OSIPP Discussion Paper : DP-2007-E-005

Does energy efficiency label alter consumers' purchase decision? A latent class approach on Shanghai data

May 11, 2007

Junyi Shen
Assistant Professor, OSIPP, Osaka University
and
Tatsuyoshi Saijo
Professor, ISER, Osaka University

【キーワード】C25, C93, D12, Q49, Energy efficiency label, Consumers' purchase decision, Latent class model, Willingness to pay, China

【要約】In this paper we apply hypothetical choice experiments through a field survey in Shanghai of China to examine whether China Energy Efficiency Label affects consumers' choices of air conditioner and refrigerator. A latent class approach is used to observe both heterogeneities among the respondents and product brands. The results suggest that the effect of energy efficiency label on consumers' preferences is twofold. First, more energy efficient air conditioners or refrigerators are preferred by consumers, no matter whether they are with foreign brands or domestic brands and whether they are new or second-hand. Second, energy efficiency label *per se* is recognized by consumers. In addition, presence of a (hypothetical) label that indicates the electricity bill's difference comparing to a standard model is significantly preferred by the respondents in most of the cases, suggesting that more information provided to consumers makes them much happier. Finally, the class probability weighted willingness to pay values for one rank upgrading in energy efficiency of refrigerator are higher than those of air conditioner, implying that consumers have an incentive to pay more for appliances used more frequently.

The authors would like to appreciate the financial support of Japanese Ministry of the Environment (Global Environmental Research Fund H-062) and Japanese Ministry of Education, Culture, Sports, Science and Technology (Grants-in-Aid for Young Scientists (B), 19730175). Comments and suggestions on the survey issues from Yoshiyuki Shimoda, Osamu Saito, Yugo Yamamoto, and Kenju Akai are greatly appreciated. All the views expressed in this paper and any errors are the sole responsibility of the authors. *Correspondence to: Junyi Shen, Osaka School of International Public Policy (OSIPP), Osaka University, 1-31 Machikaneyama, Toyonaka, Osaka 560-0043, Japan. E-mail: junyi@osipp.osaka-u.ac.jp*

1. Introduction

Studies on consumer behavior are usually conducted by policy decision makers for solutions to environmental policy problems, because they reason, at least implicitly, that environmental degradation comes from economic activity, that consumer expenditures account for most of gross domestic product, and that therefore changing consumer behavior can go a long way toward reducing environmental degradation (Stern, 1999). During the last decade, there has been a number of public policies interest in sustainable consumption and the role of consumers in environmental conservation. However, the needed change in consumption patterns toward sustainable consumption normally cannot be achieved by force, but only with a kind of "voluntary approach" such as information providing policy, which plays a key role in environmental policy targeting consumers. One of the most promising forms of environmental information policy, in terms of providing timely and relevant information for the consumer, is environmental labeling that is authenticated and monitored by a third-party (Crespi and Marette, 2005; Loureiro et al., 2002; Thøgersen, 2000). The main purpose of providing various environmental labels (also called eco-labels) to consumers is to avoid the asymmetric information problem between producers and consumers, because some environmentally friendly products normally have unobservable characteristics, which will cause potential inefficiencies resulting from imperfect information.

The idea that information provision could be an effective method of environmental regulation is a significant and even revolutionary departure from traditional thinking (Russell et al., 2005). This departure is explicitly recognized as "the third wave" in pollution control policy in Tietenberg and Wheeler (2001).[1] Beginning with the German Blue Angel in 1977, a number of environmental labeling programs in the organic food and electricity markets as well as the forestry products have developed (e.g. Nordic Swan in the Nordic countries, EU Flower in EU countries, Green Seal in USA, Environmental Choice in Canada, Eco-Mark in Japan, Green Label in Singapore, etc.). Encouraged by widely increasing environmental labeling schemes, both theoretical and empirical studies in academic society on this issue have been rapidly growing (e.g. Amacher et al., 2004; Banerjee and Solomon, 2003; Bjørner et al. 2004; Cason and Gangadharan, 2002; Crespi and Marette, 2005; Dosi and Moretto, 2001; Howarth et al., 2000; Johnston et al., 2001; Loureiro et al., 2002; Moon et al. 2002; Morris et al., 1995; Roe et al., 2001; Russell et al. 2005; Thøgersen, 2000; Tisel et al., 2002, etc.). Concerning the effect of environmental label on consumers' purchase decision, Bjørner et al. (2004)

[1] The first wave refers to as "command-and-control" regulation, while the second wave involves the introduction of attempts to alter polluter behavior through the use of economics incentives, or what are commonly called "market-based instruments" such as emissions charges, tradable discharge permits, and deposit-refund schemes (Russell et al., 2005).

used a large Danish consumer panel with detailed information on actual purchases from the beginning of 1997 to January 2001 to quantify the effect of the Nordic Swan on consumers' brand choices of toilet paper, paper towels and detergents. They found that the Nordic Swan label has had a significant effect on consumers' brand choices for toilet paper and detergent. Similar effects of various eco-labels on consumers' choice of products can also be found in the studies of dolphin-safe label (Teisl et al., 2002), eco-labeled apples (Loureiro et al., 2002), eco-labeled seafood (Johnston et al., 2001), eco-labeled agricultural products (Moon et al., 2002), and energy label (Banerjee and Solomon, 2003; Howarth et al., 2000). In addition, two theoretical studies (i.e. Amacher et al., 2004; Dosi and Moretto, 2001) stated that eco-labeling could be used as a means of reliable environmental policy to improve market outcomes by which firms adopt clean(er) technologies and produce green products based on consumers' recognition on eco-labels and willingness to pay for these certified environmentally friendly products. Furthermore, Cason and Gangadharan (2002) examined various treatments that could remedy the market failure arising from incomplete information through laboratory posted offer markets. They concluded that the only reliable way to improve product quality in the experiment is to use a third party that charges a fee to certify product quality, i.e., environmental labeling.

To provide more empirical evidence, in this study we present an analysis of the effect of a specific environmental label (China Energy Efficiency Label) on Chinese consumers' choices among different brands of air conditioner and refrigerator. Nowadays, energy labels and minimum energy performance standard are fast becoming commonplace throughout the world. It is axiomatic that the market for household energy services would be enhanced where buyers are able to take into account not just the cost of the appliance but the otherwise invisible factor of energy consumption. Energy labels improve the market's operation by displaying accurate energy consumption information on products, which is thought to be useful in the purchase decision. There are two main types of energy labels: endorsement and comparative labels. Endorsement labels indicate that products belong to the "most energy efficient" class of products or meet a predetermined standard or eligibility criteria. Comparative labels such as China Energy Efficiency Label allow consumers to form a judgment about the energy efficiency and relative ranking of all products that carry a label. Endorsement and comparative labels can coexist, and do so in many countries. The main difference between endorsement label and comparative label is that the effect of the latter on consumers' purchase decision is twofold: (i) whether or not the label *per se* is recognized by consumers; (ii) whether or not different ranks presented on the label, which indicate different levels in energy efficiency, alter consumers' preferences and purchases decisions.

Previous work on the effect of energy label on consumers' response is limited. Banerjee and Solomon (2003) presented a meta-evaluation of five US energy labeling programs: Green Seal, Scientific Certification Systems, Energy Guide, Energy Star, and Green-e. They stated that "although most people indicate a strong preference for a credible, third-party labeling system and claim to use it, very few actually use the labels for purchasing decisions" and "Such overstated responses leading to survey bias are thought to be due to the 'warm glow' effect". Acknowledging this kind of "warm glow" effect and to overcome it in our study, we apply a choice experiment approach in which respondents are asked to select a most preferable alternative from a set of alternatives based on a number of attributes and their levels. Since the respondent's choice decision is made based on the tradeoff among the associated attributes, we believe that "warm glow" effect, at least to some extents, could be avoided by this manipulation.

The analysis is based on hypothetical choice experiments for air conditioner and refrigerator through a questionnaire survey conducted at the beginning of November 2006 in Shanghai of China. In each choice experiment, we provide four alternatives named as new product A with foreign brands, second-hand product B with foreign brands, new product C with domestic brands, and second-hand product D with domestic brands, respectively.[2] This specification allows us to observe Shanghai consumers' preferences on second-hand products and different brands (foreign or domestic). In addition to the attribute associated with energy efficiency label, other attributes include the prices, the electricity consumptions, applicable space/volume, with or without air cleaning/silence function, and presence or absence of a label indicating the electricity bill's difference comparing to a standard model. Note that including the final attribute related to presence or absence of another label serves as a second goal of this study to investigate whether or not additional information provision affects consumers' purchase decision.

A Latent Class(LC) model approach is applied in the estimation. Compared to a standard Multinomial Logit (MNL) model in discrete choices, the LC approach allows the analysts to observe individual heterogeneity through identifying and characterizing various preference groups (Boxall and Adamowicz, 2002; Louviere et al., 2000; Greene and Hensher, 2003; Shen, 2006). In addition, this approach can estimate simultaneously the probability of individuals in each class, hence, it is even valid in welfare analysis which considers to aggregate welfare gained from each class.

