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## An Analysis of Household Electricity Saving Behavior Using the Stochastic Frontier Function

**[Abstract]:** The main purpose of this study is to investigate the difference between incentive effects and physical condition effects in electricity saving behaviors of households, by applying stochastic frontier models for the demand function. As for incentives, we consider both internal incentives such as environmental consciousness, and external incentives such as the price system and information feedback. This paper makes three contributions to the existing literature. First, we consider the difference in room for saving electricity among households by labeling in this paper the amount of electricity consumption which is possible to be reduced for energy saving as "consumption slack" (i.e. incentive effects), which we separate from the minimum necessary amount of consumption impossible to be reduced for energy saving (i.e. physical condition effects). Our second contribution is that we take the novel approach of using the stochastic frontier model to distinguish the reducible amount from the minimum necessary amount of electricity consumed among households. Last, we empirically examine which of the internal or external incentives are more effective in reducing household electricity consumption. Using data on 561 Japanese households in 2012, we obtain the following results. Consciousness of consumption is more important to electricity saving than external incentives such as demand response and information feedback. Without such consciousness, demand response alone increases consumption slack. Conversely, demand response can reduce consumption slack when combined with a household's conscious saving. Other findings indicate that in evaluating saving performance, it is necessary to refer to consumption slack rather than to households' self-evaluation or the observed total amount of consumption.

**[Keywords]:** Energy saving; Electricity; Stochastic frontier model; Demand response; Consumer behavior

**[JEL Classification]:** D1, M2, L9, Q4

### 1. Introduction

In the area of consumer behavior research, the electricity saving behavior of households has been an important issue. Based on implications obtained from research, policy makers have proposed various incentives to encourage households to save electricity, including demand response schemes such as peak-pricing systems and information feedback. At the same time, there has been a growing trend among consumers to save electricity voluntarily, due in large part to increased environmental consciousness or consumers' awareness of themselves as members of society. A good example of voluntary saving by consumers is the case of what happened in the aftermath of the Great East Japan Earthquake of 2011, when nuclear electricity generation was greatly reduced by damage to nuclear plants caused by the disaster. In the wake of the nuclear shutdown, there was voluntary and united movement to save electricity not only among business entities but also among households in Japan. Moreover, even after the worst of the electricity crisis had passed, many Japanese households continued to maintain the lower levels of consumption to which they had become accustomed during the energy crisis. Thus, energy saving behavior can be motivated both by external incentives such as demand response schemes in the form of price systems, information feedback, and internal incentives such as a saving consciousness or awareness of limitations.

However, room for reducing electricity consumption can differ according to households' characteristics and lifestyle, since these factors affect the minimum necessary amount of electricity households require. A house with more rooms, more family members, and more appliances naturally needs more electricity. The electricity required by a household where family members habitually stay home in the daytime exceeds that of a household where all family members go out. Nevertheless, previous studies, such as those by Dianshu et al. (2010), Ek and Soderholm (2010), and Gronhoj and Thogersen (2011), have overlooked the difference in the minimum necessary consumption of electricity among households and have focused simply on the total amount of electricity consumption observed. As far as we know, no studies have identified electricity consumption as the sum of the minimum necessary amount which cannot be reduced for electricity saving and the amount which can be reduced to achieve more efficient consumption.

The purpose of this study is to investigate the effects of internal and external incentives for households to save electricity consumption, while considering the difference in the minimum necessary amount of electricity among households. This paper makes three contributions to the existing literature.

Our first contribution is that we consider the difference in room for saving electricity among households by labeling in this paper the reducible amount of electricity consumption as "consumption slack," which we separate from the minimum necessary amount of consumption which cannot be reduced for energy saving. Although the minimum necessary amount of electricity can differ depending on households' characteristics, most previous studies simply refer to the observed amount of total electricity consumption when they discuss policies for electricity saving, instead of recognizing that the observed amount includes not only reducible consumption but also necessary consumption. Thus, they rarely consider that the effort levels to be achieved for saving are different among households depending on certain characteristics. For example, Dianshu et al. (2010) and Wang et al. (2011) implicitly assume that all electricity consumption can be classified as reducible consumption, since they do not consider that there can be necessary consumption for households to subsist. In contrast, Thogersen and Gronhoj (2010) consider that electricity consumption is determined by the physical characteristics of a house, an approach which excludes the idea that there can be extra consumption arising from the family's intention and attitude regarding efforts to save electricity.

Second, we use the stochastic frontier model because it enables us to identify electricity consumption over and above what is necessary. While the stochastic frontier model is frequently used in the area of productivity analysis, it has not been applied to other areas, such as consumer behavior. Thus, we contribute to the area of consumer behavior research by introducing this new methodology to examine the above-mentioned two types of consumption, and we contribute to the area of stochastic frontier methodology by showing its application to cases in other fields.

Last, we empirically examine which of the internal or external incentives are more effective for households. Previous studies mostly investigate either internal or external incentives. For example, Momani et al. (2009), Gronhoj and Thogersen (2011), and Karjalainen (2011) focus on external policies such as daylight saving time (DST) and information feedback about electricity consumption, environmental costs, proportion of consumption by appliance, and historical comparison. On the contrary, Dianshu et al. (2010) and Wang et al. (2011) investigate mainly internal incentives such as intention and the attitude toward saving electricity. The effects of internal and external incentives are rarely compared, except for in a few studies such as Ek and Soderholm (2010), who, however, do not consider the differences arising from household characteristics.

