MODELING GROUP DECISION-MAKING MECHANISMS IN HOUSEHOLD TRAVEL BEHAVIOR: THEORIES AND AN APPLICATION

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Abstract: Choice models with individual decision-making mechanisms have been dominating in transportation, even though it has been long recognized that in many cases, an individual makes his/her choice together with other people. This paper establishes an additional household choice model with group decision-making mechanisms based on a multi-linear household utility function, which can theoretically and endogenously deal with intra-household interaction and members’ relative influences in joint decision-making process. The model is applied to represent households’ vehicle type choices, using a data collected in two Japanese cities in 2004. The effectiveness of the model is empirically confirmed from both model performance and applicability to analysis of household car ownership behavior.

Key Words: Intra-household interaction, Multi-linear utility, Car ownership

1. INTRODUCTION

In transportation, an individual has been regarded as an independent decision maker (McFadden, 2001). Such individual-based choice models include, for example, MNL model, NL model, GEV model, MNP model (Daganzo, 1979), mixed logit model (McFadden and Train, 2000), mass point logit model (Sugie et al., 1999), PCL model (Koppelman and Wen, 2000), NPCL model (Fujiwara and Zhang, 2005), GenL model (Swait, 2001), GNL model (Wen and Koppelman, 2001, network GEV model (Bierlaire, 2002), dynamic GEV model (Swait et al., 2004), and relative utility based choice model (Zhang et al., 2004b). Thus, discrete choice models with individual decision-making mechanisms have been widely applied. Even though these choice models could be used to accommodate inter-personal interdependencies (e.g., Algers et al., 1997; Wen and Koppelman, 12), modeling approach is still statistically oriented. On the other hand, it has been long recognized that various decisions in human society occur as group decisions (Corfman and Gupta, 1993; Rose and Hensher, 2004). Up to now, many group-based models have been developed to describe different aspects (e.g., decision processes and outcomes) of group decision-making in the
disciplines such as social psychology, marketing research and economics. These models include normative models and descriptive models. Arrow’s axioms, cooperative and non-cooperative game theories are the examples of normative models. Social decision schemes, weighted linear or weighted probability model are the examples of descriptive models. Moreover, in these disciplines, group decision-making is still an active line of research.

However, little research on group decision-making issues has been conducted to date in transportation. In fact, one can observe various forms of group decision-making mechanisms in transportation. Concerning the choice issues in travel behavior, joint activity participation, household resource allocation (e.g., car ownership and use behavior), task and time allocation and role specification are all involving more or less group decision-making mechanisms (Zhang and Fujiwara, 2006; Zhang et al., 2002, 2003, 2004a, 2005a,b). The importance and necessity of introducing such group decision-making mechanisms into transportation should be evident. Recent years, it is very encouraging to find an increasing number of studies dealing with group choice behavior, especially in the activity-based approach (Bhat and Pendyala, 2005), such as the studies on empirical analysis and development of household decision-making models of maintenance activity participation (Srinivasan and Athuru, 2005; Srinivasan and Bhat, 2005), development of GA-based household scheduler (Meister et al., 2005), modeling parallel choices of full-day tour patterns by household members subject to an overarching joint choice (Gliebe and Koppelman, 2005), and a model for joint choice of daily activity pattern types of household members (Bradley and Vovsha, 2005).

This paper first briefly reviews the existing group decision-making models, which can be probably applied to household behavior analysis (Section 2). After that, one of the models are selected and built to represent household choice behavior under the principle of random utility maximization (Section 3). Section 4 introduces a data about household car ownership used in this study, estimates and examines the established model. Finally, this study is concluded in Section 5 and future research issues are also mentioned there.

2. REVIEW OF GROUP DECISION-MAKING MODELS

For group decision-making, there are several methodological issues that should be clarified, for example, decision-making rules, members’ involvement in joint decisions and their relative influences, intra-group interaction and so on. In the case of household decision-making, decision-making can be either consensual or accommodative, and consequently no one can guarantee that decision outcomes should be optimal (Zhang et al., 2005a). On the other hand, since transport demand models have been widely used in project evaluation, the models have to be consistent with microeconomic theory if it should be used for cost and benefit analysis and welfare economic analysis. From this perspective, it is still worth exploring the possibility of random utility maximization approach to approximate group decisions in transportation. How to represent and measure the intra-group interactions is one of the main challenges in the study of group decision-making. Other aspects related to group behavior including members’ involvement in joint decisions and their relative influences could be described based on the research findings in the fields of social psychology, marketing research and economics and so on. Here, group decision-making models, which have been proposed at other research fields and can be probably, or have been applied to household behavior analysis in transportation, are briefly reviewed below.
Group decision-making models can be classified into two major categories: one is normative models and another is descriptive models (Corfman and Gupta, 1993). Normative models assume that decision makers in a group should follow behavioural norms such as fairness and efficiency. In contrast, descriptive models focus on how to accurately describe actual decision-making phenomena and do not make any particular assumptions as done in the normative models. Both normative and descriptive models include many types of specific models. Under the framework of utility theory, it is first necessary to specify the utilities of members within a group. Conditional on the specifications of members’ utilities, the existing group decision-making models applicable to the analysis of household choice behavior can be re-classified into the following two types. One is to first define the household utility using its members’ utilities and then to build the household choice models using the defined household utility. Another is to first calculate the choice probabilities of household members and then to estimate the household’s choice probability. Hereafter, the former type is called utility-aggregation models and the latter is called probability-aggregation models.

