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The Effect of Demand Response on Electricity Consumption in Japan

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[Abstract]: The main purpose of this study is to investigate, by using regressions analysis, the DR effect on households' electricity consumption. We employ three kinds of estimation models: a pooled OLS model, a random effect model, and a fixed effect model. Major results are as follows. First, the DR scheme clearly reduces electricity consumption. As the peak-time price of electricity increases by 20 yen/kWh in the form of TOU and CPP, electricity consumption decreases by about 8.1% at sample mean. However, consumption after DR tends to increase, most likely due to the rebound effect. Second, the reduction effects of the DR scheme can be strengthened as households' income becomes higher. In contrast, as more people stay at home during the daytime and the temperature rises, the reduction effects of the DR scheme may become weaker. Third, electricity price, household characteristics, and external conditions are significant factors affecting electricity consumption. Fourth, the effects of some DR schemes such as requests to save electricity, TOU, and CPP, can differ largely according to household characteristics and external conditions.

[Key Words]: Demand Response, Electricity Consumption, Time of Use, Critical Peak Pricing

[JEL Classification]: L4, L5, L9

1. Introduction

Reducing electricity consumption has become an increasingly important issue in terms of resource conservation. One of the most commonly used ways to encourage consumers to save electricity is "demand response (DR)," a system by which consumers control their own level of consumption. A DR scheme can be implemented in many ways, such as Time of Use (TOU), Critical Peak Pricing (CPP), and Variable Peak Pricing (VPP). TOU sets a fixed price for electricity according to season and time, CPP sets a high price only during peak time in order to reduce consumption, and VPP is a variation on CPP in that the price during peak time is adjusted according to what demand was on the previous day. Researchers such as Faruqui and George (2005) and Herter et al. (2007) have studied the effect of the DR scheme on electricity consumption, but their analyses have limitations which will be addressed in this paper.

The purposes of this study are to examine the effect of the DR scheme on electricity consumption while considering the characteristics of households, and to simulate the differences in the effect of DR among various households. Our paper makes the following three contributions. First, we simulate the effect of DR based on different types of households and make clear its effect in various situations. For example, we examine to what degree households reduce electricity consumption under a DR scheme, in what conditions (e.g. temperature and income) households are more sensitive to a DR scheme, and the extent of a DR scheme's influence in the most and least effective cases. Previous studies have rarely simulated these situations.

Second, we analyze the effect of DR scheme while controlling for households' characteristics, such as the number of people at home in the daytime. Although electricity consumption can differ largely depending on these characteristics, previous studies have not considered this fact. Whether family members stay at home in the daytime has not been considered in any previous work, but our results suggest that when more members stay at home in the daytime, the effect of the DR scheme shifts from reducing electricity consumption to increasing it. These results suggest the importance of controlling for these factors in the analysis of the DR scheme.

Third, we define the DR scheme as an ordered variable with five levels in the estimation. Moreover, our definition of a DR scheme integrates three types of different DR schemes into one variable according to the strength of each scheme on demand levels. Previous studies mostly define the DR scheme as a dummy variable expressing merely whether the DR scheme is implemented or not (e.g. Faruqui et al. 2014; Jessoe and Rapson 2014). By defining the DR scheme as an ordered variable, we can obtain less biased results than with an estimation using a dummy variable.

This paper consists of five sections after the introduction. Section 2 reviews previous studies on the DR scheme and electricity consumption. Section 3 explains the model, data, and variables used in the estimation. Section 4 shows the estimation results by regressions and Section 5 shows the simulation results. And finally Section 6 summarizes the conclusions.

2. Previous Studies

In this section, we summarize the major previous studies on DR and electricity consumption, focusing especially on empirical analysis. Major previous studies are summarized in Table 1.

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Table 1

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Previous studies on DR and electricity consumption have certain common characteristics.

First, most studies conclude that DR has a significant effect on electricity consumption but that the impact of DR is different depending on the situation. For example, Herter and Wayland (2010) argue that DR surely reduces electricity consumption during the implementation time of DR, while it increases consumption on the previous and subsequent days. Jessoe and Rapson (2014) indicate that the effect of DR can change whether the households are provided information about the amount of their electricity consumption. Households provided more information consume less electricity, and households able to check their information on home displays more often can reduce their consumption through the learning effect. Similarly, Faruqui et al. (2014) show that ecological facilities can enhance the reduction effect of DR on electricity consumption. They indicate also that households are more sensitive than company users to DR.

Second, most studies use data only about individual households. For example, Jessoe and Rapson (2014) use data on households in Connecticut, and Faruqui and George (2005), Herter et al. (2007), and Herter and Wayland (2010) use data from California. Faruqui and Sergici (2011) use data about individual households in Baltimore, and Ida et al. (2013) use household data from Kyoto and Kitakyushu in Japan. While these studies examine the DR from the perspective of demand for electricity among households, rarely have studies examined the issue of companies' electricity consumption, though Faruqui et al. (2014) include data on corporate electricity consumers in addition to data on households.

Third, previous empirical studies have included certain variables, such as ecological technology, temperature, and the use of certain appliances, and evaluated the effect of these variables requiring large amounts of electricity as determinants of electricity consumption. For example, Herter et al. (2007), Faruqui and Sergici (2011), and Faruqui et al. (2014) include the variable of ecological facilities at home, and Herter and Wayland (2010), Faruqui and Sergici (2011), and Faruqui et al. (2014) include the temperature variable in their estimation.

