A Stated Preference Analysis of Smart Meters, Photovoltaic Generation, and Electric and Hybrid Vehicles in Japan, and Mechanisms to Enable Their Diffusion

Takanori Ida

Graduate School of Economics, Kyoto University,

Yoshida, Sakyoku, Kyoto 606-8501, Japan

E-mail: ida@econ.kyoto-u.ac.jp

Kayo Murakami

Tokyo City University,

3-3-1 Ushikubo-nishi, Tsuzuki-ku, Yokohama, Kanagawa 224-8551, Japan

E-mail: murakami@tcu.ac.jp

Makoto Tanaka

National Graduate Institute for Policy Studies,

7-22-1 Roppongi, Minato-ku, Tokyo 106-8677, Japan

E-mail: mtanaka@grips.ac.jp

Abstract: Recently, expectations about the deployment of smart grids have risen in Japan, making it important to investigate the diffusion process of smart equipment, such as smart meters, photovoltaic generation, and electric and hybrid vehicles. However, since the revealed preference data have not been accumulated for smart equipment diffusion, this paper conducts a conjoint analysis to examine consumers' stated preferences on the basis of an online survey administered in March 2011. A mixed logit model that allows for individual heterogeneity is adopted for estimation, and willingness-to-pay (WTP) values are calculated for the attributes. Furthermore, rates of diffusion, reduction in greenhouse gas (GHG) emissions, and interdependencies among types of smart equipment are investigated.

Keywords: smart grid, smart meter, electric vehicle, conjoint analysis

JEL Classifications: O33, Q48, Q51

1. Introduction

Awareness of global environmental problems has led to increased calls for renewable energy development and utilization. The 2011 earthquake and the ensuing Fukushima nuclear crisis have given rise to a radical reconsideration of Japanese energy policy. Given these circumstances, the development of a smart grid has raised hopes of meeting goals for climate change, cleaner energy, and safer electric systems and technology. This has led to many economic questions related to incentive policies for operators to implement such technology (Clastres, 2011).

Smart grids can be classified into two systems: the upstream power supply system and the downstream power demand system. This paper deals with the latter, specifically concerning residential demand for smart equipment to make up *smart homes*. In particular, we investigate the future diffusion of advanced or smart meters (SMs) measuring hourly electric consumption, photovoltaic (PV) generators installed on residential rooftops, clean-fuel electric vehicles (EVs), and hybrid electric vehicles (HEVs). The implementation of these technologies in Japan is imminent, and a policy governing these aspects is needed to prepare for smart home diffusion. This paper will conduct a conjoint analysis of the future diffusion of SM, PV generation (hereafter simply "PV"), EVs, and HEVs, using the results of an online survey administered in March 2011.

Let us briefly review the abovementioned smart equipment. The SM is an advanced electrical meter that records electric consumption in intervals of an hour or less, and relays information to the utility company for monitoring and billing. In European countries and in the USA, where power supply systems can be unstable and electricity shortages are common, governments have been aggressive in introducing SM infrastructure. However, in Japan, where the power supply used to be secure and stable, there had been lessened to control demand by deploying an hourly metering SM.[1] However, after the 2011 earthquake,

[1] METI (2006b) provides an international comparison of the length of accidental blackouts. In 2003, the yearly length of accidental blackout per customer was about 10 minutes, 70 minutes, and 80 minutes in Japan, UK, and the USA, respectively.

power shortages became a matter of concern, particularly at peak times in summer and winter; thus, the early deployment of SM infrastructure is now necessary. With advanced metering infrastructure, a local distribution company (LDC) can implement innovative service options, from resource adequacy requirements to GHG emissions reductions, in the following three ways: (1) two-way communication between the LDC and its customers, (2) hourly metering for time-variant dynamic pricing and demand management by the LDC and its customers, and (3) real-time billing information for the LDC's customers (Woo et al., 2008; Duke et al., 2005).

The residential PV system generates electrical power by converting solar radiation into electricity via semiconductors. Residential rooftop PV systems may emerge as a major new market once module prices fall below the critical level. The Japanese government introduced a net metering system in order to boost residential PV system deployment. However, despite the large potential market, inefficient energy pricing that does not adequately reflect its environmental externalities discourages prospective consumers from installing these systems, while the environmental externalities and resulting market failures make it difficult for manufacturers and homebuilders to obtain a sufficient return on their investment (Keirstead, 2007).

An EV uses one or more electric motors for propulsion, while an HEV combines an internal combustion engine with electric motors. A plug-in HEV (hereafter, PHEV) uses batteries that can be recharged via an external electric power source. When an EV or a PHEV is connected at home, it serves as a home battery for charging and discharging when necessary, and seasonal or daily fluctuations of renewable energy are mitigated. For example, the new Toyota Prius (a fully HEV) is now capable of charging from the grid using standard 120~240 V AC outlets.

As the full-scale deployment of smart equipment has not yet been realized, empirical revealed preference data have not been sufficiently accumulated. Therefore, we adopt a stated preference (SP) data method (or conjoint analysis) for the purposes of our study. SP data are hypothetical, and take into account certain types of market constraints useful for forecasting changes in consumer behaviors, although these may be affected by the degree of contextual realism of the respondents.[2]

The key study for our purpose is Banfi et al. (2008), which first evaluated consumers' willingness to pay (WTP) for energy-saving upgrades to residential buildings, including air renewal systems, and the insulation of windows and facades. The researchers found that respondents valued the benefits of the energy-saving attributes. The majority of recent studies that have examined the demands for energy-efficiency renovations have used choice experiments (Salder, 2003; Poorting et al., 2003; Grosche and Vance, 2009; Kwak et al., 2010; Achtnicht, 2011; Alberini et al., 2011). However, to the best of our knowledge, no conjoint analysis of SM and PV diffusion has been conducted to date.

On the other hand, many studies have conducted conjoint analysis of clean-fuel vehicles. Bunch (1993) conducted a conjoint analysis to determine how demand for clean-fuel vehicles and their fuels varied as a function of the attributes that distinguished these vehicles from their conventional gasoline counterparts.[3] Recently, Karplus (2010) found that vehicle cost could be a significant barrier to PHEV entry, unless fairly aggressive goals for reducing battery costs were met. The adoption of a low-cost PHEV could potentially reduce GHG emissions and refined oil demand. Other past studies on clean-fuel vehicles or EVs are summarized in Table 1 (cf. Hidrue et al., 2011).

<Table 1>

We administered the online conjoint survey in March 2011 (just before the earthquake)

---

[2] SP data, which can capture a broader array of preference-driven behaviors than revealed preference (RP) data, are rich in attribute tradeoff information, because wider attribute ranges can be built into experiments. On the other hand, SP data are only hypothetical and make it difficult to take into account certain types of real market constraints; hence, SP-derived models may not predict existing-specific constants well (see Louviere et al. (2000) for further details).

[3] Bunch (1993) considered clean-fuel vehicles to include both electric and unspecified liquid and gaseous fuel, vehicles.

to 649 households that planned to purchase or remodel a house within five years, and 694 households that did not plan to do so. We first estimated the SP data by using a mixed logit model allowing for individual heterogeneity, and then investigated WTP for attributes of SM, PV, EV, and HEV.

