}, \quad (12)$$

where

$HOUR_{k,t}$: dummy variable equal to 1 if time t corresponds to kth hour,

$DATE_{k,t}$: dummy variable equal to 1 if time t corresponds to kth date,

$D_{k,i,t}$: dummy variable equal to 1 if the kth unit electricity price is applied to household i at time t, and

ξ_i, ν_i : household fixed effects.

Dummy variables associated with pecuniary incentives for reducing electricity usage during peak hours are observed exogenous factors affecting both IHD use and electricity consumption. Each dummy variable, $D_{1,i,t}$, $D_{2,i,t}$, $D_{3,i,t}$, or $D_{4,i,t}$, is equal to 1 only when an electricity price of 20, 40, 60, or 80 cents per kWh was applied to household i at time t. The effects of dummy variables associated with hours and dates include those of weather conditions on IHD use and electricity consumption.

The household fixed effects, ξ_i and v_i, include those of demographic and housing characteristics, income, and appliance ownership on IHD use and electricity consumption. A random effects model is also estimated as an alternative specification of Eq. (12). However, because the number of time periods is large (i.e., 864 periods), a random-effects probit model cannot be estimated (Greene, 2012, E-633). Unfortunately, the Hausman test for the fixed and random effects cannot be conducted because of non-positive definite matrix associated with the test statistic (Greene, 2008, p.209). Alternative tests for the fixed and random effects, such as a variant of the Hausman test that uses the group means estimator (Greene, 2008, p.209) and Mundlak's (1978) approach that adds the household-specific means to the random effects model, cannot be applied either because the number of critical peak days is five for each price (i.e., 40, 60, or 80 cents per kWh) so that the household-specific mean of $D_{k,i,t}$ (k = 2, 3, or 4) is equal to that of $D_{h,i,t}$ ($h \neq k$; h = 2, 3, or 4). Note that the incidental parameters problem associated with a fixed-effects probit model does not arise here because of a sufficiently large number of time periods (Greene, 2008, p. 801).

4. DATA

The data used for empirical analysis were obtained from the Keinanna Eco-City Promotion Council. These data include hourly household electricity consumption, discrete choice of hourly household usage of IHDs, daily-average household electricity consumption in June 2012, and electricity contracts during the experiment. Household consumption of electricity was recorded for every half-hour during the experiment by a smart meter installed free of charge in the households. The Keinanna Eco-City

Promotion Council also collected data on whether each household used an IHD every hour during the experiment. These data were automatically recorded by an electronic device installed in each household. The half-hourly data on the electricity consumption of each household were aggregated into the hourly data because the data on whether households used IHDs were recorded only on an hourly basis.