Types of DR examined in previous studies cover a wide range: Time of Use (TOU), Critical Peak Pricing (CPP), Real Time Price (RTP), Peak Time Rebate, and Variable Peak Pricing (VPP). Faruqui and George (2005) compare the effects of CPP, VPP, and TOU, and conclude that VPP is the most effective, CPP is the second best, and TOU is the third best. Faruqui et al. (2014) investigate TOU, CPP, and PTR, while Ida et al. (2013) examine TOU and CPP. Faruqui and Sergici (2011) focus on PTR, while Herter et al. (2007), Faruqui and Sergici (2011), and Herter and Wayland (2011) focus on CPP. It is worth noting that most of these previous studies include the DR variable in the form of a dummy variable.

In addition to the above-mentioned studies, there have been other kinds of studies: policy evaluation studies such as Nishimura's (2014), which evaluates previous DR schemes in the US, France, etc., and discusses the possibility of a future DR scheme in Japan. There have also been theoretical studies, such as that by Chao and DePillis (2013).

However, previous studies leave certain issues unresolved. The most important task now is to use adequate variables in the estimation in order to control for conditional factors influencing electricity consumption and to simulate the effect of DR based on estimation results using these adequate variables. For example, although electricity consumption is determined by individual households' characteristics, previous studies tend to control only experimental conditions such as price, group, temperature, and facilities at home. Some studies such as Ida et al. (2013) and Jessoe and Rapson (2014) include the characteristics of households as a form of individual effect of a fixed panel data model. However, this method is not useful in making clear the effects of household characteristics on electricity consumption and thus does not allow us to pinpoint what kind of households are more sensitive to the DR scheme or which is the most effective DR scheme for households with different characteristics. Thus, we specify the variables expressing households' characteristics and based on the estimation results considering these characteristics we simulate the effects of the DR scheme.

3. Empirical Analysis

3.1 Model

Our model reflects the assumption that electricity consumption is determined by electricity price, DR schemes, characteristics of family, appliances, and house, and other external conditions, as shown in equation (1).

$$Q = f(P, \boldsymbol{DR}, \boldsymbol{FAM}, \boldsymbol{APP}, \boldsymbol{HSE}, \boldsymbol{OTH}) \tag{1}$$

Q is electricity consumption, P is electricity price, $\boldsymbol{DR}$ is the vector of DR effect, $\boldsymbol{FAM}$ is the vector of characteristics of a household, $\boldsymbol{APP}$ is the vector of appliances in a household, $\boldsymbol{HSE}$ is the vector of housing conditions, and $\boldsymbol{OTH}$ is the vector of the other external conditions. Based on equation (1), we specify three empirical models: (i) Pooled OLS model, (ii) Random effect model[1], (iii) Fixed effect model[2].

(Pooled OLS Model):

[1] In the random effect model, u_i is the unobserved individual effect. The covariances of u_i and explanatory variables are assumed to be zero.

[2] The fixed effect model of panel data controls the individual effect of a household. The merit of this model is that we do not need to specify the variables of individual effect in the form of the above, FAM, APP, and HSE variables, which can reduce the misspecification bias. Thus, in equation (4), FAM, APP, and HSE variables are not explicitly defined, since the variables which do not change during the experimentation period cannot be identified in the fixed effect model. These individual effects are included in u_i. The covariances of u_i and explanatory variables are assumed not to be zero.

$$lnQ_{it} = \alpha + \beta_p lnP_{it} + \Sigma_k \beta_k DR_{k,it} + \Sigma_l \beta_l FAM_{l,i} + \Sigma_m \beta_m APP_{m,i} + \Sigma_n \beta_n HSE_{n,i} + \Sigma_o \beta_o OTH_{o.t} + \Sigma_l \beta_{DRl} DR_{peak,it} \cdot FAM_{l,i} + \Sigma_m \beta_{DRm} DR_{peak,it} \cdot APP_{m,i} + \beta_{ptem} DR_{peak,it} \cdot OTH_{temp,t} + \varepsilon_{it} \tag{2}$$

(Random Effect Model):

$$lnQ_{it} = \alpha + \beta_p lnP_{it} + \Sigma_k \beta_k DR_{k,it} + \Sigma_l \beta_l FAM_{l,i} + \Sigma_m \beta_m APP_{m,i} + \Sigma_n \beta_n HSE_{n,i} + \Sigma_o \beta_o OTH_{o.t} + \Sigma_l \beta_{DRl} DR_{peak,it} \cdot FAM_{l,i} + \Sigma_m \beta_{DRm} DR_{peak,it} \cdot APP_{m,i} + \beta_{ptem} DR_{peak,it} \cdot OTH_{temp,t} + u_i + \varepsilon_{it} \tag{3}$$

(Fixed Effect Model):

$$lnQ_{it} = \alpha + \beta_p lnP_{it} + \Sigma_k \beta_k DR_{k,it} + \Sigma_o \beta_o OTH_{o.t} + \Sigma_l \beta_{DRl} DR_{peak,it} \cdot FAM_{l,i} + \Sigma_m \beta_{DRm} DR_{peak,it} \cdot APP_{m,i} + \beta_{ptem} DR_{peak,it} \cdot OTH_{temp,t} + u_i + \varepsilon_{it} \tag{4}$$

$$\begin{aligned} where\ k &= peak, pre, pos, \\ l &= income, number, daytime, \\ m &= refrig, air, \\ n &= age, size, type, elec, \\ o &= temp, weekend, sep, time. \end{aligned}$$