This paper contributes to the existing literature in three ways. First, we study SM and PV diffusion dynamics, which are not fully analyzed but are indispensable for smart homes. Second, unlike previous studies of EV diffusion, our study focuses mainly on the advantages of PHEV. Third, and most important, in addition to the diffusion analysis, we examine the reduction of GHG emissions due to these equipment and the interdependencies among them.

We now summarize the main conclusions obtained through our research. First, a decrease in price level is most effective for the future diffusion of smart or eco-friendly equipment, such as SM, PV, EV, and PHEV. On the other hand, GHG emission reduction effects vary among them, with PV being the most effective. Second, it is expected that GHG emissions will be substantially reduced with the increased diffusion of smart equipment. Assuming the present circumstances, the expected reductions are 4% per household for SM, 7% per household for PV, and 17% per car for PHEV. Further innovations will add to GHG emissions reductions. Third, the purchase of one form of smart equipment is associated with other smart equipment purchases; in particular, the diffusion of PV drives secondary equipment purchases to the largest extent.

This paper is organized as follows. Section 2 explains how we conducted the conjoint analysis through the online surveys and the experimental design. Section 3 describes the mixed logit model used for estimation. Section 4 discusses the current utilization and future deployment of smart equipment. Section 5 displays the estimation results and measures the WTP values of the attributes. Section 6 extends the analysis to various aspects: the expected diffusion, the reduction rate of GHG emissions, and the interdependencies among smart equipment diffusions. Section 7 concludes.

2. Survey and design

This section explains the survey method of conjoint analysis and the experimental design. The survey was conducted online with monitors who were registered with a consumer investigative company. When conducting the sampling, we considered geographical characteristics, gender, and age to be representative of an average Japanese population.

Data sampling was performed in two stages. In the first stage, in February 2011, we randomly drew 8,997 households from the monitors, asked basic demographic questions, and queried whether they planned to purchase or remodel a house within the next five years.[4] The purpose of this question was to classify the respondents according to interest, as smart equipment demand is supposed to be closely related to house purchases. A total of 1,630 households (18.1%) planned to purchase or remodel a house within the next five years, while 7,357 households (81.9%) did not.

In the second stage, in March 2011, we surveyed a random sample of 649 households (39.8%) from the 1,630 high-interest households. At the same time, we surveyed a random sample of 694 households (9.4%) from the 7,357 low-interest households. We conducted three kinds of conjoint analysis of SM, PV, EV, and HEV for these households after asking questions about their current and future usages of smart equipment. The respondents received a small remuneration for completing the questionnaire.

All surveys ended before March 11, 2011, and thus, our data are free from the influences of the earthquake. After the earthquake, confronted with the Fukushima nuclear crisis and power shortages, Japanese attitudes toward energy and environmental policy changed drastically. In this sense, we had collected the average Japanese preference for this study before the crisis, and thus, the conclusions obtained may apply to other countries with some caveats.

Next, we explain the conjoint analysis, which considers the attributes of a service or a product. If an excessive number of attributes and levels are included, respondents find it difficult to answer the questions. On the other hand, if too few are included, the description of alternatives becomes inadequate. Since the number of attributes becomes unwieldy if we

[4] Note that this classification according to the intention to purchase or remodel a house within five years may be arbitrary. We will compare these results in the following sections.

consider all possible combinations, we adopted an *orthogonal planning method* to avoid this problem (see Louviere et al., 2000, Ch. 4, for details). We thus obtained an appropriate number of questions for which the levels of attributes varied stochastically and put these questions to the respondents.

First, we explain the setup of the SM conjoint analysis. Advanced metering infrastructure measures residential or business electricity consumption on a real-time basis and enables dynamic pricing depending on peak and off-peak times. We include the visualization of electricity consumption and the remote control of the air conditioner in the advanced-metering or home EMS service. When peak time demand is cut or shifted by introducing SM, GHG emissions are expected to be reduced. After conducting several pretests, we determined the alternatives, attributes, and levels as follows.[5]

Attribute levels of the SM conjoint analysis

(1) Monthly usage charge

Levels: free, US$2, US$4, US$6 per month

(2) Visualization of electricity consumption

Levels: none, WEB display, additional private monitor display, additional energy-saving advice

(3) Off-peak discount (compared to the standard electricity charge)

Levels: none, 10%, 30%, 50%

(4) Peak surcharge (compared to the standard electricity charge)

Levels: none, double, four times, six times

(5) Remote control of air conditioner during a power shortage

Levels: none, automatic control at 82°F, temporary restriction, usage interception

(6) Reduction in GHG emissions (per household)[6]

---

[5] Note that these attributes are actually correlated with each other. We adopted the orthogonal planning method, and respondents were asked to answer the questions assuming that there is no correlation in the conjoint analysis.

[6] The GHG emission reduction for all the equipment considered in this study is only

Levels: none, 10%, 30%, 50%

Figure 1(a) displays an example of the SM conjoint questionnaire. There are three alternatives: Alternatives 1 and 2 denote different SM deployments, and Alternative 3, no SM deployment. All respondents were asked the same eight questions.

<Figure 1>

Second, we explain the setup of the PV conjoint analysis. Owners of residential rooftop PV systems reduce electricity bills by decreasing electricity consumption, and sometimes earn a profit by selling electricity to an LDC. Currently, the average initial cost to install a PV system is around US$20,000 in Japan; thus, a reduction in price is necessary for extensive diffusion. Since PV is a method of generating electrical power by converting solar radiation into direct current electricity using semiconductors that exhibit the photovoltaic effect, PV systems generate fewer GHG emissions compared to conventional forms of power generation. After conducting several pretests, we determined the alternatives, attributes, and levels as follows.

Attribute levels of the PV conjoint analysis

(1) Initial cost of introducing a PV system

Levels: US$10,000, US$15,000, US$20,000, US$25,000

(2) Annual reduction in fuel and lighting charges

Levels: 50%, 60%, 70%, 80%

(3) Reduction in GHG emissions (per household)

Levels: 30%, 40%, 50%, 60%

(4) Free inspection and maintenance period

Levels: none, 5 years, 10 years, 20 years

---

related to fossil fuel consumption, and not the so-called life-cycle analysis. Further, we assume that the fuel mix remains constant during the diffusion process.

(5) Stylishly designed PV panel
    Levels: none, additional

Figure 1(b) displays an example of the PV conjoint questionnaire. There are three alternatives: Alternatives 1 and 2 denote different PV deployments, and Alternative 3, no PV deployment. All respondents were asked the same eight questions.

Third, we explain the setups of the EV and HEV conjoint analyses. Driving a fuel-efficient EV or HEV can eliminate the cost of gasoline or other fuel, and the pollution generated is much lower than that of gasoline-fuelled vehicles. On the other hand, their price is relatively high compared to standard gasoline vehicles (at present, an additional US$5,000–10,000 for an EV, and an additional US$2,000–3,000 for an HEV), the driving range is still very limited, even on a full battery (100–150 km per charge for an EV), and it can take considerable time to find a charging station (up to 30 min). As plug-in is now optional for an HEV, a PHEV can serve as a home battery for charging or discharging, if necessary. After conducting several pretests, we determined the alternatives, attributes, and levels as follows.