This paper consists of five parts after the introduction. Section 2 reviews previous studies on saving electricity. Section 3 explains the theoretical background of our model and shows the empirical model. Section 4 explains the data and variables used in the estimation. Section 5 shows the estimation results. Section 6 summarizes the main conclusions.

## 2. Previous Studies

So far, there has been no research examining consumption slack separated from necessary consumption by using the stochastic frontier model to determine the relationship or to compare the effects of internal and external incentives on households' electricity saving behavior. Table 1 shows previous studies on consumer electricity-saving behavior, with a special focus on empirical studies.

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Table 1

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Previous studies have certain common characteristics. First, they investigate various determinants such as demand response[1] (DR) including price systems, saving time policies, energy efficiency labels and standards for products, environmental attitudes, social interaction, and physical aspects of houses, though they rarely categorize these factors into external or internal incentives or compare their effects on electricity saving behavior. For example, Faruqui and George (2005), Herter et al (2007), Momani et al. (2009), Herter and Wayland (2010), Faruqui and Sergici (2011), Gronhoj and Thogersen (2011), Karjalainen (2011), Ida et al. (2013), Faruqui et al. (2014), and Jessoe and Rapson (2014) focus on external incentives, such as demand response in the form of time of use (TOU), critical peak pricing (CPP), and variable peak pricing (VPP), information feedback about consumption, historical data, consultation, and saving time policy. Some studies, such as Dianshu et al. (2010), Ek and Soderholm (2010), Thogersen and Gronhoj (2010), and Wang et al. (2011), investigate internal incentives such as intention, attitude, and subjective norms for saving energy, in addition to external incentives, though most of these rarely examine the relationship between these two types of incentives or determine which type is more effective on electricity saving behavior.

The second common characteristic of previous studies is that they neglect to identify the irreducible and reducible consumption of electricity. The studies mentioned above all examine the total electricity consumption observed in experiments, instead of breaking it into the irreducible and reducible amounts of electricity consumption. Even when households consume the same amount of electricity, the consumption slack to be reduced is different among these households, since the minimum necessary amount to subsist differs according to households' physical aspects. Thus, there is a need for studies identifying the above-mentioned two types of consumption.

The third common characteristic of previous studies is that they use the logit/probit model or OLS estimation for analysis or speculate based on descriptive statistics of questionnaires. For example, Momani et al. (2009) summarize the descriptive statistics of a survey of residential and commercial sectors in Jordan. Similarly, Dianshu et al. (2010) examine survey questionnaires from 615 households in 14 cities in China based on descriptive statistics. Gronhoj and Thogersen (2011) and Karjalainen (2011) also speculate based on descriptive statistics. On the other hand, Ek and Soderholm (2010) use an ordered probit model, and Wang et al. (2011) use a logit model. Faruqui and George (2005), Herter and Wayland (2010), Ida et al. (2013), and Jessoe and Rapson (2014) implement OLS estimation. Since logit/probit model, OLS estimation, or descriptive statistics cannot identify the irreducible or reducible consumption of electricity, other methodology taking into

[1] Demand response is the system of encouraging consumers to save electricity by themselves, which is commonly implemented in many countries. TOU, CPP, and VPP are the typical examples of DR. TOU applies different price systems for peak-time and off peak-time (e.g. night-time fee). CPP applies high price during an emergency such as a sharp increase in electricity demand or a system crisis. VPP is the variable CPP in which the price varies according to the crisis level.

account this identification is needed in the analysis. In our paper, we propose the application of stochastic frontier methodology.

Other common characteristics of previous studies are that they use mostly household data from specific areas (e.g. Herter et al 2007; Dianshu et al. 2010; Ek and Soderholm 2010; Herter and Wayland 2010; Thogersen and Gronhoj 2010; Faruqui and Sergici 2011) and that they derive the data from experiments and/or questionnaires (e.g. Faruqui and George 2005; Momani et al. 2009; Faruqui et al. 2014). Our paper shares these characteristics, since we obtain data from an experiment and questionnaires yielding information from households in the Keihanna area in Japan.

## 3. Model

### 3.1 Theoretical Background

In general economics, the determination model of demand ($q$) is expressed as price ($p$) and the other control vectors. However, since electricity has the aspect of a product essential for living, we consider that the total amount of electricity consumption can be the sum of an irreducible amount required regardless of price, and a reducible amount arising from consumers' wasteful use of electricity. Thus, in our paper, the total amount of electricity consumption $q$ is expressed as equation (1).

$$q = n(\boldsymbol{H})|_{p:p_L<p<p_u} + s \tag{1}$$

Equation (1) shows, under the condition that the price $p$ is within the acceptable range for households ($p_L < p < p_u$), that the total amount of electricity consumption $q$ is the sum of the minimum necessary amount of electricity of a house $n(\boldsymbol{H})$ and reducible amount called "consumption slack," expressed as $s$. We consider that the necessary amount of electricity is determined by the physical aspects of a household, shown as $\boldsymbol{H}$. For example, a house with more rooms, more appliances, and more family members requires more electricity by nature. These physical aspects are difficult to change, or at least would require great cost for the household to change. Thus, assuming that the household maintains its current lifestyle, $n(\boldsymbol{H})$ is interpreted as fixed cost. As this $n(\boldsymbol{H})$ cannot easily or soon be changed by a household, this would be interpreted as a mid- or long-run aspect in electricity saving behavior.

On the other hand, consumption slack, $s$, is determined by a household's level of effort to save electricity, expressed as $e$ ($e \geq 0$). Therefore, this $s$ is considered a short-run aspect in electricity saving behavior. That is, $s$ is expressed as equation (2).

$$s = s(e) \tag{2}$$

$s(e)$ is a decreasing function of $e$, and $s(e) \geq 0$.

