Yoshida et al. Economic Structures (2017) 6:4
DOI 10.1186/s40008-017-0064-0

Journal of Economic Structures

RESEARCH Open Access

Which dynamic pricing rule is most preferred by consumers?—Application of choice experiment

Yumi Yoshida[1], Kenta Tanaka[2*] and Shunsuke Managi[3,4]

*Correspondence: k-tanaka@cc.musashi.ac.jp
[2] Faculty of Economics, Musashi University, 1-26-1 Toyotamakami, Nerima-ku, Tokyo 176-8534, Japan
Full list of author information is available at the end of the article

Abstract

This study investigates consumers' preference for dynamic pricing rules using a choice experiment. Among alternative electricity pricing rules, time of use (TOU) is most preferred by consumers, and our estimation results show that TOU has the highest value of WTP among pricing rules. Furthermore, consumers' characteristics affect their choice of a pricing rule. Our results show that risk preference in particular affects the choice probability of each pricing rule.

Keywords: Choice experiment, Dynamic pricing, Electricity

1 Background

In many regions, electricity demand varies significantly based on time of day. The difference in electricity demand between peak and off-peak time periods has increased annually in Japan.[1] A decreased load factor implies a high adjustment of electricity supply. Thus, electricity suppliers must increase the electricity price, which might lead to a decrease in consumer welfare. To reduce the demand gap between peak and off-peak time periods, demand-side control of energy use is an important tool to consider. In fact, the Japanese government is considering the introduction of dynamic pricing rules to decrease the electricity demand gap between peak and off-peak time periods.[2]

Dynamic pricing can reduce electricity demand by increasing the electricity rate when the electricity demand is strong. Electricity rates decrease when electricity demand weakens. The concept of dynamic pricing is based on economic incentives. Many previous studies (for example, Joskow 1975; Chao and Pecks 1996) analyze how to make the effective dynamic pricing rule maximize total welfare. Based on a theoretical analysis, several researchers have implemented field experiments to evaluate the performance of dynamic pricing rules. The empirical results of such field experiments show that

[1] According to the Agency for Natural Resources and Energy in Japan, the power demand of the household sector has increased due to the improvement of living standards. In the household sector, which widely uses air-conditioning and electric carpet, power demand is substantial on hot days of summer and cold days of winter.

[2] With the introduction of the demand response, the Ministry of Economy, Trade and Industry has expressed the view that the demand response can bring a new energy-saving mechanism to Japan. In addition, the Ministry of Economy, Trade and Industry believes that this system can prevent black outs of the power supply. For more information, see the following Web site: http://www.meti.go.jp/committee/sougouenergy/shoene_shinene/sho_ene/pdf/006_03_00.pdf.

dynamic pricing can contribute to decreasing peak-time electricity demand (Matsukawa et al. 2000; Faruqui and George 2005; Herter 2007). In addition, Allcott (2011) indicates that dynamic pricing can contribute to increasing the consumer surplus.

However, there remains an important policy question regarding dynamic pricing: Even if dynamic pricing rules have been theoretically effective, it is unclear whether consumers actually accept dynamic pricing rules. Joskow and Wolfram (2012) note that there are several factors that prevent consumers from accepting dynamic pricing rules. One reason they note is the cost of metering. Metering would be too costly for small commercial consumers. Furthermore, consumers might not easily understand the effectiveness of potentially complex designs of dynamic pricing.

We investigate whether consumers accept dynamic pricing using a choice experiment. We estimate willingness to pay (WTP) from the results of a choice experiment. Then, we analyze the most preferable dynamic pricing rules for consumers. There are several previous studies related to our study. Borenstein (2006) estimated the number of consumers who take risk aversion action. Risk aversion implies the avoidance of an electric pricing rule with high volatility, such as real-time pricing (RTP). Borenstein (2006) found that 77% of consumers investigated were risk averse. In addition, Borenstein (2013) found that consumers tend to remain in the flat-rate fee scheme. He also used field experiment data to analyze what characteristics of consumers lead them to switch to other electricity rates. As a result, he noted that low-income consumers tend to switch from a flat-rate scheme to a dynamic pricing scheme. A dynamic pricing scheme has the possibility to improve several energy problems, such as energy conservation and mitigation of CO_2 emissions. But, an effective dynamic pricing scheme requires the joining of several types of consumers (Kurakawa et al. 2016). Therefore, understanding consumer preferences for each dynamic pricing rule is important in actually implementing a dynamic pricing scheme. Furthermore, some researchers have noted that consumers may prefer an energy management system that automatically adjusts electricity usage to a dynamic pricing scheme. Therefore, we add the analysis of the preference for direct load control (DLC), which does not require the risky price change of electricity to consumers; instead, it automatically adjusts the rate based on use.