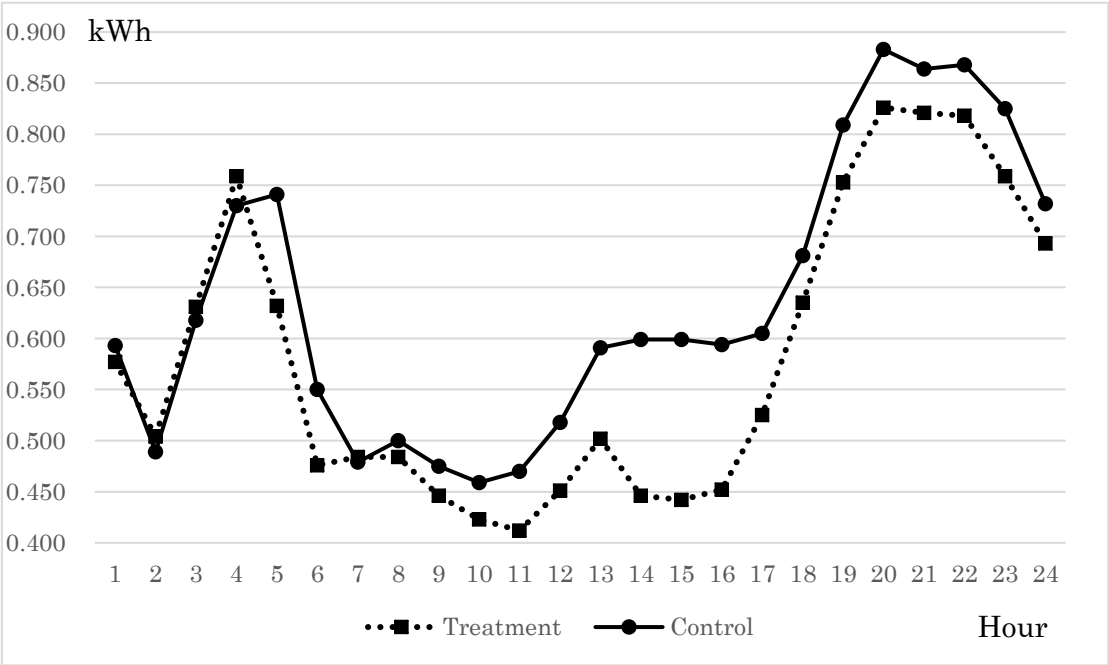

Figure 2. Average Hourly Electricity Consumption

Source: The Keihanna Eco-City Next-Generation Energy and Social Systems Demonstration Project Promotion Council

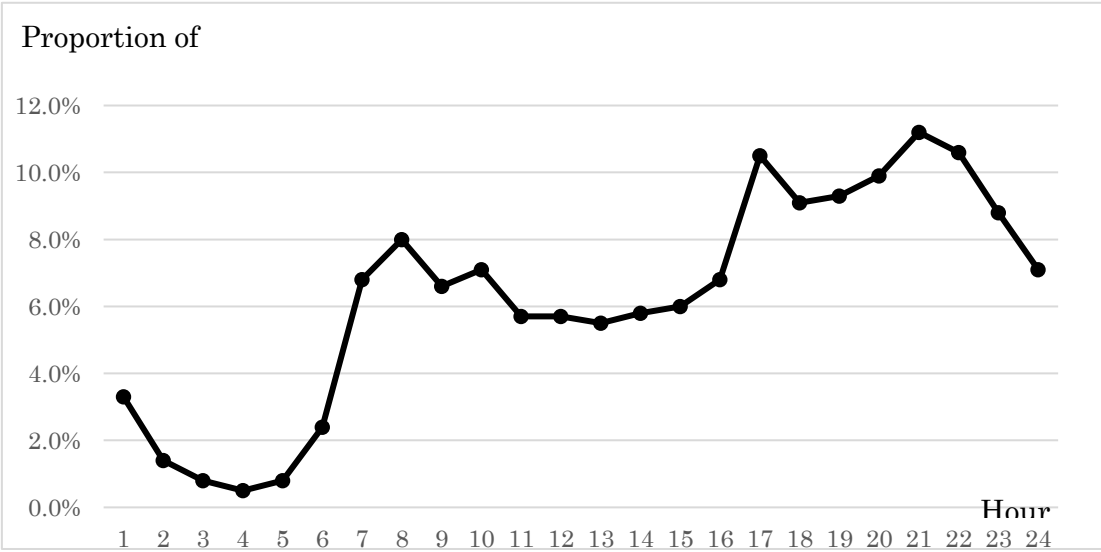

Figure 3. Proportion of Households Using IHDs by Hour of the Day

Source: The Keihanna Eco-City Next-Generation Energy and Social Systems Demonstration Project Promotion Council

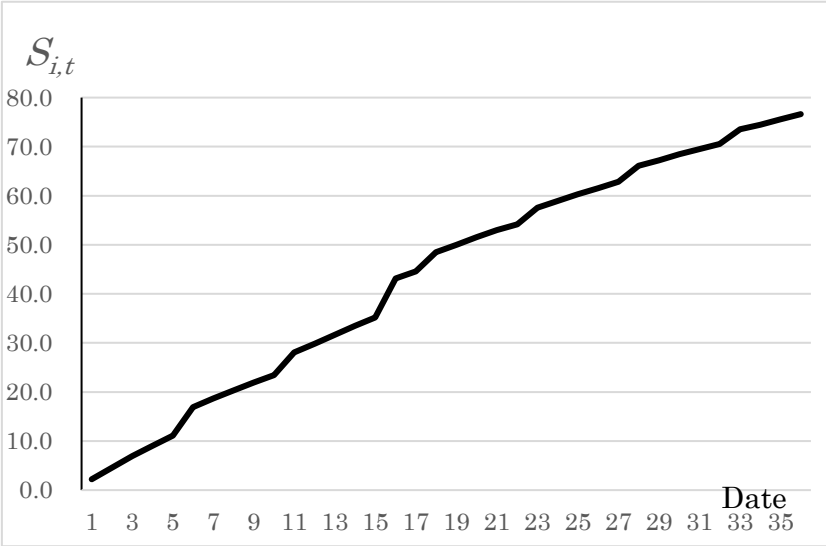

Figure 4. Average Cumulative Usage of IHDs

Note: $S_{i,t} = \sum_{k=1}^{t} \delta_{i,k}$, where $\delta_{i,t}$ is equal to 1 if household *i* uses an IHD at time *t*.