Q is the electricity consumption of household per hour, P is the electricity price, DR is the treatment variable of the implementation of DR, which takes 0 to 5 according to the strength of the DR scheme. $DR_{peak}$is the treatment variable expressing the implementation time of DR, that is, the peak time of 13:00 to 16:00, DR_{pre} is the treatment variable expressing 7 hours before the implementation of DR, and DR_{pos} is the treatment variable expressing 7 hours after the implementation of DR. DR_{pre} and DR_{pos} are included because, as Herter and Wayland (2010) argue, there can be a rebound effect of DR that increases electricity consumption before and after the implementation of DR.

A household's characteristics include the household's income (FAM_{income}), the number of family members per household (FAM_{number}), and the number of residents in a household during the daytime ($FAM_{daytime}$). The appliance conditions of a household include the number of refrigerators at home (APP_{refrig}) and the number of air conditioners at home (APP_{air}). The housing conditions include house age (HSE_{age}), floor size in the house (HSE_{size}), and type of house (HSE_{type}), and the dummy of whether the facilities at home are fully electrificated (HSE_{elec}). The other external conditions include the temperature measured at every hour (OTH_{temp}), the weekend dummy (OTH_{week}), September dummy (OTH_{sep}), and 23 time dummies for every hour (OTH_{time}).

Since our data used here consist of panel data of household and time, the error terms within a household might have a serial correlation. Therefore, we estimate the standard errors based on cluster variances.

3.2 Data

We use data from a social experiment on the effect of DR on households' electricity consumption, called *Keihanna Ecological City Next Generation's Energy and Social System Experimental Project (Keihanna Ekoshithi Jisedai d Enerugi Syakai Shisutemu Jissho Purojekuto)*. This project was carried out in Kyoto prefectures in Japan between 23 July and 28 September in 2012. This experiment was planned by the Ministry of Economy, Trade and Industry and implemented by *Keihanna Eco-City Promotion Council*, an organization consisting of local government, energy-related private companies, universities, and various research institutions, with the purpose of demonstrating an energy system for a smart community in the above areas.

Participants in this experiment were 681 households, divided into four groups, with Group A as the control group (with no treatment) and Groups B, C and D as treatment groups. Second, among treatment groups, Group B was requested to save electricity before the implementation day of CPP (Critical Peak Pricing). Furthermore, Group C and D were treatment groups under TOU (Time of Use) and CPP. Although groups C and D were, respectively, assigned to the winter experimentation, we recognize these two groups as the same in this analysis since there were no differences between them during the summer experimentation.

3.3 Variables

In this section, we will explain the definition of variables used in this study. A summary of statistics is shown in Table 2.

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Table 2

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First, *Q* is the amount of electricity hourly consumed by a household.

Second, *P* is the price for a household's consumption, defined as follows. Because the experiment data do not include electricity price, we must glean these data from other sources[3]. The value of *P* is equal to 20 yen/kWh if the monthly accumulated consumption of a household is equal to or smaller than 120 kWh. The value of *P* is equal to 25 yen/kWh if consumption is larger than 120 kWh and smaller than 200kWh. The value of *P* is equal to 26 yen/kWh if consumption is

[3] These values are based on the variable price A in the areas of Kansai Electric Power in August and September 2012.

equal to or larger than 300 kWh. In the estimation, P is included as the form of the logarithm, lnP.

In our study, three types of DR are examined: (i) a request for electricity saving, (ii) TOU (Time of Use), and (iii) CPP (Critical Peak Pricing). "A request for electricity saving" means that consumers are simply requested to reduce electricity consumption voluntarily, with no obligation to do so. "TOU" adds 20 yen/kWh to the ordinary price for the peak hours of 13:00~16:00 only. "CPP" sets a higher price if the temperature will exceed 30 degrees according to the previous day's weather forecast. Of these three types of DR, TOU is stronger than a request for electricity saving, and CPP is stronger than TOU. Moreover, our CPP has three levels: CPP40, CPP60, and CPP80. In CPP40, CPP60, and CPP80, 40 yen/kWh, 60 yen/kWh, and 80 yen/kWh are added, respectively, as peak pricing to the ordinary price. Thus, our DR scheme has five levels in ascending order: a request for electricity saving, TOU, CPP40, CPP60, and CPP80.

In the analysis, the value of DR at the peak time (DR_{peak}) is defined in Table 3. For example, DR_{peak} is equal to one, if the group is under a request for electricity saving (Group B), and the group is under a request for electricity saving on the date, and the time is between 13:00 and 16:00. As another example, the value of DR_{peak} is equal to two, if the group is any treatment group (Group C or D), the treatment day is under TOU, and the time is between 13:00 and 16:00. Furthermore, the value of DR_{peak} is equal to three, if the group is any treatment group, the day is under CPP40, and the time is between 13:00 and 16:00. Thus, as DR_{peak} becomes larger, the treatment of DR scheme as price becomes higher.