2 Data and setting of choice experiment

2.1 Data collection

We conducted a web-based questionnaire survey from March 14, 2014, to March 18, 2014, using randomly selected consumers living in Japan. The purpose of this survey was to clarify what types of dynamic electricity pricing are preferred by consumers using a choice experiment. The subjects of our survey included males and females aged 20–69 years. The number of subjects was 4122. The survey area included all prefectures in Japan. Our questionnaire included choice experiments of an electricity pricing scheme and collected other information on each respondent. Details about the choice experiment are explained in the next section. Other variables from the questionnaire results of each respondent are described in Table 1. Our questionnaire includes general questions (such as age, gender and academic record) and questions about the use of electricity for the family.

Table 1 Estimation result of conditional logit

Attributes	Definition	Coefficient	*t* value
TOU	(If respondents choose TOU = 1, if respondents choose other pricing scheme = 0)	0.350	14.180
CPP	(If respondents choose CPP = 1, if respondents choose other pricing scheme = 0)	0.151	6.110
RTP	(If respondents choose RTP = 1, if respondents choose other pricing scheme = 0)	0.308	12.720
DLC	(If respondents choose DLC = 1, if respondents choose other pricing scheme = 0)	0.312	10.610
DLCCPP	(If respondents choose DLCCPP = 1, if respondents choose other pricing scheme = 0)	0.207	7.050
Month	Willingness to pay for electricity fee per month of each option (Japanese yen)	−0.00012	−93.060
First	Willingness to pay for first fixed fee in each option (Japanese yen)	−0.00006	−33.400

The number of observation is 197,856 (4122 respondents × 8 times questions × 6 options). Log likelihood is −71,657.017, and χ^2 (7) is 19,494.09

2.2 Choice experiment modeling

In the survey, we used a choice experiment. We presented respondents information about the demand response (for details on the information given to correspondents is shown in Additional file 1: Appendix). Respondents were asked to cast eight decisions during the experiment. Although the contents of options changed each time, option 6 (general pricing rule) remained the same. (Option 6 was the general pricing rule. In short, consumers did not change the pricing rule). The general pricing rule is the most common option in Japan. The order of the choice set was random, and the contents of the choice set were different for each respondent. Each time, the value of the "monthly fee" (the variable name was "month") and the "initial cost" (the variable name is "first") was randomly changed. The initial cost for the introduction of the demand response is one important factor that determines whether consumers join new pricing schemes. To control the initial cost effect for decision making, we added the initial cost as the basic attribute to the questionnaire. Respondents chose one option they found optimal. The general pricing rule (option 6) did not change the monthly electricity rate. Before asking the question in the choice experiment, we explained each dynamic pricing rule to respondents (see Additional file 1: Appendix).

Specifically, we asked respondents the following questions: "Among the following six electricity pricing alternatives, please select one you think is most preferable. The electricity rate you pay will be always supposed to satisfy your budget constraints. Please note that you will be able to freely spend the extra money you obtain from choosing the pricing."

3 Estimation method

3.1 Conditional logit model

We assume a random utility model for the analysis. When subject n chooses profile i, the subject's utility is given by $U_{n,i} = V_{n,i} + \varepsilon_{n,i}$ where $V_{n,i}$ is the observable component of $U_{n,i}$ and $\varepsilon_{n,i}$ is the unobservable component of $U_{n,i}$. We denote the set of profiles that subject n can select on the basis of $C = \{1, 2, \ldots, j\}$. The probability that subject n chooses profile $i \in C$ is $P_{n,i}$. When subject n chooses profile i, $U_{n,i} > U_{n,j}\left(i \neq j\right)$ must be satisfied. Then, we obtain

$$\begin{aligned} P_{n,i} &= \Pr\left[U_{n,i} > U_{n,j}, \forall j \in C, j \neq i\right] \\ &= \Pr\left[V_{n,i} - V_{n,j} > \varepsilon_{n,j} - \varepsilon_{n,i}, \forall j \in C, j \neq i\right]. \end{aligned} \tag{1}$$