Moreover, $e$ is determined at the level maximizing a household's utility, as shown in equation (3).

$$\max_{e} u = r(e) - c(e) \tag{3}$$

In equation (3), the level of effort to save electricity $e$ is determined to maximize the utility, defined as the difference between the reward from electricity saving shown as $r(e)$ and the cost of saving electricity shown as $c(e)$. $r(e)$ is an increasing function of $e$, which means that more efforts result in more utility. This $r(e)$ means that, for example, by saving electricity, a household can reduce its electricity expenses. In contrast, $c(e)$ includes the negative feelings arising from having to pay attention to saving electricity, for example, by diligently switching off lights.

Meanwhile, the utility maximization in equation (3) relies on various conditions related to a household's environment and intention, such as the existence of price policy or consciousness of energy saving. Thus, the level of $e$ is determined on the premise of these surrounding conditions. The conditions are categorized into two types: (i) internal incentives and (ii) external incentives. Internal incentives include environmental consciousness and the awareness of being a member of society. For example, people who are educated that too much electricity consumption hurts the global environment can be habitually vigilant about electricity consumption. External incentives include demand response such as peak-time price system and information feedback. We assume that price, considered to be the main and the most important factor for demand in general economics, is one of the external incentives influencing a household's level of effort, and there are other incentives to be considered. Thus, the situation of utility maximization is shown in Figure 1.

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Figure 1

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In Figure 1, $\boldsymbol{I}$ is the vector of internal incentives and $\boldsymbol{E}$ is the vector of external incentives. When the value of ($\boldsymbol{I}$, $\boldsymbol{E}$) is ($\boldsymbol{I_1}$, $\boldsymbol{E_1}$), the functions of $r(e)$ and $c(e)$ are determined as $r_1(e)$ and $c_1(e)$, respectively. Similarly, when the value of ($\boldsymbol{I}$, $\boldsymbol{E}$) is ($\boldsymbol{I_2}$, $\boldsymbol{E_2}$), the functions are expressed as $r_2(e)$ and $c_2(e)$. For simplicity, we depict $c(e)$ as a linear function in Figure 1, but the discussion here can also be applied for the other functional forms. Since the maximized level of $e$ is the point at which the difference between $r(e)$ and $c(e)$ is maximized, the optimal effort level is $e_1^*$ when the value of ($\boldsymbol{I}$, $\boldsymbol{E}$) is ($\boldsymbol{I_1}$, $\boldsymbol{E_1}$) and $e_2^*$ when the value of ($\boldsymbol{I}$, $\boldsymbol{E}$) is ($\boldsymbol{I_2}$, $\boldsymbol{E_2}$). The maximized utility is $u_1^*$ and $u_2^*$, respectively. This means that there is an individual optimized effort level shown as $e^*$ according to each value of the vectors ($\boldsymbol{I}$, $\boldsymbol{E}$) and that whichever $e^*$ is chosen in reality depends on the realized value of these condition vectors.

Therefore, a household's utility is maximized by $e$ after the condition factors ($\boldsymbol{I}$, $\boldsymbol{E}$) are determined. This means that $e$ is a function of ($\boldsymbol{I}$, $\boldsymbol{E}$), as shown in equation (4).

$$e = e(\boldsymbol{I}, \boldsymbol{E}) \tag{4}$$

Substituting equation (4) into equation (2) generates equation (5).

$$s = s(\boldsymbol{I}, \boldsymbol{E}) \tag{5}$$

Substituting equation (5) into equation (1) generates equation (6).

$$q = n(\boldsymbol{H})|_{p:p_L<p<p_u} + s(\boldsymbol{I}, \boldsymbol{E}) \tag{6}$$

Equation (6) shows that the demand $q$ can be deconstructed into necessary consumption in physical aspects $n(\boldsymbol{H})$ and consumption slack $s(\boldsymbol{I}, \boldsymbol{E})$.

### 3.2 Empirical Model

In this section, based on the previous discussion, we specify the empirical model on electricity consumption. Based on equation (6), we specify the empirical model as equation (7).

$$lnq = \beta_0 + \sum_k \beta_k H_k + s + \varepsilon,$$

$$\begin{aligned} where \quad & q: total\ electricity\ consumption, \\ & H_k: physical\ aspects\ of\ household, \\ & \quad k = floor, family, air, refrig, daytime, \\ & \quad\quad age, type, led, \\ & s: consumption\ slack\ (efficiency\ term), \end{aligned}$$

$$\varepsilon: error\ term. \tag{7}$$

In this equation, the error term, ε, follows the normal distribution $N(0, \sigma_\varepsilon^2)$. We consider the minimum necessary amount of electricity to be determined by the physical aspects of a household, which include housing facilities and family characteristics. These are the factors which a household cannot change without any alteration of their current lifestyle. Among the physical aspects of households, $H_{floor}$ is floor size in the house, $H_{family}$ is the number of people in the family, $H_{air}$ is the number of air conditioners in the house, $H_{refrig}$ is the number of refrigerators in the house, $H_{daytime}$ is the number of people at home in the daytime, $H_{age}$ is house age, $H_{type}$ is house type, and $H_{led}$ is LED use for lighting. $s$ is consumption slack following truncated normal distribution $Nt(\boldsymbol{A'X}, \sigma_\mu^2)$. $s$ is specified as follows.

$$s = \alpha_0 + \sum_l \gamma_l I_l + \sum_m \delta_m E_m + \theta_{conDR} I_{con} E_{DR} + \epsilon,$$

$$\begin{aligned} where \quad & I: internal\ incentives, \\ & \quad l = con, att, will, \\ & E: external\ incentives, \\ & \quad m = DR, notice, graph, \\ & \epsilon: \text{error term.} \end{aligned} \tag{8}$$

As for internal incentives, we consider the following three types: (i) consciousness of saving energy ($I_{con}$), (ii) attitude toward real action ($I_{att}$), and (iii) willingness to save electricity ($I_{will}$). Concretely, $I_{att}$ is proxied by attitude toward renovation of the house, which is considered to relate with real action for saving.