As a preview of results, it is found that China Energy Efficiency Label does have a significant effect on Shanghai consumers' purchase decisions of air conditioner and refrigerator. Meanwhile, higher price and higher electricity consumption reduce individuals' preferences. Functions such as air cleaning of air conditioner and silence of refrigerator are preferred by consumers in most cases, while applicable space of air conditioner and volume of refrigerator are evaluated differently by the respondents.

[2] The fact that there exists a second-hand appliance market in China encourages us to examine the issue on Chinese consumers' preferences of second-hand appliances.

Furthermore, consumers prefer to have a (hypothetical) label indicating clearly the electricity bill's difference comparing to a standard model in most cases, suggesting that information provision at an explicit way such as through a label is an effective means to affect consumers' choice decisions.

The remainder of the paper is organized as follows. Section 2 provides a brief summary of China Energy Efficiency Label program. Section 3 presents the model specification. The survey issue is described in Section 4 and the empirical results are reported in Section 5. Finally, we provide conclusion remarks and future implications in Section 6.

2. China Energy Efficiency Label program

Home appliance ownership and production has increased dramatically in China in the past two decades. From extremely low levels in 1980, China's appliance industry has become one of the largest in the world, with sales topping U.S.$ 49.55 billion in 2005. Meanwhile, the ownership ratio of refrigerator by urban Chinese households increases from less than 1 percent in 1981 to over 90 percent by 2006 (China State Statistics Bureau, 2006). A similar trend has been observed for room air conditioner and other home appliances as well. Such a dramatic increase in appliance ownership has significantly led to the growth of China's electricity use. Between 1980 and 2001, per capita annual electricity consumption grew from 254.6 to 995.2 kwh, with an average annual growth rate of 8 percent, while per capita residential electricity use grew from 10.0 to 144.6 kwh, averaging 15 percent growth per year (nearly twice as fast as overall electricity consumption). The growth in household electricity consumption has contributed substantially to the tremendous increase of generating capacity in China in recent years. Since 1990, China has added on average 16 GW of new capacity each year.

Well acknowledging the environmental impacts of electricity generation, China started to implement a number of programs including energy labeling program to improve energy efficiency.[3] The basis for energy labeling program in China was established in the "Energy Conservation Law", which was approved by the National People's Congress on November 1, 1997 and came into force on January 1, 1998. The law superseded earlier laws and set the basis for measures to develop energy efficiency standards and energy labeling of appliances and equipments.

At first, the government decided to issue a voluntary endorsement label—China Energy Conservation Label (see Figure 1). The State Economic and Trade Commission

---

[3] Gains in energy efficiency has been regarded as one of the explanations for China's decline in energy intensity in recent years. For details on this issue, see Fisher-Vanden et al. (2004).

(SETC, now NDRC: National Development and Reform Commission) and the China State Bureau of Quality and Technical Supervision (CSBTS, now AQSIO: Administration for Quality, Supervision, Inspection and Quarantine) together established an independent, non-profit organization—the China Certification Center for Energy Conservation Product (CECP), aiming at developing requirements in order to certify products as being safe, high-quality, and energy-saving. The endorsement label designed by the CECP was formally launched in September 1999 and first applied in refrigerators. The application for China Energy Conservation Label is similar to the USA's Energy Star Label and so far has been awarded to over 100s of products.

In addition to the above voluntary energy conservation label, the China National Institution of Standardization (CNIS) was assigned to develop a mandatory and comparative energy information label—China Energy Efficiency Label (see Figure 2). The designed label came into effect from March 2005. The first two products were refrigerator and room air conditioner. The China Energy Efficiency Label is similar to EU Energy Label, which rates the energy efficiency of the appliance in terms of a set of energy efficiency ranks from 1 to 5 on the label. Rank 1 is the most energy efficient, while rank 5 is the least efficient. The CNIS reports that by the end of March 2006, the products with energy efficiency ranks 1 and 2 in China share about 10 percent in room air conditioner market and 68 percent in refrigerator market. In contrast, the products with energy efficiency rank 5 only occupy 7 percent in room air conditioner market and 8 percent in refrigerator market. These evidences suggest that there is an energy efficiency rank gap between air conditioner and refrigerator in China. Compared to the majority of high efficient energy-saving refrigerator on the market, most of room air conditioners are produced with medium energy efficiency level (ranks 3 and 4).

3. Model specification

Choice model is based on random utility theory. The basic assumption embodied in the random utility approach to choice modeling is that decision makers are utility maximizers, i.e., given a set of alternatives the decision maker will choose the alternative that maximizes her utility. The utility of an alternative for an individual (U) is modeled to consist of a deterministic component (V) and a random error term (ε). Formally, individual q's utility of alternative i can be expresses as:

$$U_{iq} = V_{iq} + \varepsilon_{iq} \tag{1}$$

Hence the probability that individual q chooses alternative i from a particular set J that comprises j alternatives can be written as:

$$P_{iq} = P(U_{iq} > U_{jq}; \forall \quad j(\neq i) \in J) = P(\varepsilon_{jq} < \varepsilon_{iq} + V_{iq} - V_{jq}; \forall \quad j(\neq i) \in J) \tag{2}$$

To transform the random utility model into a choice model, certain assumption about the joint distribution of the vector of random error terms is required. If the random error terms are assumed to follow the type I extreme value (EV1) distribution and be independently and identically distributed (IID) across alternatives and cases (or observations), the multinomial (or sometimes called conditional) logit (MNL) model (McFadden, 1974) is obtained. In the MNL model, the choice probability in Equation (2) is expressed as:

$$P_{iq} = \exp(\mu V_{iq}) / \sum_{j=1}^{J} \exp(\mu V_{jq}) \tag{3}$$

Then, making further assumption for the deterministic component of utility to be linear and additive in parameters, $V_{iq} = \beta' X_{iq}$, the probability in Equation (3) can be given as:

$$P_{iq} = \exp(\mu \beta' X_{iq}) / \sum_{j=1}^{J} \exp(\mu \beta' X_{jq}) \tag{4}$$

where μ represents a scale parameter that determines the scale of the utilities, which is typically normalized to 1.0 in the MNL model. X_{iq} are explanatory variables of V_{iq}, normally including alternative-specific constants (ASCs), the attributes of the alternative i and the social-economic characteristics of the individual q, β' is the parameter vector associated with the matrix X_{iq}.

It is well known that heterogeneity among individuals is extremely difficult to examine in the MNL model. This limitation could be relaxed, to some extents, by interacting individual-specific characteristics with various of the choices. However, this method is limited because it requires *a priori* selection of key individual characteristics and attributes and only involved a limited selection of individual specific variables (Boxall and Adamowicz, 2002). One way of circumventing this difficulty is through estimating the model by the Latent Class (LC) model. The LC model assumes that the population consists of a number of latent classes S and the unobserved heterogeneity among individuals can be captured by these classes through estimating a different parameter vector in the corresponding utility function. Formally, the choice probability of individual q of class s is expressed as:

$$P_{iq|s} = \exp(\mu_s \beta_s' X_{iq}) / \sum_{j=1}^{J} \exp(\mu_s \beta_s' X_{jq}) \quad s = 1, \ldots, S \tag{5}$$

where μ_s and β_s' are class-specific scale and utility parameters, respectively. Then, following Boxall and Adamowicz (2002), Louviere et al. (2000), and Swait (1994, 2007), the probability of individual q in class s (H_{qs}) can be expressed as:

$$H_{qs} = \exp(\alpha \lambda_s' Z_q) / \sum_{s=1}^{S} \exp(\alpha \lambda_s' Z_q) \tag{6}$$

where α is a scale factor normally normalized to 1.0, λ_s' is the parameter vector in class s, and Z_q denotes a set of characteristics (e.g. individual-specific characteristics) determining the classification probability. Combining conditional choice equation (5) and membership classification equation (6), the unconditional probability of choosing alternative i is given as:

$$P_{iq} = \sum_{s=1}^{S} P_{iq|s} H_{qs} = \sum_{s=1}^{S} \left[\exp(\mu_s \beta_s' X_{iq}) / \sum_{j=1}^{J} \exp(\mu_s \beta_s' X_{jq}) \right] \left[\exp(\alpha \lambda_s' Z_q) / \sum_{s=1}^{S} \exp(\alpha \lambda_s' Z_q) \right] \quad (7)$$

In equation (7), when we set μ_s and α equal to one[4], the parameter vectors β_s' and λ_s' can be simultaneously estimated by the maximum likelihood method to explain choice behavior.[5]

However, the LC model cannot be estimated unless S (the number of classes) in equation (7) is given, because S is discrete but maximum likelihood estimation theory requires that the parameter space be continuous and estimates be in the interior of the space (Swait, 2007). Therefore, the central issue in the LC model is how to determine S. The literature has recommended a number of information criteria to determine S (e.g. Boxall and Adamowicz, 2002; Greene and Hensher, 2003; Louviere et al., 2000; Morey el al., 2006; Shen, 2006; Swait, 2007, etc.). Among them, four measures based on the log likelihood at convergence with s classes, sample size and number of parameters are popular to be used to determine S. They are defined as:

Akaike Information Criterion, $AIC = -2(\log L_s^* - K_s)$ (8)

Akaike's ρ^2, $\bar{\rho}_s^2 = 1 - [AIC_s / (2 \cdot \log L_0)]$ (9)

Bozdogan Akaike Information Criterion, $AIC3 = -2 \log L_s^* + 3K_s$ (10)

Bayesian Information Criterion, $BIC = -\log L_s^* + (K_s \cdot \log N)/2$ (11)

where $\log L_s^*$ is the log likelihood at convergence with s classes, K_s is the number of parameters in the model with s classes, L_0 is the log likelihood of the sample with equal choice probabilities, and N is the sample size.