Source: The Keihanna Eco-City Next-Generation Energy and Social Systems Demonstration Project Promotion Council

Figure 2 compares the average hourly electricity consumption of the treatment group with that of the control group during the experiment. During the peak hours (i.e., from 1 PM to 4 PM), the electricity consumption of the treatment group was lower than that of the control group by approximately 0.15 kWh or 25% of the average hourly consumption of electricity. This difference arises because of pecuniary incentives for reducing electricity consumption during peak hours. For the rest of hours, electricity consumption of the treatment group was slightly lower than that of the control group. As shown by Table A.2 in the Appendix, on average, there is a slight difference in hourly electricity consumption between these two groups during the experiment. This difference, which is found to be statistically insignificant in Table A.2, is approximately 0.05 kWh or 8% of the hourly average consumption of the control group.

Figure 3 presents the proportion of households using IHDs to the treatment group by hour of the day during the experiment. On average, approximately 6.2% of the treated households used IHDs each hour during the experiment. The proportion of households using IHDs was relatively high in the morning (approximately 7–8%) and evening (approximately 9–11%) when household members are likely to be present at home. This implies that the use of IHDs depends on the presence of household members, which also affects electricity consumption. Figure 4 shows the average cumulative use of an IHD at the end of each day during the experiment. On average, the cumulative use of an IHD amounts to approximately 77 times at the end of the experiment, implying approximately 2.1 times of IHD use per day for the average household.

5. ESTIMATION RESULTS

5.1 IHD Equation

Table 3 presents the estimation results of the fixed-effects binary probit model for the hourly usage of IHDs in Eq. (11). A random-effects probit model cannot be estimated because of the large number of time periods (i.e., 864 periods) (Greene, 2012, E-633). The maximum likelihood method was employed to estimate parameters in the model based on the panel data of 864 time periods (i.e., 24 hours by 36 days) and 375 households of the treatment group. Hourly and date dummy variables, which are not listed in the table, are included in the estimation of the model. A likelihood ratio test statistic distributing Chi-squared indicates the validity of the model as this statistic is significant at the 1% level. Although the model correctly predicts 93.8% of the observations, McFadden's likelihood ratio index is relatively low (i.e., 0.102).

The dummy variables for all levels of electricity prices associated with the peak-reducing incentives exhibit positive coefficients that are statistically significant at either the 1% or 5% level in Table 3. The marginal effects of these dummy variables range from 0.008 to 0.014. The marginal effect of the dummy variable is the largest for $D_{2,i,t}$ = 1 (i.e., the price of 40 cents per kWh is applied) while it is the smallest for $D_{3,i,t}$ = 1 (i.e., the price of 60 cents per kWh is applied). These results imply that although pecuniary incentives for reducing electricity consumption during peak hours encourage households to use IHDs, raising the level of these incentives does not necessarily promote the use of IHDs.

Table 3. Estimation Results of the Hourly IHD Usage Equation in (11)

Variables	Coefficients	Marginal Effects
$D_{1,i,t}$ (1 = 20 cents/kWh)	0.163*** (0.033)	0.013
$D_{2,i,t}$ (1 = 40 cents/kWh)	0.178*** (0.041)	0.014
$D_{3,i,t}$ (1 = 60 cents/kWh)	0.101** (0.042)	0.008
$D_{4,i,t}$ (1 = 80 cents/kWh)	0.141*** (0.042)	0.011
Hourly dummies	Yes	
Date dummies	Yes	
Number of observations	324,000	
Number of households	375	
Number of periods	864	
Log likelihood at convergence	–64,447.9	
Likelihood ratio test statistic	14,308***	
McFadden's likelihood ratio index	0.102	
Proportion of correctly predicted (%)	93.8	

Notes: The fixed-effects binary probit model for $\delta_{i,t}$ (i.e., dummy for IHD use) is estimated. Hourly and date dummy variables, which are not listed in the table, are included in the estimation of the model. Standard errors are in parentheses.

