Analysis of Ownership and Usage of In-home Appliances and Vehicles based on the Multiple Discrete-Continuous Extreme Value (MDCEV) model*

by Biying YU**, Junyi ZHANG** and Akimasa FUJIWARA**

1. Introduction

Household energy consumption comes from the uses of appliances at home and vehicles outside to support various activity participations, which aim at meeting various household and individual needs. Traditionally, the in-home and out-of-home energy consumption behaviors have been separately treated. This might be influenced by the idea of the widely adopted sector-oriented policy decision scheme. However, since ownership and usage of appliances at home and vehicles results in the reduction of disposal household income, in-home and out-of-home energy consumption might be interrelated with each other. Such interrelationships might be observed with respect to ownership and/or usage of various appliances (e.g., refrigerator, air-conditioner, and washing machine) and vehicles (e.g., passenger car and motorcycle), implying that some multi-dimensional modeling approaches are required. Representing the aforementioned interrelationships also has an important implication to clarify the rebound effects. For example, these days, energy-saving technologies have been actively developed and have even become an indispensible part of products to win the competition among manufactures. However, the introduction of energy-saving technology does not mean that household energy consumption will be automatically reduced. One of the worrying concerns is that households might become environmentally insensitive to their energy consumption behavior and as a result, total amount of energy consumption might even increase, i.e., the rebound effects might occur. Since energy-saving technologies in different appliances and vehicles have not been equally developed and households might show different preferences for these new technologies, the sources of the rebound effects might vary across appliances and vehicles as well as households.

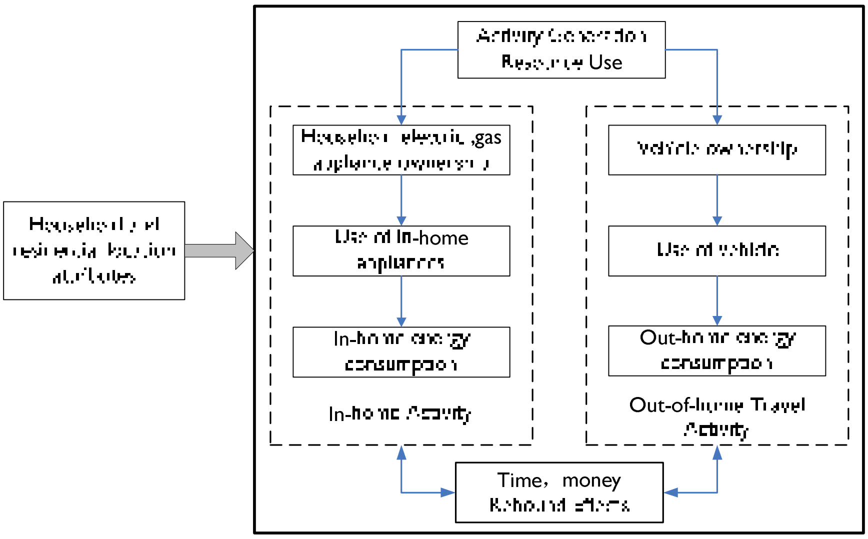

Figure 1. Household Energy Consumption Mechanisms

The above concerns motivate us to develop an integrated model to cover both in-home and out-of-home energy consumption. For this purpose, we build a household energy consumption model based on the multiple discrete-continuous extreme value (MDCEV) model (Bhat, 2005, 2008), and collected relevant household energy consumption data from 1,014 households living in Beijing, China in 2009. The data is used to estimate the MDCEV model and clarify influential factors affecting household energy consumption.

The remaining part of this paper is organized as follows. Section 2 gives a brief review of existing literature. The MDCEV model used in this study is illustrated in Section 3. Section 4 explains the survey data. Results of model estimation are shown and influential factors are examined in Section 5. This study is concluded in Section 6.

*Keywords: global environmental problems, household energy consumption, MDCEV model, in-home and out-of-home activities

** Graduate School for International Development and Cooperation, Hiroshima University, Higashi Hiroshima, Japan
(1-5-1 Kagamiyama, Higashi-Hiroshima 739-8529, Japan, Phone & Fax: 082-424-6919)

2. Review

To date, there are a large number of studies related to household energy analysis. The existing research can be summarized into two types. The first type is based on aggregation analysis[1)-4)] and can grasp the energy consumption trends at the macro level (e.g., country or city) and explore the advanced measures of reducing energy use from energy efficient countries/cities. The second type attempts to identify the contribution of each end-use towards the aggregate energy consumption at the residential level[5)-6)]. In the late 1980s, researchers began to pay attention to the impacts of consumers' behavior with regard to energy use which can illustrate problems more deeply, and introduced the concept of lifestyle into the study of personal energy consumption[7)-9)]. However the literatures above all focus on the relationship between residential lifestyle and aggregate energy use, instead of deeply understanding the energy consumption behavior from the perspective of ownership and usage at the household level. Energy studies have identified household characteristics such as income, household size, age structure, and levels of urbanization as key impact factors of direct residential energy demand[10)]. Some researchers proved that the main determinants for the increase of household energy consumption are the rise in incomes and household size[11)-13)].