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Table 3

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Demand response by individual users is also affected before and after the DR scheme is implemented. We set up the variable of DR 7 hours before the plan is announced (DR_{pre}) and the variable of DR 7 hours after the plan is announced (DR_{pos}). The variables DR_{pre} and DR_{pos} are defined in a way similar to DR_{peak}. That is, the value of DR_{pre} (DR_{pos}) is equal to one, if the group is B, the day is under the request for electricity saving, and the time is 7 hours before (after) the DR implementation, and so on.

Household characteristics have an important effect on demand for electricity. We also include three kinds of household characteristics. First, FAM_{income} is the income level of a household. This variable is an index from 1 to 12 categories. 1 is the lowest category (less than 2 million yen) , 2 is the second lowest (2 to 3 million yen) and 12 is the highest category (more than 15 million yen). Second, FAM_{number} is the number of people per household. Third, we also include daytime residence. $FAM_{daytime}$ is the number of residents present in a household during the daytime.

Appliance conditions and housing conditions are also important factors determining demand for electricity. As for these conditions, first, APP_{refrig} is the number of refrigerators at home and APP_{air} is the number of air conditioners at home. Second, HSE_{age} is house age and HSE_{size} is the floor area in a house. HSE_{type} is the dummy variable which takes a value of one if the house is a communal building, otherwise zero. HSE_{elec} is the dummy variable which takes a value of one if the facilities at home are fully electrificated, otherwise zero.

Finally, we include five kinds of other external conditions. First, OTH_{temp} is the temperature measured every hour. Second, OTH_{week} is the weekend dummy variable. This takes a value of one if the day is a weekend day, otherwise zero. Third, OTH_{sep} is the dummy variable on a date in September. This takes a value of one if the day is in September, otherwise zero. Finally, we include temperature variable of the day, OTH_{temp}. In this study, we take this variable as the form of the logarithm, $lnOTH_{temp}$.

4. Estimation Results

Table 4 shows the estimation results of equations (2) to (4), which are the pooled OLS model, the random effect model and the fixed effect model. As this table shows, most coefficients show a reasonable sign. Furthermore, the coefficients of significant variables are relatively stable among these models, which suggests that the results are robust in terms of model specification in panel data models (the fixed effect and the random effect models). Among these three models, test results show that the fixed effect model is considered as best and the random effect model as second best[4]. Therefore, we base our discussion on the results of the fixed effect model.

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Table 4

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As we mentioned before, the results seem reasonable because important coefficients show the expected signs. For example, the coefficient of electricity price *(lnP)* is negative with statistical significance, which indicates that higher price leads to less consumption of electricity. Since the magnitude of the coefficient is between -0.059 and -0.074, as the price increases by one hundred percent, the electricity consumption decreases by 5.9% to 7.4%.

Next, we will explain the results of the effect of the DR. First, the most important result is

[4] First, according to the Breusch-Pagan test, the random effect model is better than the pooled OLS model. Second, according to the robust F test, the fixed effect model is better than the pooled OLS model. Third, according to the robust Hausman test, the fixed effect model is better than the random effect model.

that DR_{peak} has a negative sign with strong statistical significance, which means that DR surely reduces electricity consumption. As the peak-time price of electricity increases by 20 yen/kWh in the form of TOU and CPP, electricity consumption decreases by about 8.1%. This value of change rate is calculated based on the interpretation of the semi-log linear model. The change rate in the semi-log linear model, which we specify here as DR_{peak} variable and cross-terms, can be calculated approximately as $exp\left[\beta_{peak} + \sum_l \beta_{DRl}\, DR_{peak,it} \cdot FAM_{l,i} + \sum_m \beta_{DRm}\, DR_{peak,it} \cdot APP_{m,i} + \beta_{ptem} DR_{peak,it} \cdot OTH_{temp,t}\right] - 1$. Thus, in the fixed effect model, since values for DR_{peak} variable and cross-terms are about -0.084, the value of exp(-0.084)-1 is about -0.081, that is, about -8.1%[5]. It is worth noting that the results of the random effect model are similar to those of the fixed effect model[6].

As for consumption 7 hours after and before DR implementation, the following results are obtained. First, since the coefficient of DR_{pos} is positive with statistical significance, the consumption after DR time tends to increase. Presumably this result reflects a rebound effect. This is consistent with the result of Herter and Wayland (2010), which shows that DR reduces electricity consumption during the implementation time, but increases it after the DR time. Our results also suggest that consumers shift electricity consumption from the DR time (the peak time of 13:00 to 16:00) to non-DR time (the off-peak time of 16:00 to 23:00). However, second, the coefficient of DR_{pre} is not statistically significant. Consumption before the DR time would not change.

Some cross-terms of DR_{peak} with other factors are statistically significant. For example, $DR_{peak} \cdot FAM_{income}$ shows the negative sign with statistical significance. This result shows that the reducing effects of DR would be larger as households' income becomes higher. In contrast, the coefficients of $DR_{peak} \cdot FAM_{daytime}$ and $DR_{peak} \cdot lnOTH_{temp}$ show a positive relationship with statistical significance. These results mean that as more people stay at home in the daytime and the weather becomes hotter, the reducing effects of DR could diminish.

