MAKING SENSE OF RESIDENTIAL ENERGY BEHAVIROR: AN EMPIRICAL ANLAYSIS OF HOME COOLING DECISION IN CALIFORNIA

Gloria JinaKim, Graduate School of Green Growth, KAIST College of Business, Republic of Korea
+82.10.5628.2680, jnkim0305@business.kaist.ac.kr
Jiyong Eom, Graduate School of Green Growth, KAIST College of Business, Republic of Korea
+82.10.8612.1606, eomjiyong@business.kaist.ac.kr

Overview

While demand-side management (DSM) of energy in general and residential energy efficiency programs in particular are gaining increasing attention as a means to achieve both customers' electricity bill savings and substantial greenhouse gas abatement, there still are major opportunities to improve their cost-effectiveness implementation. One potential direction for improvement is to improve the accounting of the heterogeneity of household energy behavior. Previous studies have proposed discipline-specific models and theories on individual households' decision making and its determinants [1]. However, little has been known concerning the interrelationship among the households' characteristics, which range from socio-demographic and techno-economic attributes to contextual environmental factors, and their collective influence on residential energy behavior [2].

The purpose of this research is to investigate space cooling behavior of households, which accounts for 13.2% of the residential electricity demand [3], in terms of their socio-demographic *and* techno-economic characteristics, offering practical guidelines to the design of residential energy efficiency programs. Based on the literature of household energy behavior and random utility theory [4], we develop a multinomial logit choice model to characterize household energy behavior regarding space-cooling choice. Heterogeneity in the preference for space cooling is captured by specifying hierarchical random coefficients for choice attributes that influence the decision and the individual-level parameters [5]. The parameters are estimated by a Bayesian procedure. We employ household-level micro-data from the 2009 Residential Appliance Saturation Study (RASS) of the California Energy Commission.

The results reveal that there are significant differences in the preference for space-cooling choice in the California households, as characterized by the combination of their socio-demographic and/or techno-economic attributes. Making sense of space cooling behavior from such an integrated perspective could help to design tailored energy efficiency program portfolios with an improved benefit-cost ratio. The choice model will be extended for other related behaviors, such as air conditioner purchase and maintenance, which then provides a balanced, multi-level understanding of household energy behaviors.

Methods

Model Construction

The Base Model—Multinomial Logit: Our base model specifies a random utility function faced by the individual households as a function of attributes that relate to each space cooling alternative. The households' tastes are represented by the coefficients to the attribute variables. Based on the understanding of residential energy behavior [6] and viable policy options [7, 8], we suggest two policy-relevant attributes: space cooling cost (X_C) and cooling service quality (X_S). Specifically, the decision maker's utility consists of three components: the alternative specific constant α_j, which is specific to each alternative; the deterministic utility V_{nj}, expressed as a function of the attributes, $X_{ncj}$and X_{nsj}, and the importance weights of the respective attributes, β_c and β_s; and the unobservable random part ϵ_{nj} that is assumed to have a type I extreme value distribution. The utility is thus specified as

$$U_{nj}^* = \alpha_j + V_{nj} + \epsilon_{nj} = \alpha_j + \beta_c X_{ncj} + \beta_s X_{nsj} + \epsilon_{nj}$$

The Random Coefficient Model with Bayesian Estimation: We thus extend the base model to a random coefficient framework to account for the heterogeneity in households' taste or, equivalently, importance weight for each attribute variable [9]. That is, the random coefficient model incorporates household variation in the importance weights, β_{cn} and β_{sn}. Their variations are assumed to follow the probability distributions, $f_c(\Theta_c)$ and $f_s(\Theta_s)$, respectively. The random coefficient model estimates the distributional parameters, Θ_c and Θ_s, and eventually the importance weights, β_{cn} and β_{sn}. We assume lognormal distributions, given that the coefficient for space cooling cost (cooling service quality) is expected to have the same negative (positive) sign for all households with only their magnitude differing across them. To conduct a Bayesian estimation procedure, a total of 150,000 random draws are generated using Gibbs sampling [8]. After discarding the first 140,000 draws, we take 1,000 draws from rest of 10,000 draws by taking 1 draw after skipping 9 draws.