Techniques used to model residential energy consumption behavior are very limited. Households make choices of different appliances/vehicles and decide how much energy to use conditional on these choices. Several discrete and discrete-continuous choice models have been proposed in literature to model behavior of holding and usage, but they are mainly utilized in personal travel energy consumption analysis[14)-16)], except "Dubin and McFadden[17)], which modeled jointly the demand for appliance and the demand for electricity by appliance". However most of these studies use standard discrete choice models (multinomial logit, nested logit, mixed logit or probit) for ownership and a continuous linear regression model for the usage dimension. These traditional discrete and discrete-continuous models deal with situations in which a decision maker can choose only one alternative from a range of mutually exclusive alternatives. Models with multiple alternatives have been developed recently in several fields (see Bhat[19)] for a review). Among these, Bhat[18)] introduced a simple and parsimonious econometric approach to handle multiple discreteness. Bhat's model, labeled the multiple discrete-continuous extreme value (MDCEV) model, is analytically tractable in the probability expressions and is practical even for situations with a large number of discrete consumption alternatives.

3. MDCEV Model

Here we follow the multiple discrete-continuous extreme value (MDCEV) model proposed by Bhat (2005, 2008) which is a utility maximization-based resource allocation model. Compared to traditional discrete continuous models, MDCEV model can deal with the choice of multiple alternatives simultaneously.

Assume that there are K different end-uses that a household can potentially allocate income to. Let x_k be the money spent on end-use k $(k = 1,2,\cdots,K)$. It is specified that the utility accrued to a household as the sum of the utilities derived from investing money in each end-use operation.

The MDCEV model defines utility over alternatives as follows:

$$U(x) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \varphi_k \left\{ \left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} \tag{1}$$

Where $U(x)$ is the total utility derived from allocating a non-negative amount x_k of the total budget to each consumption (or expenditure) category (or alternative) k, including savings. φ_k is the baseline utility for money spent on end-use k, and α_k and γ_k are satiation and translation parameters, respectively.

A statistical model can be developed from the utility structure in equation (1) by adopting a random utility specification. Specifically, a multiplicative random element is introduced to the baseline utility as follows:

$$\varphi(z_k, \varepsilon_k) = \varphi(z_k) \cdot e^{\varepsilon_k} \tag{2}$$

Where z_k is a set of attributes characterizing alternative k and the decision-maker, and ε_k captures unobserved characteristics that impact the baseline utility for good j. The exponential form for the introduction of the random term guarantees the positivity of the baseline utility as long as $\varphi(z_k) > 0$. To ensure this latter condition, $\varphi(z_k)$ is further parameterized as $\exp(\beta' z_k)$, which then leads to the following form for the baseline random utility associated with good k:

$$\varphi(z_k, \varepsilon_k) = \exp(\beta' z_k + \varepsilon_k) \quad (3)$$

The overall random utility function of Eq. (1) then is reconstructed as:

$$U(x) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} [\exp(\beta' z_k + \varepsilon_k)] \left\{ \left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} \quad (4)$$

From the analyst's perspective, the individual is maximizing random utility subject to the binding linear budget constraint that $\sum_{k=1}^{K} e_k = E$ where E is total expenditure or income (or some other appropriately defined total budget quantity), $e_k = p_k x_k$, and p_k is the unit price of good k.

This utility specification leads to a surprisingly simple closed-form expression for the discrete-continuous probability (likelihood) (of consuming zero quantities of certain options and consuming given levels of the remaining options). When the error term ε_k has an i.i.d. Gumbel distribution, the probability that the respondent chooses I alternatives from among K alternatives is determined by Eq. (5) and (6) (Bhat, 2005, 2008):

The expression for the probability of the consumption pattern of the goods:

$$P(x_1^*, x_2^*, x_3^*, \cdots, x_M^*, 0, 0, \cdots, 0) = \frac{1}{p_1} \cdot \frac{1}{\sigma^{M-1}} \left[\prod_{i=1}^{M} f_i \right] \left[\sum_{i=1}^{M} \frac{p_i}{f_i} \right] \left[\frac{e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{V_k/\sigma} \right)^M} \right] (M-1)! \quad (5)$$

