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HOW DOES INFORMATION PROVISION AFFECT RESIDENTIAL ENERGY CONSERVATION? EVIDENCE FROM A FIELD EXPERIMENT

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ABSTRACT

This paper attempts to measure the benefits of information about efficient usage of electric appliances consumers receive through energy conservation, using data from a Japanese experiment. In the experiment, households could easily obtain information on how to achieve efficient usage of electric appliances through a display installed at their residence. The data were used to estimate a utility-consistent, discrete−continuous model of display usage and electricity demand. Full information maximum likelihood estimates of a translog indirect utility function and electricity cost share function indicate that information provision contributed to energy conservation and to welfare improvements of consumers in the experiment.

Keywords:
information effects, energy conservation, discrete−continuous model

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INTRODUCTION

The widespread usage of the Internet has increasingly provided opportunities for consumers to find sought-after commodities without incurring large information search costs. Information on consumer durables is particularly valuable because better choices are made when consumers can take into account a wide range of product attributes, including size, make, model, and vintage, as well as prices and interest payments.

Of these items of information, the efficient use of durables is crucial for maximizing utility, subject to constraints on resources such as income, time, and effort. Examples include information concerning the setup of personal computers and cellular phones. It is sometimes difficult for consumers owning these goods to find the 'best' setup that maximizes their satisfaction subject to resource constraints. In response, suppliers of durables have attempted to facilitate consumer access to information on the efficient operation of their products by developing user-friendly interfaces. Homepages that show how to use products with charts and animation are just one example of such interfaces. Since the development and maintenance of user-friendly interfaces is costly, the benefit of easy access to information on the efficient usage of consumer durables is an important factor that impacts upon the markets for consumer durables.

This paper attempts to measure the benefits of providing consumers with information on the usage of durables by using experimental data on Japanese households. The focus of the paper is on providing consumers with information about the efficient usage of energy-using durables. This information could be easily obtained at any time through a display that had been installed in each consumer's residence during the experiment. Consumers did not incur the costs of installing the display nor the cost of the electricity used to operate the display. Thus, consumers could, without incurring additional costs, obtain information on how to use their electrical appliances more efficiently. However, consumers did incur the costs of time and effort spent on operating the display if they were busy and not familiar with its operation. If these costs were larger than the benefits obtained from the information, consumers would not use the display. The consumers' choice of display usage and electricity consumption was then investigated to measure consumers' net benefits of information on the efficient usage of electrical appliances.

A discrete−continuous model of display usage and electricity demand is developed to measure information benefits. Discrete−continuous models assume consumers face two choices:

(1) which alternative to adopt from a finite and exhaustive set of mutually exclusive alternatives; and
(2) how much of a particular good to purchase, where the amount of the good can be represented by a continuous variable (Train, 1986, p. 82).

Since a discrete−continuous model combines the discrete choice of display usage and continuous demand for electricity by Roy's identity (see Pollak and Wales, 1992, p.10, about Roy's identity), it allows for the exact welfare measurement of information provision. The current analysis uses a nonhomothetic translog indirect utility function, which imposes no restrictions on substitution or income elasticities, as against previous models applying linear or log-linear demand functions that impose restrictions on substitution or income elasticities (Burtless and Hausman, 1978; Hausman, 1979; King, 1980; Dubin and McFadden, 1984; Hausman and Trimble, 1984; Train and Mehrez, 1994; Lohr and Park, 1995).[1]

This paper empirically investigates energy-conservation effects of information provision that have important policy implications because energy conservation has increasingly received attention as an effective way to mitigate global warming by reducing the emission of greenhouse gases such as carbon dioxide. The extensive literature on energy conservation has investigated the effectiveness of a number of policy measures, including carbon taxes (Dumagan and Mount, 1992; Conrad and Schröder, 1991), deduction of investment taxes (Hassett and Metcalf, 1995), efficiency standards of energy-using durables (Hausman and Joskow, 1982; Greening, Sanstad, and McMahon, 1997), government or utility-funded programs of energy-efficiency improvements (Joskow and Marron, 1992; Dumagan and Mount, 1993; Parfomak and Lave, 1996; DeCanio and Watkins, 1998; Horowitz, 2001), and energy auditing (Waldman and Ozog, 1995; Anderson and Newell, 2004). Although the experiment from which the analysis is derived directly provided consumers with information on energy efficiency, as in energy auditing, previous work on energy auditing has not employed a utility-consistent model and fails to conduct a welfare analysis of information provision. The welfare analysis in this paper provides evidence that information provision is beneficial for consumers and is a promising policy option.