An alternative approach accounting for individual heterogeneity is called Random Parameter Logit (RPL) or Mixed Logit (ML) model, which allows model parameters to vary randomly through assumed distributions (e.g. normal, log-normal, triangular, etc.) over individuals (e.g. Bhat and Gossen, 2004; Bjørner et al., 2004; Greene and Hensher, 2003; Hess et al., 2005; McFadden and Train, 2000; Revelt and Train, 1998; Train, 1998, etc.). In this approach, each individual has their own set of scale and utility parameters.

---

[4] Boxall and Adamowicz (2002) note that utilizing the LC model in empirical estimation requires that all the scale factors in equation (7) are set equal to one.

[5] The parameter vector λ_s' in one of the latent classes must be normalized to zero (e.g. $\lambda_1' \equiv 0$) to run the estimation. Therefore, the remaining λ's are identified relative to this normalization.

From this viewpoint, one could regard the RPL/ML model as the case where each individual in the sample could be considered as an individual class, which is indeed the LC model with N (sample size) classes. In other words, the LC model controls individual heterogeneity with s classes where s is between 1 and N. Compared to the RPL model, the potential advantages of the LC model are twofold. First, the LC approach is semiparametric, therefore, it does not require the analyst to make specific assumptions about the distributions of parameters across individuals (Greene and Hensher, 2003). Second, the LC model yields the probabilities in each class. This means that although each respondent is assumed to belong to one class, it is taken into account that there is uncertainty about a respondent's class membership.

4. Survey issue

4.1 Choice experiment design

In the choice experiment, a number of attributes and assigned levels are used to generate hypothetical scenarios. The attributes and their levels included in each scenario for this study are summarized in Tables 1 (air conditioner) and 2 (refrigerator). We have four alternatives (products) named as new product A with foreign brands, second-hand product B with foreign brands, new product C with domestic brands, and second-hand product D with domestic brands, respectively for both air conditioner and refrigerator.[6] Each air conditioner or refrigerator has six attributes. For air conditioner, they are

(i) price (three different levels for each alternative)
(ii) hourly electricity consumption (two same levels for A and C, and two same levels for B and D)
(iii) applicable space (two levels for all alternatives)
(iv) whether there is an air cleaning function (two levels for all alternatives)
(v) energy efficiency ranks presented on the label (four levels for all alternatives)
(vi) whether there is a label of indicating the electricity bill's difference comparing to a standard model (two levels for all alternatives).[7]

[6] A non-choice (the choice not to select one of the available alternatives) alternative could be considered to provide. However, following the argument of Hensher et al. (2005) that "if the objective of the study is to examine the impact of the relationships different attribute levels have upon choice, then any non-choice alternative is likely to be a hindrance to the analyst", we did not provide a non-choice alternative in this study.
[7] Including the label of indicating the electricity bill's difference comparing to a standard model as an attribute of appliance is to examine in addition to energy efficiency label whether information provision about running cost saving through a label could be an effective issue influencing consumer's purchasing decision. This could

For refrigerator, three attributes are the same as (i), (v), and (vi) for air conditioner, another three attributes are considered as daily electricity consumption (two same levels for A and C, and two same levels for B and D), volume (two levels for all alternatives), and whether there is a silent function (two levels for all alternatives).

Choice experiment design is concerned with how to create the choice sets in an efficient way, i.e. how to combine attributes levels into profiles of alternatives and profiles into choice sets (Alpízar et al., 2003). It is obvious that it would generate too many choice sets if we apply a full factorial design, which is too much for respondents to answer even we divide the choice sets into a number of versions. In this study, we adopt the D-optimal design approach for choice experiments based on multinomial logit model. The objective of the D-optimal design is to extract the maximum amount of information from the respondents subject to the number of attributes, attribute levels and other characteristics of the survey such as cost and length of the survey (Carlsson and Martinsson, 2003). The D-optimal design is implemented to maximize a chosen optimality criterion (e.g. D-, A-, and G-efficiency) based on the pre-specified model (e.g. multinomial logit model in a choice experiment). One common measure of efficiency is called D-efficiency that is applied in this study and given as

$$\text{D-efficiency} = \left[|\Omega|^{1/K} \right]^{-1} \tag{12}$$

where K is the number of parameters to estimate, Ω is the covariance matrix of a vector of parameters. Besides D-efficiency, there are also several other criteria of efficiency such as A- and G-efficiency. The main reason for choosing D-efficiency is that it is less computationally burdensome and could be directly run by a number of statistical software.[8]

As a result of running the D-optimal design through Design-Expert 7.0 (Stat-Ease, Inc.), we created 48 choice sets for air conditioner and 48 choice sets for refrigerator, respectively. These choice sets were further randomly divided into 8 versions, i.e., each version of the questionnaire consists of 6 choice sets for air conditioner and 6 choice sets for refrigerator. The respondents were asked to select the most favorite air conditioner or refrigerator in each choice set and answer several other questions related to their socioeconomic characteristics. The examples of choice sets for air conditioner and refrigerator are presented in Tables 3 and 4, respectively.

4.2 Data collection

A survey study was conducted at the beginning of November 2006 in Shanghai of China.

---

be viewed as an additional test for the validity of information provision through label programs.

[8] For more details on D-optimal design, see, for example, Alpízar et al. (2003), Carlsson and Martinssonb (2003), and Huber and Zwerina (1996), etc.

This survey aimed to evaluate Shanghai residents' preferences and awareness on China Energy Efficiency Label, which is a mandatory and comparative energy information label in China (see detailed introductions in Section 2). The survey was conducted by two professional marketing firms. One firm called Nikkei Research was in charge of collecting 600 observations through face-to-face interview. The respondents were randomly recruited on the street of two districts (business center district and residential district), with 300 observations in each district. The trained investigators were assigned to ask the respondents various questions according to the questionnaire. The average time for the face-to-face interview was approximate 15 minutes. In addition, another firm called Searchina Research conducted the web-based survey and also collected 600 valid samples. The questionnaires for both surveys were with the same contents, which include (i) a number of questions to reveal the respondents' environmental concern[9]; (ii) choices of air conditioner and refrigerator; and (iii) respondent's socioeconomic characteristics such as gender, age, education level, occupation, annual household income, and household size, etc. The summary of socioeconomic characteristics for both samples is provided in Appendix 1. From the summary, we may find out that both samples cover most types of the residents and households in Shanghai. In addition, compared to face-to-face interview sample, web-based sample seems encounter a potential bias in age and education level.

5. Empirical results

Tables 5-13 present the results associated with the MNL/LC specifications and WTP and elasticity estimates. The results presented were analyzed by using NLOGIT 3.0, a specialist discrete choice modeling package in LIMDEP (Econometric Software, Inc.). The definition of the variables used in this study can be found in Appendix 2. As a whole impression of the MNL and LC estimates, we may find that compared to the MNL model, the goodness of fit measures (Pseudo R^2 and predictive power) gets significantly improved after applying the LC approach.

5.1 Likelihood Ratio test for sample selection

We start by discussing the results of Likelihood Ratio (LR) test for whether or not the two samples (face-to-face interview, hereinafter interview, and web-based survey, hereinafter web) could be pooled. It is said that if the estimated utility parameter are

[9] These questions aiming at revealing the respondents' environmental concern are for the purpose of another study, which examines the socioeconomic determinants of individual environmental concern. See Shen and Saijo (2007) for details.

equal across interview sample, web sample, and the pooled sample, then we may estimate the model by pooling these two samples. The null hypothesis on equal utility parameters is formally given as

$$\text{H0:} \quad \beta^{interview} = \beta^{web} = \beta^{interview+web}$$

The statistics of the likelihood ratio test suggested by Swait and Louviere (1993) are calculated as: for air conditioner model, LR=-2(-7100.49-(-3212.07-3804.55))=167.76; for refrigerator model, LR=-2(-7360.61-(-3332.92-3949.71))=155.97. Since the critical value of the chi-square is 38.93 at the 1% significance level on 21 degree of freedom, the null hypothesis that the vector of common utility parameters is equal across two samples can be rejected in both air conditioner and refrigerator cases. Therefore, the following estimations are conducted by each sample.