As stated above, the negative coefficient of *lnP* indicates that higher price leads to less electricity consumption. Since the magnitude of the coefficient is between -0.059 and -0.074, as the price increases by one percent, electricity consumption decreases by 5.9% to 7.4%.

The coefficients of most other variables are also reasonable. For example, since FAM_{number} APP_{refrig} and APP_{air} are positive, as the family becomes larger or has more refrigerators and air conditioners, electricity consumption would be larger. As the number of household increases by one, electricity consumption increases by about 11.5%. As the number of refrigerators increases by one, electricity consumption increases by 7.9%. As the number of air conditioners

[5] In this case, we calculate values at sample mean for DR_{peak} variable and the cross terms with statistical significance. From Table 4, we obtain results as follows: $\beta_{peak} + \beta_{peakincome} DR_{peak} \cdot FAM_{income} + \beta_{peakdaytime} DR_{peak} \cdot FAM_{daytime} + \beta_{ptem} DR_{peak} \cdot lnOTH_{temp} = -0.084$. Therefore, the value of exp(-0.084)-1 is about -0.081.

[6] Results in the case in the random effect model, obtained in a similar way, are about -7.8%.

increases by one, electricity consumption increases by 11.6%. On the other hand, the coefficients of FAM_{income} and $FAM_{daytime}$ show a positive sign but the magnitudes are very small: the effects of an increase in income or in the number of residents present in the daytime are only 1.1% and 3.7%, respectively. Similarly, the coefficients of HSE_{age}, HSE_{size}, and HSE_{elec} have positive signs. These results indicate that, as the house becomes older or larger, or the house is fully electrificated, electricity consumption is larger.

Moreover, since $lnOTH_{temp}$ and OTH_{week} show the positive sign with statistical significance, electricity consumption tends to increase on a hot day or during the weekend. As the temperature increases by one percent, electricity consumption also increases by about 33%. Thus, electricity consumers are more sensitive to changes in the weather than to changes in price. In contrast, the coefficients of OTH_{sep} show the negative sign so that households consume less electricity if the day is in September. Variables such as HSE_{type}, $DR_{peak} \cdot FAM_{number}$, $DR_{peak} \cdot APP_{air}$, $DR_{peak} \cdot APP_{refrig}$, and DR_{pre} are not statistically significant.

5. Simulation Results

In this section, based on the regression results, we simulate how much electricity consumption would be changed by the implementation of DR. When households need a large amount of electricity, DR is inadequate to bring about electricity saving, as DR works least effectively in severe situations such as "when the weather is hot, a household has a low income, and people stay at home during the daytime." Table 5 shows the effect of each DR on electricity consumption. In this case, we take three different scenario cases: (i) the least effective case, (ii) the case of average effectiveness, and (iii) the most effective case.

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Table 5

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The combination of the conditions such that "temperature is 34.1℃, income category is 3, and the number of residents during the daytime is 2" is the case in which DR is least effective. In contrast, households can control their electricity consumption largely by DR when they face a favorable situation. The combination of conditions such that "temperature is 27.5℃, income category is 10, and the number of residents during daytime is 0" is the most effective case. The case such that "temperature is 31.4℃, income category is 5, and the number of people at home in the daytime is 1" is the average effective case.

Based on these calculations, Table 5 shows the following results. First, the effect on electricity consumption of a request for electricity saving is -0.7% at the least and -11.6% at the most. This means that only showing the quantitative indicators for consumers to save electricity, if it works most effectively, can reduce electricity consumption more than in the case of TOU working averagely. Second, the TOU can reduce by between 1.4% and 21.9%. The most effective case of TOU is nearly the same as the averagely effective case of CPP80. Third, CPP can reduce electricity consumption by 2.1% to 41.0%. If the effect of CPP80 were to be maximized, electricity consumption could be reduced nearly by a half. Thus, the effect of each DR can differ largely depending on household characteristics and external conditions.

Because electricity consumption increases immediately subsequent to a period of DR implementation, it is important to see the net effect of the scheme. As stated in the previous section, while DR surely reduces electricity consumption, it also induces a rebound effect in that a household consumes more electricity than usual after the DR time. Next, in Table 6, we see the simulation results of the net consumption of electricity during and after DR.

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Table 6

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The left side of Table 6 shows the effect of this rebound, and the right side shows the net effect of DR in a day, which is calculated by taking the difference between the reduction rate during DR and the increase rate after DR. In this table, we consider three scenario cases: (i) the least effective case, (ii) the case of average effectiveness, and (iii) the most effective case. These are the same as in Table 5.

In Table 6, there are cases where the rebound effect outweighs the reduction effect of DR on consumption. The positive sign of the change rates means that DR increases electricity consumption. In the cases where DR works least effectively, net consumption increases by at least 1.0% and at most 5.4%. However, if DR works at least averagely, it can reduce electricity consumption as a net effect over the course of a day.

Last, Table 7 shows the simulation results of the DR effect depending on temperature, income, and the number of people at home in the daytime.

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Table 7

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The case on the left has temperature changing, the other two factors being fixed as “income category of 5 and with one person staying at home in the daytime.” The case in the middle has income changing, the temperature being fixed at 31.4℃ and with one person staying at home in the daytime. The case on the right has the number of people at home in the daytime changing, with the income category being 5 and the temperature 31.4℃. As more people stay at home during the daytime, as the temperature becomes higher, or as the income level becomes lower, DR loses its reducing effect. When the household income category is at 10, CPP80 can reduce electricity consumption by 32.5%. Higher income leads to a greater reduction rate of electricity use perhaps because high-income households generally use more electricity than lower income households and thus have more room in which to reduce consumption.