Providing households with appropriate information about the efficient usage of appliances is a potential policy to promote energy conservation because it helps to remove a 'market barrier' to energy conservation arising from consumers' lack of information on energy efficiency (Southerland, 1991). In sharp contrast to industrial customers, whose well-informed staff efficiently monitor and control energy usage at factories and office buildings, residential customers often find it difficult to monitor and control energy usage at home. For residential customers using a large number of energy appliances with different levels of energy efficiency, it is difficult to see how to use these appliances in a more efficient manner. In addition to energy efficiency labels that help identify energy efficient products, providing residential customers with information on the efficient usage of energy durables is expected to promote energy conservation at home.

The paper is organized as follows. The discrete−continuous model of the choice of display usage and electricity consumption is developed in Section 1. In Section 2, the data and estimation results of the model are discussed, along with the information effects on energy conservation and welfare analysis. Section 3 presents some conclusions.

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1 Although Hausman and Trimble (1984) applied an almost ideal demand system to peak and off-peak electricity demand models, they assumed a linear expenditure system for total electricity demand and composite goods, which imposes restrictions on substitution and income elasticities. King (1980) applied a homothetic translog model, which assumes that income elasticity is unity, to the analysis of a discrete−continuous model of tenure choice and housing demand.

1. THE MODEL

1.1 Discrete Continuous Choices of Display Usage and Electricity Demand

For each month during the experiment, households are assumed to allocate expenditure into two commodities: electricity service, S, and other goods, Z, given their ownership of durables. Electricity service is defined as the comfort and convenience that households obtain from the usage of electrical appliances. For instance, electricity service represents some measurable output of residential heating. The given level of electricity service is assumed to depend on electricity consumption, E, and the technical energy efficiency of appliances, q. This efficiency of appliances is defined as the ratio of service output to energy input. The technical efficiency of appliances depends on various factors, including appliance attributes, space, weather conditions, and appliance usage. Providing households with information on the efficient usage of appliances is expected to improve the technical efficiency of appliances.

Given appliance attributes, space, and weather conditions, access to information on the efficient usage of electrical appliances is assumed to affect the level of electricity service through the improvement of energy efficiency, and the level of electricity service is assumed to be the product of electricity consumption and energy efficiency:[2]

$$S = E \cdot q(M^k, X), \qquad k = 0, 1, \tag{1}$$

where M^k represents a variable associated with the kth level of display usage and X represents factors affecting energy efficiency of appliances that are not associated with display usage during the experiment. Examples of factors included in X are ownership levels and attributes of electrical appliances, space, weather conditions, and households' ability to process information about energy efficiency. A value of $k = 1$ indicates that households obtain information on the efficient usage of appliances through the display installed at their residence during the experiment, and $k = 0$ indicates that they never use the display.

Access to information on the efficient usage of appliances is assumed to improve energy efficiency so that $q(M^1) > q(M^0)$. Equation (1) implies that, given the level of electricity service, electricity consumption is reduced by the improvement of energy efficiency through access to information. For instance, given a thermostat setting of an electric room air conditioner, access to information on the efficient operation of the air conditioner could improve its energy efficiency, thereby reducing electricity consumption and expenditure.

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[2] Following Wirl (1997, p. 19), for simplicity, Equation (1) assumes a linear relationship between the level of electricity service and electricity consumption. The linear relationship between electricity service and consumption may not hold for some electrical appliances. For instance, Dubin, Miedema, and Chandran (1986) assume a quadratic relationship between electricity service and consumption for heating and cooling.

Households' allocation of income into electricity service and other goods can be described by the following utility maximization problem, subject to the technological constraint in Equation (1) and the budget constraint: [3]

$$\max_{S,\,Z}\; U^{k}(S, Z; M^{k})$$

$$\text{subject to } S = E \cdot q(M^{k}, X),$$

$$p_e E + p_z Z \leq y\,, \tag{2}$$

where p_e, p_z, and y are the electricity price, price of nonelectrical goods, and monthly income, respectively. $U^{k}(S, Z; M^{k})$ represents a direct utility function conditional on the choice of the kth level of display usage. It is assumed that $U^{1} < U^{0}$, given the level of electricity service and consumption of nonelectrical goods. This assumption indicates that access to information on the efficient usage of appliances requires households to incur costs of time and effort, thereby lowering the utility level of households.

Households are assumed to choose the kth level of display usage to maximize their utility levels. Household i's choice of display usage in month t is described by the following indirect utility function:

$$V_{it}(p_{eit}, p_{zit}, y_i; M_{it}, X1_{it}, X2_{it}, w_{eit}, w_{zit}, e_{it}) = \max\{V^{0}_{it}(p_{eit}, p_{zit}, y_i; M^{0}_{it}, X1_{it}, X2_{it}, w_{eit}, w_{zit}, e^{0}_{it}), V^{1}_{it}(p_{eit}, p_{zit}, y_i; M^{1}_{it}, X1_{it}, X2_{it}, w_{eit}, w_{zit}, e^{1}_{it})\}, \tag{3}$$