Following McFadden (1973), we assume that $\varepsilon_{n,i}$ and $\varepsilon_{n,j}$ are independent with a univariate type I extreme value distribution. Then, the probability that subject n chooses profile i is

$$P_{ni} = \frac{e^{\mu V_{n,i}}}{\sum_{j \in C} e^{\mu V_{n,j}}}, \tag{2}$$

where μ is a scale parameter. In this paper, μ is normalized to 1. This model is known as a conditional logit model. Hence, we obtain the log-likelihood function:

$$\ln L = \sum_{n=1}^{N} \sum_{i \in C} \delta_n^i \ln P_{n,i}, \tag{3}$$

where N is the number of subjects, and δ_n^i is the dummy variable, such that $\delta_n^i = 1$ if subject n chooses profile i and 0 otherwise. By maximizing the log-likelihood function, we estimate the parameters.[3]

3.2 Marginal willingness to pay (MWTP)

$V_{n,i}$ is the observable component of the utility of individual n when choosing the ith option. The utility component is assumed to have the following linear form:

$$V_{n,i} = a_i d_i + \beta p_i. \tag{4}$$

where d_i is the alternative-specific constant and p_i is the price of option i. a_i and β are parameters. Assuming that $V_{n,i}$ is equal to the observable component of the utility associated with the status quo option, we obtain the following equation for marginal willingness to pay (MWTP) for option i, which is given by the difference in the price between option i and the status quo:

$$\mathrm{MWTP} = -\frac{a_i}{\beta} \tag{5}$$

MWTP is the willingness to pay for the monthly electricity rates.

4 Results

4.1 Choice from electricity pricing options and its WTP

The estimation results of the conditional logit model are presented in Table 1. Furthermore, Table 2 shows the estimation results of MWTP based on the results of a

[3] In this study, we apply the conditional logit estimation method to estimate the parameters. However, conditional logit estimation relies on the assumption of independence from irrelevant alternatives (IIA). Thus, we cannot consider the utilities of each alternative to be correlated in this estimation.

Table 2 Estimation results of marginal willingness to pay

Attributes	Marginal willingness to pay: MWTP (Japanese yen)
TOU	3020.927
CPP	1306.136
RTP	2658.764
DLC	2691.283
DLCCPP	1789.777

conditional logit estimation. We include alternative-specific constants. We can estimate the MWTP for the electricity rate per month based on Eq. (5). Each MWTP is calculated by the ratio of the coefficient of each alternative-specific constant (coefficient of "TOU," "CPP," "RTP," "DLC" and "DLCCPP" in Table 2) to that of the electricity fee per month (coefficient of "month" in Table 2). Based on the calculation results of WTP, time of use (TOU) is the most preferable pricing rule for respondents. The second most preferable pricing rule for respondents is DLC.[4]

Previous studies note that consumers do not tend to accept the dynamic pricing rule, but our results show that TOU is the most preferable rule for the electricity rate. These results imply that consumers want to adapt the dynamic pricing rule in Japan. In fact, the WTP of RTP is also high, but consumers also want to avoid the risk of large electricity price changes. Thus, the WTP of critical peak pricing (CPP) is lower than that of other pricing schemes. In addition, the WTP of RTP is similar to that of DLC. These results imply that consumers may also accept the DLC for the electricity pricing rule.

4.2 Characteristics of motivating acceptance of dynamic pricing

Next, we discuss how much respondents' characteristics affect their selection of each electricity pricing rule. The conditional logit model cannot include the effect characteristics of each respondent on the choice of probability of each pricing rule. In this study, we apply the multinomial logit model to confirm the effect of respondents' characteristics for choice probability of each pricing rule. Under the multinomial logit model, the observable component of the utility is assumed to be written as

$$V_{n,i} = b_i X_n \tag{6}$$

where X_n denotes respondents n's characteristics. In the conditional logit model, $\sum_{i=1} P_{ni} = 1$ an equivalent model is obtained by defining $V_{n,i}$ to be deviations of regressors from values of alternative 1, and setting $V_{n,i} = 0$. When instead the regressors do not vary over alternatives, the multinomial logit model is used (Cameron and Trivedi 2009). A positive (negative) regression parameter does not mean that an increase in the regressor leads to increase (decrease) in the probability of that alternative. Instead, interpretation for the multinomial logit model is relative to the reference.[5]

[4] In addition, we calculate the MWTP for initial cost in each pricing scheme. The MWTP for initial cost is calculated by the ratio of the coefficient of each price scheme to that of "First." Preference ranking of each pricing scheme for initial cost and monthly fee is exactly same. This tells we can understand which dynamic pricing rules better for consumers as both calculation results of MWTP show the same ranking. However, consumers might not clarify well the difference between initial cost and monthly fee.

