# Evaluating a Behavioral Demand Response Trial in Japan: Evidence from the Summer of 2013

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## ABSTRACT

This paper presents results from the first phase (31 days, from August 7 to September 6, 2013) of a behavioral demand response trial to evaluate the impact of interventions on peak electricity usage. The interventions include weekly reports that provide a comparison of neighbors' electricity usage during peak times, and peak saving information. More concretely, we evaluated the treatment effects of the following four interventions: (1) a tiered rate that has three increasing-tier prices that apply to usage measured during each 30-minute period during the month, (2) real-time feedback on electricity usage provided via an in-home display, (3) a weekly report, and (4) an email alert to reduce electricity usage during peak grid time.

Through a randomized controlled trial on the almost 230 residential customers of a condominium in Funabashi, a city located in Greater Tokyo, we found that the total average treatment effect of the four interventions was 11.1% on the peak grid time (1 pm – 4 pm), 8.7% on the peak time of the targeted condominium (7 pm – 10 pm), and 6.9% over the whole day (0 am – 12 pm). Even though the estimates were not statistically significant likely due to the small sample size, the results implied that the effect on peak times were likely to be higher than for off-peak times. We also evaluated the relationships between the treatment effects and households' demographic data, and obtained several findings, including that, if the household members' ages are high, the treatment effects tend to increase. Furthermore, questionnaire survey data showed that the interventions were influential in changing customers' consciousness of electricity saving. The tendencies observed through the analysis were beneficial in terms of understanding the features of interventions and improving our evaluation framework.

It should be noted that existing studies show that the effects of behavioral interventions tend to weaken over time. The second phase of this trial has been conducted with an additional enrollment of participants to facilitate a more rigorous evaluation.

## Introduction

The importance of effective demand reduction and energy efficiency measures has been widely recognized in Japan. Pivotal to this recognition were the 3.11 Tohoku earthquake, the 2011 tsunami, and the subsequent summers when the nation was threatened by the severe lack of electricity supply. As the acuteness of the supply shortage has diminished over the years, the importance of the aforementioned measures has been examined from various perspectives, including the possibility of utilities reducing costs for electricity supply during peak times, and energy service providers fostering new services to allow customers to conserve usage and thereby reduce their monthly electric bills.

Utilities and energy service providers in the United States began to conduct pilot projects on behavioral interventions for energy efficiency in 2008 (Rosenberg, et al., 2012). A well-known example is Opower's monthly (also available quarterly) "home energy report" that provides personalized energy use feedback, social comparisons, and energy conservation information. This is typical of a "*Nudge*" notion – anything that helps to shape better conditions under which people make decisions (Thaler and Sunstein, 2008). The home energy report is also used for behavioral demand response programs in order to save electricity usage during peak times (Lich, et al. 2014). However, evidence of *behavioral* demand response has not been well documented yet while there are a large body of literature that looks at demand response directly (Allcott, 2011; Faruqui and Sergici, 2010).

Since the summer of 2013, the authors have been conducting a behavioral demand response trial to evaluate the impact of interventions, including a *weekly report* that provides a comparison of neighbors' electricity usage during peak times and peak saving information. More concretely, the trial has been evaluating the treatment effects of the following four interventions:

*(1) a tiered rate that has three increasing-tier prices that apply to usage measured during each 30-minute period during the month*
*(2) Real-time feedback on electricity usage provided via an in-home display*
*(3) A weekly report on behavioral demand response*
*(4) An email alert to reduce usage during peak grid time.*

The trial's participants are the residential customers of a condominium in Funabashi, a city located within Greater Tokyo, Japan. Their rooms have electricity usage meters with 30-minute intervals, enabling the provision of the four interventions above.

This paper presents the evaluation results from the first phase (31 days, from August 7 to September 6, 2013) of this trial, in which 228 of a total of 573 residents (almost 40%) were signed up. The evaluation strategy in this paper is three-fold. Firstly, the average treatment effects (ATEs) of the interventions are estimated by applying a random-effects model to daily usage data of the households. Secondly, the relationships between the treatment effects and the household characteristics are examined. Understanding the variation in treatment effects may contribute to targeting households with higher effects for interventions, leading to improved cost effectiveness. Thirdly, the impacts of the interventions on the conscious level of saving usage were assessed using questionnaire survey data. It is our opinion that taking the preliminary step in reducing electricity consumption by evaluating the impact of interventions on the degree to which households consciously seek to save electricity, will facilitate a better comprehension of the interventions' effects.

## Experimental Design

The interventions evaluated in this trial are divided into two groups. The first group consists of rate-based interventions. There are two types of tiered rate structures in this trial, one for control and another for treatment. The rate for control is a conventional tiered rate that escalates as cumulative electricity usage on a monthly bill cycle increases. The conventional tiered rate in this trial is the same as "Meter Rate Lighting B" provided by TEPCO. It is used as a benchmark to measure the impact of the 30-minute tiered rate. The rate for treatment is a tiered rate based on 30-minute interval data, that is, the rate increases as a function of electricity usage for every 30 minutes. As shown in Figure 1, each tier is named as follows; (1) *Green Zone*, around 24 JPY (26 cents) per kWh, from 0 to 400 Wh per hour; (2) *Yellow Zone*, around 29 JPY (29 cents) per kWh, from 400 to 1500 Wh per hour; (3) *Red Zone*, 40 JPY (39 cents) per kWh, from 1500 Wh per hour. The 30-minute tiered rate is designed to reduce peak-time residential electricity usage, such as when the family spends time together after dinner. The 30-minute tiered rate is the standard for the condominium, and thus all the residents in the condominium were billed with it prior to the trial. During the trial, only those of the group C and D were assigned the conventional monthly tiered rate.

The second group comprises information-based interventions. The first type of this group is an in-home display (IHD) to provide real-time feedback on electricity usage. As shown in Figure 2, the feedback information is colored green, yellow, and red, corresponding with the names of the 30-minute tiered rate zones. That is, the IHD is intended to make it easier for customers to grasp how much the electricity rate is at a particular time.