The expression for the probability of the expenditure pattern of the goods:

$$P(e_1^*, e_2^*, e_3^*, \cdots, e_M^*, 0, 0, \cdots, 0) = \frac{1}{\sigma^{M-1}} \left[\prod_{i=1}^{M} c_i \right] \left[\sum_{i=1}^{M} \frac{p_i}{c_i} \right] \left[\frac{e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{V_k/\sigma} \right)^M} \right] (M-1) \quad (6)$$

Where σ is a scale (σ can be normalized to one if there is no variation in unit prices across goods), and

$f_i = \left(\frac{1-\alpha_i}{x_i^* + \gamma_i} \right)$, $c_i = \left(\frac{1-\alpha_i}{e_i^* + \gamma_i p_i} \right)$, $V_k = \beta' z_k + (\alpha_k - 1) \ln \left(\frac{e_k^*}{p_k} + 1 \right) - \ln p_k$ $(k = 1,2,3,\cdots,K)$, for the α-profile (γ_k=1),

and $V_k = \beta' z_k - \ln \left(\frac{e_k^*}{\gamma_k p_k} + 1 \right) - \ln p_k$ $(k = 1,2,3,\cdots,K)$, for the γ-profile ($\alpha_k \to 0$).

4. Data

The source of data used for this analysis is the Household Energy Consumption Behavior Survey conducted by the authors' lab in Beijing in 2009. This survey was designed to collect information on expenditures/energy consumption patterns of households in Beijing. The data contains the following information: (1) Individual determinants, such as gender, age, education, environment consciousness, which are personal physical and psychological variables influencing decision-making; (2) Household characteristics, such as household size, income, composition, area, dwelling type, accessibility, which form household context for a resident's decision-making; (3) Consumption choice, such as ownership and usage of in home appliances and personal travel vehicles, which can reflect the behavior of energy use; (4) Consequence, such as energy use or expenditure, which are the results of consumption behavior.

Table 1 provides descriptive details of household end-use ownership and expenditure. The second column indicates the percentage of individuals owing each type of end-use, the third and fourth columns indicate the mean annual energy expenditure and annual energy consumption caused by each kind of end-use, respectively. In spite of the different transformation coefficients from expenditure to energy for electric, gas and gasoline end-uses, the energy consumption and the monetary expenditure are reflecting the same propensity of end-uses' usage. So it is feasible to scale the energy consumption by monetary expenditure.

5. Estimation Results

The estimation result of MDCEV model is presented in Table 2. Disposal money, expenditures of 7 kinds of end-uses are regarded as alternatives and here disposal money serves as the base alternative for all variables (and, thus, this category does not appear in the table as a column). Several different types of explanatory variables including household socio-economics, personal demographics, and residential variables are considered as determinants of end-use ownership and usage decisions of the household. In MDCEV model, the coefficients reflect the ownership and usage behavior simultaneously. A positive (negative) coefficient for a certain variable-category means that an increase in the explanatory variable increases (decreases) the likelihood of buying and allocating the budget to that expenditure category relative to the base expenditure categories which is disposal money.

Table 1: Descriptive statistics of household end-use ownership and expenditure

End-use type	Total percentage of household owning (%)	Annual operating cost (Yuan)	Annual energy consumption (GJ)	No. of household who own (%)	
				Only one piece	2+ pieces
Refrigerator	91%	146.1	2.97	93%	7%
AC	78%	443.5	9.02	40%	60%
Fan	46%	28.4	0.58	47%	53%
Clothes washer	89%	56.9	1.16	89%	11%
Electrical shower	38%	244.9	4.98	97%	3%
Gas shower	41%	805.4	18.11	98%	2%
Car	32%	5814.8	33.36	93%	7%

Household income: As household income increases, the probability of owning AC and vehicle, and the proportion of total income share expended on them increases, while the probability of owning refrigerator, fan, clothes washer and shower, and expenditure spent on them decrease. This is consistent with the ownership and usage of money intensive end-uses by high income households. It can be interpreted in the same way between household income and energy consumption.

Household size: The household size coefficients are positive for fan and negative for AC and gas shower. This suggests a preference for owner and usage of less energy intensive end-use rather than energy intensive ones. Household size have a positive effect on personal travel behavior, however the result is not significant.

Household area: As household area increases, the ownership and usage of all end-uses increase except gas shower. The reason might be that household area is an outcome of household income and size, larger household area means higher income or higher size or both higher, so the ownership and usage of whatever energy intensive or less intensive end-uses rise.

Residential duration and household type play an important role in the ownership and usage of in-home appliances, but no obvious effect on personal travel behavior. With the increase of dwelling years, the possibility of owning refrigerator, AC and gas shower and the expenditure proportion increase. Households who owned their house are more likely to own and use AC but less likely to for fan. Households whose highest education is bachelor or above don't have significant influence on energy related behavior except the refrigerator.