where $V^{k}_{it}(.)$ denotes the indirect utility function that is conditional upon the choice of the kth level of display usage for household i in month t, $k = 1$ indicates that households use the display at least once in month t, $k = 0$ indicates that they never use it in month t, and p_{eit}, p_{zit}, and y_i are the electricity price, price of nonelectrical goods, and income for household i in month t, respectively. Since monthly data on income were not available, y_i is assumed to be identical across all months for household i. M_{it} is a variable associated with the usage of the display for household i in month t. It is assumed that $M^{1}_{it} = 1$ and $M^{0}_{it} = 0$ for all households and months. $X1_{it}$ is a vector of household characteristics, appliance holdings, and monthly dummies that are not associated with the choice of the level of display usage, and $X2_{it}$ is a vector of those variables that affect the choice of the level of display usage. w_{eit} and w_{zit} represent unobserved factors affecting the consumption of electricity and other commodities and e^{k}_{it} represents an unobserved factor affecting the choice of the kth level of display usage.

Assuming a probability distribution of error terms in Equation (3), the choice of display usage is described by a probabilistic discrete choice model. The application of Roy's identity to the conditional indirect utility function leads to the conditional demand function of electricity. Thus, the discrete choice of information

[3] Display usage is not treated as a good, because of the difficulty in defining "the price of display usage" in the model. In the experiment, households did not pay for display installation and usage. Thus, display usage cannot be treated as a good in the model.

acquisition and continuous demand for goods are jointly modeled and estimated so as to be theoretically consistent with utility maximization.

1.2 Translog Indirect Utility Function and Electricity Cost Share Function

The indirect utility function that is conditional upon the choice of the kth level of display usage for household i in month t is assumed to take the following form of a translog function (Christensen, Jorgenson, and Lau, 1975):[4]

$$\begin{aligned}\log V^{k}_{it} &= -a_e \log(p_{eit}/y_i) - a_z \log(p_{zit}/y_i) - 0.5\, b_{ee}[\log(p_{eit}/y_i)]^2 - 0.5\, b_{zz}[\log(p_{zit}/y_i)]^2 \\ &- 0.5(b_{ez}+b_{ze})[\log(p_{eit}/y_i)][\log(p_{zit}/y_i)] - a_{em}\log(p_{eit}/y_i)\, M^{k}_{it} - (a_{ex}X1_{it})\log(p_{eit}/y_i) \\ &- (a_{zx}X1_{it})\log(p_{zit}/y_i) + c^k X2_{it} - w_{eit}\log(p_{eit}) - w_{zit}\log(p_{zit}) + e^{k}_{it}, \qquad (4)\end{aligned}$$

where a_e, a_z, b_{ee}, b_{zz}, b_{ez}, b_{ze}, and a_{em} are parameters, and a_{ex}, a_{zx}, and c^k are a vector of parameters. The translog model is flexible in the sense that there are no restrictions on substitution or income elasticities and it has been widely applied to empirical studies on energy demand (Aigner and Hausman, 1980; Caves and Christensen, 1980; Cameron, 1985; Jorgenson, Slesnick, and Stoker, 1988). Another attractive feature of the translog function is that the underlying indirect utility function is known and exact welfare measurement is possible. In contrast to familiar flexible functional forms such as the almost ideal demand system, generalized logit, Rotterdam and generalized Leontief models, the translog indirect utility function is linear in parameters and is more easily estimated than other flexible functional forms. Almost ideal demand system and generalized Leontief models have complicated indirect utility functions.[5] Generalized logit and Rotterdam models have no explicit form of indirect utility function.

Assuming that the error terms e^0_{it} and e^1_{it} are normal with zero means, the term $e^0_{it} - e^1_{it}$ is also normally distributed with mean zero and with variance σ.[6] Assuming further that $\sigma = 1$, the probability of using the display is described by the following probit model:

[4] The model in Equation (1) assumes no interaction between electricity price and the unobservable factor affecting monitor usage, so as not to make model specification too complicated. However, the unobservable factor affecting monitor usage may interact with electricity prices, as the increase in electricity prices may make information from the display usage more valuable.

[5] Although the cost share functions associated with the nonhomothetic translog model are not linear in parameters, it was not difficult, as shown in Section 3.2, to jointly estimate the indirect utility function and cost share functions by a full information maximum likelihood estimation procedure.