5.2 Determining the number of latent classes

As discussed in Section 3, the measures of AIC, $\bar{\rho}^2$, AIC3 and BIC were applied to help determining the number of latent classes. We attempted various number of classes (1, 2, 3, 4 and 5 classes) and summarize the statistics in Table 5. The log likelihood values at convergence reveal that in all cases the model fit improves with the numbers of classes, especially with the 2- and 3-class models. This is not surprising because log likelihood values normally increase in magnitude when there are more parameters need to be estimated. From the measures of AIC3 and BIC (columns 6 and 7), we may find that the minimum values of AIC3 and BIC are clearly related to the 3-class model in all cases, suggesting that 3-class model is optimal. Furthermore, the minimum AIC and the maximum $\bar{\rho}^2$ seem also support 3-class model as the best solution in most cases. There is an exception in refrigerator model of interview sample, which suggests that 4-class model is better than 3-class one. However, it is noteworthy that in this case the improvement from 3-class to 4-class is negligible because the reduction of AIC and increase of $\bar{\rho}^2$ are so small. Based on the above discussions, we therefore determined to select 3-class for estimating the LC models in this study.

5.3 Characterizing the class members

Results of class membership for the 3-class LC model in air conditioner and refrigerator are reported in Tables 6 and 7. We classified the 3 latent classes of the respondents by their socioeconomic characteristics.[10] Note that the variables associated with household

[10] An argument can be made for including the respondent's environmental concern score in the class membership classification model, since the respondent's environmental concern could also be associated with the classification of various class membership. However, as we analyzed in another study (Shen and Saijo, 2007), we found that the

size and occupation status are not listed in the tables, due to the reason that these two socioeconomic characteristics are not significant even at 10% significance level in any cases.[11] The parameters for the third class in both tables (columns 4 and 7) are set to 0 due to their normalization during estimation. Therefore, the parameters of the other two classes should be explained relative to this third class.

In air conditioner case, the first class of interview sample could be classified as "middle age (36-55 years old) or old age groups (above 56 years old), or university/college graduates" because the dummy variables of *mid-age*, *old-age*, and *high-edu* are significant at 5% significance level. We may find that the effect of age on determining class membership is larger than that of education for this class, since the estimated parameters of *old-age* and *mid-age* are about 1.3 times bigger than that of *high-edu*. For the second class, since *male* is estimated with significantly negative sign and *old-age* is with significantly positive sign, we label this class as "old age group or females". Besides the labeled two classes, the remained respondents in interview sample are classified to be in the third class. On the other hand, in web sample, class 1 and class 2 are characterized as "middle age group or university/college graduates" and "high income group with annual household income more than 100 thousand Chinese yuan", respectively.[12]

With respect to refrigerator case, the classification of three classes for interview sample is similar to that in air conditioner case, with the difference that instead of old age group, high household income group is more likely to be in class 2. For web sample, based on the statistical significance and sign of each variable, the first class is characterized as "university/college graduates or income group with annual household income below 100 thousand yuan", while the second class is classified as " income group with annual household income below 100 thousand yuan or males".

5.4 Results of the 3-class LC model

The estimated results of the 3-class LC model are listed in Tables 8-11. For purpose of comparison, the MNL estimates are also provided in these tables. We estimate the alternative specific constants (ASCs) of air conditioners A, B, C in air conditioner model and refrigerators A, B, C in refrigerator model. Note again that for both appliances, A, B,

---

socioeconomic characteristics are highly correlated with each environmental concern measure. Therefore, if we include these measures into classification model, it would cause serious co-linearity among the independent variables. Hence, in this study it is assumed that the respondents' environmental concern measures influence the class membership through their socioeconomic characteristics. We believe that this should be the issue.

[11] There is no any significant effects on the model's goodness of fit and other variables' significance when we drop these two characteristics from the model.

[12] 100 thousand yuan approximates 12.82 thousand US$ if 1 US$=7.8 yuan.

and C stand for new product with foreign brands, second-hand product with foreign brands, and new product with domestic brands, respectively. Besides the ASCs, we estimate the alternative specific attributes to examine the respondents' preferences on all the specified attributes in detail. We believe that this approach can allow us make the respondents' preferences on different alternatives more clear. In other words, heterogeneity in alternative specific attributes can be examined.

Alternative specific constants (ASCs)

Look at first the parameters of three alternative specific constants *(A_asc*, *B_asc*, and *C_asc*) in Tables 8-11. Most of the ASCs of A and C are estimated with significantly positive signs, suggesting that individuals prefer new air conditioner or refrigerator *per se* no matter it is a foreign or domestic product. In both interview and web samples, the *A_asc* of refrigerator in class 3 and *C_asc* of air conditioner in class 2 are not significant, implying that at least some respondents do not care whether it is a new product or not. Note that these effects are absent in the single MNL model, exhibiting that the heterogeneity among individuals could be captured by the latent class approach. The results of *B_asc* are somewhat mixed. In interview sample, the constant of air conditioner B is insignificant in all classes, while that of refrigerator B is significant in all classes. In particular, the *B_asc* of refrigerator in class 1 is estimated with negative sign, suggesting that individuals belonging to this class dislike used refrigerator even it is with foreign brands. This kind of disfavor with used refrigerator or air conditioner can also be found in web sample, for example, in class 3 for refrigerator (see *B_asc* in Table 11) and class 2 for air conditioner (see *B_asc* in Table 9). Considering the probabilities of respondents in these classes, we may conclude that compared to used seasonal appliance (i.e. air conditioner), more respondents dislike second-hand daily appliance (i.e. refrigerator).

Energy efficiency ranks listed on energy label

The key issue being worthy of remark in this study is how individuals evaluate the energy efficiency ranks presented on energy label. From Tables 8-11, it is noteworthy to see that all the parameters associated with energy efficiency ranks are significant and with expected negative sign in all the classes of both samples. As we discussed in the Introduction section, the effect of energy efficiency label on consumer's preference is twofold, i.e. if the information provided by the means of energy efficiency label works, consumers should significantly react on the ranks indicating energy efficiency on the label. Thus, the explanations on these estimated significant and negative parameters can be made as (i) more energy efficient air conditioners and refrigerators are preferred, no matter whether they are new or second-hand and whether they are with foreign or domestic brands; (ii) an energy efficiency label *per se* is recognized by the consumers, otherwise consumers would not have significant effect of the energy efficiency ranks on their preferences. We argue that this highly significant effect is most possible due to the fact that in recent years individuals' environmental consciousness and concern have been rapidly increasing in Shanghai.[13]

To illustrate how individuals evaluate the energy efficiency ranks with monetary value, we provide the Willingness to Pay (WTP) values for both two appliances in Table 12. Consumers' willingness to pay for one rank upgrading in energy efficiency is given by the equation:

$$WTP_{a|s} = \left| \frac{\beta_{a|r|s}}{\beta_{a|p|s}} \right| \tag{13}$$

where $\beta_{a|p|s}$ and $\beta_{a|r|s}$ denote the estimated parameters associated with attributes of price and energy efficiency ranks in each class s for alternatives a, respectively. Because these two parameters vary across classes and alternatives, therefore, the estimated WTP values could identify heterogeneity among individuals for the energy efficiency ranks of different air conditioners and refrigerators. In addition, class probability weighted WTP in Table 12 is calculated by applying the following equation:

$$WTP_{a\_weighted} = \sum_{s=1}^{3} WTP_{a|s} P_s \tag{14}$$

where P_s is the probabilities of respondents in class *s*. Note that in several cases, the estimated parameter of energy efficiency ranks is not significant. We treat the WTP values associated with these insignificant parameters as zero.

From table 12, we observe several evidences. First, the WTP values do vary across the groups, alternatives, and appliances. Second, the estimated class specific WTP as

[13] In the questionnaire, we created nine questions in order to reveal the respondents' concern about general environmental issue and some specific environmental problems including global warming, cross-boundary and acid rain, air/water/soil pollution, urban energy problem, green land and ecological problem, the effect of harmful substances on health, disposal/reduction/recycling of waste, and living environmental problems. The surveyed respondents were asked to choose to what extent they concern about these environmental issues. The percentages of answers of "concern" and "somewhat concern" in interview and web samples are respectively 91% and 93.2% for general issue, 80.7% and 87% for global warming, 67.3% and 83.5% for cross-boundary and acid rain, 78.5% and 87.2% for air/water/soil pollution, 74.2% and 83.8% for urban energy problem, 83.3% and 91.2% for green land and ecological problem, 89.5% and 91.3% for the effect of harmful substances on health, 86.5% and 88.3% for disposal/reduction/recycling of waste, and 93.8% and 91.2% for living environmental problems. See more details in Shen and Saijo (2007).

well as class probability weighted WTP values for refrigerator are larger than those corresponding values for air conditioner in most cases of both samples, suggesting that in contrast to an appliance used seasonally, consumers are willing to pay more money for energy efficiency if the appliance is used frequently. Similar effect has been also found in Bjørner et al. (2004), which stated that environmental labeling may be more effective on products purchased more frequently, as consumers may feel that it would make a greater environmental impact. Third, the WTP values for second-hand appliances B are lower than other two alternatives A and C in each class. However, the result of comparison between A and C is mixed. In some cases, the WTP values for A's energy efficiency ranks are higher than those for C, while in other cases they are reversed. Taking into account the class probability, we find that the class probability weighted WTP values for C are larger than those for A. This evidence indicates that individuals are willing to pay more on energy efficiency ranks of those appliances with domestic brands.