The consciousness of saving energy leads to energy efficient lifestyle directly. People who act on their own initiative to save energy, possess and use energy intensive end-uses such as AC and vehicle less than other people. This personal attribute affect in-home and out-of-home energy related behavior conjointly.

The access factor related to household's residential location have no obvious impact on in-home energy consumption behavior, but have a negative influence on personal travel energy consumption behavior. The longer distance to bus stop or subway station, the larger probability of buying a vehicle and use it.

Household demographic variables and personal attributes, e.g., income, household area, iron, and environmental consciousness, significantly influence both in-home and out-of-home energy consumption. When social or dwelling structures change, in-home energy use patterns and personal travel patterns will alter jointly. And due to the rebound effects between them, analyses considering only one category whereas fixing the other category are not applicable. To explain residents' daily energy consumption behavior correctly, an integrated study should be done in future.

Table 2: Estimation results of household end-use energy expenditure

Explanatory variables	refrigerator	AC	Fan	Clothes washer	Electrical shower	Gas shower	vehicle
Baseline preference constants							
Constant term	-6.575***	-6.840***	-11.741***	-8.601***	-8.185***	-9.578***	-9.955***
Household attribute							
Income	-0.188***	0.036	-0.372***	-0.224***	-0.409***	-0.014	0.165**
Household size	-0.063	-0.231**	0.430***	0.012	-0.114	-0.651***	0.134
Household area	0.0061*	0.006*	0.007	0.005	0.011**	-0.003	0.021***
Residential duration	0.030*	0.045***	0.0038	0.015	-0.020	0.064**	0.027
Iron	0.313	1.014***	-0.980***	0.276	0.477	-0.299	-1.445***
Household type	0.397	0.980***	-1.152***	0.171	-0.317	0.398	0.135
Education	0.518**	-0.059	0.185	0.395	-0.339	0.590	0.080
Conscious	-0.103	-0.866***	0.544**	-0.275	-0.460*	0.151	-0.666***
Access	-0.115	-0.130	0.178	0.007	0.253	0.023	0.318*
Scale parameter	2.348						

***. significant at the 1% level. **. significant at the 5% level. *. significant at the 10% level.

To further clarify the influence effect of each explanatory variable, next, we calculate the proportion of variance for each explanatory variable in the total variance of the baseline preference for both ownership and usage as follows. The calculation is based on the assumption that all explanatory variables are independent. Note that this assumption is already made when the model was estimated. The variance proportions are shown in Table 3. It is revealed that unobserved influential characters play greater role on the ownership and usage of in-home end-uses like refrigerator, AC, Clothes washer and Gas shower, whereas for personal travel behavior it is inverse. In addition, the influential degrees of some observed factors for different end-uses are quite discrepant. For refrigerator, fan, clothes washer and electric shower, the top influential factor is income while consciousness for AC, household size for gas shower and household area for vehicle.

Table 3: Proportions of Variances Explained by the Introduced Variables

Contribution ratio	refrigerator	AC	Fan	Clothes washer	Electrical shower	Gas shower	vehicle
Income	16.92%	0.51%	35.76%	23.54%	44.36%	0.09%	7.71%
Household size	0.19%	2.04%	4.72%	0.01%	0.34%	18.65%	0.50%
Household area	3.69%	3.26%	2.78%	2.73%	6.89%	0.83%	24.54%
Residential duration	2.13%	3.83%	0.02%	0.49%	0.52%	8.89%	1.00%
Iron	0.96%	8.10%	5.07%	0.73%	1.23%	0.81%	12.04%
Household type	1.68%	8.21%	7.63%	0.30%	0.59%	1.56%	0.11%
Education	2.86%	0.03%	0.20%	1.63%	0.68%	3.44%	0.04%
Conscious	0.29%	16.45%	4.37%	2.02%	3.19%	0.58%	7.12%
Access	1.26%	1.30%	1.64%	0.00%	3.40%	0.05%	5.70%
Unobserved characters	70.02%	56.27%	37.82%	68.54%	38.79%	65.09%	41.23%

6. Conclusions

This paper presents a comprehensive analysis of household expenditures across an array of end-uses owned and used by households. While previous research focused exclusively on total energy consumption or just transportation energy consumption, this study examines the expenditure patterns across some major end-uses and extends it to the energy consumption analysis. MDCEV model proposed by Bhat (2005) is performed and estimated on a data collected in Beijing in 2009, including in-home and out-of-home energy consumption. Model results show that a range of household socio-economic and demographic characteristics affect the ownership probability and the proportion of income allocated to various categories and savings. However, unobserved characteristics also significantly influence energy consumption behavior. Furthermore, it is confirmed that there is an in-depth relationship between in-home energy consumption behavior and out-of-home travel energy consumption. To explore more convincible results, more careful analysis is further required in the future.

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