[5] In this estimation, we define the choice of status quo as the reference.

Table 3 Estimation results of multinomial logit model (economic incentive rules)

Attributes	Economic incentive					
	TOU		CPP		RTP	
	Time-of-use rate		Critical peak price		Real-time price	
	Estimate	*t* value	Estimate	*t* value	Estimate	*t* value
Fee	0.00000004	0.03	−0.0000	−1.61	−0.0000	−0.43
Knowledge	0.0063***	3.63	0.0098***	5.45	−0.0031*	−1.75
All	−0.5624***	−25.33	−0.4675***	−19.98	−0.2586***	−11.14
Family	−0.0400***	−3.94	0.0242**	2.33	0.0336***	3.35
Age	−0.0024***	−3.95	−0.0009	−1.37	0.0016**	2.55
Gender	0.0158	1.01	0.0679***	4.17	0.0923***	5.86
Education	0.0825***	18.68	0.0706***	15.39	0.0756***	17.08
Income	0.0002***	7.06	0.0002***	6.16	0.0003***	10.61
Risk	−0.0184	−1.48	0.0142	1.11	0.0543***	4.39
Tokyo	0.0350**	2.12	0.0560***	3.27	0.0641***	3.90
Time	−0.0873***	−5.30	−0.1109***	−6.44	−0.1364***	−8.21
Ownership	0.0373**	2.15	−0.0930***	−5.17	−0.0144	−0.83
Three generations	−0.2100***	−6.57	−0.1505***	−4.59	−0.3250***	−10.07
Single-life	−0.1861***	−6.16	−0.1060***	−3.39	−0.1142***	−3.77
Month	−0.0000***	−5.85	0.0000***	2.83	−0.0000***	−5.16
First	0.0000**	2.49	−0.0000**	−2.20	−0.0000**	−2.45
Constants	0.1435**	2.20	−0.2657***	−3.92	−0.4735***	−7.21

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. Log likelihood is −351,225.27, and χ^2 (80) is 3411.29

The results of the multinomial logit model are shown in Tables 3 (economic incentive rules) and 4 (DLC and general rules). Each variable that we use in our estimation is shown in Table 5. We show the descriptive statistics in Table 6. The baseline choice is an option of the general rule. "Knowledge" shows a positive correlation with the choice probability of TOU and CPP. These results indicate that people with more knowledge about electricity conservation tend to choose TOU and CPP but not the real-time pricing scheme. TOU and CPP are easily understandable in terms of the effective timing for electricity conservation. RTP is difficult to understand in terms of such timing. Thus, people who have more knowledge about electricity conservation prefer TOU and CPP.

"All" and "time" show a negative coefficient with the choice probability of all economic incentive schemes. All-electric homes need to manage all energy usage with electricity. In short, people who live in such homes need to use more electricity than others do. Thus, such people dislike the electricity price change. Furthermore, people who spend a considerable amount of time in their home use more electricity than others do. Therefore, they do not tend to choose the dynamic pricing schemes.

"Education" shows a positive coefficient with the choice probability of all dynamic pricing schemes. A high educational background leads to a strong understanding of the merit of dynamic pricing schemes. This result shows the characteristic may increase the choice probability of dynamic pricing schemes. "Risk" shows a positive coefficient with the choice probability of CPP and RTP, but a high-risk preference leads to a decrease in the choice probability of DLC and TOU. These results show that consumers consider the

Table 4 Estimation results of multinomial logit model (DLC and general rule)