Finally, we provide direct elasticities of energy efficiency ranks on choice probability in Table 13. As shown in the table, all the elasticity values, although small in magnitude, are negative to choice probability. This result combined with the above discussions are intuitive to both firm leaders and government decision makers because energy efficiency ranks presented on the energy label is well recognized by the consumers and alter consumers' purchase decision. Therefore, China Energy Efficiency Labeling program could be regarded as effective based on the criterion of consumer response.[14]

Other attributes effect

Concerning the attributes of monetary costs i.e. price and electricity consumption that could be viewed as a kind of running cost, almost all the parameters associated with A and C of both appliances are estimated with significant and negative to individual's preference in both samples, which is consistent with economic theory as expected. For air conditioner B in interview sample, these two parameters are not significant. We doubt that this is most probably due to the reason that second-hand air conditioner B has no effect on consumers' preferences in this sample (see *B_asc* in Table 8).

An air conditioner with air cleaning function or a refrigerator with silent function is preferable in most classes of both samples, no matter it is a new or second-hand product. In addition, compared to those estimated parameters in web sample, more applicable space of air conditioner almost does not affect individual's preference in interview

[14] To formally evaluate a labeling program, it is necessary to consider both consumer response and producer response. However, examining the effect of energy efficiency label on firms' production decision is not the issue of the present study and will be left as our future task.

sample. Concerning the volume of refrigerator, high-capacity refrigerator raises the preferences of those respondents belonging to classes 1 for all products in interview sample. However, for other class members in interview sample and all the respondents in web sample, the preference of this attribute differs according to different alternatives. For example, in class 2 of both samples, the respondents care about the volume of new refrigerators, while in class 3 of web sample, the members prefer high-capacity refrigerators with foreign brands for both new and second-hand ones.

Meanwhile, another attribute, which is presence or absence of a label indicating clearly the electricity bill's difference comparing to a standard model, is estimated with significant and positive sign in most cases especially for new products A and C. This evidence suggests that individuals would be more pleased if more information is provided explicitly. Combined with the results of energy efficiency label, it suggests that information provision, at least to some extent, could be viewed as a valid means to affect consumers' preferences and consequently their behavior.

6. Conclusion

In this study we apply a survey data set to estimate models for consumers' choices among different brands of air conditioners and refrigerators, aiming at examining the effect of China Energy Efficiency Label on consumers' preferences. The latent class approach allows us to control heterogeneity among individuals that cannot be observed through a simple multinomial logit model. Four alternatives, which include two new ones with foreign and domestic brands and two second-hand ones with foreign and domestic brands, are considered in our choice experiments. This manipulation makes it possible for us to investigate consumers' preferences on second-hand products and consequently their attributes.

From the empirical analysis, it appears that energy efficiency ranks presented on energy label have a significant effect on the choice of air conditioner and refrigerator, perhaps because in recent years individuals' environmental consciousness and concern have been rapidly increasing in Shanghai. The results from the class specific willingness to pay for one rank upgrading in energy efficiency indicate that for second-hand products the values are relatively lower than other two new products. Furthermore, the class probability weighted willingness to pay values suggest that consumers prefer to pay more on products used more frequently, as they probably feel that it would make a greater environmental impact and/or increase their running cost. However, examining more deeply to distinguish between these two possible reasons is impossible in the present study. We leave this issue as a future task.

Presence of another label indicating clearly the electricity bill's difference comparing to a stand model is also estimated to have significant effect on consumers' preferences in most cases. This evidence suggests that information provided explicitly through a label is preferred by consumers and could be considered as a valid alternative to solve asymmetric information problem caused from market failure.

The fact resulted from this study that Shanghai consumers do react to the energy efficiency ranks presented on China Energy Efficiency Label is intuitive to both firm leaders and policy decision makers. For the government, it is a great confidence to say that environmental labeling is one of the effective policies to solve environmental issues. For the firms, it may create an incentive to invest in green technology or make them more confident in enlarging the scale of green production to meet consumers' needs. An unanswered question whether the effects of China Energy Efficiency Label on consumers' purchase decision found in Shanghai will also be found in other provinces of China is remained. We leave it as an open question and encourage a great effort to study this issue at much deeper extents.

References

Alpízar F., F. Carlsson, and P. Martinsson. 2003 Using choice experiments for non-market valuation. *Economic Issues* 8: 83-110.

Amacher, G. S., E. Koskela, and M. Ollikainen. 2004. Environmental quality competition and eco-labeling. *Journal of Environmental Economics and Management* 47: 284-306.

Banerjee, A. and B. D. Solomon. 2003. Eco-labeling for energy efficiency and sustainability: a meta-evaluation of US programs. *Energy Policy*. 31: 109-123.

Bhat C. R. and R. Gossen. 2004. A mixed multinomial logit model analysis of weekend recreational episode type choice. *Transportation Research Part B* 38: 767-787.

Bjørner, T. B., L. G. Hansen, and C. R. Russell. 2004. Environmental labeling and consumers' choice – an empirical analysis of the effect of the Nordic Swan. *Journal of Environmental Economics and Management* 47: 411-434.

Boxall, P. C. and W. L. Adamowicz. 2002. Understanding heterogeneous preferences in random utility models: A latent class approach. *Environmental and Resource Economics* 23: 421-446.

Carlsson F. and P. Martinsson. 2003. Design techniques for stated preference methods in health economics. *Health Economics* 12: 281-294.

Cason, T. N. and L. Gangadharan. 2002. Environmental labeling and incomplete consumer information in laboratory markets. *Journal of Environmental Economics and Management* 43: 113-134.

China State Statistics Bureau. 2006. *China Statistics Yearbook 2006*.

Crespi, J. M. and S. Marette. 2005. Eco-labelling economics: is public involvement necessary?. in S. Krarup and C. S. Russell (eds), *Environment, Information and Consumer Behaviour*. Edward Elgar Publishing.

Dosi, C. and M. Moretto. 2001. Is ecolabelling a reliable environmental policy measure?. *Environmental and Resource Economics* 18: 113-127.

Fisher-Vanden, K., G. H. Jefferson, H. Liu, and Q. Tao. 2004. What is driving China's declined in energy intensity?. *Resource and Energy Economics* 26: 77-97.

Greene, W. H. and D. A. Hensher. 2003. A latent class model for discrete choice analysis: contrast with mixed logit. *Transportation Research Part B* 37: 681-698.

Hensher, D. A., J. M. Rose, and W. H. Greene. 2005. *Applied Choice Analysis: A Primer*. Cambridge University Press.

Hess S., M. Bierlaire, and J. W. Polak. 2005. Estimation of value of travel-time saving using mixed logit models. *Transportation Research Part A* 39: 221-236.

Howarth, R. B, B. M. Haddad, and B. Paton. 2000. The economics of energy efficiency: insights from voluntary participation programs. *Energy Policy*. 28: 477-486.

Huber, J. and K. Zwerina. 1996. The importance of utility balance in efficient choice design. *Journal of Marketing Research* 33: 307-317.

Johnston, R. J., C. R. Wessells, H. Donath, and F. Asche. 2001. Measuring consumer preferences for ecolabeled seafood: an international comparison. *Journal of Agricultural and Resource Economics* 26: 20-39.

Loureiro, M. L., J. J. McCluskey, and R. C. Mittelhammer. 2002. Will consumers pay a premium for eco-labeled apples?. *Journal of Consumer Affairs* 36: 203-219.

Louviere J. J., D. A. Hensher, and J. D. Swait. 2000. *Stated Choice Methods: Analysis and Applications*. Cambridge University Press.

McFadden D. 1974. Conditional logit analysis of qualitative variables in econometrics, Zarembka P. (ed.), *Frontiers in Econometrics*, New York, Academic Press, 105-142.

McFadden, D. and K. Train. 2000. Mixed MNL models for discrete response. *Journal of Applied Econometrics* 15: 447-470.

Moon, W., W. J. Florkowski, B. Brückner, and I. Schonhof. 2002. Willingness to pay for environmental practices: implications for eco-labeling. *Land Economics* 78: 88-102.

Morey, E., J. Thacher, and W. Breffle. 2006. Using angler characteristics and attitudinal data to identify environmental preference classes: A latent-class model. *Environmental and Resource Economics* 34: 91-115.

Morris, L. A., M. Hastak, and M. B. Mazis. 1995. Consumer comprehension of environmental advertising and labeling claims. *Journal of Consumer Affairs* 29: 328-350.