6. Conclusions

By using regression analysis and simulating how much electricity consumption can be saved through DR schemes, this paper investigates the DR effect on households’ electricity consumption. We employ three kinds of estimation models: a pooled OLS model, a random effect model, and a fixed effect model. The main results of our analyses are as follows.

First, the DR scheme clearly reduces electricity consumption. As the peak-time price of electricity increases by 20 yen/kWh in the form of TOU and CPP, electricity consumption decreases by about 8.1% depending on the other factors specified. However, consumption after DR tends to increase, probably due to the rebound effect. This suggests that consumers shift their electricity consumption from DR time (the peak time of 13:00 to 16:00) to non-DR time (the off-peak time of 16:00 to 23:00).

Second, the effect of the DR scheme is related to the other factors. For example, the reduction effects of the DR scheme can be strengthened as households’ income becomes higher. In contrast, as more people stay at home during the daytime and the temperature rises, the reduction effects of DR scheme can diminish.

Third, electricity price, households’ characteristics, and external conditions are significant factors related to electricity consumption. A higher price surely leads to less electricity consumption. When the price increases by one hundred percent, electricity consumption decreases by 5.9% to 7.4%. The household with more family members, more air conditioners and more refrigerators, consumes more electricity. Electricity consumption tends to increase on hot days or on the weekend.

Fourth, the effects of certain DR schemes such as a request for electricity saving, TOU, and CPP, can largely differ depending on household characteristics and external conditions. At its most effective, the mere practice of showing consumers quantitative indicators to motivate them to save electricity can reduce electricity consumption more than in the case where TOU works averagely.

Fifth, there are some cases in which the rebound effect outweighs the reduction effect of the DR scheme on electricity consumption. In the cases where the DR scheme works least effectively, the net electricity consumption increases by 1.0% to 5.4%. However, if DR works at least averagely, it can reduce electricity consumption as a net effect over the course of a day. The net reduction of electricity is between 3.4 and 32.2%.

Last, the effect of the DR scheme depends on the number of residents present during daytime, temperature, and income. A higher number of people at home in the daytime, a higher temperature, and a lower income level lead to a lower reduction effect created by the DR scheme.

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Table 1 Previous Studies

Study	Data and Method	Major Results
Faruqui and George (2005)	Data: California, US; Household and Business; July, 2003 – December, 2004 Method: No explanation (probably regression analysis)	-Effect of electricity consumption saving through DR, -All DR schemes (VPP, CPP, TOU) are effective: VPP＞CPP>TOU.
Herter (2007)	Data: California, US; Household; 2003 - 2004 Method: Matching estimation	-CPP can reduce household electricity consumption. -High-use customers respond significantly more in kW reduction than do low-use customers, while low-use customers save significantly more in percentage reduction of annual electricity bills than do high-use customers.
Herter et al. (2007)	Data: California, US; Household; July 2003 - September 2004 Method: Matching estimation	-CPP can reduce household electricity consumption. -Households with automated air-conditioning controls can reduce electricity consumption more than those without the device through the CPP scheme.
Faruqui and Sergici (2010)	Summarize 15 DR social experiments in the US. Method: Survey research	-CPP can reduce electricity consumption. -Households with automatic controlling devices can reduce electricity consumption more than those without the device through the CPP scheme.
Capper et al. (2010)	Summarize the existing contribution of DR resources in U.S. electric power markets.	-The currently existing DR resource contribution, in terms of potential peak load reduction, has increased since 2006 by about 10%.
Herter and Wayland (2010)	Data: California, US; Household, July and September 2004 Method: OLS	-Effect on electricity consumption per hour -Negative effect: Peak-time of DR day (-) -Positive effect: Next day of DR day (+), Previous day of DR day (+)
Kim and Shchervakova (2011)	Summarize obstacles to DR scheme success	-Consumer barriers: (i) customer knowledge of DR scheme, (ii) availability of technology, (iii) information feeds, (iv) response fatigue, (v) technology cost and financing, (vi) potential saving of electricity, (vii) sacrificing behavior in switching patterns -Producer barriers: (i) investment recovery, (ii) promotional responsibility, (iii) managerial incentives -Structural barriers: (i) DR program structure, (ii) regulatory process and policy support
Faruqui and Sergici (2011)	Data: Baltimore, US; Household, 2008 and 2009	-Model 1: effect on peak-off peak ratio of electricity consumption per day; Price ratio・THI Difference (-), THI Difference (+), Price ratio・THI