The Hierarchical Random Coefficient Model with Bayesian Estimation: For a more complete analysis, we hierarchically integrate the households' socio-demographic and techno-economic characteristics to explain their tastes [10]. Specifically, the taste coefficients are expressed as a linear combination of a set of characteristics, $\boldsymbol{z_n}$, including household configuration, education level, insulation level, heating system type, bill payment type, and climatological zone, such that $\beta_{cn} = \gamma_c + \boldsymbol{\Gamma_c z_n} + \zeta_{cn}$ and $\beta_{sn} = \gamma_s + \boldsymbol{\Gamma_s z_n} + \zeta_{sn}$, where $\boldsymbol{\Gamma_c}$ and $\boldsymbol{\Gamma_s}$ are parameters to estimate.

Data and Variables

Data Sources: Household-level data on space cooling behavior and associated socioeconomic and technological characteristics have been provided by the California Energy Commission's Consortium Residential Appliance Saturation Study (RASS). Average diurnal temperature variation information for each of 50 climate zones in California have been obtained from the U.S. DOE's EnergyPlus Weather Format and matched with the household-level data.

Model Variables: We specify cooling temperature settings in the cooling season as the multinomial choice alternatives. The choice from the alternatives, which is our dependent variable, is representative of the household's deliberate decision making on indoor thermal comfort. In our model, the choice reflects the potential trade-off between the level of cooling service quality, X_S, and the associated cost requirements, X_C. In the dataset, six temperature setting options are represented for each of four time periods within the day, totaling 25,820 choice situations for 6,455 households located in 16 climate regions.

Attribute Measurement: This study proposes the proxies for the two attributes, X_S and X_C. The cooling service quality X_S is measured by the Humidex implied by each choice, an commonly used index for thermal discomfort [11]; the disutility from inadequate service is therefore quantified. The cooling cost requirement X_C is scaled by the implied gap in indoor and outdoor temperatures with the assumption that the cooling cost is proportional to the temperature gap all else being equal.

Results

The Base Model: The model parameters are all significant and have the expected signs—both of the importance weights, (β_{nc}, β_{ns}), have negative values. That is, the households prefer to choose options with lower cooling costs and discomfort levels.

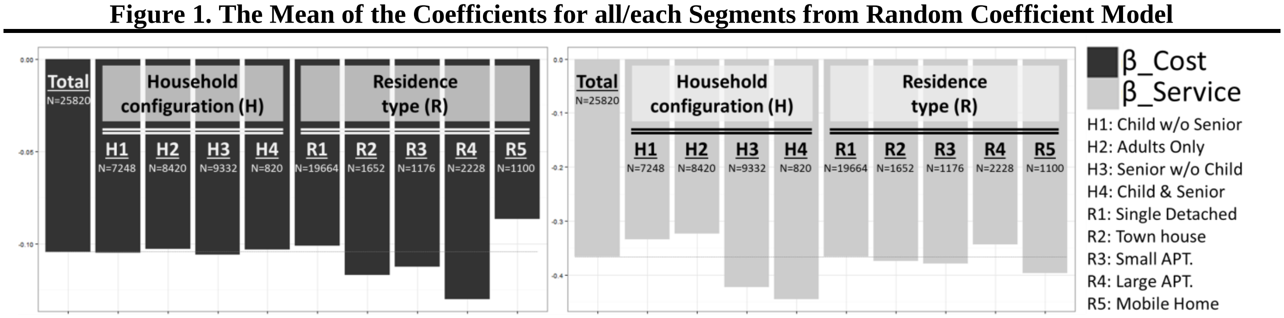
Table 1. Estimation Results of the Base Model