The second type of information-based interventions is the weekly report. As shown in Figure 3, the report is an A4-sized paper consisting of graphics, which we call “modules,” some of which visualize electricity usage and others that show information on how to save during peak usage. The four modules were arranged to construct a “story” to strengthen the impact on the consciousness and behavior of the residents during peak times. Figure 4 shows an example of the story templates. The aim of this storyline is to reduce usage during grid peak time, around 2 pm on weekdays, by showing how much electricity is being used and by what. In total, we designed almost 20 story templates that have varied aims. We also developed a system to automatically personalize reports by using each residential customer’s 30-minute usage data. The personalized reports were mailed on a Tuesday, five times in total (Figure 5).

The third type of information is an email alert to remind users that it is grid peak time. We selected four days for the alerting event, with careful consideration of weather forecasts and the previous day’s peak demand (Figure 5). The email alerts were sent three times for each event: at 6 pm of the previous day, and 9 am and 1 pm of the day.

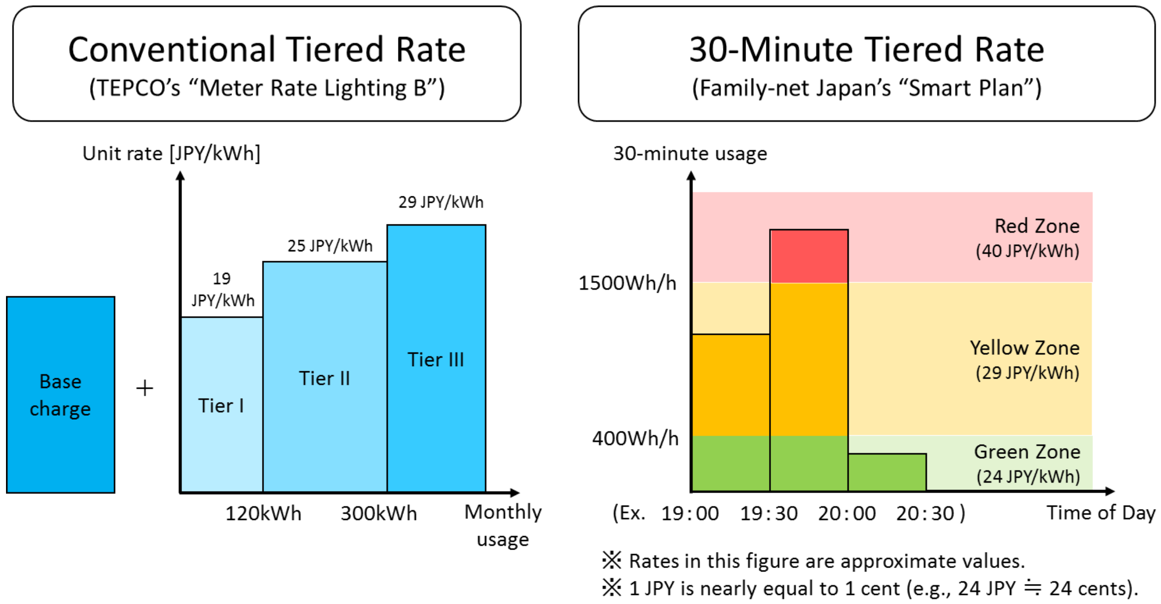



**Figure 1.** Tiered rates (Note that the rates in this figure are approximate values.)

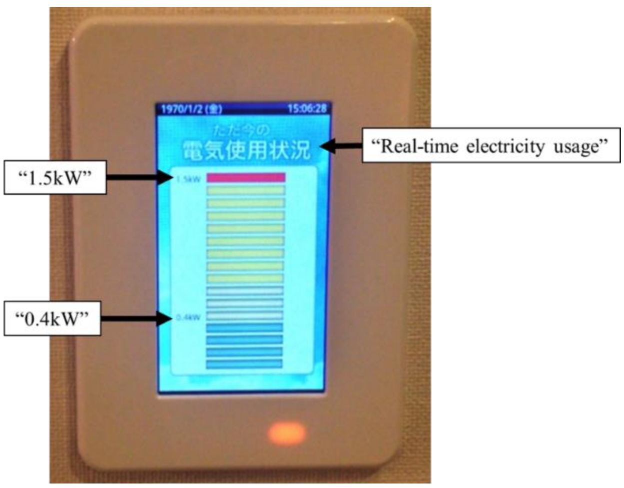



**Figure 2**. In-home display

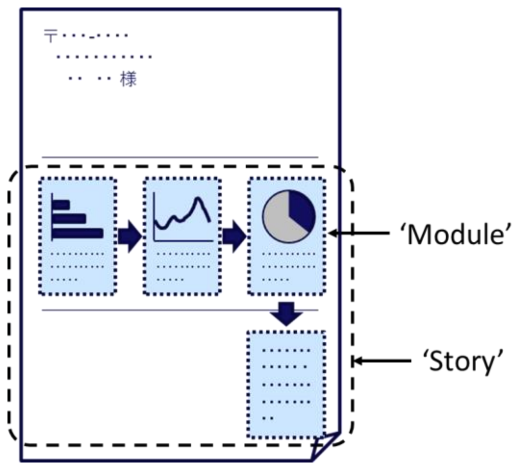



**Figure 3.** Image of weekly report

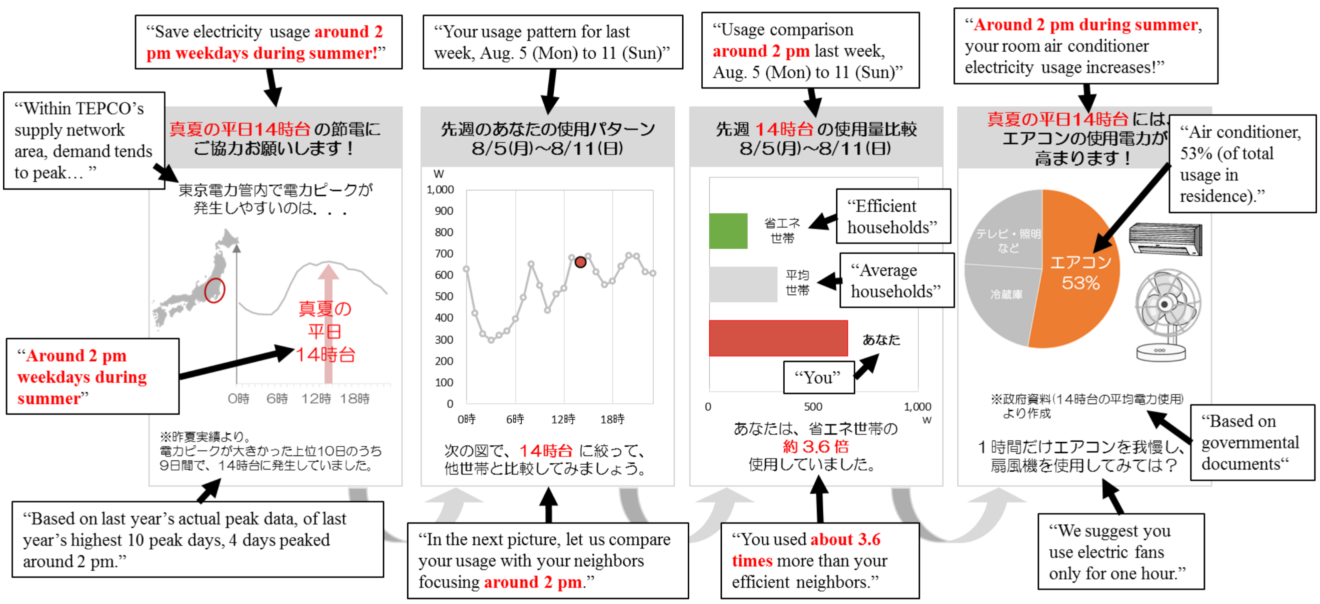



**Figure 4**. Examples and module messages consisting of a story

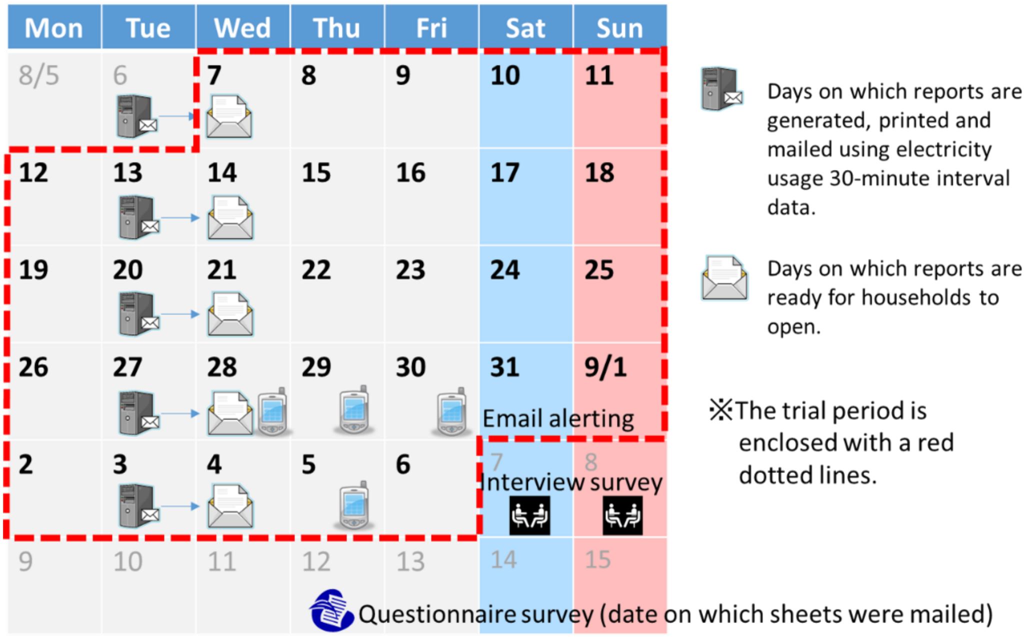



**Figure 5.** Trial schedule

## Participants' overview

Trial participants were chosen after holding several briefing sessions for residents of the condominium from June 10 to 30. The application form included a brief questionnaire on basic demographic information. Of 573 condominium residents, 228 were signed up for the trial.

To measure the impact of the interventions, we established four types of packaged interventions, consisting of both rate structure and information-based interventions. These packages were then randomly assigned to participants. As shown in Figure 6, the control group, or Group D, is a group of participants assigned a conventional tiered rate without an information-based intervention. The first treatment group, Group A, was assigned a 30-minute tiered rate and IHD, which are standard services provided to the condominium's residents. As such, Group A was intended to evaluate how much electricity the residents can save using the condominium's standard services. The second treatment group, Group B, was assigned the 30-minute rate structure and all the information-based interventions. Group B was intended to measure the maximum potential outcome of all the trial's interventions. The third treatment group, Group C, was assigned the conventional rate structure and all the information-based interventions with the aim of measuring the potential outcome of all the respective interventions under a conventional tiered rate.

Figure 7 shows the participants' main characteristics that may influence electricity usage. The average household size is 2.73 persons. More than 90% of the households are married couples, with or without a child. Floor space averages 80 square meters. In the process of grouping the participants, we did not find any statistically significant differences between the monthly usage among the four groups. In addition, the average family size and floor space of all the residents of the condominium (N=573) are available in the figure. Although the trial participants seem to have slightly large family size and smaller floor space, we checked that there are no statistically significant difference between the participants and the non-participants.