Attributes	Direct load control			
	DLC		Mixed with DLC and CPP	
	Estimate	*t* value	Estimate	*t* value
Fee	0.0000***	6.66	0.0000***	6.82
Knowledge	0.0005	0.27	−0.0013	−0.69
All	−0.3621***	−15.25	−0.4422***	−18.19
Family	0.0028	0.27	−0.0083	−0.76
Age	−0.0021***	−3.21	−0.0014**	−2.02
Gender	0.1865***	11.28	0.2292***	13.26
Education	0.0568***	12.33	0.0535***	11.13
Income	0.0002***	7.81	0.0003***	9.73
Risk	−0.0234*	−1.80	−0.0119	−0.87
Tokyo	0.1331***	7.77	0.0645***	3.59
Time	0.0054	0.31	0.0152	0.84
Ownership	−0.0572***	−3.16	−0.0457**	−2.41
Three generations	−0.2039***	−6.18	−0.1654***	−4.82
Single-life	−0.2532***	−7.90	−0.1907***	−5.71
Month	0.0000***	4.81	−0.0000***	−5.49
First	−0.0000*	−1.69	−0.0000***	−4.27
Constants	−0.4148***	−6.07	−0.4255***	−5.98

Values in parentheses are *t* values

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. Log likelihood is −351,225.27, and χ^2 (80) is 3411.29

risk of price change. "Single-life" shows a negative coefficient with the choice probability of all dynamic pricing schemes. People who live alone do not want to think about the electricity price change, as their consumption is small. They may think of the switching of the price rule as bothersome. These results imply that the characteristics of people and families affect their choice of a dynamic pricing scheme in the near future.

However, we need to calculate the marginal effect based on the result of the multinomial logit estimation to understand how much each characteristic affects the choice probability of each pricing scheme. Tables 7 and 8 show the estimation results of the marginal effect based on the results of the multinomial logit estimation. From these results, we can understand which characteristics affect pricing scheme choice behavior. For example, these results show that risk preference is one of the important factors that influence the choice probability. The "risk" value of most risky people in our sample is 3. Thus, high-risk people's choice probability of RTP increases by approximately 3%. Furthermore, we can understand "All" as an important factor for decision making. For example, the choice probability of TOU decreases by 4% if the person lives in an all-electric home.

5 Discussion and conclusion

In this paper, we estimate the WTP for each dynamic pricing rule of electricity based on choice experiment. In addition, we analyze what factors influence the choice of each dynamic pricing scheme. As a result, we produce several important findings regarding consumers' choice of a dynamic pricing rule.

Table 5 List of variables

Variables	Definitions	Contents
Fee	The average electricity rate of spring, summer, fall and winter (The electricity rate is what respondents are paying)	Numerical value
Knowledge	Respondents' degree of knowledge about energy-saving behavior (i.e., what respondents suppose is a good way to save energy use). Variables show the number of such questioner choices. Total numbers of such questions are 14	1. Turning off the air conditioner 2. Setting the temperature of the air conditioner to 28 °C 3. Cleaning the air conditioner's filter frequently 4. Turning off the TV frequently when you are not watching it 5. Putting the refrigerator in an appropriate place 6. Setting the refrigerator's temperature properly 7. Organizing the contents of the refrigerator 8. Setting the temperature of the air conditioner to 20° in the winter 9. Lowering the temperature setting of the water heater 10. Turning on the heater only when necessary 11. Unplugging electrical products when not in use 12. Not leaving the shower running 13. Setting the temperature of electrical carpet properly 14. Not reheating a bath
All	Whether respondents live in an all-electric home	Respondents live in an all-electric home = 1 Other = 0
Family	The number of households of respondents	Numerical value
Job	Whether the respondent has a job in an electric power industry	Yes = 1 No = 0
Age	Age of respondent	Numerical value
Gender	Gender of respondent	Male = 1 Female = 0
Education	Academic record	Respondents graduated from Primary school = 0 Junior high school = 1 High school = 2 National College of Technology = 3 Vocational school = 4 Junior college = 5 University = 6 Master's degree program = 7 Doctoral degree program = 8
Income	Annual income of respondents	Numerical value
Risk	The risk-level preference of respondents	Numerical value
Tokyo	Whether the respondents live in the Tokyo metropolitan area	Respondents lived in the Tokyo metropolitan area = 1 Other = 0
Time	Whether respondents stay at home almost all day	Respondents stay at home almost all day = 1 Other = 0
Ownership	Whether respondents live a self-owned home	Respondents live in self-owned home = 1 Other = 0
Rent	Whether respondents live in a rented house	Respondents live in rented house = 1 Other = 0
Apart	Whether respondents live in an apartment	Respondents live in an apartment = 1 Other = 0