	$\boldsymbol{\beta_{nc}}$	$\boldsymbol{\beta_{ns}}$	$\boldsymbol{\alpha_2}$	$\boldsymbol{\alpha_3}$	$\boldsymbol{\alpha_4}$	$\boldsymbol{\alpha_5}$	$\boldsymbol{\alpha_6}$
Estimate	-0.1421	-0.0441	-2.555	-1.4822	-0.9953	-0.354	-1.5258
Std.Error	0.0166***	0.0169**	0.0393***	0.0288***	0.0233***	0.0186***	0.0256***

† P<0.10, * P<0.05, ** P<0.01, *** P<0.001

The Random Coefficient Model with Bayesian Estimation: From the Bayesian procedure, the taste coefficients have been recovered for the individual households. We then aggregate the entire households according to their household configuration (H) and residence type (R), such that four segments with different household configurations and five segments with different residence type are generated.

Figure 1. The Mean of the Coefficients for all/each Segments from Random Coefficient Model



In addition, the difference in the taste coefficients between the nine groups has been tested using the multivariate analysis of variance (MANOVA). Interestingly, the inter-group difference in taste coefficients for cooling service quality is found to be significant for those with different household configurations, whereas the inter-group difference in taste coefficients for cooling cost requirement remain prominent for those with different residence types.

Conclusions

Our study shows that each household's preferences for space cooling are extremely heterogeneous. It nevertheless demonstrates that such heterogeneous preferences can be identified and explained by their underlying socio-demographic and techno-economic characteristics by using the random coefficient discrete choice model. At an aggregate level, the household preferences for cooling service quality were found to be sensitive to household configurations (socio-demographic), while those for cooling cost requirement remained sensitive to residence types (techno-economic). Such results imply that more detailed policy pathways are possible to policy designers. For example, the policy strategy depending on consumers' cost sensitivities, such as dynamic price feedback system, could be considered for the areas where houses are concentrated.

The integrated, household-level perspective revealed by this work, as opposed to the conventional average household approach, points out to the need of more extensive empirical study on residential energy behavior that explicitly accounts for household heterogeneity. Similar analyses can also be extended to other energy behaviors with major implications for energy savings, such as appliance purchase and maintenance decisions, which is a promising direction for future research. Such studies will help utility planners to develop household efficiency programs with lower marketing costs and increased customer participation, ultimately improving the cost-effectiveness of the programs.

References

1. Wilson, C. and H. Dowlatabadi, *Models of decision making and residential energy use.* Annu. Rev. Environ. Resour., 2007. **32**: p. 169-203.
2. Lutzenhiser, L., et al., *Sticky points in modeling household energy consumption.* ACEEE Summer Study on Energy Efficiency in Buildings, American Council for an Energy Efficient Economy, Washington, DC, 2010.
3. EIA, *Annual Energy Outlook 2015*, 2015, U.S Energy Information Administration.
4. McFadden, D., *The measurement of urban travel demand.* Journal of public economics, 1974. **3**(4): p. 303-328.
5. Tversky, A. and D. Kahneman, *The framing of decisions and the psychology of choice.* Science, 1981. **211**(4481): p. 453-458.
6. Amato, A.D., et al., *Regional energy demand responses to climate change: Methodology and application to the Commonwealth of Massachusetts.* Climatic Change, 2005. **71**(1-2): p. 175-201.
7. Wilhite, H., et al., *The legacy of twenty years of energy demand management: we know more about individual behaviour but next to nothing about demand*, in *Society, behaviour, and climate change mitigation*2000, Springer. p. 109-126.
8. Lutzenhiser, L., et al., *Behavioral assumptions underlying California residential sector energy efficiency programs.* Prepared for the California Institute for Energy and Environment Behavior and Energy Program, 2009.
9. Train, K.E., *Discrete choice methods with simulation*2009: Cambridge university press.
10. Allenby, G.M. and P.J. Lenk, *Modeling household purchase behavior with logistic normal regression.* Journal of the American Statistical Association, 1994. **89**(428): p. 1218-1231.
11. Beccali, M., et al., *Short-term prediction of household electricity consumption: Assessing weather sensitivity in a Mediterranean area.* Renewable and Sustainable Energy Reviews, 2008. **12**(8): p. 2040-2065.