As for external incentives, we also consider the following two types: (i) demand response (DR) scheme and (ii) information feedback. $E_{DR}$ is the variable expressing the DR scheme, that is, the number of days on which the household is under the DR scheme. $E_{notice}$ and $E_{graph}$ are the variables expressing information feedback. $E_{notice}$ is the frequency of checking the demand information, and $E_{graph}$ is the frequency of checking the graph of electricity consumption. Moreover, in order to clarify the relationship between internal and external incentives, we generate the cross terms of $I_{con}$ and $E_{DR}$, $I_{con}E_{DR}$. The cross-terms of these variables are used to test whether or not these incentives jointly contribute to households' saving on electricity consumption.

We apply the stochastic frontier model for the system of equations (7) and (8). Originally, the stochastic frontier model was used in the area of efficiency and productivity analysis. It estimates the theoretically-derived frontier, that is, the set of levels which actors (mostly firms) can achieve when they operate most efficiently. This frontier is defined as production or cost function, based on economic theory. And the distance of the observed production or cost level from the frontier is defined as inefficiency. Therefore, the stochastic frontier model identifies inefficiency and the frontier from the observed production or cost level.

Applying this model to our case, the frontier is defined as the minimum necessary amounts of electricity for households, as these have in common that they express the resources actors require to maintain their lives even when they operate most efficiently. Consumption slack is an analogy for inefficiency, since both signify resources arising from wasteful use that can be reduced.

For the estimation, equations (7) and (8) are estimated simultaneously by the maximum likelihood method.

## 4. Data and Variables

The data for the estimation is obtained from a project named *Experimental Project for Energy and Social Systems for the Future Generation in Keihanna Eco City*. This project was organized by the city, electric companies, related private companies, and research institutes in order to conduct social experiments regarding energy optimization in the area of Kyoto, Japan. We obtained summer-time experimental data from July 23th to September 28th in 2012. The data consists of observed households' electricity consumption, the characteristics and profiles of households, and the questionnaires implemented at the end of the experiment. Some data, such as on electricity consumed, temperature of individual days, and the various actions of households during the experiment are panel data, while some data related to questionnaires and the characteristics of households are cross-section data. We transformed panel data into cross-section data through aggregating the data by household. As a result, our data consists of the cross-section data of 561 households in the summer of 2012.

In the experiment, each household is categorized into Groups A, B, C, or D, respectively, according to the treatment of the demand response (DR) scheme. Group A is the control group, which is provided information monthly on electricity consumption in the previous period through a web page but is precluded from any DR scheme. Group B is the treatment group, which is notified monthly of information on electricity consumption in the previous period but is precluded from any DR scheme. The difference between Groups A and B is whether there is notification of information about electricity consumption from the previous period. Groups C and D are treated as the same in the summer-time experiment, that is, the treatment group which is provided information on electricity consumption in 30 minute-units as a graph on a web page, and subject to two types of DR, TOU and CPP.

The definitions and the summary statistics of the variables are shown in Table 2.

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Table 2

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$q$ is the total amount of electricity consumption in the experimental period, which is the observed data obtained by the experiment. The other data are obtained by questionnaires. $H_{floor}$ is floor size in the house, $H_{family}$ is the number of people in the family, $H_{air}$ is the number of air conditioners in the house, $H_{refrig}$ is the number of refrigerators in the house, $H_{daytime}$ is the number of residents at home in the daytime, and $H_{age}$ is house age. $H_{type}$ is the dummy of house type which takes a value of one if the house is detached, otherwise zero. $H_{led}$ is the dummy of LED use which takes a value of one if the house uses mainly LED for lighting, otherwise zero. $H_{floor}$ and $H_{age}$ are category variables which take higher value when the floor size becomes larger and the house becomes older, respectively.

The data for internal incentives are also obtained by questionnaires. $I_{con}$ is the consciousness of saving energy, $I_{att}$ is intention to renovate the house, and $I_{will}$ is willingness to save energy. $I_{con}$, $I_{att}$, and $I_{will}$ are category variables which take higher value when the consciousness, the attitude for real action, and the willingness become higher, respectively.

The data for external incentives are obtained from the experiment. $E_{DR}$ is the number of days on which the household is under DR (TOU or CPP). $E_{notice}$ and $E_{graph}$ are the variables related to information feedback. $E_{notice}$ is the frequency of the household's checking the demand information. $E_{graph}$ is the frequency of the household's checking the graph of electricity consumption. $E_{DR}$ and $E_{graph}$ take an integer value only for Groups C and D, while they take zero for Groups A and B, since the demand response and the information feedback by graph are implemented only for Groups C and D. $E_{notice}$ takes an integer value only for Group B, otherwise zero. This means that the base group is Group A, which is provided information in the simplest way. Hence, $E_{notice}$ expresses the difference between notification and simple feedback through a web page, and $E_{graph}$ expresses the difference of more frequent feedback and visualization by graph.