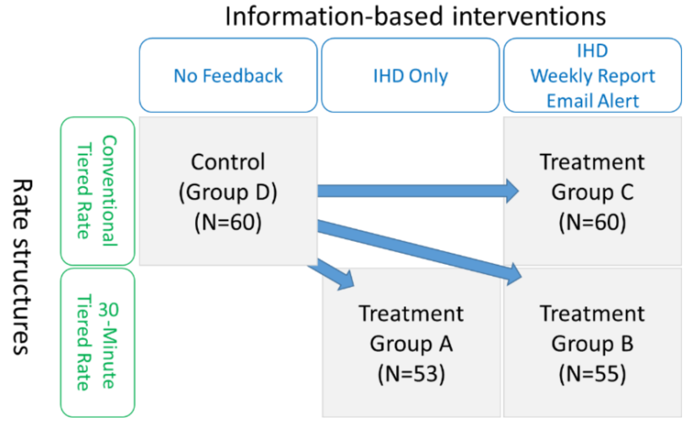



**Figure 6.** Four types of packaged interventions and the number assigned

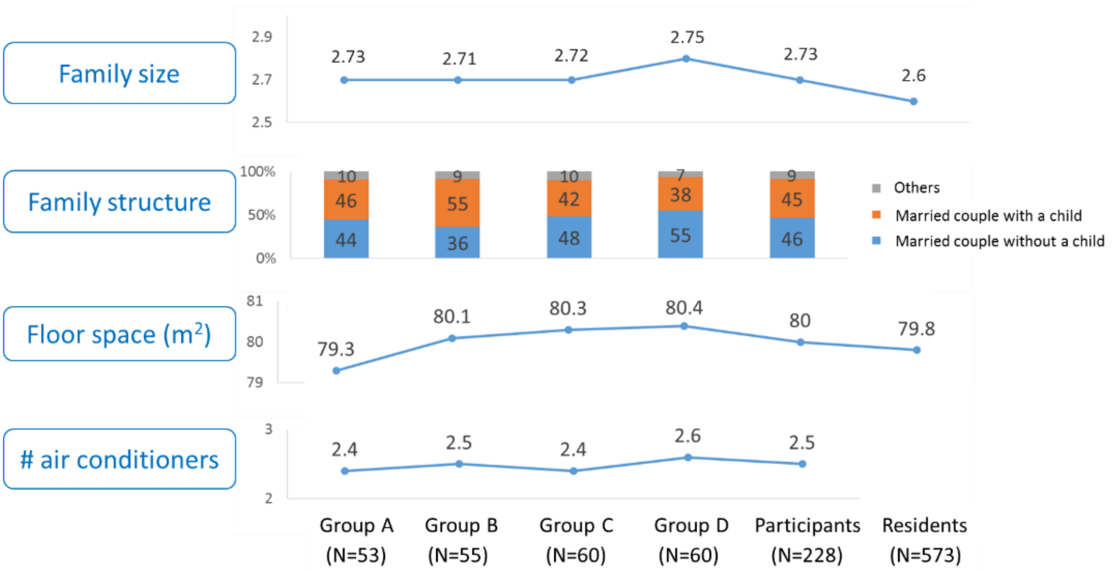



**Figure 7.** The characteristics of each group (N=228) and all the residents of condominium (N=573)

## Results

### Load curve

Figure 8 illustrates the variation in the average electricity usage for each group over time. It shows that electricity usage by treatment group decreased compared with Group D.

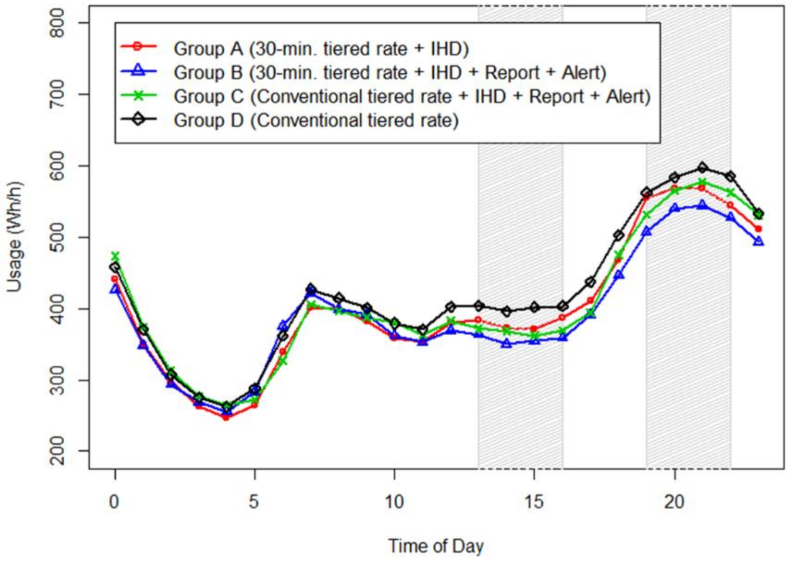



**Figure 8.** Consumption by Time of Day

### Average Treatment Effects

We evaluated the average treatment effects (ATEs) of each packaged intervention by household via a random-effects regression model using electricity consumption data from after the treatments had started. Let $y_{it}$ be a household $i$'s electricity usage at time $t$, normalized by the average usage of across both control group customers and days in the trial period[1]. Then the ATEs of treatment groups, $\beta_A$, $\beta_B$, and $\beta_C$, are estimated as

$$y_{it} = \alpha + \beta_A TreatA_i + \beta_B TreatB_i + \beta_C TreatC_i + \boldsymbol{\gamma}\mathbf{T}_{it} + c_i + u_{it} \tag{1}$$

where $TreatA_{it}$, $TreatB_{it}$ and $TreatC_{it}$ are treatment indicators taking 1 if household $i$ is assigned to the group. The matrix of variables $\mathbf{T}_{it}$ is the factors likely to influence usage. In our analysis, this included the average temperature of the peak times, the average humidity of the peak times, and the average temperature of the previous three days. We used Newey-West robust standard errors.

Table 1 shows the results of the estimation for (1) grid peak time, (2) condominium peak time, and (3) the whole day. The ATEs of grid peak time for Group A, B, and C are, respectively, 6.6%, 11.2% and 6.0%. The ATEs of condominium peak time for Group A, B, and C are, respectively, 2.9%, 8.7%, and 4.0%. The ATEs of the whole day for Group A, B, and C are, respectively, 4.9%, 6.9%, and 3.9%[2]. Note that the estimates were not found to be statistically significant.

Note the estimates of intercepts, representing a feature of reduction rate of group D, are interpreted with the estimates of weather variables. Obviously reduction rate of group D is equivalent

[1] The normalized data express what percentage consumption was *reduced*; for example, if a household $i$ on day $t$ uses 10% less electricity than the average usage of control group, then $y_{it} = 10$.