[6] Correlations in both usage levels and display usage over time may exist and cause bias the standard errors. In addition, the carry-over effect of information provision from month to month may exist. Ideally, these serial correlations and carry-over effect should be accounted for in the analysis. Because of the extremely small number of time series (three months) and because of the technical difficulty of accounting for a dynamic model in a discrete−continuous framework, however, it is difficult to extend the model to allow for serial correlations and to allow for the carry-over effect. In fact, the previous literature using a utility-consistent framework assumed a static model.

$$\Pr\{d_{it}=1\} = \Pr\{\log V^1{}_{it} \geq \log V^0{}_{it}\} = \Phi(R_{it})$$
$$\Pr\{d_{it}=0\} = \Pr\{\log V^1{}_{it} < \log V^0{}_{it}\} = 1 - \Pr\{d_{it}=1\} = 1 - \Phi(R_{it}), \tag{5}$$

where $\Phi(.)$ is the standard normal distribution function, and

$$R_{it} = -a_{em}\log(p_{eit}/y_i)(M^1{}_{it} - M^0{}_{it}) + (c^1 - c^0)\,X2_{it}\,.$$

d_{it} is a dummy variable that becomes unity when the display is used at least once for month t by household i and zero otherwise.

The following assumptions are made in Equation (4) for all households in all months:

$$b_{ez} = b_{ze}\,,$$
$$a_e + a_z + a_{ex}X1_{it} + a_{zx}X1_{it} + a_{em}[d_{it}M^1{}_{it} + (1-d_{it})M^0{}_{it}] = 1,$$
$$p_{zit} = 1.$$

The first assumption indicates a symmetry restriction, which follows from the Slutsky symmetry conditions. The second assumption represents a normalization rule (Pollak and Wales, 1992, p. 56). The third assumption is necessary because no data on the prices of nonelectrical goods were available for households participating in the experiment. Then, the application of Roy's identity to the conditional indirect utility function in Equation (4) leads to the following form of a cost share function of electricity CS_{it}:

$$CS_{it} = [a_e + b_{ee}\log(p_{eit}) - (b_{ee} + b_{ez})\log(y_i)$$
$$+ a_{em}(d_{it}M^1{}_{it} + (1-d_{it})M^0{}_{it}) + a_{ex}X1_{it}]/D + (w_{eit}/D), \tag{6}$$

Where $D = 1 + (b_{ee} + b_{ez})\log(p_{eit}) - (b_{ee} + b_{zz} + 2b_{ez})\log(y_i)$.

The sum of cost shares should be unity for all observations, and the cost share equation for nonelectrical goods is dropped in estimation. The error terms $(e^1{}_{it} - e^0{}_{it})$ and w_{eit}/D are assumed to be distributed according to a bivariate normal distribution, and Equations (5) and (6) are jointly estimated with the parameter restrictions associated with symmetry and normalization.[7]

1.3 Econometric Considerations

The probabilistic choice model of display usage and the electricity cost share model contain two endogenous variables: the electricity price (p_{eit}) and the display usage dummy (d_{it}). The marginal price of electricity is used for p_{eit}. Inverted block

[7] Since the error term in Equation (6) depends on explanatory variables, the assumption of constant variance is not valid and efficiency is reduced. Given the highly nonlinear form of the variance, however, the maximum likelihood estimator is not manageable numerically in the analysis of a discrete−continuous model, as indicated by Train and Mehrez (1994, p.273).

rates are applied to Japanese households, and the marginal price of electricity depends on which consumption block is chosen. The tariffs have a three-tier inverted block rate structure and consist of energy and demand charges.[8] During the experiment, the first block of 120 kilowatt hours (kWh) had a marginal price of 17.64 cents per kWh (assuming one US dollar = 100 yen). Beyond that, and up to 280 kWh, the marginal price rose to 23.29 cents per kWh. The highest price was 25.59 cents per kWh for consumption over 280 kWh.

The unobserved factors affecting households' choice of electricity price may be correlated with the error terms e^k_{it} and w_{eit}/D. Because of the endogeneity of electricity prices, the estimates of Equations (5) and (6) are biased. A predicted value of the marginal price of electricity was used to correct for a bias associated with the endogeneity of electricity prices. This predicted value was obtained from the fitted value of electricity consumption, which was computed by regressing monthly electricity consumption of each household on selected exogenous variables (Train and Mehrez, 1994). These exogenous variables are the contracted amount of electricity, the number of household members, the number of electric room air conditioners, the number of TV sets, ownership dummy variables for electric clothes driers and dishwashers, and dummy variables for the months of July and August. All of these variables displayed significant positive coefficients at the 1% level.

Equation (6) also contains the display usage dummy, d_{it}, which is considered to be an endogenous variable. The level of display usage is assumed to be affected by the unobserved factors that are correlated with the error term in Equation (6). Because of the endogeneity of display usage, estimates of Equation (6) are biased. A Heckman-type correction term is added to Equation (6) to correct for the endogeneity bias (Heckman, 1979; Metcalf and Hassett, 1999). Specifically, the correction term, H_{it}, is given by:

$$H_{it} = \varphi(R_{it})/\Phi(R_{it}) \text{ if } k = 1$$
$$H_{it} = -\varphi(R_{it})/\Phi(-R_{it}) \text{ if } k = 0, \qquad (7)$$

where $\varphi(.)$ is the standard normal density function. The coefficient of H_{it} that is added to Equation (6) implies covariance between the error terms w_{eit}/D and $(e^1_{it} - e^0_{it})$.