Revelt D. and K. Train. 1998. Incentives for appliance efficiency in a competitive energy environment: random parameters logit models of households' choices. *Review of Economics and Statistics* 80: 647-657.

Roe, B., M. F. Teisl, A. Levy, and M. Russell. 2001. US consumers' willingness to pay for green electricity. *Energy Policy* 29: 917-925.

Russell, C. S., S. Krarup, and C. D. Clark. 2005. Environment, information and consumer behaviour: an introduction. in S. Krarup and C. S. Russell (eds), *Environment, Information and Consumer Behaviour*. Edward Elgar Publishing.

Shen, J. 2006. A Review of Stated Choice Method. *International Public Policy Research* 10(2): 97－121.

Shen, J. and T. Saijo. 2007. The socioeconomic determinants of individual environmental concern: Evidence from Shanghai data. *Discussion Paper in Osaka School of International Public Policy (OSIPP), DP-2007-E-003, Osaka University*.

Stern, P. C. 1999. Information, incentives, and proenvironmental consumer behavior. *Journal of Consumer policy* 22: 461-478.

Swait, J. 1994. A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data.. *Journal of Retailing and Consumer Services* 1: 77-89.

Swait, J. 2007. Advanced choice models. in B. J. Kanninen (eds), *Valuing Environmental Amenities Using Stated Choice Studies*. Springer.

Swait J. D. and Louviere J. J. 1993. The role of the scale parameter in the estimation and comparison of multinomial logit models. *Journal of Marketing Research* 30: 305-314.

Teisl, M. F., B. Roe, and R. L. Hicks. 2002. Can eco-labels tune a market? Evidence from dolphin-safe labeling. *Journal of Environmental Economics and Management* 43: 339-359.

Thøgersen J. 2000. Psychological determinants of paying attention to eco-labels in purchase decisions: model development and multinational validation. *Journal of Consumer Policy* 23: 285-313.

Tietenberg, T. and D. Wheeler. 2001. Empowering the community: information strategies for pollution control. in H. Folmer, H. Landis Gabel, S. Gerking and A. Rose (eds), *Frontiers of Environmental Economics*. Edward Elgar Publishing.

Train, K. 1998. Recreation demand models with taste differences over people. *Land Economics* 74: 230-239.

Figure 1. China Energy Conservation Label

Figure 2. China Energy Efficiency Label

Table 1. Air conditioner attributes and their levels in the survey

Attributes	Levels of attributes			
	New air conditioner **A** with foreign brands	Second-hand air conditioner **B** with foreign brands	New air conditioner **C** with domestic brands	Second-hand air conditioner **D** with domestic brands
Price (yuan)	2500/3400/4300	1400/2000/2600	1800/2700/3600	800/1400/2000
Hourly electricity consumption (kwh)	0.9/1.4	1.0/1.5	0.9/1.4	1.0/1.5
Applicable space (m^2)	16/24	16/24	16/24	16/24
Air cleaning function	with/without	with/without	with/without	with/without
Energy efficiency ranks on the label	1/2/3/4	1/2/3/4	1/2/3/4	1/2/3/4
Label of indicating the electricity bill's difference comparing to a standard model	presence/ absence	presence/ absence	presence/ absence	presence/ absence

Table 2. Refrigerator attributes and their levels in the survey

Attributes	Levels of attributes			
	New refrigerator **A** with foreign brands	Second-hand refrigerator **B** with foreign brands	New refrigerator **C** with domestic brands	Second-hand refrigerator **D** with domestic brands
Price (yuan)	2300/3500/4700	1200/1800/2400	1600/2800/4000	800/1400/2000
Daily electricity consumption (kwh)	0.3/0.8	0.4/0.9	0.3/0.8	0.4/0.9
Volume (liter)	190/240	190/240	190/240	190/240
Silent function	with/without	with/without	with/without	with/without
Energy efficiency ranks on the label	1/2/3	1/2/3	1/2/3	1/2/3
Label of indicating the electricity bill's difference comparing to a standard model	presence/ absence	presence/ absence	presence/ absence	presence/ absence

Table 3. An example of choice set from the choice experiment for air conditioner

Features	New air conditioner **A** with foreign brands	Second-hand air conditioner **B** with foreign brands	New air conditioner **C** with domestic brands	Second-hand air conditioner **D** with domestic brands
Price (yuan)	3400	2000	2700	1400
Hourly electricity consumption (kwh)	0.9	1	1.4	1
Applicable space (m^2)	24	16	16	16
Air cleaning function	with	with	without	with
Energy efficiency ranks on the label	3	4	4	3
Label of indicating the electricity bill difference comparing to a standard model	absence	absence	absence	presence
Please choose one most desirable air conditioner and ✔ in ☐	☐	☐	☐	☐

Table 4. An example of choice set from the choice experiment for refrigerator

Features	New refrigerator **A** with foreign brands	Second-hand refrigerator **B** with foreign brands	New refrigerator **C** with domestic brands	Second-hand refrigerator **D** with domestic brands
Price (yuan)	4700	1800	2800	1400
Daily electricity consumption (kwh)	0.8	0.9	0.8	0.4
Volume (liter)	240	190	240	190
Silent function	with	without	with	without
Energy efficiency ranks on the label	2	3	3	3
Label of indicating the electricity bill difference comparing to a standard model	absence	presence	presence	presence
Please choose one most desirable air conditioner and ✔ in ☐	☐	☐	☐	☐

Table 5. Information criterions for different numbers of latent classes

Classes	#Par	Log Lik	AIC	$\bar{\rho}^2$	AIC3	BIC
Air conditioner – Interview sample						
1	21	-3212.07	6466.14	0.1129	6487.14	3249.41
2	48	-3092.15	6280.30	0.1384	6328.30	3177.50
3	75	-2903.56	5957.12	0.1828	6032.12	3036.92
4	102	-2891.25	5986.50	0.1787	6088.50	3072.62
5	129	-2877.66	6013.33	0.1751	6142.33	3107.04
Air conditioner – Web sample						
1	21	-3804.55	7651.09	0.0450	7672.09	3841.89
2	48	-3665.71	7427.42	0.0729	7475.42	3751.06
3	75	-3511.26	7172.51	0.1048	7247.51	3644.62
4	102	-3485.12	7174.23	0.1045	7276.23	3666.49
5	129	-3463.93	7185.85	0.1031	7314.85	3693.31
Refrigerator – Interview sample						
1	21	-3332.92	6707.83	0.1054	6728.83	3370.26
2	48	-3110.65	6317.29	0.1575	6365.29	3196.00
3	75	-2959.16	6068.31	0.1907	6143.31	3092.52
4	102	-2931.78	6067.56	0.1908	6169.56	3113.15
5	129	-2908.47	6074.93	0.1898	6203.93	3137.85
Refrigerator – Web sample						
1	21	-3949.71	7941.42	0.0370	7962.42	3987.05
2	48	-3738.27	7572.54	0.0818	7620.54	3823.62
3	75	-3542.46	7234.93	0.1227	7309.93	3675.83
4	102	-3519.01	7242.02	0.1218	7344.02	3700.38
5	129	-3494.46	7246.91	0.1213	7375.91	3723.84

Table 6. Results of class membership for the 3-class LC model in *Air conditioner* case

Variables	*Face-to-face interview*			*Web-based survey*		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
constant	0.7163**	-1.1397*	0	0.3502	-1.1807**	0
	(2.06)	(-1.95)		(0.96)	(2.43)	
old-age	0.7792**	1.1201*	0	-0.5679	-0.0140	0
	(2.24)	(1.89)		(-1.15)	(-0.02)	
mid-age	0.7700**	0.9468	0	0.5156*	0.5249	0
	(2.29)	(1.63)		(1.72)	(1.41)	
male	-0.2597	-1.0486***	0	-0.2124	0.2385	0
	(-1.02)	(-2.60)		(-0.91)	(0.76)	
high-inc	-0.4042	-0.4760	0	0.2815	0.5257**	0
	(-1.23)	(-0.88)		(1.13)	(2.06)	
high-edu	0.5909**	0.3565	0	0.2359**	0.0521	0
	(2.11)	(0.81)		(2.35)	(0.11)	

Notes: *t* statistics are in parentheses.*,**, and*** denote that the parameter is significantly different from zero at the 10%, 5%, and 1% level, respectively.

Table 7. Results of class membership for the 3-class LC model in *Refrigerator* case

Variables	*Face-to-face interview*			*Web-based survey*		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
constant	0.2132	-0.1094	0	0.6094	0.5497	0
	(0.65)	(-0.28)		(1.57)	(1.38)	
old-age	0.7247**	0.4815	0	-0.3756	-0.2848	0
	(2.24)	(1.24)		(-0.70)	(-0.51)	
mid-age	0.6864**	0.3006	0	0.0847	-0.3838	0
	(2.19)	(0.77)		(0.28)	(-1.12)	
male	-0.3181	-0.6034**	0	0.1261	0.1410**	0
	(-1.34)	(-2.12)		(0.49)	(2.05)	
high-inc	-0.0026	0.3363***	0	-0.5597**	-0.5110*	0
	(-0.01)	(2.29)		(-2.15)	(-1.79)	
high-edu	0.4577*	0.2655	0	0.6080*	0.1923	0
	(1.80)	(0.86)		(1.82)	(0.49)	

Notes: *t* statistics are in parentheses.*,**, and*** denote that the parameter is significantly different from zero at the 10%, 5% and, 1% level, respectively.