The variables of $PFM_{self}$, $PFM_{savecon}$, and $PFM_{saveact}$ are not included in the estimation of equations (7) and (8) but are used in the analysis after the estimation to see the relationship between consumption slack and the other evaluation measures of the saving performance of a household. $PFM_{self}$ is the monthly average of self-evaluation for energy saving performance in a day. $PFM_{savecon}$ is the household's self-recognition of room for saving energy. $PFM_{saveact}$ is the household's self-recognition of the extent to which they act to save energy. These data are obtained from the questionnaires implemented after the summer experiment.

## 5. Estimation Results

### 5.1 Results of the Stochastic Frontier Model

The estimation results are shown in Table 3.

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Table 3

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The upper part shows the result of equation (7) which has $lnq$ as a dependent variable. The lower part shows the result of equation (8) which has electricity consumption slack, $s$, as a dependent variable. As we stated before, these two equations are simultaneously estimated, and we show six cases from Case 1 to Case 6 according to the explanatory variables included.

These estimation results seem to be reasonable for several reasons. First, most variables show the expected signs and they are consistent among different cases. For example, the coefficients of $H_{family}$, $H_{air}$, $H_{refrig}$, and $H_{daytime}$ are positive, showing that as a family becomes larger and a household has more air conditioners and refrigerators, more electricity is needed. We estimated more cases in addition to those shown in Table 3 in order to check the robustness of the main variables. Obtained results are similar to the results shown in Table 3. Second, the magnitudes of coefficients of the variables are also consistent among these cases. Third, the value of the Wald chi-squares is large enough. This means that the results have significant importance to explain electricity consumption. Fourth, we estimated the same models but with different estimation methods in order to test our data specification (i.e. cross-section data of each household vs. panel data of each household plus time difference). That is, we also apply the random effect model for the panel data and compared with the results shown in Table 3. We concluded that the results achieved by using the cross-section model shown in Table 3 reflect the attitudes and the actions of households more properly than by using the panel data model. Since $\boldsymbol{H}$ and $\boldsymbol{I}$ are the cross-section variables whose data were obtained by the questionnaires implemented after the experiment, the time-varying variables are only $\boldsymbol{E}$ and $q$, whose data had been obtained continually during the experiment. The combination of these variables in the estimation generates a large time-gap between real actions and the recognition after the experiment by households, and this leads to results which cannot be reasonably interpreted. Hence, we decided to use the data as a cross section by summing $\boldsymbol{E}$ and $q$ as the total amount in the experimental period. Thus, we will proceed to discuss the results in Table 3, focusing mainly on the significant variables.

The upper part showing the result of equation (7) is mostly reasonable. The fact that the coefficients of $H_{floor}$, $H_{family}$, $H_{air}$, $H_{refrig}$, $H_{daytime}$, and $H_{type}$ are positive indicates that, as the household becomes larger or has more air conditioners or refrigerators, the more people stay at home in the daytime, or the house is detached or has larger floor, more electricity is required to maintain the household's lifestyle. These results are consistent with Thogersen and Gronhoj (2010), showing that larger households consume more electricity, and Faruqui and George (2005), suggesting that household characteristics are important in electricity consumption. In contrast, since the coefficient of $H_{age}$ is negative, an older house requires less electricity to be maintained. This might be because newer houses tend to have more electric facilities and thus require more electricity. However, $H_{led}$ is not significant.

Focusing on the lower part (i.e. consumption slack) showing the result of equation (8), the important results are the following three: (i) the consciousness of households to save is more important than external incentives such as demand response and information feedback, (ii) without the consciousness of households, demand response alone increases consumption slack, and (iii) demand response can reduce consumption slack when combined with the saving consciousness of households.

First, as the coefficient of $I_{con}$ is negative with statistical significance, the consciousness to save energy surely reduces consumption slack. This suggests that the media and advertisements to establish a social atmosphere conducive to saving electricity might constitute good policy which can truly influence the individual's consciousness to save. In fact, in the electricity crisis occurring as a result of the Great East Japan Earthquake in 2011, the government, through nationwide TV commercials and various other advertising venues, widely publicized the necessity of saving electricity, and consumers willingly complied. Similarly, the willingness to save energy shown as $I_{will}$ tends to reduce consumption slack, but the coefficient is not significant. This might mean that the consciousness for electricity consumption works enough for reducing slack, even when a household has no overt will to save electricity.

Second, the result that the coefficient of $I_{att}$ is positive is not consistent with our expectation. We expected that households whose attitudes for saving energy are more firmly established tend to have less consumption slack. The possible reason might be that this variable does not accurately proxy the household's attitude for saving electricity. We assumed that the intention to renovate houses is positively related to this attitude, but our result of $I_{att}$ might indicate that this assumption is not correct. Thus, apart from the proxy function of the household's saving attitude, the coefficient of $I_{att}$ can be simply interpreted as the fact that households with the intention to renovate their houses tend to consume extra electricity. That might be because households interested in renovating their houses tend to lean on the facilities rather than on their own efforts for saving energy and hence their consumption outweighs the saved amount. However, the minimum necessary amount of electricity can be reduced by renovation, an issue that needs to be addressed in future studies.

Third, as the coefficient of $E_{DR}$ is positive with statistical significance, the results suggest that the demand response scheme alone is not effective to bring about electricity saving by households. Previous studies such as Faruqui and George (2005), Herter et al (2007), and Jessoe and Rapson (2014) have shown that DR can reduce electricity consumption, a result not consistent with ours. However, Herter and Wayland (2010) suggest that DR has the rebound effect of inducing excess consumption after DR implementation time, during which households have tried to reduce their electricity consumption. Based on their discussion, our result that DR can increase consumption slack during the season as a whole seems to be reasonable.