2. DATA AND ESTIMATION RESULTS

2.1 The Data

The New Energy and Industrial Technology Development Organization (NEDO) and the Kyushu Electric Power Company (KEPCO) jointly conducted an experiment during the summer working days in 1996. In the experiment, participating households could obtain information on the efficient usage of electrical appliances through a display at their dwellings. Households could easily see how to use electrical appliances such as room air conditioners, refrigerators, TV sets, and

[8] The demand charge depends on the contracted amount of electricity. Since no households changed the contracted amount of electricity during the experiment, the demand charge levels were constant and not modeled in this paper.

clothes washers through the display at any time during the experiment. Households did not incur any of the costs of display installation or of the electricity used to operate the display. During the period of the experiment, no monetary incentives were paid to participating households.

The NEDO and KEPCO began soliciting participants for the experiment in 1994. They used a random sampling procedure to select households living in the Maebaru District of Fukuoka City. The population of Fukuoka City is approximately 1.3 million, and Maebaru is located in the west of Fukuoka City. The experiment lasted from the beginning of July to the end of September in 1996, excepting weekends and public holidays. Participation in the experiment was voluntary, and the ratio of the number of the participants to the number of households that were asked to participate was 23.8%. The participants were randomly assigned either to an experimental group (299 households) or to a control group (291 households). Participants in the control group did not have any display at home.

Use of the display was recorded whenever the participants in the experimental group activated the display at least once during each month. Through the display, participants could see eight programs for the efficient usage of electrical appliances at any time during the experiment. Each program explained how to use electrical appliances more efficiently with elaborate charts and illustrations on the screen of the display. Examples included room air conditioners, refrigerators, TV sets, washing machines, clothes driers, and microwave ovens.

Table 1: Examples of Information on the Efficient Usage of Electrical Appliances

Appliance	**Item**	**Suggestion**
Room air conditioners	Filters	Clean air conditioner filters at least once in two weeks.
	Timers	Use a timer to operate an air conditioner only when heating or cooling is necessary.
Refrigerators	Food storage	Do not store too much food in a refrigerator.
	Cleaning	Keep the door seals of a refrigerator clean.
TV sets	Brightness	Do not make the screen too bright.
	Operation	Turn off a TV set when you are not watching it.
	Standby power	Unplug a TV set to save standby power.

Table 1 presents some examples of the information provided on the efficient usage of these appliances.

Table 2 presents information on electricity usage per day, the ratio of households using the display at least once each month, demographic characteristics, and appliance holdings for the experimental group. Data on income, demographic characteristics, and appliance holdings were collected from a questionnaire mailed during the experiment. Daily electricity usage was recorded by the electric utility. After eliminating those observations with missing data, data were available on 194 households. We excluded participants whose data on electricity consumption and display usage were not completely recorded because of equipment failure during the experiment.

Table 2: Description of Sample Characteristics

Description	Means (standard deviations)
Electricity usage in July (kWh per day)	14.1 (6.2)
Electricity usage in August (kWh per day)	15.6 (6.7)
Electricity usage in September (kWh per day)	10.4 (4.4)
Ratio of households using the display in July (%)	83.2
Ratio of households using the display in August (%)	75.8
Ratio of households using the display in September (%)	61.3
Household income (1 million yen per year)	7.3 (3.2)
Contracted amount of electricity (ampere)	37.6 (10.7)
Number of household members	3.6 (1.5)
Number of children, 0-6 years old	0.2 (0.6)
Number of elderly, over 65 years old	0.4 (0.7)
Age of household head	54.3(12.6)
Number of electric room air conditioners	2.4 (1.3)
Number of TV sets	2.3(1.0)
Ratio of households owning dishwashers (%)	9.3
Ratio of households owning dish driers (%)	50.5
Ratio of households owning electric cloth driers (%)	22.2
Number of Households	194

Electricity consumption in September was much lower than in previous months. The ratio of households using the display was largest during the first month of the experiment and lower in later months. This may imply that the length of learning period differed across households, depending on their eagerness and ability to process information.

2.2 Estimation Results

Pooled data on 194 households and three months (July, August, and September in 1996) were used to jointly estimate the parameters in display usage choice (Equation (5)) and electricity cost share (Equation (6)) with the variable H_{it} (Equation (7)). A full information maximum likelihood (FIML) estimation procedure was employed to obtain estimates of these parameters. These FIML estimates of the discrete−continuous choice model are asymptotically unbiased and efficient.[9] A two-step estimation of Equations (5) and (6), which first estimates Equation (5) and then estimates Equation (6) with the predicted value of H_{it} obtained from the parameters of Equation (5) at the first step, was also conducted to obtain starting values for the FIML estimation. The FIML estimates are expected to converge by setting the two-step estimates as the starting values (Hanemann, 1984). The BHHH (Berndt–Hall–Hall–Hausman) method was used to compute the covariance matrix of coefficients.