[2] We also evaluated the impact of an email alert with the household random-effects model. The ATE of an email alert for Group B and C are respectively, 2.7% and 1.1%, both of which are not statistically significant. The results implied that the additional effects of the email alert were relatively small in this trial.

to zero since usage data are normalized based on the usage of group D. For instance, we can confirm the zero reduction rate of group D in grid peak time as follows; given that average temperature during grid peak time is 31.3 degrees Celsius (C), average temperature in past 3 days is 28.1 degrees C and average humidity of grid peak time is 59.3%, reduction rate of group D is $199.3 - 2.9 \times 31.3 - 3.2 \times 28.1 - 0.3 \times 59.3 \fallingdotseq 0$. In addition, the estimates for weather variables have negative signs since these variables are, in general, negatively correlated with reduction rates (positively correlated with usage).

Figure 9 shows the ATEs and their 95% confidence intervals. Even though the estimates are not statistically significant, some tendencies are observed. First, the ATEs of peak times are likely to be higher than those of the whole day. This implies that the interventions that focus on peak usage reduction performed well. Additionally, the ATE of Group B for peak times is likely to be higher than that of Group A. This implies that the effect on the groups with various interventions was larger than on those with fewer interventions.

**Table 1.** Average Treatment Effects

| | I. Grid Peak (13:00 – 16:00, Weekdays Only) | II. Condominium Peak (19:00 – 22:00) | III. Whole Day (0:00 – 24:00) |
|---|---|---|---|
| Group A | 6.6 | 2.9 | 4.9 |
| | (8.9) | (7.1) | (6.7) |
| Group B | 11.1 | 8.7 | 6.9 |
| | (8.8) | (7.0) | (6.7) |
| Group C | 6.0 | 4.0 | 3.9 |
| | (8.6) | (6.9) | (6.5) |
| Average temperature of 13:00 – 16:00 (weekdays only) | -2.9<br>(0.6) *** | --- | --- |
| Average humidity of 13:00 – 16:00 (weekdays only) | -3.2<br>(0.8) *** | --- | --- |
| Average temperature of 19:00 – 22:00 | --- | -3.6<br>(0.3) *** | --- |
| Average humidity of 19:00 – 22:00 | --- | -2.0<br>(0.5) *** | --- |
| Average temperature of 0:00 – 24:00 | --- | --- | -4.6<br>(0.3) *** |
| Average humidity of 0:00 – 24:00 | --- | --- | -0.9<br>(0.3) *** |
| Average temperature of past 3 days | -0.3<br>(0.1) *** | -0.4<br>(0.1) *** | -0.5<br>(0.1) *** |
| Weekday dummy | --- | 0.1<br>(1.5) | 8.6<br>(1.0) *** |
| Intercept | 199.3<br>(17.6) *** | 185.2<br>(14.1) *** | 185.8<br>(9.7) *** |
| Household Random-Effects | Yes | Yes | Yes |
| # Households | 228 | 228 | 228 |
| # Days | 23 | 31 | 31 |
| Adjusted $R^2$ | 0.038 | 0.051 | 0.169 |
| F Statistic | 34.9 | 54.0 | 206.5 |

Notes:
- Standard errors are in parenthesis.
- Statistical Significance: *** 1%, ** 5%, and * 1%.

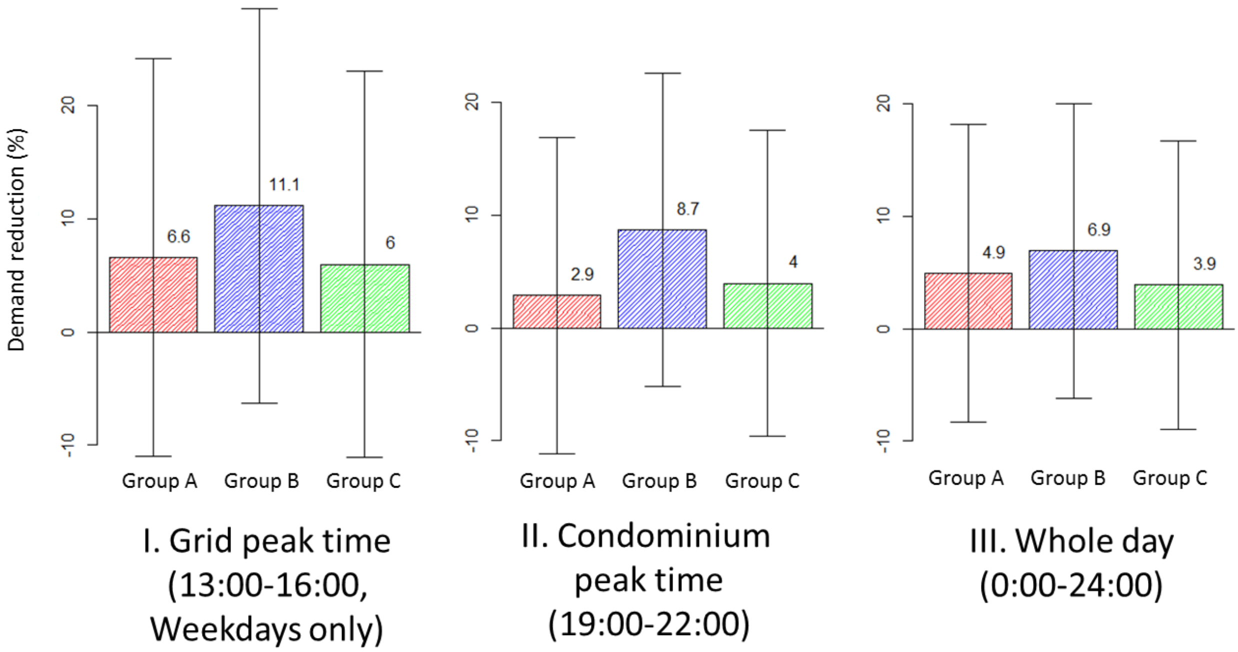



**Figure 9.** Average Treatment Effects with 95% confidence intervals

**Variation of Treatment Effects by Household Characteristics**

Here we evaluated the relationships between treatment effects and household characteristics (ages, sizes, incomes, and consciousness). Clarifying the variation in treatment effects may contribute to targeting households with higher treatment effects for the interventions, leading to improved trial cost effectiveness. Treatment effects were quantified on the basis of the electricity usage of the same demographical segments of control group, Group D. Note that this section's discussion is, likely due to the small sample size, limited to a comparison of treatment effects among different demographical segments. More rigorous discussions, such as the statistical significance of the differences, will be done as part of our future work.