Attribute levels of the EV conjoint analysis

(1) EV premium (relative to the same class of gasoline vehicle)
    Levels: none, US$3,000, US$5,000, US$10,000
(2) Annual reduction in fuel cost for the same distance covered (relative to the same class of gasoline vehicle)
    Levels: 60%, 70%, 80%, 90%
(3) Driving range on a full battery (km)
    Levels: 100 km, 200 km, 300 km, 400 km
(4) Reduction in GHG emissions (relative to the same class of gasoline vehicle)
    Levels: 70%, 80%, 90%, 100%
(5) Time to find a charging station (min)
    Levels: up to 10 min, up to 30 min

Attribute levels of the HEV conjoint analysis

(1) HEV premium (relative to the same class of gasoline vehicle)

Levels: none, US$1,000, US$3,000, US$5,000

(2) Annual reduction in fuel cost for the same the distance covered (relative to the same class of gasoline vehicle)

Levels: 20%, 40%, 60%, 80%

(3) Driving range before refueling (km)

Levels: 700 km, 1,000 km, 1,500 km, 2,000 km

(4) Reduction in GHG emissions (relative to the same class of gasoline vehicle)

Levels: 40%, 50%, 60%, 70%

(5) Home plug-in

Levels: none, additional

Figure 1(c) displays an example of the EV/HEV conjoint questionnaire. There are three alternatives, where Alternative 1, Alternative 2, and Alternative 3 denote EV, HEV, and gasoline vehicle purchases, respectively. There are sixteen questions in total, divided into two versions. All respondents were asked either version (consisting of eight questions) at random.

3. Model specification

This section describes the estimation model. Conditional logit (CL) models, which assume independent and identical distribution (IID) of random terms, have been widely used in past studies. However, independence from the irrelevant alternatives (IIA) property derived from the IID assumption of the CL model is too strict to allow flexible substitution patterns. Compared to the non-nested alternatives, a nested logit (NL) model partitions the choice set and allows alternatives to have common unobserved components, by partially relaxing strong IID assumptions. However, the NL model is not suited for our analysis because it cannot deal with the distribution of parameters at the individual level (Ben-Akiva et al., 2001). Consequently, the best model for this study is a mixed logit (ML) model, which accommodates differences in the variance of random components (unobserved heterogeneity). This model is flexible enough to overcome the limitations of CL models by allowing for random taste variation, unrestricted substitution patterns, and the correlation of random terms over time (McFadden and Train, 2000).

Assuming that parameter β_n is distributed with density function $f(\beta_n)$ (Train 2003, Louviere et al., 2000), the ML specification allows for repeated choices by each sampled decision maker in such a way that the coefficients vary by person, but are constant over each person's choice situation. The logit probability of decision maker *n* choosing alternative *i* in choice situation *t* is expressed as

$$L_{nit}(\beta_n) = \prod_{t=1}^{T} [\exp(V_{nit}(\beta_n)) / \sum_{j=1}^{J} \exp(V_{njt}(\beta_n))], \qquad (1)$$

which is the product of normal logit formulas, given parameter β_n, the observable portion of utility function V_{nit}, and alternatives $j = 1, ..., J$ in choice situations $t = 1, ..., T$. Therefore, ML choice probability is a weighted average of logit probability $L_{nit}(\beta_n)$ evaluated at parameter β_n with density function $f(\beta_n)$, which can be written as

$$P_{nit} = \int L_{nit}(\beta_n) f(\beta_n) d\beta_n . \qquad (2)$$

Accordingly, we can demonstrate variety in the parameters at the individual level using the maximum simulated likelihood (MSL) method for estimation with a set of 100 Halton draws.[7] Furthermore, since each respondent completes eight questions in the conjoint analysis, the data form a panel, and we can apply standard random effect estimation.

---

[7] Louviere et al. (2000, p. 201) suggested that 100 replications are normally sufficient for a typical problem involving five alternatives, 1,000 observations, and up to 10 attributes (also see Revelt and Train, 1998). The adoption of the Halton sequence draw (Halton, 1960) is an important issue. Bhat (2001) found that for simulating an ML model, 100 Halton sequence draws are more efficient than 1,000 random draws.

In the linear-in-parameter form, the utility function can be written as

$$U_{nit} = \gamma' x_{nit} + \beta_n' z_{nit} + \varepsilon_{nit}, \qquad (3)$$

where x_{nit} and z_{nit} denote observable variables, γ denotes a fixed parameter vector, β_n denotes a random parameter vector, and ε_{nit} denotes an independently and identically distributed extreme value (IIDEV) term.

Because ML choice probability is not expressed in closed form, simulations must be performed for the ML model estimation. Let θ denote the mean and (co-)variance of parameter density function $f(\beta_n | \theta)$. ML choice probability is approximated through the simulation method (see Train, 2003, p. 148 for details). We can also calculate the estimator of the conditional mean of random parameter s conditional on individual specific choice profile y_n (see Revelt and Train, 1998 for details), given as

$$h(\beta | y_n) = [P(y_n | \beta) f(\beta)] / \int P(y_n | \beta) f(\beta) d\beta. \qquad (4)$$

From Eq. (4), $h(\beta | y_n)$, and the conditional choice probabilities $\hat{P}_{nit}(\beta_n)$ can be calculated individually.

$$\hat{P}_{nit}(\beta_n) = \exp(V_{nit}(h(\beta | y_n)) / \sum_{j=1}^{J} \exp(V_{njt}(h(\beta | y_n))). \qquad (5)$$

After conducting three kinds of conjoint analysis, we expect that a person who has a higher preference for energy conservation is more likely to install/use various types of smart equipment, including SM, PV, EV, and HEV. As such, this conjunction leads to a positive interdependency among these choice probabilities. Letting the number of conjoint analyses be $m = 1,2,3$, given that the conditional choice probability $\hat{P}_{nit}^{M=m}$ is influenced by the other conditional choice probabilities $\hat{P}_{nit}^{M\neq m}$, the random utility function for choosing *m* can be written as

$$U_{nit}^{m} = \gamma' x_{nit} + \beta_n' z_{nit} + \gamma_n' \hat{P}_{nit}^{M\neq m}(\beta_n) + \varepsilon_{nit}. \qquad (6)$$

At this point, parameter γ_n indicates interdependencies among the smart equipment adoptions.[8] We will analyze these interdependencies with the utility function shown in Eq. (6) in Section 6.

4. Data description

This section discusses the data used for the estimation. Table 2 carries the demographic characteristics of the respondent households. The highly interested respondents who plan to purchase or remodel a house are shown to the left, households with little interest appear in the center, and the weighted average is shown in the column to the right.

<Table 2>

No remarkable differences are observed between households with high interest and those with little interest with respect to residential information, such as owned/rented and detached/apartment. There is also little difference among individual characteristics and annual electricity expenses. On the other hand, those who are married, employed, and have higher household income, appear more often in the highly interested group. These observations are intuitive.

4.1 Utilization of smart meter

Table 3(a) shows SM utilization. Remarkable differences are observed between the highly interested and the little interested households.

<Table 3>

[8] Note that this assumption of interdependency among the choice probabilities may be arbitrary, because the sequence of purchase of smart equipment influences purchase decisions differently. As explained later, we analyze the correlation and not the causality.

At present, the overall SM utilization rate is only 1% and the degree of recognition is higher for the highly interested households. The future utilization rate is only a few percent higher than the present rate and is higher for highly interested households. Value addition to advanced metering or the HEMS will increase future utilization.