[9] Since a full information maximum likelihood method, which jointly estimates display usage and electricity consumption and explicitly includes the correction term in the log-likelihood function, is employed, the estimated standard errors do not need to be corrected. However, the two-step estimation procedure used to correct for the endogeneity of the price requires the correction of standard errors, which was not done in this paper.

Table 3 summarizes the estimation results of the indirect utility function and electricity cost share function. The electricity cost share was normalized so that the share of electricity expenditure was 50% at the sample mean. Of the explanatory variables, income and the nondummy variables associated with $X1_{it}$ were also normalized to unity at their sample means. Explanatory variables associated with household characteristics, appliance holdings and monthly dummies were only included if they were significant at the 10% level of significance or lower.[10]

Table 3: Full Information Maximum Likelihood Estimates of the Indirect Utility Function and Electricity Cost Share Equation (standard errors are in parentheses)

a_{em} : display usage	-0.132 (0.050)***
a_e	0.202 (0.035)***
Variables associated with $X1_{it}$	
Contracted amount of electricity	0.045 (0.012)***
Number of household members	0.109 (0.008)***
Number of elderly, over 65 years old	-0.006 (0.002)**
Age of household head	0.054 (0.017)***
Number of electric room air conditioners	0.036 (0.005)***
Number of TV sets	0.029 (0.006)***
Dish drier dummy	0.019 (0.006)***
July dummy	0.142 (0.013)***
August dummy	0.147 (0.011)***
Variables associated with $X2_{it}$	
Constant	0.023 (0.105)
Number of children, 0-6 years old	0.433 (0.112)***
July dummy	0.600 (0.138)***
August dummy	0.396 (0.136)***
b_{ee}	0.349 (0.065)***
b_{ez}	-0.075(0.058)
b_{zz}	-0.139(0.061)**
σ_{de} : covariance between w_{eit}/D and $(e^1{}_{it} - e^0{}_{it})$	0.074 (0.031)**
standard deviation of w_{eit}/D	0.065 (0.002)***
Log likelihood at convergence	439.47

Note: * denotes statistically significant at the 10% level, ** denotes 5%, and *** denotes 1%.

2.2.1 *Conservation Effects of Information Provision*

The effect of display usage on the household demand for electricity is found to be statistically significant. As shown in Table 3, the estimated coefficient a_{em} in Equations (5) and (6) is statistically significant at the 1% level. The negative estimated coefficient a_{em} implies that the use of the display promoted energy

[10] The list of $X1_{it}$ and that of $X2_{it}$ are determined by statistical significance. Variables in the list of $X2_{it}$ affect only display usage, while variables in the list of $X1_{it}$ affect only electricity demand. Since variables in $X2_{it}$ are independent of the price and income, they are not modeled with the effects of price and income.

conservation. The energy-conservation effect of information is also indicated by Sexton et al. (1989) and Matsukawa (2004). Sexton et al. (1989) estimated the effect of the exogenous dummy variable for the presence of the monitor in a time-of-day pricing experiment in the USA. Sexton et al. (1989) found that the presence of the monitor contributed to a reduction in electricity usage during the peak period by providing consumers with detailed information on their expenditure of electricity and time-of-day prices. Matsukawa (2004) also found the energy-conservation effect of monitor-provided information about households' own usage of electricity in a Japanese experiment. Matsukawa (2004) concluded that the contribution of monitor usage to energy conservation was modest, as indicated by small estimates of the elasticity of electricity demand with respect to monitor usage.

While the information provided by monitors was associated with electricity prices and households' usage of electricity in these previous studies, the present paper examines information about how to use electric appliances efficiently. Thus, the estimates of this paper reflect direct effects of information on energy conservation. It should be noted that these previous studies did not use a utility-consistent model for the analysis of information effects on energy conservation, while the present paper applies a discrete−continuous model to the analysis of information effects on energy conservation.

Using the estimated coefficient a_{em} in Table 3, the information effect of energy conservation was computed at the sample mean for each month in Table 4. Information provision was found to reduce daily electricity consumption of a participating household by approximately 0.141 kWh, or by 1.05% of the average daily consumption of electricity per household during the experiment (13.3 kWh per day). This reduction in electricity consumption is relatively modest. Three reasons are speculated: (1) information provided through the display was associated only with some major appliances so that energy conservation activities of the household were confined to these appliances; (2) households using the display did not necessarily see all programs, and information on some appliances was disregarded; and (3) households using the display did not perfectly implement energy conservation activities because of constraints on resources such as time and effort.