Figure 10 shows the variation of treatment effects for different levels of the household members' ages. The figure shows that elderly households tend to obtain higher treatment effects. On the other hand, Figures 11 and 12 show that treatment effects for different levels of household size and income tend to be weakly related. These results are broadly consistent with other feedback studies on electricity conservation (Allcott, 2009; Davis, 2011). This implies that the interventions for peak reduction in our trial have treatment effects analogous to that of energy conservation.

Furthermore, we assessed the impact of behavioral interventions on participants' change in saving consciousness. The latter was measured in three steps: firstly, *before* the trial, the participants were required to answer how conscious they were of saving electricity based on a five-point scale. Secondly, *immediately after* the trial, the participants again answered the same question. Thirdly, the changes in consciousness were quantified by subtracting the *ex-ante* conscious level from the *ex-post*. The results in Figure 13 show that if one's conscious level of saving electricity increases through interventions, then the change tends to have a positive impact on the actual electricity usage.

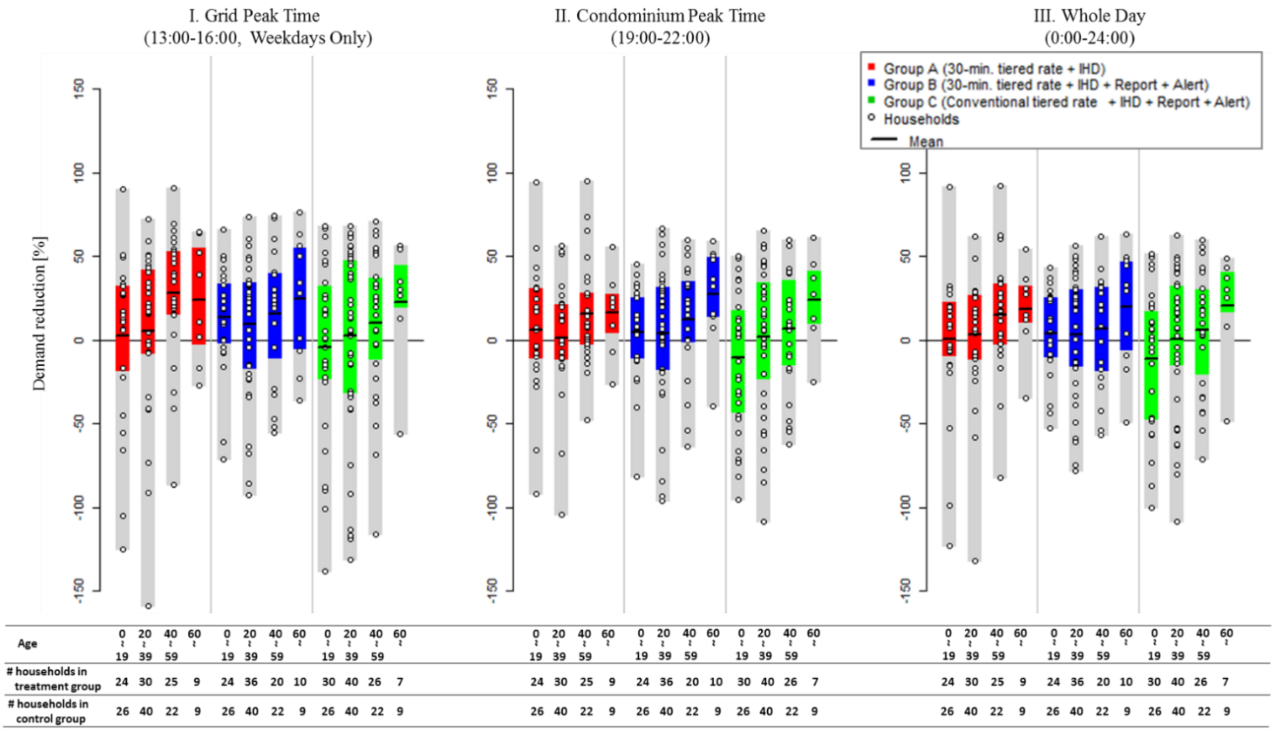



**Figure 10.** Variation in treatment effects for different levels of family members' ages. The values in this figure's first row indicates the family members' ages, with the segments of (1) less than 19 years old, (2) from 20 to 39 years old, (3) from 40 to 59 years old, and (4) more than 60 years old. The bars in red, blue, and green show the range of treatment effects from the 25th to 75th percentiles, and the bars in grey show those from minimum to maximum.