	Method: SUR, Fixed effect model, Simulation by PRISM	Difference・PTR (+), Price ratio・THI Difference・Tech (-) -Model 2: effect on average electricity consumption per day; Price・THI (-)
Joskow and Wolfram (2012)	Summarize lessons of DR schemes based on previous studies	-Merits of DR schemes: (i) saving electricity consumption at peak time, (ii) saving excess investment in facilities, (iii) suppression of electric power company's market control -Possibility of implementation of DR schemes: (i) technology innovation, (ii) public opinion on deregulations, (iii) aging of existing facilities, (iv) promotion of renewable energy -Problems of DR schemes: (i) installation cost of meters, (ii) increase of cost of firms due to complexity of price system, (iii) lack of understanding by consumers, (iv) redistribution of income
Ida et. al. (2013)	Data: Kyoto and Kita-Kyushu, Japan; Household; July – September 2012 Method: Fixed effect model	-Electricity consumption per 30 minutes -Negative effect: Warning (-), Warning・income (-), CPP (-) -Positive effect: CPP・income (+), CPP・Mean Usage (+)
Faruqui et al. (2014)	Data: Connecticut, US; Household and small business; June-August 2009 Method: SUR, Fixed effect model, Simulation by PRISM	-Model 1: effect on peak-off peak ratio of electricity consumption per day; Price ratio・THI Difference (-), THI Difference (+), Price ratio・THI Difference・PTR (+), Price ratio・THI Difference・Tech (-) -Model 2: effect on average electricity consumption per day; Price・THI (-)
Jessoe and Rapson. (2014)	Data: Connecticut, US; Household; July - August 2011 Method: OLS for ITT, 2SLS for TOT, Fixed effect model	-Effect on electricity consumption per 15 minutes -Price (-), Price+IHD(-), (Price+IHD)・(number of seeing IHD) (-), (Price+IHD)・(number of confirming DR announcement) (-), (Price+IHD)・post DR (+)

Table 2 Summary of Statistics

Variable	Mean	Std. Dev.	Min	Max
Q (Hourly electricity consumption: kwh)	0.565	0.592	0.000	13.800
P (Electricity price)	23.388	2.605	20.000	26.000
DR_{peak} (Demand response at peak hours)	0.168	0.699	0.000	5.000
DR_{pre} (Demand response at pre-hours)	0.296	0.905	0.000	5.000
DR_{pos} (Demand response at post-hours)	0.296	0.905	0.000	5.000
FAM_{income} (Income category: 1 - 12)	5.915	2.715	1.000	12.000
$FAM_{daytime}$ (Residence at home during daytime)	1.298	0.965	0.000	4.000
FAM_{number} (Number of people per household)	3.191	1.198	1.000	7.000
APP_{refrig} (Number of refrigerators per household)	1.136	0.432	0.000	3.000
APP_{air} (Number of air conditioners per household)	3.576	1.705	0.000	10.000
HSE_{age} (House age: year)	3.156	1.616	1.000	6.000
HSE_{size} (Floor area per house: m^2)	4.306	1.057	1.000	7.000
HSE_{type} (Type of house: collective housing = 1, otherwise = 0)	0.773	0.419	0.000	1.000
HSE_{elec} (Dummy of fully-electrificated house: fully-electrificated house=1, otherwise=0)	0.312	0.463	0.000	1.000
OTH_{temp} (Temperature measured every hour : C degree)	26.635	4.074	14.900	35.800
OTH_{week} (Weekend dummy: weekend=1, otherwise=0)	0.288	0.453	0.000	1.000
OTH_{sep} (September dummy: September=1, otherwise=0)	0.475	0.499	0.000	1.000

(Note) The number of the observations is 698,088 for each variable.

Table 3 Definition of Variable of DR_{peak}

Variable of DR_{peak}	Group	Date	Time
$DR_{peak} = 1$	Treatment group (Group B)	Date of the request for electricity saving	13:00 to 16:00
$DR_{peak} = 2$	Treatment group (Group C or D)	Date of TOU	13:00 to 16:00
$DR_{peak} = 3$	Treatment group (Group C or D)	Date of CPP40	13:00 to 16:00
$DR_{peak} = 4$	Treatment group (Group C or D)	Date of CPP60	13:00 to 16:00
$DR_{peak} = 5$	Treatment group (Group C or D)	Date of CPP80	13:00 to 16:00
$DR_{peak} = 0$	otherwise		

Table 4 Estimation Results

Model	Pooled OLS	Random Effect	Fixed Effect
lnP	0.897*** (0.070)	-0.059** (0.023)	-0.074*** (0.023)
DR_{peak}	-1.007*** (0.114)	-0.745*** (0.101)	-0.741*** (0.102)
DR_{pre}	0.001 (0.006)	0.002 (0.004)	0.002 (0.004)
DR_{pos}	0.017** (0.007)	0.017*** (0.004)	0.017*** (0.005)
FAM_{income}	0.010* (0.005)	0.011* (0.006)	
$FAM_{daytime}$	0.033** (0.016)	0.036** (0.017)	
FAM_{number}	0.099*** (0.012)	0.109*** -0.013	
APP_{refrig}	0.068*** (0.012)	0.076*** (0.013)	
APP_{air}	0.108*** (0.038)	0.110*** (0.040)	
HSE_{age}	0.021** (0.009)	0.023** (0.010)	
HSE_{size}	0.035** (0.017)	0.038** (0.019)	
HSE_{type}	0.0266 (0.0440)	0.0326 (0.0488)	
HSE_{elec}	0.287*** (0.031)	0.329*** (0.034)	
$lnOTH_{temp}$	0.718*** (0.034)	0.343*** (0.020)	0.337*** (0.020)
OTH_{week}	0.0521*** (0.008)	0.051*** (0.006)	0.051*** (0.006)
OTH_{sep}	-0.016** (0.007)	-0.084*** (0.006)	-0.085*** (0.006)
$DR_{peak} \cdot FAM_{income}$	-0.006** (0.003)	-0.005** (0.002)	-0.005** (0.002)
$DR_{peak} \cdot FAM_{daytime}$	0.016* (0.009)	0.018** (0.007)	0.018** (0.007)
$DR_{peak} \cdot FAM_{number}$	0.002 (0.006)	-0.004 (0.005)	-0.004 (0.005)
$DR_{peak} \cdot APP_{refrig}$	0.003 (0.004)	0.001 (0.004)	0.001 (0.004)