*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

5.2 Electricity Equation

Table 4 summarizes the estimation results of Eq. (12) based on the panel data of 864 time periods (i.e., 24 hours by 36 days) and 500 households of both the treatment and control groups. Because of one missing electricity consumption value for June 2012 in the treatment group, the number of households decreased from 501 to 500. Standard errors are clustered at the household level to correct for serial correlation in the electricity consumption of each household in Eq. (12). The estimated coefficients of the fixed-effects binary probit model in Section 5.1 are used to compute the inverse Mills ratio, $M_{i,t}$, in Eq. (7). Hourly and date dummy variables, which are not listed in the table, are included in the estimation of the model.

Table 4. Estimation Results of the Hourly Electricity Consumption Equation in (12)

Variables	Coefficients	
	Fixed Effects	Random Effects
$\log(1 + S_{i,t\text{-}1} + \delta_{i,t})$ (log of cumulative IHD use)	0.0290^{***} (0.0057)	0.0136^{**} (0.0057)
$\log(1 + S_{i,t\text{-}1} + \delta_{i,t}) \times \log(KWH\_6_i)$	-0.0106^{***} (0.0023)	-0.0038^{*} (0.0023)
$M_{i,t}$ (Inverse Mill's ratio)	-0.0820^{***} (0.0020)	-0.0809^{***} (0.0020)
$D_{1,i,t}$ (1 = 20 cents/kWh)	-0.1291^{***} (0.0063)	-0.1289^{***} (0.0063)
$D_{2,i,t}$ (1 = 40 cents/kWh)	-0.2187^{***} (0.0092)	-0.2183^{***} (0.0092)
$D_{3,i,t}$ (1 = 60 cents/kWh)	-0.2110^{***} (0.0092)	-0.2107^{***} (0.0092)
$D_{4,i,t}$ (1 = 80 cents/kWh)	-0.2392^{***} (0.0092)	-0.2389^{***} (0.0092)
Hourly dummies	Yes	Yes
Date dummies	Yes	Yes
Adjusted R^2	0.498	0.074
Number of observations	432,000	432,000
Number of households	500	500
Number of periods	864	864

Notes: The dependent variable is the natural log of hourly electricity consumption. The dummy variable $\delta_{i,t}$ is equal to 1 if household i uses an IHD at time t, and $S_{i,t\text{-}1} = \sum_{k=1}^{t-1} \delta_{i,k}$. The variable KWH_6_i indicates daily-average electricity consumption in June 2012, prior to the experiment. The estimated parameters of the fixed-effects probit model in Eq. (11) are used to compute $M_{i,t}$ in Eq. (7). Hourly and date dummy variables, which are not listed in the table, are included in the estimation of the model. Standard errors, which are clustered at the household level, are in parentheses. Because of a missing observation on electricity consumption in June 2012, the number of households decreased from 501 to 500.

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

For both the fixed and random effects models, $\pi_{1,3}^{0}$ is positive, implying energy-using effects of IHDs. In contrast, the coefficient of the interaction term

"log(1 + $S_{i,t\text{-}1}$ + $\delta_{i,t}$) × log(KWH_6_i)" is negative (i.e., $\pi^1_{1,3} < 0$) for both models, implying that the learning effects of IHD usage on electricity consumption decrease along with the pre-experiment level of electricity consumption. The coefficient of the interaction term is statistically significant at the 1% level for the fixed-effects model while it is significant at the 10% level for the random-effects model.

The estimation results of Eq. (12) imply the dependence of the learning effects of IHDs on the pre-experiment electricity usage. For example, the estimates of $\pi^0_{1,3}$ and $\pi^1_{1,3}$ in the fixed effects model indicate that for households that consumed less than 15.55 kWh per day in June 2012 (i.e., approximately the four-fifths of all households), the energy-using effects of IHDs are dominant. On the contrary, these estimates indicate that the energy-saving effects of IHDs are dominant for households that consumed more than 15.55 kWh per day in June 2012 (i.e., approximately the one-fifth of all households).