Fourth, as the coefficient of $I_{con}E_{DR}$ is negative with statistical significance, demand response can reduce consumption slack when combined with $I_{con}$. This might be because the rebound effect mentioned above can be weakened by the consciousness of a household. Thus, our result suggests the importance of the consciousness of households for saving electricity. Without such consciousness, demand response does not work effectively but rather induces the rebound effect of excess consumption.

The fact that $E_{notice}$ and $E_{graph}$ are not significant suggests that the notification of information about the amount consumed and the visualization of information by 30-minute interval result in the same effect as the simple monthly information feedback.

### 5.2 Consumption Slack and the Other Measures for Saving Performance

We analyzed the relationship between consumption slack and the other measures for the evaluation of electricity saving performance by checking the correlations between them. The result is shown in Table 4.

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Table 4

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In Table 4, $s_1$, $s_2$, $s_3$, $s_4$, $s_5$ and $s_6$ are consumption slack calculated based respectively on Case 1, 2, 3, 4, 5 and 6 in Table 3. The most important implication is that we should evaluate the household's saving performance based on consumption slack rather than self-evaluation by the household or the observed amount of total electricity consumption, since these do not fully explain the reducible consumption. First, there seems to be no clear correlation between each consumption slack and $PFM_{self}$ or $PFM_{saveact.}$ This suggests that, even when households consider that they save electricity effectively, from the perspective of consumption slack, there is still much room for more saving. Similarly, as the correlation between consumption slack and $PFM_{savecon}$ is very low, the room for saving recognized by households themselves does not necessarily correspond to consumption slack. Thus, consultation based on consumption slack objectively calculated might be a good policy for the proper recognition of room for saving by households. Moreover, the relationship between consumption slack and the total amount of consumed electricity is also ambiguous, since the correlation is only about 0.378 at most. Thus, focusing on the observed amount of total consumption can lead to misinterpretation of the saving performance of households.

## 6. Conclusions

We investigated the effects of internal and external incentives for households to save electricity while considering the difference in the minimum necessary amount of electricity among households. Using data of 561 Japanese households in 2012 in the analysis of the stochastic frontier model, we obtained the following results. First, as the household becomes larger or has more air conditioners or refrigerators, the more people stay at home in the daytime, or the house is detached or has larger floor, more electricity is required to maintain the household’s lifestyle. In contrast, an older house requires less electricity to be maintained.

Second, the consciousness of a household is more important than external incentives such as demand response and information feedback. Without the saving consciousness of a household, demand response alone increases consumption slack. This might be because households try to reduce their electricity consumption during DR time but consume more electricity on the rebound after DR time. However, demand response can reduce consumption slack when combined with the saving consciousness of a household. In contrast, households who are willing to renovate their houses tend to consume extra electricity. This might suggest that households interested in renovating their houses tend to lean on the facilities rather than on their own efforts to save energy and hence their consumption outweighs the saved amount.

Third, in evaluating performance in saving electricity, we should observe consumption slack rather than households’ self-evaluation or the observed total amount of consumption. Even when households consider they save electricity effectively, from the perspective of consumption slack, there is still much room for saving. In addition, focusing on the observed amount of total consumption can lead to misinterpretation of the saving performance of households.

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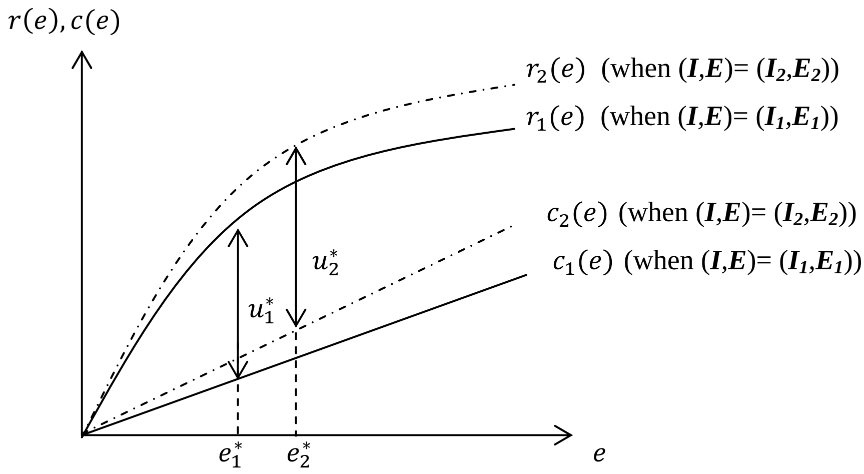