Table 5 continued

Variables	Definitions	Contents
Couple	Whether households of respondents are composed of only a married couple	Households of respondents are composed only of a married couple = 1 Other = 0
Couple child	Whether households of respondents are composed of a married couple and a child	Households of respondents are composed of a married couple and a child = 1 Other = 0
Three generations	Whether households of respondents are composed of three generations	Households of respondents are composed of three generations = 1 Other = 0
Single-life	Whether respondents live alone	Respondents live alone = 1 Other = 0
Month	Electricity rate per month	Numerical value
First	Initial cost to introduce the tool for dynamic pricing	Numerical value
Constant	Constant term	Numerical value

Table 6 Descriptive statistics for multinomial logit model

Variable	Mean	SD	Min	Max
Fee	11,122.760	6964.586	500	40,500
Knowledge	5.005	4.270	1	14
All	0.845	0.362	0	1
Family	2.798	1.275	1	9
Age	42.572	14.224	20	60
Education	5.810	1.765	2	9
Income	596.373	360.211	1,500,000	15,000,000
Risk	0.720	0.733	0	3
Gender	0.537	0.499	0	1
Tokyo	0.319	0.466	0	1
Time	0.383	0.486	0	1
Ownership	0.544	0.498	0	1
Rent	0.026	0.160	0	1
Apart	0.166	0.372	0	1
Couple	0.248	0.432	0	1
Couple child	0.449	0.497	0	1
Three generations	0.081	0.273	0	1
Single-life	0.159	0.365	0	1
Month	12,618.980	12,354.880	1000	40,000
First	7472.510	5108.150	0	15,000

First, TOU is the most preferable pricing rule for consumers. Our estimation results show that TOU has the highest value of WTP of all pricing rules. Second, the characteristics of each consumer affect the choice of a pricing rule. Borenstein (2006) notes that the risk of a pricing change is one of the important factors in choosing a pricing rule. In fact, we find that consumers who have a preference for risk aversion tend not to choose the RTP. In addition, our results show several characteristics influence the choice of a pricing rule. Our estimation results show that household characteristics are important factors in the choice of a dynamic pricing rule (economic incentive schemes and DLC). Regarding personal characteristic, a strong academic record increases the choice

Table 7 Estimation results of marginal effects (economic incentive rules)

Attributes	Economic incentive					
	TOU		CPP		RTP	
	Time-of-use rate		Critical peak price		Real-time price	
	Estimate	*t* value	Estimate	*t* value	Estimate	*t* value
Fee	−0.0000**	−2.54	−0.0000***	−4.70	−0.0000***	−3.23
Knowledge	0.0008***	3.82	0.0012***	6.39	−0.0009***	−4.54
All	−0.0412***	−17.01	−0.0202***	−8.63	0.0147***	5.70
Family	−0.0078***	−6.42	0.0035***	3.20	0.0058***	4.93
Age	−0.0003***	−4.12	−0.0000	−0.17	0.0004***	5.94
Gender	−0.0136***	−7.33	−0.0034*	−1.92	0.0005	0.29
Education	0.0049***	9.16	0.0023***	4.62	0.0036***	6.74
Income	0.0000	0.22	−0.0000	−0.70	0.0000163***	5.87
Risk	−0.0041***	−2.75	0.0017	1.22	0.0092***	6.29
Tokyo	−0.0039**	−2.00	0.0000***	0.00	0.0015	0.78
Time	−0.0058***	−2.95	−0.0087***	−4.69	−0.0146***	−7.44
Ownership	0.0116***	5.63	−0.0107***	−5.57	0.0020	0.97
Three generations	−0.0064*	−1.66	0.0039	1.10	−0.0273***	−7.05
Single-life	−0.0092**	−2.55	0.0048	1.41	0.0040	1.11
Month	−0.0000***	−6.56	0.0000***	6.55	−0.0000***	−5.46
First	0.0000***	5.84	−0.0000	−1.50	−0.0000*	−1.88

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table 8 Estimation results of marginal effects (DLC and general rule)