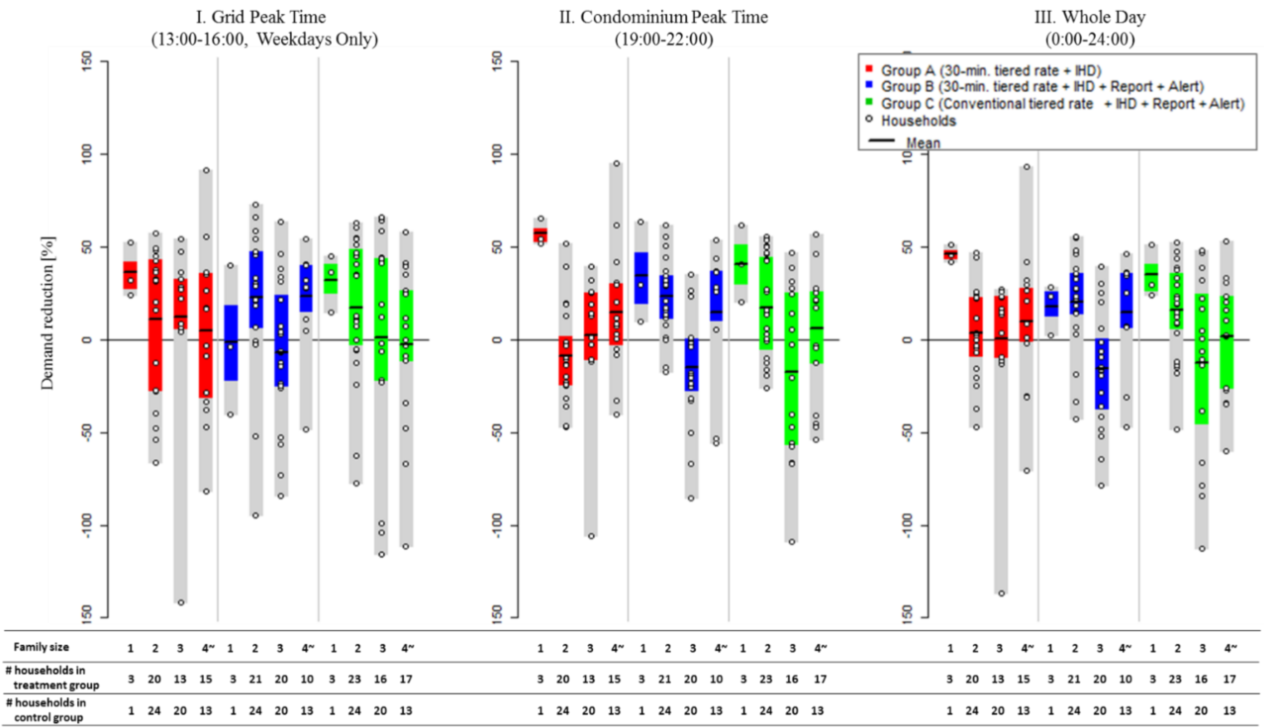
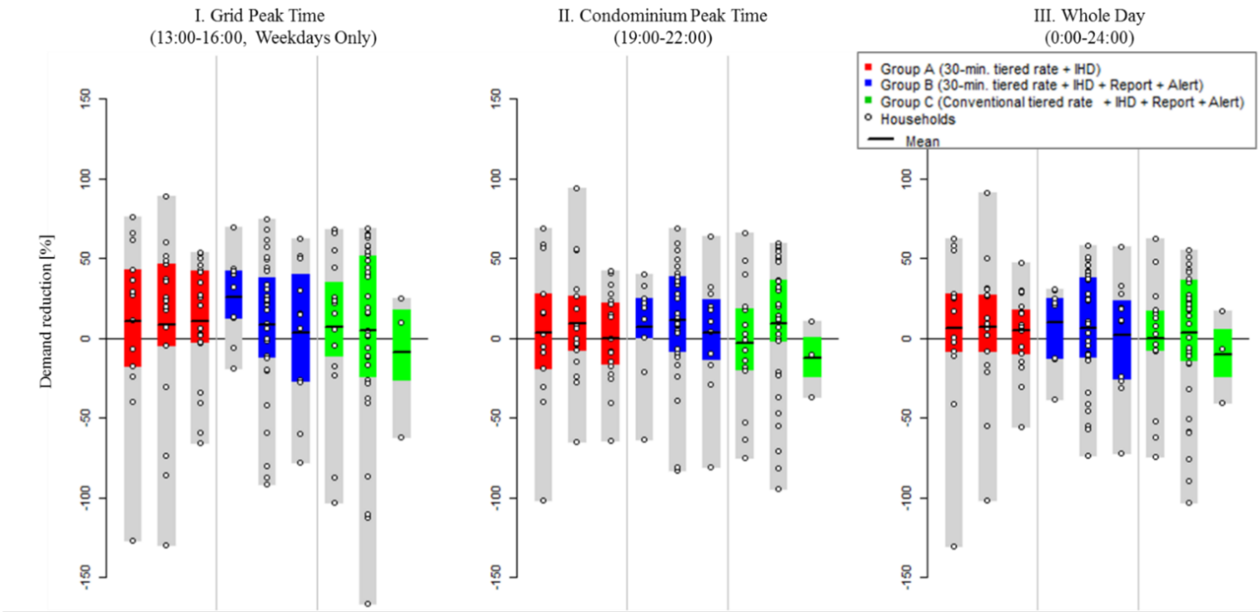



**Figure 11** Variation in treatment effects for different levels of family size. The values in this figure's first row indicate family size, with segments of 1, 2, 3, and 4 or more persons.

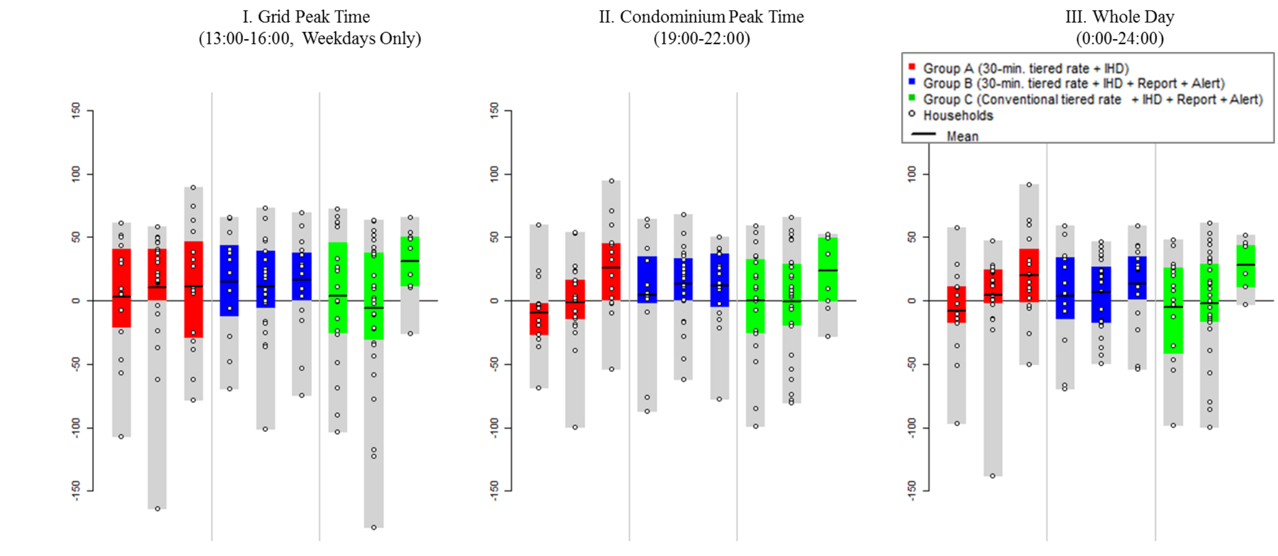



| Family income (million JPY) | ~6 | 6~10 | 10~ | ~6 | 6~10 | 10~ | ~6 | 6~10 | 10~ |
|---|---|---|---|---|---|---|---|---|---|
| # households in treatment group | 13 | 17 | 19 | 9 | 31 | 11 | 15 | 34 | 3 |
| # households in control group | 16 | 28 | 12 | 16 | 28 | 12 | 16 | 28 | 12 |