Table 8. Estimation results for *Air conditioner* choice in *Face-to-face interview* sample

Attribute	MNL	LC		
		Class 1	Class 2	Class 3
A_asc	6.4401(17.54)***	8.5357(18.18)***	5.6345(3.15)***	5.6204(7.03)***
B_asc	0.7626(1.19)	1.7324(1.27)	21.3357(0.23)	0.2582(0.34)
C_asc	5.4774(17.00)***	7.8559(18.43)***	-7.3070(-0.24)	3.2838(5.36)***
A_price	-0.0009(-16.58)***	-0.0012(-17.13)***	-0.0015(-3.66)***	-0.0013(-9.96)***
A_elechour	-0.9069(-5.72)***	-1.2009(-6.23)***	-1.1493(-1.49)	-1.2136(-3.43)***
A_space	0.0070(0.71)	0.0204(1.71)*	0.0682(1.29)	0.0395(1.80)*
A_airclean	0.4489(5.71)***	0.3263(3.50)***	1.7579(3.96)***	1.5817(8.82)***
A_energyrank	-0.3115(-8.83)***	-0.3695(-8.80)***	-0.4200(-2.13)**	-0.1881(-2.48)**
A_difflabel	0.3185(4.07)***	0.2593(2.74)***	0.1126(0.25)	0.9784(5.44)***
B_price	-0.0002(-1.07)	0.00001(0.24)	-0.0017(-1.64)	-0.0001(-0.85)
B_elechour	-0.5591(-1.90)*	-0.7077(-1.07)	-20.1221(-0.21)	-0.4504(-1.33)
B_space	0.0190(1.05)	-0.0718(-1.55)	0.1289(1.13)	0.0484(2.42)**
B_airclean	0.9008(5.70)***	1.8120(3.56)***	-0.3970(-0.537)	0.9146(5.79)***
B_energyrank	-0.2290(-3.55)***	-0.4190(-2.80)***	0.4124(1.33)	-0.3017(-4.73)***
B_difflabel	0.3699(2.48)**	0.5347(1.49)	-0.0781(-0.11)	0.2518(1.86)*
C_price	-0.0005(-9.32)***	-0.0006(-8.74)***	-0.0023(-4.25)***	-0.0006(-6.32)***
C_elechour	-2.1471(-7.54)***	-1.4336(-7.70)***	-1.7735(3.41)***	-1.0827(-3.66)***
C_space	-0.0068(-0.71)	-0.0142(-1.21)	0.0262(0.43)	0.0009(0.05)
C_airclean	0.5408(7.20)***	0.3274(3.48)***	10.7518(0.36)	1.3409(9.05)***
C_energyrank	-0.2909(-8.68)***	-0.3971(-9.39)***	-0.3556(-1.79)*	-0.2677(-4.26)***
C_difflabel	0.2460(3.25)***	0.2292(2.46)**	1.2665(2.67)***	0.2613(1.77)*
Class probability		0.726	0.092	0.182
Log-likelihood	-3212.07	-2903.56		
Pseudo R^2	0.119	0.203		
Predictive power	50.75%	68.94%		
Observations	3600	3600		

Notes: *t* statistics are in parentheses.*,**, and*** denote that the parameter is significantly different from zero at the 10%, 5%, and 1% level, respectively. Predictive power index refers to the proportion of choices correctly predicted by the model.

Table 9. Estimation results for *Air conditioner* choice in *Web-based survey* sample

Attribute	MNL	LC		
		Class 1	Class 2	Class 3
A_asc	3.8303(11.41)***	5.7310(11.63)***	3.9483(4.19)***	2.8898(5.46)***
B_asc	0.7476(1.44)	3.6905(2.89)***	-14.6620(-2.48)**	0.6563(1.24)
C_asc	3.7008(12.29)***	6.3605(14.30)***	-0.8529(-0.69)	1.4017(3.29)***
A_price	-0.0004(-8.33)***	-0.0007(-8.96)***	-0.0004(-2.32)**	-0.0005(-6.37)***
A_elechour	-0.9114(-6.13)***	-1.5300(-7.36)***	-0.5472(-1.18)	-0.4509(-1.90)*
A_space	0.0196(2.13)**	0.0448(3.49)***	0.0702(2.25)**	0.0105(2.71) ***
A_airclean	0.2793(3.78)***	0.2478(2.45)**	1.2440(6.95)***	0.4029(3.02) ***
A_energyrank	-0.1176(-3.57)***	-0.1709(-3.70)***	-0.1200(-2.19)**	-0.1295(-2.43)**
A_difflabel	0.4705 (6.39)***	0.6185(6.09)***	0.4805(2.14)**	0.5833(4.91)***
B_price	-0.0001(-0.71)	-0.0001(-0.45)	-0.0059(-2.61)***	-0.0004(-3.60)***
B_elechour	-0.4580(-2.01)**	-1.8711(-3.07)***	-4.1496(-1.87)*	-0.1432(-0.64)
B_space	0.0226(1.59)	-0.0272(-0.77)	0.2710(2.12)**	0.0291(2.06)**
B_airclean	0.2580(2.25)**	0.7454(2.54)**	0.5374(0.76)	0.2325(2.12)**
B_energyrank	-0.1467(-2.96)***	-0.2446(-1.99)**	-0.3714(-1.05)	-0.0999(-2.08)**
B_difflabel	0.6494(5.52)***	0.0634(0.22)	1.9459(1.79)*	0.8590(7.51)***
C_price	-0.0003(-6.07)***	-0.0004(-5.97)***	-0.0003(-2.77)***	-0.0003(-3.18)***
C_elechour	-0.8503(-5.95)***	-1.4546(-7.40)***	-1.1885(-2.38)**	-0.3822(-1.78)*
C_space	0.0048(0.54)	-0.0167(-1.33)	0.0576(1.79)*	0.0277(2.16)**
C_airclean	0.4139(5.82)***	0.3081(3.10)***	1.0767(6.77)***	0.5031(4.80)***
C_energyrank	-0.1412(-4.48)***	-0.0622(-2.43)**	-0.0655(-5.27)***	-0.2673(-5.79)***
C_difflabel	0.4884(6.83)***	0.4784(4.84)***	0.8179(3.40)***	0.6163(5.94)***
Class probability		0.544	0.150	0.306
Log-likelihood	-3804.55	-3511.26		
Pseudo R^2	0.050	0.123		
Predictive power	41.42%	60.69%		
Observations	3600	3600		

Notes: *t* statistics are in parentheses.*,**, and*** denote that the parameter is significantly different from zero at the 10%, 5%, and 1% level, respectively. Predictive power index refers to the proportion of choices correctly predicted by the model.

Table 10. Estimation results for *Refrigerator* choice in *Face-to-face interview* sample

Attribute	MNL	LC		
		Class 1	Class 2	Class 3
A_asc	3.5344(9.26)***	9.4728(10.96)***	8.1802(2.75)***	1.1297(1.60)
B_asc	0.3148(0.49)	-14.7612(-2.78)***	5.5393(1.75)*	2.0669(3.28)***
C_asc	4.1513(10.92)***	8.4262(9.93)***	7.9693(2.67)***	2.6112(4.27)***
A_price	-0.0005(-11.89)***	-0.0011(-12.56)***	-0.0002(-3.70)***	-0.0005(-5.93)***
A_elecday	-1.9514(-12.32)***	-3.6563(-11.50)***	-2.0865(-8.26)***	-1.5420(-5.22)***
A_volume	0.0060(3.84)***	0.0054(2.00)**	0.0105(3.87)***	0.0051(1.80)*
A_silent	0.6660(8.50)***	0.5763(4.42)***	0.6546(8.63)***	0.9152(6.13)***
A_energyrank	-0.2538(-5.30)***	-0.5967(-7.16)***	-0.2949(-3.96)***	-0.1915(-2.23)**
A_difflabel	0.2344(2.99)***	0.3939(2.81)***	0.3775(3.06)***	0.1932(1.29)
B_price	-0.0002(-1.51)	0.0010(1.57)	0.0003(1.24)	-0.0006(-4.39)***
B_elecday	-1.0160(-3.69)***	-2.0241(-1.80)*	-3.3638(-4.88)***	-0.6065(-2.46)**
B_volume	0.0043(1.65)*	0.0676(3.37)***	0.0038(0.74)	-0.0037(-1.32)
B_silent	0.8950(6.44)***	1.3620(2.48)**	0.7843(2.86)***	1.0775(8.17)***
B_energyrank	-0.2412(-2.84)***	-0.6627(-1.78)*	-0.2377(-2.30)**	-0.1616(-1.88)*
B_difflabel	0.3211(2.32)**	0.7568(1.28)	1.2237(3.77)***	0.1482(1.07)
C_price	-0.0006(-15.05)***	-0.0014(-14.95)***	-0.0003(-3.91)***	-0.0005(-8.48)***
C_elecday	-0.6398(-4.31)***	-1.1445(-4.05)***	-1.0933(-4.22)***	-1.1361(-4.80)***
C_volume	0.0031(2.06)**	0.0106(3.58)***	0.0046(1.65)*	0.0025(1.00)
C_silent	0.5941(7.94)***	0.8959(6.80)***	0.8481(6.34)***	0.5439(4.90)***
C_energyrank	-0.3733(-8.14)***	-0.5627(-6.49)***	-0.3028(-3.76)***	-0.5351(-7.33)***
C_difflabel	0.1721(2.33)**	0.2938(2.21)**	0.6479(4.98)***	0.5770(4.98)***
Class probability		0.506	0.269	0.225
Log-likelihood	-3332.92	-2959.16		
Pseudo R^2	0.111	0.211		
Predictive power	49.14%	67.42%		
Observations	3600	3600		

Notes: *t* statistics are in parentheses.*,**, and*** denote that the parameter is significantly different from zero at the 10%, 5%, and 1% level, respectively. Predictive power index refers to the proportion of choices correctly predicted by the model.