At this point, we asked the respondents to rate how much emphasis they placed on added value, using a five-point scale (from "very important" to "not important at all"). The values in Table 3(a) show the sum of the ratio of respondents who replied "very important" to those who replied "quite important."

The value of both a WEB display and a private monitor display is around 45% for the weighted average, and is 10% higher for the highly interested group. The value of an energy-saving advice device, an on-peak surcharge, and an off-peak surcharge is around 50% for each, and is 15%, 10%, and 10% higher, respectively, for the highly interested. The values of an automatic air conditioner control at 82°F and of temporary restriction remain at only 25%, while that of usage interception remains at 20%, each value being 10% higher for the highly interested group. In addition, the value of reduction in GHG emissions is around 40%, and is 15% higher for the highly interested group.

Finally, when we asked the respondent households how much they wanted to pay monthly for overall service, 40% stated that they wanted to pay nothing, while some were willing to pay US$3 per month. The ratio of willing fee-payers is 10% higher for the highly interested group. Some of them were willing to pay more, at around US$5.

4.2 Utilization of residential photovoltaic generation

Table 3(b) shows the PV utilization. The overall PV utilization rate is only a few percent at present, with the degree of recognition being higher for the highly interested group. The future utilization rate moves up to 10% for the weighted average, and is higher for highly interested households. Therefore, there is a strong possibility for the future utilization of PV to increase.

Regarding the emphasis on added value, Table 3(b) shows the sum of the ratio of those who replied "very important" to those who replied "quite important." The average value of reduction in fuel and lighting charges is around 70% on average, and is 10% higher for the highly interested group. The value of selling surplus electricity is also around 70%, and is 5% higher for the highly interested group. The value of reduction in GHG emissions is around 50%, and is 15% higher for the highly interested group. Furthermore, 70% of respondents attached importance to free inspection and maintenance periods, while 45% deemed a stylishly designed PV panel as important.

Finally, when we asked the respondent households their WTP for deploying a residential PV system, 25% replied that they would rather pay nothing, while some were willing to pay US$10,000. The ratio of fee-payers is 10% higher for the highly interested group. In fact, some of them were willing to pay even higher amounts, at around US$15,000.

4.3 Utilization of electric and hybrid electric vehicles

Table 3(c) shows the utilization of EV and HEV. The overall EV utilization rate is less than 1% at present, with the degree of recognition being higher for the highly interested group. The future utilization rate rises to 10%, and is higher for the highly interested group. On the other hand, the overall HEV utilization rate is around several percent at present, and once again, the degree of recognition is higher for the highly interested group. The future utilization rate increases to 30%, and is much higher for the highly interested group.

The average values in Table 3(c) show the sum of the ratio of those who replied “very important” to those who replied “quite important,” for emphasis on added value. The value of annual reduction in fuel cost is around 75% on average, and is 10% higher for the highly interested group. The value of driving range on a single recharge or refuelling is around 70%, and is 10% higher for the highly interested group. The value of reduction in GHG emissions is around 50%, and is 10% higher for the highly interested group. Furthermore, 65% of the respondents attached importance to a home plug-in option.

5. Estimation results and analysis

This section displays and discusses the estimation results of SM, PV, EV, and HEV for both the highly interested households and those with less interest. The number of observations is 5,192 (649 respondents × 8 questions) for the former and 5,552 (694 respondents × 8 questions) for the latter.

5.1 Estimation results for a smart meter

Table 4(a) shows the estimation results of the SM conjoint analysis, where the column on the left displays results for the highly interested group, and that on the right, for the less interested group. The McFadden R^2 values are 0.2167 for the former and 0.3148 for the latter, both of which are sufficiently high for a discrete choice model. We assume that, except for a monthly usage charge, which is set as a numeraire, the parameters are distributed normally, and the mean and standard deviation values are reported. (Note that *** denotes 1% significance; **, 5% significance; and *, 10% significance.)

<Table 4(a)>

First, for the highly interested group, the statistically significant estimates (mean) are for monthly usage charge (-), private monitor display (+), energy-saving advice (+), off-peak discount (+), peak surcharge (-), automatic control at 82°F (-), and reduction in GHG emissions (+). Note that the symbols in the parentheses are the signs for each estimate. The statistically significant estimates (standard deviation) are WEB display, private monitor display, off-peak discount, peak surcharge, usage interception, and reduction in GHG emissions.[9]

Next, for the group with little interest, the statistically significant estimates (mean) are monthly usage charge (-), private monitor display (+), energy-saving advice (+), off-peak discount (+), peak surcharge (-), automatic control at 82°F (-), and usage interception (-). The statistically significant estimates (standard deviation) are WEB display, private

[9] Note that the standard deviations of some attributes are insignificant. In this case, we may consider the parameters to be fixed, rather than random.

monitor display, off-peak discount, peak surcharge, and reduction in GHG emissions.

It follows that the results for both groups are similar overall. However, the highly interested group has a statistically significant preference for a reduction in GHG emissions, unlike the other group.

The WTP values are derived by subtracting the parameter of the attribute divided by the numeraire. The WTP values are summarized in Figure 2(a) for statistically significant attributes, and are found to be almost the same for the two groups. Note that the average WTP value is close to that of the group with little interest, since the ratio for this group accounts for around 80% of the total respondents.

<Figure 2>

The average WTP values show the positively evaluated items to be a private monitor display (US$0.7/month), energy-saving advice (US$1.1/month), off-peak discount (10% or US$0.2/month), and reduction in GHG emissions (10% or US$0.1/month). On the other hand, negatively evaluated items are peak surcharge (double or US$-0.6/month), automatic control at 82°F (US$-0.4/month), and usage interception (US$-0.5/month).

5.2 Estimation results of photovoltaic generation

Table 4(b) lists the estimation results of the PV conjoint analysis. The McFadden R^2 values are 0.4214 and 0.5305 for the highly interested and the little interested group respectively, both of which are very high for a discrete choice model.

For the highly interested, the statistically significant estimates (mean) are initial cost (-), annual reduction in fuel and lighting charges (+), reduction in GHG emissions (+), and free inspection and maintenance period (+). The statistically significant estimates (standard deviation) are an annual reduction in fuel and lighting charges, reduction in GHG emissions, and free inspection and maintenance period.

Next, for the group with little interest, the statistically significant estimates (mean) are initial cost (-), annual reduction in fuel and lighting charges (+), reduction in GHG emissions (+), free inspection and maintenance period (+), and stylishly-designed premium PV panel (+). The statistically significant estimates (standard deviation) are an annual reduction in fuel and lighting charges, reduction in GHG emissions, and free inspection and maintenance period.

The WTP values are summarized in Figure 2(b) for the statistically significant attributes. The two groups show significantly different WTP values. The highly interested group is willing to pay an additional US$1,500 for the initial cost of deploying a PV, and the group with little interest, an additional US$600 to take advantage of a 10% reduction in fuel and lighting charges. Thus, the highly interested group is relatively sensitive to a reduction in fuel and lighting charges, while the latter group is relatively sensitive to a reduction in initial costs. Note that it is this latter group alone that is willing to pay US$1,000 for a stylishly designed PV panel.

Average WTP values for the all households show the positively evaluated items to be an annual reduction in fuel and lighting charges (10% or US$750), a reduction in GHG emissions (10% or US$1,400), free inspection and maintenance period (10 years or US$300), and a stylishly designed PV panel (US$800).