The finding on the energy-using effect of households' IHD usage contrasts with the previous finding on the energy-conservation effect of the presence of an IHD (Sexton et al., 1989; Matsukawa, 2004; Abrahamse et al., 2005; Darby, 2006; Houde et al., 2013; Attari et al., 2014; Lynham et al., 2016). A couple of explanations for this difference in an IHD's effect on electricity consumption are possible. First, this study's model for household electricity consumption explicitly includes the effect of information acquisition, which has not been investigated in the literature that focuses on the presence of an IHD. For example, Houde et al. (2013) indicate that the presence of a real-time feedback technology yielded reductions in residential electricity consumption an average of 5.7%. Houde et al. (2013), however, did not take account

of significant heterogeneity in the treatment effect regarding how much households actually used IHDs. Information acquisition through IHD use should be investigated rather than the presence of IHDs because the difference in the frequency of IHD usage across households affects electricity consumption.

Second, a "boomerang effect" of IHD use may occur among households that had already reduced electricity usage more than they had planned before starting IHD use (Schultz et al., 2007; Ayres, Raseman and Shih, 2009). In the wake of the nuclear accident in Fukushima, many have been deeply concerned about the security of Japan's electricity supply. This concern may have motivated Japanese households to save electricity. In fact, according to a survey by the Keihanna Eco-City Promotion Council, approximately 4,500 out of 9,000 households in the Kansai region undertook activities in 2012 that conserved energy in response to rising concern about the electricity supply. As a result, Kansai households achieved an approximately 10% reduction in the peak electricity consumption in the summer of 2012 (JMETI, 2012). Without IHDs, these households could not have realized how much electricity consumption they had reduced and they may have reduced their consumption more than they had targeted. This may have led to under-consumption of electricity prior to the experiment. Because of under-consumption, providing Kansai households with IHDs would have raised their electricity usage by letting them be aware of excessive electricity saving and increase their consumption of electricity to achieve the conservation targets.

Turning to pecuniary incentives for reducing electricity usage during peak hours, the dummy variables for all levels of electricity prices exhibit negative coefficients that are statistically significant at the 1% level for both the fixed and random effects models in Table 4. Without any IHD usage, an average energy-saving

effect of pecuniary incentives on peak-time consumption would range from 12.9% to 23.9%. These effects are close to those in Faruqui, Sergici and Akaba (2014), and Fenrick et al. (2014).

The coefficient of the inverse Mills ratio is statistically significant at the 1% level for both the fixed and random effects models in Table 4. The negative coefficient implies that $\omega_{1,2}$ is positive and there is a positive correlation between the error terms in Eqs. (11) and (12).

6. CONCLUSION

This article uses hourly data on whether each household uses an IHD in a randomized field experiment to investigate how acquiring information from an IHD affects electricity consumption through attention and learning over time. Households in the treatment group could see a graph of their half-hourly electricity consumption in real time with IHDs at any time during the experiment. Providing an IHD is a promising policy intervention that corrects for the consumption biases associated with inattention and limited capacity by promoting attention and learning over time. The immediate effect of providing an IHD is heightened household attention to information on consumption, and the repetition of attention is expected to improve households' capacity to process information.

The estimation results of a simultaneous equation model with discrete choice of hourly IHD usage and continuous hourly consumption of electricity indicate statistically significant effects of cumulative usage of IHDs on residential electricity consumption. The increase in IHDs' effects along with households' experience of using IHDs implies

that households' capacity to process information could be improved by the repetition of attention to electricity information. The empirical evidence offered by this study also indicates that the effects of the cumulative usage of IHDs on residential electricity consumption depend on the pre-experiment level of electricity consumption. While the cumulative usage of IHDs reduced the electricity consumption of "energy-using" households (i.e., households consuming far more electricity before the experiment than other households), it raised that of "energy-saving" households whose electricity consumption had been relatively modest before the experiment. Thus, providing households with IHDs, which was found to be an effective policy instrument for energy conservation in previous studies, could have an adverse effect on energy conservation.

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APPENDIX

Table A.1. Number of Critical Peak Days by Ambient Temperature

	Temperature	40cents/kWh	60cents/kWh	80cents/kWh	Total
Summer in 2012, 15 days	Below 33.0℃	2	2	1	5
	33.0 – 34.9℃	2	3	3	8
	35.0 ℃ or above	1	0	1	2

Note: Ambient temperature is the maximum temperature during the peak period, which was from 1 PM to 4 PM.