Table 11. Estimation results for *Refrigerator* choice in *Web-based survey* sample

Attribute	MNL	LC		
		Class 1	Class 2	Class 3
A_asc	2.3200(6.57)***	4.7116(7.87)***	1.0719(1.79)*	0.6148(0.73)
B_asc	1.0714(2.09)**	-0.5693(-0.43)	2.4022(4.52)***	-4.6923(-1.92)*
C_asc	2.3649(6.68)***	3.6624(6.53)***	1.1533(2.13)**	2.3198(2.44)**
A_price	-0.0003(-7.63)***	-0.0006(-8.56)***	-0.0005(-6.86)***	-0.0003(2.24)**
A_elecday	-1.0088(-6.86)***	-1.9038(-8.03)***	-1.5441(-6.11)***	-0.3500(-1.06)
A_volume	0.0041(2.77)***	0.0030(1.34)	0.0055(2.16)**	0.0168(4.82)***
A_silent	0.3175(4.32)***	0.1313(1.16)	0.8627(6.90)***	0.5068(2.90)***
A_energyrank	-0.0719(-1.71)*	-0.1280(-2.30)**	-0.0821(-2.08)**	-0.4023(-5.21)***
A_difflabel	0.2966(4.05)***	0.3895(3.30)***	0.3373(2.68)***	0.5009(3.26)***
B_price	-0.0001(-0.96)	-0.0005(-1.92)*	-0.0004(-3.46)***	0.0001(0.18)
B_elecday	-0.5726(-2.71)***	-1.3560(-2.31)**	-0.6853(-3.10)***	0.8293(1.02)
B_volume	0.0001(0.04)	0.0094(1.78)*	0.0066(2.99)***	0.0254(2.56)**
B_silent	0.5615(5.25)***	0.2944(1.11)	0.6558(7.71)***	0.8079(1.62)
B_energyrank	-0.1830(-2.77)***	-0.0540(-3.00)***	0.0147(0.21)	-0.7955(-2.95)***
B_difflabel	0.4019(3.72)***	-0.1143(-0.43)	0.6964(6.39)***	-0.0005(-0.00)
C_price	-0.0003(-7.78)***	-0.0007(-10.88)***	-0.0004(-3.42)***	-0.0003(-3.00)***
C_elecday	-0.5533(-3.94)***	-0.7116(-3.23)***	-1.0897(-4.76)***	-1.4043(-3.79)***
C_volume	0.0033(2.32)**	0.0097(4.35)***	0.0007(0.30)	-0.0019(-0.52)
C_silent	0.4579(6.49)***	0.4181(3.78)***	0.9721(8.73)***	0.3726(2.05)**
C_energyrank	-0.1444(-3.34)***	-0.2247(-2.06)**	-0.2202(-3.17)***	-0.3405(-2.38)**
C_difflabel	0.3229(4.60)***	0.1132(1.05)	0.8433(7.43)***	0.6273(3.43)***
Class probability		0.414	0.277	0.309
Log-likelihood	-3949.71	-3542.46		
Pseudo R^2	0.042	0.141		
Predictive power	42.06%	61.61%		
Observations	3600	3600		

Notes: *t* statistics are in parentheses.*,**, and*** denote that the parameter is significantly different from zero at the 10%, 5%, and 1% level, respectively. Predictive power index refers to the proportion of choices correctly predicted by the model.

Table 12. Willingness to Pay (WTP) measures (yuan) for energy efficiency rank

Alternative	Latent class model			Class probability weighted WTP
	Class 1	Class 2	Class 3	
Interview sample				
Air conditioner A	307.92	280.00	144.69	275.64
Air conditioner B	—	—	—	—
Air conditioner C	661.83	154.09	446.17	575.87
Refrigerator A	542.45	1474.50	383.00	757.30
Refrigerator B	—	—	269.33	60.60
Refrigerator C	401.93	1009.33	1070.20	956.48
Web sample				
Air conditioner A	244.14	300.00	259.00	257.07
Air conditioner B	—	—	249.75	76.42
Air conditioner C	155.50	216.67	891.00	389.74
Refrigerator A	213.33	164.20	1341.00	548.17
Refrigerator B	108.00	—	—	44.71
Refrigerator C	321.00	550.50	1135.00	636.10

Notes: Signs of "—" denote that the estimated WTP measures are not statistically significant due to the insignificance of the estimated parameters. WTP for energy efficiency rank refers to willingness to pay for one rank upgrading in energy efficiency listed on the label such as rank 3 to rank 2 or rank 2 to rank 1, etc.

Table 13. Direct elasticities of energy efficiency rank on choice probability

Alternative	Interview sample	Web sample
Air conditioner A	-0.288	-0.128
Air conditioner B	-0.740	-0.383
Air conditioner C	-0.316	-0.152
Refrigerator A	-0.317	-0.135
Refrigerator B	-0.459	-0.238
Refrigerator C	-0.259	-0.090

Notes: The elasticities in the table are probability weighted.

Appendix 1. Socioeconomic characteristics of the sample

Characteristics	Face-to-face interview		Web-based survey	
	n	%	n	%
Gender				
Male	300	50.00	283	47.17
Female	300	50.00	317	52.83
Age (years)				
Below 20	0	0.00	22	3.67
20-29	120	20.00	401	66.83
30-39	120	20.00	125	20.83
40-49	120	20.00	20	3.33
50-59	120	20.00	25	4.17
Over 60	120	20.00	7	1.17
Education level				
Elementary school	8	1.33	0	0.00
Junior high school	93	15.50	4	0.67
Senior high school	168	28.00	34	5.67
Technical degree	43	7.17	35	5.83
Undergraduate degree	273	45.50	488	81.33
Graduate degree	15	2.50	39	6.50
Household annual income				
< 30,000 RMB	99	16.50	44	7.33
30,000-49,999 RMB	163	27.17	77	12.83
50,000-69,999 RMB	129	21.50	115	19.17
70,000-99,999 RMB	100	16.67	146	24.33
100,000-149,999 RMB	70	11.67	121	20.17
150,000-199,999 RMB	21	3.50	55	9.17
>200,000 RMB	18	3.00	42	7.00
Household size				
1 person	30	5.00	27	4.50
2 persons	117	19.50	122	20.33
3 persons	313	52.17	322	53.67
4 persons	87	14.50	62	10.33
5 persons	42	7.00	61	10.17
Above 6 persons	11	1.83	6	1.00
Occupation				
Fulltime-employed	350	58.33	522	87.00
Self-employed	42	7.00	1	0.17
Part time	20	3.33	6	1.00
Retired	145	24.17	2	0.33
Student	36	6.00	62	10.33
Unemployed	7	1.17	7	1.17
Total observations	600	100	600	100

Appendix 2. Definition of the variables

Variables	Definition
A_asc	Alternative specific constant of new air conditioner or refrigerator A with foreign brands
B_asc	Alternative specific constant of used air conditioner or refrigerator B with foreign brands
C_asc	Alternative specific constant of new air conditioner or refrigerator C with domestic brands
price	Price of air conditioner or refrigerator
elechour	Hourly electricity consumption
elecday	Daily electricity consumption
space	Applicable space for air conditioner
volume	Volume of refrigerator
airclean	=1 if the air conditioner is with air cleaning function
silent	=1 if the refrigerator is with silent function
energyrank	Ranks of energy efficiency presented on energy label
difflabel	=1 if a label indicating the electricity bill's difference comparing to a standard model is presented
Old-age	=1 if age of the respondent is above 56
Mid-age	=1 if age of the respondent is between 36 and 55
Male	=1 if the respondent is male
High-inc	=1 if the respondent's household annual income is higher than 100,000 yuan
High-edu	=1 if the respondent has at least an undergraduate degree