5.3 Estimation results of electric and hybrid vehicles

Table 4(c) lists the estimation results of the EV and HEV conjoint analyses. The McFadden R^2 values are 0.3107 for the highly interested group and 0.3625 for those with little interest, both of which are sufficiently high for a discrete choice model.

For the highly interested, the statistically significant estimates (mean) are the premium for an EV/HEV (-), annual reduction in fuel costs (+), and driving range on a full battery for an EV (+), as well as annual reduction in fuel costs (+), driving range upon refueling (+), and home plug-in for an HEV (+). The statistically significant estimates (standard deviation) include all parameters for both EV and HEV.[10]

---

[10] One reason for the attributes in GHG emissions being insignificant is that the respondents prefer HEVs to EVs in terms of the price and the driving range, although the

Next, for the less interested group, the statistically significant estimates (mean) are premium for an EV/HEV (-), annual reduction in fuel costs (+), driving range on a full battery (+), and reduction in GHG emissions for an EV (-), as well as annual reduction in fuel costs (+), driving range upon refueling (+), and home plug-in for an HEV (+). The statistically significant estimates (standard deviation) include all parameters for both EV and HEV, except for home plug-in for the latter.[11]

Figures 2(c) and 2(d) summarize the WTP values for the statistically significant attributes, which indicate that the positively evaluated items are annual reduction in fuel costs (10% or US$240) and driving range on a full battery (100 km or US$200) for an EV,[12] as well as annual reduction in fuel costs (10% or US$150), driving range upon refuelling (100 km or US$90), and home plug-in for an HEV (US$770).

6. Discussions and implications

This section discusses the elements of smart equipment deployment. We begin by calculating the diffusion rates for four different scenarios, and then calculate the reductions in GHG emissions on the basis of the diffusion rates. Finally, we investigate the interdependencies of smart equipment deployments.

6.1 Analysis of diffusion rates

We assume two levels for two key attributes (price and GHG emission reductions) and

---

latter is less polluting than the former.

[11] The WTP values for reduction in GHG emissions differ between the EV and the HEV. It is counterintuitive for the reduction in GHG emissions for an EV to have a negative sign. One reason for this may be that an EV is a vehicle using cleaner fuel compared to the fuel combination of an HEV, but few respondents chose the EV as an alternative. Consequently, the reduction in GHG emissions due to EV usage is not associated with a gain in utility.

[12] See Note 2 on this point.

then calculate the diffusion rates for SM, PV, EV, and HEV.

First, we assume the existing standard prices and estimated reductions of GHG emissions, which were calculated from the available data, to be the default values (see the APPENDIX for details). The estimated reduction rates of GHG emissions are as follows:

- Visualization with a smart meter: -1.1% per household
- Peak surcharge (triple): -3.7% per household
- PV deployment: -38.2% per household
- EV deployment: -83.5% per car
- HEV deployment: -52.4% per car
- PHEV deployment: -64.8% per car

In the following analysis, which was based on a discussion with experts, we also determine the targeted ranges of price and emission reductions for a 5-year period.

6.1.1 Diffusion rates of a smart meter

We determine the attribute levels for calculating SM diffusion rates as follows:

- Monthly usage charge: nil or US$3
- Visualization and energy-saving advice: present
- Off-peak discount: 50%
- Peak surcharge: triple
- Automatic air conditioner control at 82°F
- Reduction in GHG emissions: 10% or 30%

We calculated SM diffusion rates for the highly interested group, the group with little interest, and the weighted average of the two groups. The results are listed in Table 5(a). Scenario 1 denotes a combination of [monthly usage charge, reduction in GHG emissions] = [US$3, 10%]; Scenario 2, [US$0, 10%]; Scenario 3, [US$3, 30%]; and Scenario 4, [US$0, 30%]. Therefore, for consumers, Scenario 1 and 4 are the worst and the best scenario, respectively.

In Scenario 1, the diffusion rates are 61.4% for the highly interested group, 36.0% for the other group, and 40.6% for the weighted average of both groups. On the other hand, in Scenario 4, the diffusion rates are 87.8%, 73.4%, 76.0% for the highly interested group, the less interested group, and the weighted average of both groups, respectively. Note again that the average diffusion rate is closer to that of the group with little interest, as this group accounts for around 80% of the respondents.

Furthermore, comparisons of Scenarios 1 and 2, and Scenarios 3 and 4 reveal the differences to be more than 30% for the average. These differences are much larger for the group with little interest, as they are sensitive enough to the SM price so as to want it for free. On the other hand, few differences are observed when comparing Scenarios 1 and 3, and Scenarios 2 and 4. This is because the highly interested group has a very small—though statistically significant—preference for a reduction in GHG emissions, while the group with little interest lacks a statistically significant preference. In short, for the diffusion of SM infrastructure, the free charge policy is very effective while the incentive of a decrease in GHG emissions is less so.

<Table 5>

6.1.2 Diffusion rates of residential photovoltaic generation

We determine the attribute levels for calculating PV diffusion rates as follows:

- Initial cost: US$15,000 or US$20,000
- Annual reduction in fuel and lighting charges: 60%
- Reduction in GHG emissions: 40% or 60%
- Free inspection and maintenance period: 10 years
- Stylishly designed PV panel: present

The PV diffusion rates are listed in Table 5(b). Scenario 1 denotes a combination of [initial cost, reduction in GHG emissions] = [US$20,000, 40%]; Scenario 2, [US$15,000, 40%]; Scenario 3, [US$20,000, 60%]; and Scenario 4, [US$15,000, 60%].

In Scenario 1, the diffusion rates are 48.2% for the highly interested group, 9.8% for the other group, and 16.8% for the average of both. On the other hand, in Scenario 4, the diffusion rates are 86.6%, 52.8%, 58.9% for the highly interested group, the less interested group, and the average, respectively. As expected, the gaps between the two groups are very large.

Furthermore, comparisons of Scenarios 1 and 2, and Scenarios 3 and 4 reveal the average differences between the two groups to be around 20 to 30%. This means that the current initial cost is around US$20,000, but this must be decreased to US$15,000 to encourage further PV diffusion. On the other hand, comparisons of Scenarios 1 and 3, and Scenarios 2 and 4 highlight gaps of 10 to 20%. We, therefore, see that a reduction in GHG emissions works as a strong motivation for PV deployment, which is very unlike the case of an SM. It would be hasty to attribute this finding to the varying effects of emission reduction incentives depending on the appliance type. Instead, one possible answer could be that consumers care about reducing GHG emissions, but the process of reducing emissions through PV deployment is more explicit than in the case of an SM. Accordingly, a reduction in GHG emissions is effective in PV deployment.

The effects of emission reduction incentives on diffusion rates are likely to depend on the consumer "literacy" regarding smart equipment. Note that PVs for households have been sold in Japan for more than a decade. The initial cost of introducing a PV into a household is considerable (up to $20,000). Thus, PV manufacturers and sellers in Japan have been making every effort to advertise several appealing aspects of PV, specifically its powerful ability to reduce GHG emissions, in addition to its helping reduce annual fuel and lighting charges. As a result, Japanese consumers have become increasingly aware of the ability of PV to reduce GHG emissions. In contrast, SMs and PHEVs do not enjoy similar levels of diffusion in Japan. Thus, the effects of emission reduction incentives on diffusion rates may increase if there is an increase in consumer literacy regarding types of smart equipment, such as PHEV, after these have been introduced into the market in the near future.