$DR_{peak} \cdot APP_{air}$	0.016	0.017	0.017
	(0.016)	(0.013)	(0.013)
$DR_{peak} \cdot lnOTH_{temp}$	0.274***	0.204***	0.202***
	(0.030)	(0.023)	(0.023)
Constant	-7.068***	-2.957***	-1.665***
	(0.311)	(0.140)	(0.116)
N	693417	693417	693417
R^2	0.276	0.259	0.137
log likelihood	-686987	-	-597149
Number of households	-	493	493

(Note) Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 5 Simulation Results of the Effects of DR Policy

DR Type	Least effective case	Average effective case	Most effective case
Random Effect Model			
Request for Electricity Saving	-0.7%	-5.1%	-11.6%
TOU	-1.4%	-9.9%	-21.9%
CPP40	-2.1%	-14.5%	-30.9%
CPP60	-2.8%	-18.8%	-38.9%
CPP80	-3.5%	-22.9%	-41.0%
Fixed Effect Model			
Request for Electricity Saving	-0.7%	-5.0%	-11.6%
TOU	-1.3%	-9.8%	-21.8%
CPP40	-2.0%	-14.4%	-30.8%
CPP60	-2.7%	-18.7%	-38.8%
CPP80	-3.3%	-22.8%	-40.9%

(Note)
(1) The least effective case is temperature of 34.1℃, income category of 3, daytime residence of 2.
(2) Average effective case is temperature of 31.4℃, income category of 5, daytime residence of 1.
(3) The most effective case is temperature of 27.5℃, income category of 10, daytime residence of 0.

Table 6 Net Effect of DR by Simulation

DR Type	Increasing rate of electricity consumption after 7 hours of DR	Net effect of DR		
		Least effective case	Average effective case	Most effective case
Random Effect Model				
Request of Electricity Saving	1.7%	1.0%	-3.4%	-9.9%
TOU	3.4%	2.0%	-6.5%	-18.5%
CPP40	5.1%	3.0%	-9.3%	-25.8%
CPP60	6.9%	4.1%	-11.9%	-32.0%
CPP80	8.7%	5.3%	-14.2%	-32.3%
Fixed Effect Model				
Request of Electricity Saving	1.7%	1.0%	-3.4%	-9.9%
TOU	3.4%	2.1%	-6.4%	-18.4%
CPP40	5.1%	3.1%	-9.2%	-25.7%
CPP60	6.9%	4.3%	-11.8%	-31.9%
CPP80	8.7%	5.4%	-14.1%	-32.2%

(Note)

(1) Net effect is calculated by taking the difference between the reduction rate during DR and the increase rate after DR.

(2) The least effective case is temperature of 34.1℃, income category of 3, daytime residence of 2.

(3) Average effective case is temperature of 31.4℃, income category of 5, daytime residence of 1.

(4) The most effective case is temperature of 27.5℃, income category of 10, daytime residence of 0.

Table 7 DR Effects on Temperature, Income, and the Number of Residents of Households

	Temperature (℃)			Income Category			Number of Residence of Household		
	27.1	31.4	34.5	3	5	10	0	1	2
Random Effect Model									
Request for Electricity Saving	-7.6%	-5.1%	-3.5%	-4.1%	-5.1%	-7.6%	-6.7%	-5.1%	-3.4%
TOU	-14.6%	-9.9%	-6.8%	-8.0%	-9.9%	-14.6%	-13.0%	-9.9%	-6.7%
CPP40	-21.1%	-14.5%	-10.1%	-11.7%	-14.5%	-21.0%	-18.9%	-14.5%	-9.8%
CPP60	-27.1%	-18.8%	-13.2%	-15.3%	-18.8%	-27.0%	-24.4%	-18.8%	-12.9%
CPP80	-32.7%	-22.9%	-16.2%	-18.8%	-22.9%	-32.5%	-29.5%	-22.9%	-15.8%
Fixed Effect Model									
Request for Electricity Saving	-7.6%	-5.0%	-3.4%	-4.0%	-5.0%	-7.5%	-6.7%	-5.0%	-3.3%
TOU	-14.5%	-9.8%	-6.8%	-7.9%	-9.8%	-14.5%	-13.0%	-9.8%	-6.6%
CPP40	-21.0%	-14.4%	-10.0%	-11.6%	-14.4%	-20.9%	-18.8%	-14.4%	-9.7%
CPP60	-27.0%	-18.7%	-13.1%	-15.2%	-18.7%	-26.9%	-24.2%	-18.7%	-12.7%
CPP80	-32.5%	-22.8%	-16.1%	-18.6%	-22.8%	-32.4%	-29.3%	-22.8%	-15.6%

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