Table 4: Energy Conservation Effect of Information Provision at Sample Mean

	Electricity reduction (kilowatt hours per day)	Ratio of electricity reduction to total electricity consumption (%)
July	0.148	1.05
August	0.163	1.04
September	0.109	1.05
Monthly average	0.141	1.05

The relatively modest effect of monitor usage on energy conservation is in contrast with greater effects found in the previous literature. Darby (2006, p.11) indicates that the estimates of household energy savings from using relatively simple displays are typically of the order of 10%. Abrahamse et al. (2005, p.277) indicate that providing households with information about energy-saving measures by cable TV led to a 10 % decrease in energy usage. These studies did not consider household decisions of information acquisition and energy usage in a utility-consistent framework, and assumed that all households in the treatment group more or less made use of information. This may lead to a relatively greater effect of information on energy conservation.

2.2.2 *Effects of Price, Income, and Household Characteristics on Electricity Demand*

Using the parameter estimates in Table 3, price and income elasticities were computed at the sample mean. The results are shown in Table 5. Except for the uncompensated elasticity of electricity demand with respect to the price of nonelectrical goods, all elasticity estimates are significant at the 1% level of statistical significance. The compensated own-price elasticities are negative whereas the compensated cross-price elasticities are positive. This implies that consumer preferences are well behaved, at least, at the sample mean. In fact, all observations exhibited negative values of the compensated own-price elasticities and positive values of the compensated cross-price elasticities.

Table 5: Price and Income Elasticities at Sample Mean (standard errors are in parentheses)

Uncompensated elasticity of the demand for electricity with respect to the price of electricity	-0.583 (0.120)***
Uncompensated elasticity of the demand for non-electricity goods with respect to the price of non-electricity goods	-1.066 (0.118)***
Uncompensated elasticity of the demand for electricity with respect to the price of non-electricity goods	0.065 (0.116)
Uncompensated elasticity of the demand for non-electricity goods with respect to the price of electricity	-0.425 (0.122)***
Compensated elasticity of the demand for electricity with respect to the price of electricity	-0.321 (0.118)***
Compensated elasticity of the demand for non-electricity goods with respect to the price of non-electricity goods	-0.328 (0.120)***
Compensated elasticity of the demand for electricity with respect to the price of non-electricity goods	0.321 (0.118)***
Compensated elasticity of the demand for non-electricity goods with respect to the price of electricity	0.328 (0.120)***
Income elasticity of the demand for electricity	0.517 (0.017)***
Income elasticity of the demand for non-electricity goods	1.492 (0.017)***

Note: * denotes statistically significant at the 10% level, ** denotes 5%, and *** denotes 1%.

Uncompensated price elasticities, which hold income but not utility constant, are also presented in Table 5. The uncompensated elasticity of electricity with respect to price of nonelectrical goods is positive. In contrast, the uncompensated elasticity of nonelectricity demand with respect to electricity price is negative, because the income effect on nonelectricity demand is dominant. The uncompensated own-price elasticity of electricity was –0.58 at the sample mean. This own-price elasticity of electricity lies close to the estimate (–0.55) of Barnes, Gillingham, and Hagemann (1981). The improvement in energy efficiency may raise energy consumption if the own-price elasticity of electricity in absolute terms is larger than unity (Wirl, 1997, p. 28). This 'conservation paradox' would not happen in our case because the uncompensated own-price elasticity of electricity is far less than unity in absolute terms.

The elasticity of residential electricity demand with respect to income is 0.52 at the sample mean and is significant at the 1% level. This level of income elasticity is slightly larger than that found for summer (0.46) in Herriges and Kuester (1994). The estimates of income elasticities are significantly different from unity for both electrical and nonelectrical goods. This implies that consumer preferences are not homothetic. In fact, the null hypothesis of homotheticity, i.e., $b_{ee} = b_{zz} = -b_{ez}$, was rejected at the 1% level according to a Wald test.

Turning to household characteristics associated with $X1_{it}$, contracted amount of electricity, the total number of household members, and the age of the household head have positive impacts on electricity demand. Given the number of household members, the number of the elderly in the household only slightly reduced electricity usage. Electrical appliances such as room air conditioners, TV sets, and dish driers significantly raised electricity demand. When compared with the month of September, households used more electricity in July and August, which is also suggested by the positive coefficients for the monthly dummies in Table 3.

Display usage was affected by the number of children 0–6 years old in the household, which is associated with $X2_{it}$ in Equation (5). The positive coefficient of this variable implies that households with small children tended to use the display more than those without small children during the experiment. The ratio of households using the display was highest in July and lowest in September, as shown by the coefficients of monthly dummies associated with $X2_{it}$.

Finally, unobserved factors affecting display usage choice may be positively correlated with electricity demand, as the estimated covariance between the error terms w_{eit}/D and $(e^1_{it} - e^0_{it})$, denoted by σ_{de}, was positively significant at the 5% level. Thus, households using more electricity were more active in obtaining information on energy conservation.