6.1.3 Diffusion rates of electric and hybrid electric vehicles

We determine the attribute levels for calculating the EV and HEV diffusion rates as follows:

EV

- EV premium: US$5,000 or US$10,000
- Annual reduction in fuel cost: 80%
- Driving range on a full battery: 200 km
- Reduction in GHG emissions: 80% or 100%
- Time to find a charging station: up to 10 min

HEV

- HEV premium: US$2,500 or US$5,000
- Annual reduction in fuel costs: 60%
- Driving range on a full battery: 1,500 km
- Reduction in GHG emissions: 60% or 80%
- Home plug-in

Tables 5(c) and (d) list the EV and HEV (henceforth PHEV, as a home plug-in appears as an attribute level) diffusion rates, respectively. For an EV, Scenario 1 denotes a combination of [EV premium, reduction in GHG emissions] = [US$10,000, 80%]; Scenario 2, [US$5,000, 80%]; Scenario 3, [US$10,000, 100%]; and Scenario 4, [US$5,000, 100%]. On the other hand, for PHEV, Scenario 1 denotes a combination of [PHEV premium, reduction in GHG emissions] = [US$5,000, 60%]; Scenario 2, [US$2,500, 60%]; Scenario 3, [US$5,000, 80%]; and Scenario 4, [US$2,500, 80%].

In Scenario 1, the EV diffusion rates are 1.0% for the highly interested group, 0.2% for those with little interest, and 0.3% for the average of the two groups. The PHEV diffusion rates are 61.1% for the highly interested group, 21.5% for those with little interest, and

28.7% for the average. On the other hand, in Scenario 4, the EV diffusion rates are 5.1%, 1.6%, and 2.2% for the highly interested group, the less interested group, and the average, respectively. The corresponding PHEV diffusion rates are 81.4% for the highly interested group, 51.4% for the less interested, and 56.8% for the average. It is important to note that the gaps between EV and PHEV diffusion rates are extremely large. One possible reason for the significantly low rates of EV diffusion might be its limited driving range. The EV's driving range on a full battery is currently much lower than that of a standard gasoline engine car, whereas the EV premium is quite high. Technological innovations that decrease production costs and enable a much longer driving range would enhance the future diffusion of EVs.

Furthermore, comparisons of Scenarios 1 and 2, and Scenarios 3 and 4 show that even if the EV premium decreases from US$10,000 to US$5,000, its diffusion rates do not increase drastically. On the other hand, if the PHEV premium decreases from US$5,000 to US$2,500, its diffusion rates double. We might thus say that a premium approaching less than US$5,000 is necessary for the full-scale deployment of EVs (especially PHEVs).

On the other hand, as with the diffusion of SMs, a reduction in GHG emissions does not influence EV deployment, even though we may expect a large reduction in GHG emissions by driving EVs. Although the clean efficiency of a PHEV now compares favorably with that of an EV, the difference in emission reductions is neither distinct nor critical for the respondents. So far, sales of EVs and PHEVs have been sluggish in Japan. As discussed before, the effects of emission reduction incentives on diffusion rates could increase if there is an increase in consumer literacy regarding these vehicles in the near future.

6.2 Analysis of reduction in greenhouse gas emissions

We now analyze the aggregate reductions in GHG emissions calculated from the diffusion rates discussed in Section 6.1. The aggregate reductions are derived as follows.

- Reduction rate of GHG emissions for the highly interested group = the diffusion rate of the group × estimated reduction rates

- Reduction rate of GHG emissions for the group with little interest = the diffusion rate of the group × estimated reduction rates
- Expected reduction rate of GHG emissions = 0.181 × reduction rate of the highly interested group + 0.819 × reduction rate of the group with little interest

Table 6 lists the expected reduction rates of GHG emissions for various smart equipment. The definitions of the scenarios are listed in the previous section.

<Table 6>

First, for the SM reduction rate (per household), the values resulting from Scenario 1 (the worst case) are 6.1%, 3.6%, and 4.1% for the highly interested group, those with less interest, and the average of the two groups, respectively. On the other hand, the values resulting from Scenario 4 (the best case) are 26.3% for the highly interested group, 22.0% for the less interested, and 22.8% for the average.

Second, for the PV reduction rate (per household), the values resulting from Scenario 1 are 19.3%, 3.9%, and 6.7% for the highly interested group, those with less interest, and the average of the two groups, respectively. On the other hand, the values resulting from Scenario 4 are 52.0% for the highly interested group, 31.7% for those with less interest, and 35.4% for the average.

Third, for the EV reduction rate (per car), the values resulting from Scenario 1 are 0.8%, 0.2%, and 0.3% for the highly interested group, those with less interest, and the average of the two groups, respectively. On the other hand, the corresponding values resulting from Scenario 4 are 4.1%, 1.3%, and 1.8%.

Fourth, for the PHEV reduction rate (per car), the values resulting from Scenario 1 are 36.7% for the highly interested group, 12.9% for the less interested group, and 17.2% for the average of the two. On the other hand, the corresponding values resulting from Scenario 4 are 65.1%, 41.1%, and 45.5%.

To summarize, extensive reductions in GHG emissions are possible through the diffusion of smart equipment. Assuming the present business-as-usual (BAU) scenario, the reductions are estimated to be 4% for SM, 7% for PV, and 17% for PHEV. If we were to make value additions to the equipment, larger reductions can be expected. However, note that we might have overestimated the aggregate reductions in GHG emissions, because we did not account for a possible adverse impact of such benefits arising from rebound effects.[13]

The aggregate reductions in GHG emissions depend on the balance of the diffusion rate of smart equipment and the individual reduction rate of GHG emissions. SMs have a much lower individual GHG emissions reduction rate than PV, whereas the diffusion rate of SMs is higher than that of PV. Consequently, the difference between SM and PV in terms of aggregate reductions is not so large. Moreover, the reductions of EVs are particularly small because its diffusion rate is extremely low. In contrast, the diffusion rate of PHEVs and their individual GHG emissions reduction rate are somewhat balanced, which results in a relatively great amount of reductions for PHEV.

6.3 Analysis of interdependencies among smart equipment diffusion

We have thus far analyzed three different conjoint studies separately. However, there are interdependencies among consumer preferences for smart equipment used in a smart home. For example, a consumer who is interested in a PHEV is likely to receive a time-of-use electricity price by using an SM, whereas a household that installs a residential PV may consider a PHEV as a convenient home battery.

We try to ascertain these interdependencies by inserting other choice probabilities depicted in Eq. (6) into the estimation equation of certain smart equipment as explanatory variables. Table 7 lists the main estimation results (selectively, the choice probability parameters) for those with high and little interest, respectively. The estimates are transformed into elasticities, which indicate the extent by which a percentage increase in a

---

[13] Rebound effects denote the counterintuitive increased consumption of energy services in response to improved energy efficiency. See, for example, Madlener and Harmsen-van Hout (2011) for further discussion.

choice probability would increase another choice probability. Note that the values in the parentheses are t values, where *** denotes 1% significant; **, 5% significant; and *, 10% significant. As stated before, we adopted an orthogonal planning method in establishing the questionnaire, and therefore, the correlation is eliminated among explanatory variables. Thus, the introduction of expected choice probabilities has almost no influence on the estimates of the conjoint attributes. Moreover, we verify that the estimation results remain very robust.