| Family income (million JPY) | ~6 | 6~10 | 10~ | ~6 | 6~10 | 10~ | ~6 | 6~10 | 10~ |
|---|---|---|---|---|---|---|---|---|---|
| # households in treatment group | 13 | 17 | 19 | 9 | 31 | 11 | 15 | 34 | 3 |
| # households in control group | 16 | 28 | 12 | 16 | 28 | 12 | 16 | 28 | 12 |

| Family income (million JPY) | ~6 | 6~10 | 10~ | ~6 | 6~10 | 10~ | ~6 | 6~10 | 10~ |
|---|---|---|---|---|---|---|---|---|---|
| # households in treatment group | 13 | 17 | 19 | 9 | 31 | 11 | 15 | 34 | 3 |
| # households in control group | 16 | 28 | 12 | 16 | 28 | 12 | 16 | 28 | 12 |

**Figure 12.** Variation in treatment effects for different levels of family income. The values in this figure's first row named "Family income" are as follows: (1) "~6" indicates the participants with family income less than 6 million JPY, (2) "6~10" indicates those with family income in the range of 6 to 10 million JPY, (3) "10~" indicates those with family income of more than 10 million JPY.




| Level of electricity saving consciousness | - | 0 | + | - | 0 | + | - | 0 | + |
|---|---|---|---|---|---|---|---|---|---|
| # households in treatment group | 14 | 22 | 15 | 12 | 24 | 16 | 19 | 30 | 9 |
| # households in control group | 28 | 19 | 10 | 28 | 19 | 10 | 28 | 19 | 10 |

| Level of electricity saving consciousness | - | 0 | + | - | 0 | + | - | 0 | + |
|---|---|---|---|---|---|---|---|---|---|
| # households in treatment group | 14 | 22 | 15 | 12 | 24 | 16 | 19 | 30 | 9 |
| # households in control group | 28 | 19 | 10 | 28 | 19 | 10 | 28 | 19 | 10 |

| Level of electricity saving consciousness | - | 0 | + | - | 0 | + | - | 0 | + |
|---|---|---|---|---|---|---|---|---|---|
| # households in treatment group | 14 | 22 | 15 | 12 | 24 | 16 | 19 | 30 | 9 |
| # households in control group | 28 | 19 | 10 | 28 | 19 | 10 | 28 | 19 | 10 |

**Figure 13.** Variation in treatment effects for different levels of the change in consciousness of saving electricity. The signs in this figure's first row indicate the segments of participant in terms of the change in consciousness as follows: (1) the negative sign, "-", indicates the segment of participants with decreased consciousness of saving electricity, (2) zero, "0", indicates that saving consciousness was unchanged, and (3) a positive sign, "+", indicates that saving consciousness increased.

**Impact of interventions on conscious level of saving electricity**

For a more rigorous analysis of the conscious level of electricity saving, we conducted covariance analysis in the form of pre-post design. Pre-post design, adding the *ex-ante* conscious levels as an explanatory variable, enables us to correct for the differences in consciousness among the respondents. The dataset used for this analysis is the same as that in the previous section.

As shown in Table 2, all the estimation results of the intervention variables, Group A, B, and C, have positive values. In addition, the results for Group A and B are statistically significant at the 5% level. That is, the level of electricity saving consciousness increased if participants received interventions. In addition, Group B's result is higher than that of others, implying that those groups that received more interventions have higher values. It is worth noting that these results show a tendency analogous to the results from usage data analysis in Table 1/Figure 9.

**Table 2.** The results of the covariance analysis of the impact of interventions on the participants' consciousness to save electricity

| | ***Ex-post*** conscious level on electricity saving |
|---|---|
| Intercept | 2.05 (0.30)*** |
| Group A | 0.31 (0.15)** |
| Group B | 0.36 (0.15)** |
| Group C | 0.14 (0.15) |
| ***Ex-ante*** conscious level on electricity saving | 0.39 (0.07)*** |
| # respondents | 226 |
| $R^2$ (adjusted) | 0.13 |
| F-value | 9.7 |

Notes:
- Standard errors are in parenthesis.
- Statistical Significance: *** 1%, ** 5%, and * 1%.

## Conclusion

The analysis showed that the average treatment effect of the four interventions, (1) a tiered rate for electricity usage increasing every 30 minutes, (2) real-time feedback on electricity usage provided via an in-home display, (3) a weekly report, and (4) an email alert to reduce electricity usage during peak grid time, was 11.1% on the grid peak time (1 pm – 4 pm), 8.7% on the peak time of the targeted condominium (7 pm – 10 pm), and 6.9% for the whole day (0 am – 12 pm). Even though the results are not statistically significant likely due to the small sample size, it implied that the effect on the peak time was higher than that on the others. We also examined the relationships between the treatment effects and the demographic data for households in the dataset. Most of the results were likely to be consistent with the literature, such as that, if the household members' ages are high, the treatment effects are likely to increase. Furthermore, questionnaire survey data showed evidence of the impact on improving consciousness, such as that the households with interventions were significantly more conscious of saving electricity than the others.

It should be noted that the estimates of the average treatment effects in this study were not statistically significant likely due to the small sample size. Additionally, some existing studies show that the effects of behavioral interventions tend to weaken over time (e.g. Houde, et al, 2013). To rigorously evaluate the persistency of treatment effects, we continue the examination in the winter of 2013 with an additional enrollment of participants.

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