Figure 1 Utility Maximization under Internal and External Incentives

Table 1 Previous Empirical Studies

| Study (Year) | Sample, Data, and Method | Results or Determinants of Electricity Saving |
|---|---|---|
| Faruqui and George (2005) | Sample: Households and business entities in California<br>Data: Experimental data<br>Method: OLS | Determinants: Demand response (time of use (TOU) and critical peak pricing (CPP)), household characteristics, weather |
| Herter et al (2007) | Sample: Households data from 2003 to 2004<br>Data: Experimental data<br>Method: Descriptive statistics | Determinants: Critical peak pricing, weather, income, automatic facilities to save electricity at home |
| Momani et al. (2009) | Sample: Residential and commercial sectors in Jordan<br>Data: Survey questionnaire<br>Method: Descriptive statistics | Determinants: Daylight saving time (DST) |
| Dianshu et al. (2010) | Sample: 615 Chinese households in 14 cities within Liaoning Province in 2008<br>Data: Survey questionnaire<br>Method: Descriptive statistics of survey for households and interviews to the government and relevant officials | Results: 55 % of the sample households have the intention to save electricity. Government's policy needs to be modified to overcome the distrust in energy efficiency labels and product standards. |
| Ek and Soderholm (2010) | Sample: Swedish household<br>Data: 1200 questionnaires by postal survey<br>Method: Ordered probit model (Dep.Vars.: Laundry service, lightning, heating, hot water use) | Determinants: Costs, environmental attitudes, social interactions, concrete and specific information about available savings |
| Herter and Wayland (2010) | Sample: 483 households in California<br>Data: Experimental data<br>Method: OLS | Determinants: Critical peak pricing |
| Thogersen and Gronhoj (2010) | Sample: 312 Danish households in 2007<br>Data: Survey and experiment<br>Method: Structural model | Determinants: Home size, household size, teenagers, behavior, other's behavior, perceived impediments, self-efficacy |
| Faruqui and Sergici (2011) | Sample: Baltimore households in 2008 and 2009<br>Data: Experimental data<br>Method: SUR | Determinants: Demand response (dynamic peak pricing, peak time rebate high, peak time rebate low) |
| Gronhoj and Thogersen (2011) | Sample: 20 Danish households for 5 month<br>Data: Qualitative interviews to the households<br>Method: Descriptive statistics | Determinants: Detailed feedback about the electricity consumption |
| Karjalainen (2011) | Sample: 14 households in Finland<br>Data: Qualitative interviews to the households<br>Method: Descriptive statistics | Determinants: Feedback on energy consumption (especially, presentations of costs, proportion of consumption by appliance, and historical comparison) |
| Wang et al. (2011) | Sample: 816 randomly selected households in China<br>Data: Survey questionnaire<br>Method: Logit model | Determinants: Attitude (environmental awareness and information), subjective norms (policy and social norms and social interaction), residue effect (past experience), perceived behavioral |

| | | |
|---|---|---|
| | | control (economic benefits, perceived inconvenience), and demographic variable |
| Ida et al. (2013) | Sample: Japanese households<br>Data: Experimental data and survey<br>Method: OLS | Determinants: Demand response (time of use (TOU), critical peak pricing (CPP)) |
| Faruqui et al. (2014) | Sample: Households and small business entities in Connecticut<br>Data: Experimental data in 2009<br>Method: SUR | Determinants: Demand response (time of use (TOU), critical peak pricing (CPP), and variable peak pricing (VPP)) |
| Jessoe and Rapson (2014) | Sample: Households in Connecticut<br>Data: Experimental data in 2011<br>Method: OLS, 2SLS | Determinants: in-home display (IHD) and demand response |

Table 2 Summary Statistics

| Variable | Definition | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| $q$ | Total amount of electricity consumption in the experimental period (kWh) | 561 | 932.866 | 451.645 | 107.300 | 2756.200 |
| $H_{floor}$ | Floor size in the house (category variable) | 561 | 4.301 | 1.076 | 1.000 | 7.000 |
| $H_{family}$ | The number of people in the family | 561 | 3.152 | 1.204 | 0.000 | 7.000 |
| $H_{air}$ | The number of air conditioners in the house | 561 | 3.565 | 1.704 | 0.000 | 10.000 |
| $H_{refrig}$ | The number of refrigerators in the house | 561 | 1.130 | 0.430 | 0.000 | 3.000 |
| $H_{daytime}$ | The number of residents at home in the daytime | 561 | 1.326 | 0.959 | 0.000 | 4.000 |
| $H_{age}$ | House age (category variable) | 561 | 3.178 | 1.619 | 1.000 | 6.000 |
| $H_{type}$ | Dummy of hose type (detached house=1, otherwise=0) | 561 | 0.754 | 0.431 | 0.000 | 1.000 |
| $H_{led}$ | Dummy of LED (house using mainly LED=1, otherwise=0) | 561 | 0.109 | 0.312 | 0.000 | 1.000 |
| $I_{con}$ | Consciousness of saving energy (category variable) | 561 | 2.863 | 0.903 | 1.000 | 4.000 |
| $I_{att}$ | Intention to renovate the house (category variable) | 561 | 2.800 | 1.415 | 1.000 | 5.000 |
| $I_{will}$ | Willingness to save energy (category variable) | 561 | 4.301 | 0.589 | 2.000 | 5.000 |
| $E_{DR}$ | The number of days in which the household is under DR (takes an integer number only for Groups C and D, otherwise 0) | 561 | 22.620 | 20.709 | 0.000 | 46.000 |
| $E_{notice}$ | The frequency of checking demand information (takes an integer number only for Group B, otherwise 0) | 561 | 6.016 | 17.752 | 0.000 | 148.000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| $E_{graph}$ | The frequency of checking graph of electricity consumption (takes an integer number only for Groups C and D, otherwise 0) | 561 | 69.111 | 111.995 | 0.000 | 1354.000 |
| $I_{con}E_{DR}$ | Cross term of $I_{con}$ and $E_{DR}$ | 561 | 64.332 | 65.463 | 0.000 | 184.000 |
| $PFM_{self}$ | Monthly average of self-evaluation for electricity saving performance in a day (average of category variable) | 133 | 2.072 | 0.507 | 0.222 | 3.000 |
| $PFM_{savecon}$ | Self-recognition of room for saving energy (category variable) | 561 | 1.957 | 0.487 | 1.000 | 3.000 |
| $PFM_{saveact}$ | Self-recognition of actions for saving energy (category variable) | 558 | 3.771 | 0.730 | 1.000 | 5.000 |