<Table 7>

First, for the SM estimation results (choice probability elasticities), the statistically significant items are PV (0.319**) and PHEV (0.863***) for the highly interested group, and PHEV (0.892***) for the other group. We can therefore see that PHEVs will be the deciding element in the uptake of an SM. It is pertinent to reiterate that our study is concerned with correlation and not causality. Thus, several interpretations are possible. For example, with PHEV diffusion, the economic value of SM introduction increases, or only households with a preinstalled SM are willing to purchase a PHEV.

Next, for the PV estimation results, the statistically significant items are SM (1.748***), EV (0.773***), and PHEV (0.933***) for the highly interested group; and SM (1.162***), EV (0.395***), and PHEV (1.352***) for the other group. All smart equipment influences PV adoption, and the effects of SM and PHEV are sometimes elastic. These results may reflect the fact that early adopters who have already deployed residential PV systems have high environmental consciousness (cf. Rogers, 1962). A PV system is essentially a renewable energy technology and explicitly contributes to the reduction in GHG emissions.

Finally, for the EV estimation results, the statistically significant items are SM (0.365***) and PV (0.698***) for the highly interested group, and SM (0.378***) and PV (0.491***) for the other group. On the other hand, for the PHEV estimation results, the statistically significant items are SM (0.251***) and PV (0.286***) for the highly interested group, and SM (0.162***) and PV (0.273***) for the other group. Once more, we see that the preferences for an EV/PHEV are associated with other smart equipment deployments. This is partially because an EV/PHEV serves as a home battery, which alleviates the problem of an unstable power supply associated with a renewable energy source.

To summarize, the choice behaviors for smart equipment are not independent, and instead, reinforce the purchases of other smart equipment. Therefore, an incentive policy that induces consumers to make concurrent purchases of different types of "aligned" smart equipment should be considered.

7. Concluding remarks

This paper conducted three kinds of conjoint analyses with a mixed logit model using data from an online survey conducted in March 2011. First, we examined the WTP values for the attributes of smart equipment. Furthermore, we investigated the diffusion rates, the reduction in GHG emissions, and interdependencies among smart equipment deployments. We arrived at the following conclusions. First, a decrease in price is the most effective method to promote smart equipment deployments. On the other hand, the effects of GHG emissions reduction varied across different types of equipment, although they were highest for PV deployment. The effects of emission reduction incentives may also depend on consumer literacy concerning smart equipment. Second, smart equipment diffusion would decrease GHG emissions. Under the standard scenario, the reduction rates were 4% for SM, 7% for PV, and 17% for PHEV deployment. Third, we observed interdependencies among the different types of smart equipment deployments, with PV deployment being particularly associated with all other smart equipment deployments. As a final remark, we acknowledge that all of these results are based on a data analysis of stated preference, which must be reconfirmed using a revealed preference data analysis in the future. Furthermore, we have not dealt with non-adopters in the analysis. Therefore, we must note that the reported reductions in GHG emissions obtained in this analysis result from new technology purchases alone. Nevertheless, the results of these analyses offer important guidelines for future policy creation in this field.

Appendix

In Japan, an average household consumes 4500 kWh of electricity and 600 m^3 of gas to emit 3216 kg of carbon dioxide (CO_2) on an annual basis (CRIEPI, 2007; MIC, 2011). The CO_2 emission rates of the electric power companies when generating power are 0.44 kg-CO_2/kWh in the daytime and 0.39 kg-CO_2/kWh in the nighttime, which works out to 0.42 kg-CO_2/kWh on average (MOE, 2009).

- Visualization with an SM

The introduction of an SM and private monitor display reportedly reduced the electricity use of an average household by 1.8% (MRI, 2008). This corresponds to an annual reduction of 81 kWh in electricity usage and 34 kg-CO_2 emissions per household (considering the average CO_2 emission rate). Thus, the reduction rate of CO_2 is 1.1% (34/3216 × 100 kg-CO_2) per household.

- Peak surcharge

Faruqui et al. (2010) surveyed existing demand response (DR) programs in the U.S. and reported that the price elasticity of electricity demand ranged from 0.073 to 0.13.[14] In this study, we assume that the price elasticity of electricity demand is 0.1. When the electricity tariff during the peak period is tripled, a household will reduce its electricity usage by 270 kWh per year (in relation to the annual electricity usage in the peak period defined in the time-of-use tariff, i.e., 1350 kWh (METI, 2011)). This amounts to an annual reduction of 119 kg-CO_2 in CO_2 emissions (considering the CO_2 emission rate in the daytime). Thus, the CO_2 reduction rate is 3.7% (119/3216 × 100 kg-CO_2) per household.

[14] Unfortunately, the price elasticity of electricity demand has rarely been reported for Japan. One exception is Hosoe and Akiyama (2009), who estimated the regional power demand functions for nine regions in Japan, and reported the price elasticity of industrial and commercial demand to be 0.09–0.30. Note that the price elasticity of industrial and commercial demand is considered to be higher than that of residential demand.

- PV deployment

The power output of home solar PV systems is 3 kW on average, generating 3000 kWh of electricity annually (MOE, 2011). Considering the CO_2 emission rate in the daytime, this translates into an annual emissions reduction of 1230 kg-CO_2 (we deduct CO_2 emissions generated during the manufacturing process of the PV panels, i.e., 0.44 kg-CO_2/kWh - 0.03 kg-CO_2/kWh). Thus, the CO_2 reduction rate is 38.2% (1230/3216 kg-CO_2) per household.

In Japan, the average distance travelled annually by a gasoline engine car is 9188 km (MLIT, 2004). The annual CO_2 emissions amount to 2345 kg-CO_2 per car, based on a fuel efficiency of 9.1 km/L and a CO_2 emission rate of 2.32 kg-CO_2/L (MLIT, 2009).

- EV deployment

The electric efficiency of an EV is estimated to be 10.0 km/kWh (METI, 2006a). Based on this estimate, the annual reduction in CO_2 emissions per EV is 1959 kg-CO_2. Thus, the reduction rate of CO_2 per EV is 83.5% (1959/2345 kg-CO_2).

- HEV deployment

The fuel efficiency of HEV is 19.1 km/L (catalog values of the Toyota and Honda). Based on this estimate, the annual reduction in CO_2 emissions is per HEV 1228 kg-CO_2. Thus, the reduction rate of CO_2 per HEV is 52.4% (1228/2345 kg-CO_2).

- PHEV deployment

The PHEV is estimated to run on gasoline and electric power for 60% and 40% of the travel distance (METI, 2006a). Based on this estimate, the annual reduction in CO_2 emissions per PHEV is 1520 kg-CO_2. Thus, the reduction rate of CO_2 per PHEV is 64.8% (1520/2345 kg-CO_2).

References

[1] Achtnicht, M., 2011. Do environmental benefits matter? Evidence from a choice experiment among house owners in Germany. Ecological Economics 70, 2191-2200.

[2] Ahn, J., Jeong, G., Kim, Y., 2008. A forecast of household ownership and use of alternative fuel vehicles: A multiple discrete-continuous choice approach. Energy Economics 30. 2091-2104.