2.3 Welfare Analysis of Information Provision

To examine the benefits of the information consumers received, the compensation for changes in display usage was estimated by using the estimation results of the discrete−continuous model of display usage and electricity demand. The compensation corresponds to income changes that would counterbalance a change in display usage level and leave the indirect utility level unchanged. The estimates of compensation presented indicate the benefits to consumers of the information received during the experiment.

Consumers receive the benefits of information on the efficient usage of appliances through the improvement of energy efficiency. This improvement in energy efficiency raises the direct utility level through two paths: (1) holding electricity consumption constant, the improvement of energy efficiency raises the level of electricity service, thereby increasing the direct utility level; and (2) holding the level of electricity service constant, the improvement of energy efficiency reduces electricity consumption, thereby increasing the consumption of nonelectrical goods and the direct utility level. Consumers also incur costs of information through the decrease in their direct utility levels, given the consumption of electrical and nonelectrical goods. The compensation for a change in display usage measures the amount of net benefits that consumers obtain from access to information on the efficient usage of appliances.

The total compensation required to make household *i* indifferent both to the case of $k = 1$ (using the display) and to the case of $k = 0$ (not using the display) in month *t*, denoted by CV_{it}, is defined in the following equation (Parks and Weitzel, 1984):

$$V^0_{it}(p_{eit}, p_{zit}, y_i) = V^1_{it}(p_{eit}, p_{zit}, y_i + CV_{it}). \tag{8}$$

Information acquisition can be said to benefit household *i* in month *t* whenever CV_{it} is negative, and $(-CV_{it})$ measures the size of the information benefit. If households choose display usage so as to maximize their utility in the experiment, the inequality $V^0_{it} \leq V^1_{it}$ holds according to Equation (3). Thus, CV_{it} in Equation (8) should be nonpositive.

Neglecting the error terms and substituting Equation (4) into Equation (8), yields the following quadratic equation with respect to $\log(y_i + CV_{it})$, which is solved to calculate the compensating variation for a change in display usage:

$$\begin{aligned}&-0.5(b_{ee} + b_{zz} + 2b_{ez})[\log(y_i + CV_{it})]^2 + [1 + (b_{ee} + b_{ez})\log(p_{eit})]\log(y_i + CV_{it}) + \\ &(c^1 - c^0)X2_{it} - a_{em}\log(p_{eit})(M^1_{it} - M^0_{it}) + 0.5(b_{ee} + b_{zz} + 2b_{ez})[\log(y_i)]^2 \\ &-[1 + (b_{ee} + b_{ez})\log(p_{eit})]\log(y_i) = 0. \end{aligned} \tag{9}$$

Note that M 1 it = 1 and M 0 it = 0 for all households and months. Two different solutions for (–CVit) were obtained from Equation (9); one solution exhibited an extremely large value. Having excluded this extreme solution, the solution of Equation (9) for (–CVit) was 2.5% of their monthly income level in the last month of the experiment (September) for households that chose the largest usage block of electricity (i.e., p_{eit} = 25.59 cents per kWh), earned the mean monthly income, and had no small children.[11] This compensation was approximately 13 % of the annual average of electricity expenditure for Japanese households. So long as the sum of the installation and operating costs of the display and software and lost profits of the electric utility is less than the sum of the compensation for the change in display usage (–CVit) and the environmental benefits of energy conservation, the provision to households of information on efficient usage of appliances through the display deserves to be considered as a favorable policy option for energy conservation.

CONCLUSION

This paper investigated the effect of information about the efficient usage of appliances on the residential demand for electricity using data from a Japanese experiment. In the experiment, a small display was installed in the residence of

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[11] The value of $(-CV_{it})$ ranged from 0.3% to 5.5%, depending on monthly income

participating households. The display was designed so that each household could easily obtain information on the efficient usage of electrical appliances at any time. Participating households that were eager to conserve energy could learn about how to use their appliances more efficiently without incurring any installation costs or the cost of electricity associated with use of the display.

A discrete−continuous choice model of display usage and electricity consumption, which is consistent with utility maximization, was estimated by a full information maximum likelihood (FIML) estimation procedure. FIML estimates of a translog indirect utility function and electricity cost share function indicate that display usage contributed to a reduction in electricity consumption and that the energy conservation effect of display usage was relatively modest.

The findings of this paper suggest that energy conservation can be enhanced by providing consumers with appropriate suggestions on the efficient usage of energy durables. An example includes the Internet, which enables consumers to obtain such information at relatively low cost. The effectiveness of such services can be explored by investigating how consumers respond to alternative forms of information on energy conservation. The estimates of information effects in this paper will be of value in the investigation of consumer responses to information on energy conservation. Other topics that have promise for future research include the effects of information on energy conservation by appliance and the effects of resources such as time and effort on the ability of households to implement energy conservation activities.

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