Attributes	Direct load control			
	DLC		Mixed with DLC and CPP	
	Estimate	*t* value	Estimate	*t* value
Fee	0.0000***	7.54	0.0000***	7.54
Knowledge	−0.0002	−1.26	−0.0004**	−2.47
All	−0.0034	−1.47	−0.0135***	−6.29
Family	0.0002	0.13	−0.0013	−1.30
Age	−0.0002***	−2.87	−0.0001	−1.16
Gender	0.0148***	8.54	0.0184***	11.24
Education	0.0001	0.24	−0.0004	−0.76
Income	0.0000*	1.76	0.0000***	4.79
Risk	−0.0041***	−3.00	−0.0020	−1.57
Tokyo	0.0118***	6.64	0.0011	0.66
Time	0.0093***	5.14	0.0093***	5.47
Ownership	−0.0049**	−2.59	−0.0027	−1.51
Three generations	−0.0044	−1.26	0.0013	0.41
Single-life	−0.0179***	−5.26	−0.0071**	−2.24
Month	0.0000***	9.40	−0.0000***	−5.59
First	−0.0000	−0.74	−0.0000***	−4.41

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

probability of economic incentive rules. Borenstein (2013) notes that lower-income consumers tend to prefer dynamic pricing rule, but our results do not show a robust relationship between income and the choice probability of dynamic pricing schemes.

Therefore, the relationship between the choice of each pricing rule and income level could be more complex.

Energy conservation is an important policy problem worldwide. In the near future, demand-side control will become a more important policy for countries and regions because dynamic pricing schemes are one of the best tools to control the demand of electricity. However, many consumers need to support the dynamic pricing rule to achieve effective control of energy demand. Therefore, we need to consider not only the direct effect of each pricing rule but also whether consumers want to support such a pricing rule.

Additional file

Additional file 1.

Authors' contributions
YY contributed to the design of the web survey and analysis of the data. KT analyzed the data, wrote the manuscript and submitted this manuscript to this journal as corresponding author. SM helped in conception of this research and writing the manuscript. All authors read and approved the final manuscript.

Author details
[1] Faculty of Engineering, Fukui University of Technology, Gakuen 3-6-1, Fukui-shi, Fukui 910-8505, Japan. [2] Faculty of Economics, Musashi University, 1-26-1 Toyotamakami, Nerima-ku, Tokyo 176-8534, Japan. [3] Urban Institute and School of Engineering, Kyushu University, 744, Motooka, Nishi-ku, Fukuoka 819-0395, Japan. [4] QUT Business School, Queensland University of Technology, Level 8, Z Block, Gardens Point, 2 George St, Brisbane, QLD 4000, Australia.

Acknowledgements
This paper was supported by CREST of Japan Science and Technology (in particular, this funding supports data collection by web survey). Also, this paper was supported by Grant-in-Aid for Specially Promoted Research (26000001) by the Japan Society for the Promotion of Science (in particular, this funding supports our analysis) and S16 by Ministry of Environment (in particular, this funding supports our interpretation of data).

Competing interests
The authors declare that they have no competing interests.

Received: 11 October 2015 Accepted: 21 February 2017
Published online: 02 March 2017

References
Allcott H (2011) Rethinking real-time electricity pricing. Resour Energy Econ 33:820–842
Borenstein S (2006) Customer risk from real-time retail electricity pricing: bill volatility and hedgability. NBER working paper no. 12524
Borenstein S (2013) Effective and equitable adoption of opt-in residential dynamic electricity pricing. Rev Ind Organ 42(2):127–160
Cameron CA, Trivedi KP (2009) Microeconometrics: methods and applications. Cambridge University Press, New York
Chao H, Pecks S (1996) A market mechanism for electric power transmission. J Regul Econ 10:25–59
Faruqui A, George SS (2005) Quantifying customer response to dynamic pricing. Electr J 18:53–63
Herter K (2007) Residential implementation of critical peak pricing of electricity. Energy Policy 35:2121–2130
Joskow P (1975) Applying economic principles to public utility rate strictures: the case of electricity industry. In: Cicchetti C, Jurewinz J (eds) Studies in electric utility regulation. Ballinger Publishing Company, Cambridge, pp 17–71
Joskow LP, Wolfram DC (2012) Dynamic pricing of electricity. Am Econ Rev 102(3):381–385
Kurakawa Y, Sawada E, Tanaka K, Akao K, Managi S (2016) Eliminating instability under real-time pricing utilizing peer-effect **(Unpublished)**
Matsukawa I, Asano H, Kakimoto H (2000) Household response to incentive payments for load shifting. Energy J 21(1):73–86
McFadden D (1973) Conditional logit analysis of qualitative choice behavior. Academic Press, London