Source: The Keihanna Eco-City Next-Generation Energy and Social Systems Demonstration Project Promotion Council

Table A.2. Comparison between the Control and Treatment Groups

	Control	Treatment	
	Mean	Mean	Difference
Daily-average electricity usage in June 2012 (kWh/day)	12.36 (7.35)	11.89 (6.20)	–0.47 (–0.63)
All electric = 1	0.36 (0.48)	0.28 (0.45)	–0.08 (–1.57)
Hourly-average electricity usage during the experiment (kWh)	0.618 (0.620)	0.568 (0.569)	–0.05 (–0.80)

Notes: The column "Difference" indicates the difference in each variable for the treatment group with respect to the control group. In the column "Mean," standard deviations are in parentheses. In the column "Difference," *t*-statistics are in parentheses.

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Source: The Keihanna Eco-City Next-Generation Energy and Social Systems Demonstration Project Promotion Council

Table A.3. Summary Statistics of Households' Characteristics in the Treatment Group

	Treatment	Kansai Region
Household size	3.20 (1.21)	2.67
Number of room air conditioners	3.58 (1.50)	3.00
Income < $30,000	0.11	0.21
Income ≥ $30,000 and < $60,000	0.43	0.41
Income ≥ $60,000 and < $90,000	0.26	0.23
Income ≥ $90,000	0.20	0.15
Floor space, sq. ft. < 861	0.22	0.49
Floor space, sq. ft. ≥ 861 and < 1,292	0.68	0.27
Floor space, sq. ft. ≥ 1,292	0.10	0.24
Age of home < 10 years	0.37	0.28
Age of home ≥ 10 years and < 20 years	0.41	0.30
Age of home ≥ 20years	0.22	0.42
Detached (1 = yes)	0.71	0.55

Notes: The data on all variables but income are obtained from a pre-experiment survey, which did not include the control group. An additional survey that was conducted after the experiment provides data on income for the treatment group. The data on the Kansai region are obtained from a survey in which 9,000 households responded. These households did not include any participant in the experiment. Standard deviations are in parentheses.

Source: The Keihanna Eco-City Next-Generation Energy and Social Systems Demonstration Project Promotion Council

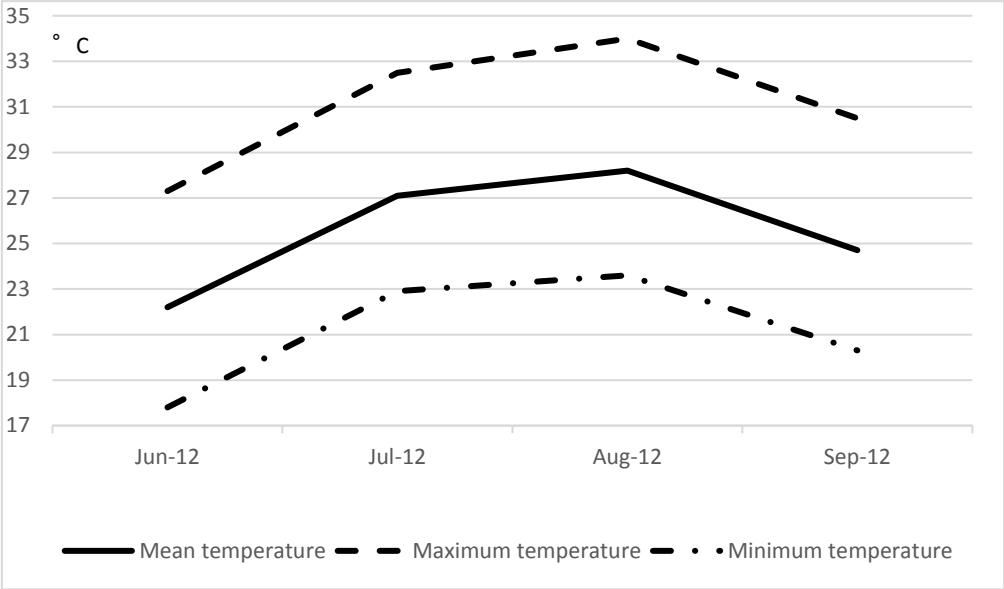

Figure A.1. Ambient Temperature during Experimentation

Source: Japan Meteorological Agency. http://www.jma.go.jp.