Table 3 Estimation Results

| Dependent | Explanatory | Case 1 | | | Case 2 | | | Case 3 | | | Case 4 | | | Case 5 | | | Case 6 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Variable | Coef. | | Std. Error | Coef. | | Std. Error | Coef. | | Std. Error | Coef. | | Std. Error | Coef. | | Std. Error | Coef. | | Std. Error |
| | $H_{floor}$ | 0.032 | * | (0.019) | 0.031 | | (0.019) | | | | | | | 0.032 | * | (0.019) | 0.033 | * | (0.020) |
| | $H_{family}$ | 0.093 | *** | (0.014) | 0.093 | *** | (0.014) | 0.094 | *** | (0.014) | 0.094 | *** | (0.014) | 0.093 | *** | (0.014) | 0.097 | *** | (0.014) |
| | $H_{air}$ | 0.061 | *** | (0.013) | 0.061 | *** | (0.013) | 0.065 | *** | (0.012) | 0.065 | *** | (0.012) | 0.060 | *** | (0.013) | 0.068 | *** | (0.013) |
| | $H_{refrig}$ | 0.127 | *** | (0.043) | 0.126 | *** | (0.043) | 0.130 | *** | (0.043) | 0.131 | *** | (0.043) | 0.131 | *** | (0.043) | 0.113 | *** | (0.044) |
| *lnq* | $H_{daytime}$ | 0.051 | *** | (0.017) | 0.051 | *** | (0.017) | 0.053 | *** | (0.017) | 0.054 | *** | (0.017) | 0.050 | *** | (0.017) | 0.047 | *** | (0.017) |
| | $H_{age}$ | -0.022 | ** | (0.011) | -0.022 | ** | (0.011) | -0.020 | * | (0.011) | -0.020 | * | (0.011) | -0.021 | ** | (0.011) | -0.014 | | (0.010) |
| | $H_{type}$ | 0.199 | *** | (0.048) | 0.201 | *** | (0.048) | 0.235 | *** | (0.043) | 0.235 | *** | (0.043) | 0.199 | *** | (0.048) | 0.207 | *** | (0.048) |
| | $H_{led}$ | 0.035 | | (0.053) | 0.028 | | (0.052) | | | | | | | 0.034 | | (0.052) | 0.029 | | (0.053) |
| | *constant* | 5.136 | | (49.485) | 5.193 | | (66.776) | 5.212 | | (53.235) | 5.174 | | (54.846) | 5.212 | | (73.199) | 5.092 | | (158.409) |
| | $I_{con}$ | -0.052 | * | (0.027) | -0.057 | ** | (0.027) | -0.059 | ** | (0.027) | -0.055 | ** | (0.027) | -0.051 | * | (0.027) | | | |
| | $I_{att}$ | 0.042 | *** | (0.012) | 0.042 | *** | (0.012) | 0.042 | *** | (0.012) | 0.042 | *** | (0.012) | 0.042 | *** | (0.012) | | | |
| | $I_{will}$ | -0.037 | | (0.029) | | | | | | | -0.034 | | (0.029) | -0.037 | | (0.029) | | | |
| *s* | $E_{DR}$ | 0.005 | * | (0.003) | 0.004 | * | (0.003) | 0.004 | | (0.003) | 0.005 | * | (0.003) | 0.004 | * | (0.003) | 0.008 | *** | (0.002) |
| | $E_{notice}$ | 0.001 | | (0.001) | | | | | | | 0.001 | | (0.001) | | | | 0.000 | | (0.001) |
| | $E_{graph}$ | 0.000 | | (0.000) | | | | | | | 0.000 | | (0.000) | | | | 0.000 | | (0.000) |
| | $I_{con}E_{DR}$ | -0.002 | * | (0.001) | -0.002 | ** | (0.001) | -0.002 | * | (0.001) | -0.002 | * | (0.001) | -0.002 | * | (0.001) | -0.003 | *** | (0.001) |
| | *constant* | 0.838 | | (49.485) | 0.648 | | (66.776) | 0.716 | | (53.235) | 0.878 | | (54.846) | 0.763 | | (73.199) | 0.642 | | (158.409) |
| N (sample size) | | 561 | | | 561 | | | 561 | | | 561 | | | 561 | | | 561 | | |
| Wald chi-square | | 275.88 | | | 273.75 | | | 269.48 | | | 271.19 | | | 275.85 | | | 299.28 | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Log likelihood | -252.0273 | -253.48438 | -254.92415 | -253.60014 | -252.65402 | -260.71515 |

(Note) Significant at 1% (***), 5% (**) and 10% (*).

Table 4 Correlation of Measures for Saving Performance

| | $PFM_{self}$ | $PFM_{savecon}$ | $PFM_{saveact}$ | $q$ |
|---|---|---|---|---|
| $s_1$ | -0.081 | 0.205 | -0.284 | 0.343 |
| $s_2$ | -0.043 | 0.224 | -0.195 | 0.342 |
| $s_3$ | -0.039 | 0.231 | -0.199 | 0.378 |
| $s_4$ | -0.073 | 0.212 | -0.280 | 0.368 |
| $s_5$ | -0.078 | 0.206 | -0.282 | 0.321 |
| $s_6$ | 0.005 | 0.174 | -0.224 | 0.334 |
| N | 133 | 561 | 558 | 561 |

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