[3] Alberini, A., S. Banfi, C. Ramseier, 2011. Energy Efficiency Investments in the Home: Swiss Homeowners and Expectations about Future Energy Prices. Working paper No.80, Center for Energy Policy and Economics (CEPE), ETH Zurich.

[4] Axsen, J., Mountain, D.C., Jaccard, M., 2009. Combining stated and revealed choice research to simulate the neighbor effect: The case of hybrid-electric vehicles. Resource and Energy Economics 31, 221-238.

[5] Banfi, S., Farsi, M., Filippini, M., Jakob, M., 2008. Willingness to pay for energy-saving measures in residential buildings. Energy Economics 30, 503-516.

[6] Beggs, S., Cardell, S., Hausman, J., 1981. Assessing the Potential Demand for Electric Cars. Journal of Econometrics 16, 1–19.

[7] Ben-Akiva, M., Bolduc D., Walker J., 2001. Specification, estimation and identification of the logit kernel (or continuous mixed logit) model. Department of Civil Engineering, MIT, Working Paper.

[8] Bhat, C., 2001. Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. Transportation Research B35, 677-693.

[9] Brownstone, D., Train, K.E., 1999. Forecasting new product penetration with flexible substitution patterns. Journal of Econometrics 89, 109-129.

[10] Brownstone, D., Bunch, D.S., Train, K.E., 2000. Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transportation Research B34, 315-338.

[11] Bunch, D.S., Bradley, M., Golob, T.F., Kitamura, R., Occhiuzzo, G.P., 1993. Demand for clean-fuel vehicles in California: A discrete-choice stated preference pilot project. Transportation Research A27 (3), 237-253.

[12] Calfee, J.E., 1985. Estimating the demand for electric automobiles using disaggregated probabilistic choice analysis. Transportation Research B: Methodological 19 (4), 287–301.

[13] Clastres, C., 2011. Smart grids: Another step towards competition, energy security and climate change objectives. Energy Policy, DOI: 10.1016/j.enpol.2011.05.024.

[14] Central Research Institute of Electric Power Industry, CRIEPI. 2007. A question on the report "Do all-electric houses contribute to preventing global warming" (in Japanese)

[15] Dagsvike, J.K., Wetterwald, D.G., Wennemo, T., Aaberge, R., 2002. Potential demand for alternative fuel vehicles. Transportation Research Part B: Methodological 36, 361–384.

[16] Duke, R., Williams, R., Payne, A., 2005. Accelerating residential PV expansion: demand analysis for competitive electricity markets. Energy Policy 33, 1912-1929.

[17] Ewing G., Sarigollu, E., 2000. Assessing consumer preferences for clean-fuel vehicles: A discrete choice experiment. Journal of Public Policy & Marketing 19 (1), 106-118.

[18] Faruqui, A., Hledik, R., Sergici S., 2010. Rethinking Prices: The changing architecture of demand response in America. Public Utilities Fortnightly, January.

[19] Grösch, P., C. Vance, 2009, "Willingness to Pay for Energy Conservation and Free-Ridership on Subsidization: Evidence from Germany," The Energy Journal 30 (2), 135-153.

[20] Halton, J.E., 1960. On the efficiency of certain quasi-random sequences of points in evaluating multi-dimensional integrals. Numerische Mathematik 2, 84-90.

[21] Hidrue, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. Resource and Energy Economics 33, 686-705.

[22] Hosoe, N., Akiyama S. 2009. Regional electric power demand elasticities of Japan's industrial and commercial sectors. Energy Policy 37 (11), 4313-4319.

[23] Karplus, V.J., Paltsev, S., Reilly, J.M., 2010. Prospects for plug-in hybrid electric vehicles in the United States and Japan: A general equilibrium analysis. Transportation Research A44, 620-641.

[24] Keirstead, J., 2007. Behavioural responses to photovoltaic systems in the UK domestic

sector. Energy Policy 35, 4128-4141.

[25] Kwak, S.-Y., S.-H. Yoo, S.-J. Kwak, 2010. Valuing energy-saving measures in residential buildings: A choice experiment study. Energy Policy 38, 673-677.

[26] Louviere, J.J., Hensher D.A., SwaitJ.D.,2000. Stated choice methods: analysis and applications. Cambridge University Press.

[27] McFadden, D., Train K.E., 2000. Mixed MNL models of discrete choice models of discrete response. Journal of Applied Econometrics 15, 447-470.

[28] Madlener R., Harmsen-van Hout M. J.W. 2011. Consumer behaviour and the use of sustainable energy, in Galarraga I., González-Eguino M., Markandya A. (Eds.), Handbook of sustainable energy, Edward Elgar Publishing, Northampton Mass.US,

[29] Mau, P., Eyzaguirre, J., Jaccard, M., Collins-Dodd, C., Tiedemann, K., 2008. The 'neighbor effect': Simulating dynamics in consumer preferences for new vehicle technologies. Ecological Economics 68, 504-516.

[30] Ministry of Economy, Trade and Industry, METI. 2006a. A proposal for the future of batteries of next-generation vehicles (in Japanese).

[31] Ministry of Economy, Trade and Industry, METI. 2006b. Report by the subcommittee to evaluate system reforms: reference materials.

[32] Ministry of Economy, Trade and Industry, METI. 2011. Estimation for demand structure of maximum electric power consumption in summer peak (in Japanese).

[33] Ministry of Environment, MOE. 2009. Introduction of seasonal average emission factor (in Japanese).

[34] Ministry of Environment, MOE. 2011. Illustration of calculating the reduction effect of greenhouse gases by ecological action (in Japanese).

[35] Ministry of Internal Affairs and Communications, MIC. 2011. Family income and expenditure survey (in Japanese).

[36] Ministry of Land, Infrastructure, Transport, and Tourism, MLIT. 2004. Survey of automobile use (in Japanese).

[37] Ministry of Land, Infrastructure, Transport, and Tourism, MLIT. 2009. Annual report of road statistics (in Japanese).

[38] Mitsubishi Research Institute, MRI. 2008. Report on the cost benefit analysis of smart

meter (in Japanese).

[39] Poortinga, W., L. Steg, C. Vlek, G. Wiersma, 2003. Household preferences for energy-saving measures: A conjoint analysis. Journal of Economic Psychology 24, 49-64.

[40] Potoglou, D., Kanaroglou, P.S., 2007. Household demand and willingness to pay for clean vehicles. Transportation Research D12, 264-274.

[41] Revelt, D., Train K.E., 1998. Mixed logit with repeated choices: Households' choices of appliance efficiency level. Review of Economics and Statistics80, 647-657.

[42] Rogers, E.M. (1962). Diffusion of Innovations. Free Press of Glencoe, Macmillan Company.

[43] Sadler, M., 2003. Home energy preferences & Policy: Applying stated choice modeling to a hybrid energy economy model. Report to Natural Resources Canada, Simon Fraser University.

[44] Segal, R., 1995. Forecasting the Market for Electric Vehicles in California Using Conjoint Analysis. The Energy Journal 16 (3), 89-111.

[45] Train, K.E., 2003. Discrete Choice Methods with Simulation. Cambridge University Press.

[46] Woo, C.K., Kollman, E., Orans, R., Price, S., Horii, B., 2008. Now that California has AMI, what can the state do with it? Energy Policy 36, 1366-1374.