2.1 Utility-Aggregation Models
Within this modelling framework, it is important how to define the household utility using its members’ utilities. It is expected that different types of households may show different group decision-making mechanisms. For example, some households may attempt to maximize the utility of the weak (e.g., children) or the utility of the strong (e.g., wage-earners), while others might balance the utilities of the household members. To represent such differing household decision-making mechanisms, there are two major methods to aggregate household members’ utilities into the household utility: one is to adopt a multi-linear (ML) utility function and another is to use an iso-elastic (IE) class of utility function. The effectiveness of these two types of utility functions was already confirmed in our previous in the context of household time allocation behavior (Zhang and Fujiwara, 2006; Zhang et al., 2002, 2003, 2004a, 2005a,b).

(1) Multi-linear household utility function
The ML utility function is defined as follows:

\[ U_h = \sum_{i=1}^{n} w_i u_i + \lambda \sum_{i=1}^{n} \sum_{i' > i} (w_{i'} u_i, u_{i'}) \]

where,
- \( U_h \) denotes household utility function,
- \( u_i \) is household member \( i \)'s utility,
- \( \lambda \) is parameter of intra-household interaction,
- \( w_i \) is member \( i \)'s weight parameter, reflecting the relative influence of each member, and
- \( n \) is the number of household members.

The weight \( w_i \) can be interpreted as a measure of a member's power or relative influence within the household. It also reflects the influence of the degree of involvement and/or the types of strategies adopted in the household decision-making process. The second term in the right side of equation (1) represents the influence of intra-household interaction, and the interaction parameter \( \lambda \) reflects household members’ concerns for achieving equality of utilities. The ML household utility function finds its theoretical roots in “group decision theory” (e.g., Harsanyi, 1955), and can include additive-type, compromise-type, capitulation-type and autocracy-type of utilities as special cases.
(2) Iso-elastic household utility function
The IE household utility function is defined as follows:

\[ U_h = \frac{1}{1-\alpha} \sum_i w_i u_i^{1-\alpha}, \quad w_i \geq 0 \text{ and } \sum_i w_i = 1 \]  

where, \( \alpha \) is a parameter indicating intra-household interaction and other notions are the same as shown in equation (1).

The IE function is drawn from the research of social welfare function (Atkinson, 1983). The parameter \( \alpha \) describes how and to what extent the household positions its members (or considers the existence of its members) in the decision-making process and consequently makes its final decision. Therefore, different values of \( \alpha \) and \( w_i \), and the sign of \( \alpha \) represent different household decision-making mechanisms. In other words, equation (3) can include various types of household utility functions as special cases. The above-mentioned additive-type, compromise-type, capitulation-type and autocracy-type of utilities are its special cases. Other special cases include minimum-type, maximum-type, and Nash-type of utilities.

Note that in representing intra-household interaction, ML and IE utility functions adopt different modelling strategies and overlay functionally, but they cannot completely replace each other.

2.2 Probability-Aggregation Models
These types of models have not been applied and examined in transportation. Therefore, here, we select some promising models which might be applied to model household behaviour, based on our subjective judgment. Readers can find the relevant literature in review papers by Corfman and Gupta (1993) and Wilson et al., (1989).

1) Proportionality model: It is assumed that the probability of a group choosing an alternative, A, in choice set is the proportion of its members for whom A is the first choice.

2) Equiprobability model: It is assumed that a group is likely equally to choose all the alternatives which are the first choice of one or more members.

3) Majority model: If an alternative, A, is the first choice of at least half (or 2/3) of the group members, then the group also chooses A.

4) Plurality or voting model: A group chooses the first-choice alternative of the largest number of its members.

5) Truth wins model: If one or more members most prefer the alternative, A, and this choice is correct, then the group also chooses A.

6) Highest expected value model: A group choose an alternative with the highest expected value among those in choice set, which are the first choice by one or more members.

7) Extreme member wins model: A group choose an alternative with the highest (or lowest) risk among those in choice set, which are the first choice by one or more members.

8) Neutral member wins model: A group chooses the most neutral alternative from those in choice set, which are the first choice by one or more members.

9) Risk (Caution)-supported wins model: A group chooses an alternative with the highest (or lowest) risk from choice set, which are the first choice by two (or more) or more members.

10) Binomial model: This model is widely used in jury decisions. This model depends on the binary characteristic of jury decisions (the two alternatives being guilt or acquittal).
(11) Weighted probability model: This model calculates the probability of a group based on the weighted probabilities of its members. This model has been widely used to represent household buying or organizational buying behavior.

(12) Minimum endorsement model: It is assumed that to be selected by a group, an alternative has to be the choice of a pre-specified number of its members involved in the decision.

(13) Preference perturbation model: If the decision cannot be made unanimously, a group is most likely to choose the alternative that perturbs individual members’ preferences least.

It is expected that the above-described models might be applicable at different contexts. However, this study only deals with the utility-aggregation models, considering the fact that the effectiveness of such household utility functions has been empirically examined in the context of household continuous choice (i.e., time allocation) behavior, but has not been verified in the context of discrete choice behavior.

3. MODEL DEVELOPMENT

In transportation, group decision-making mechanisms have been incorporated mainly through the use of individual-based discrete choice models including multivariate probit, nested logit model, nested covariate heterogeneity logit model, mixed logit model, and latent class segmentation model (see Rose and Hensher, 2004). If one can clearly identify which member makes the decisions on the choice of an alternative, these models are acceptable and applicable. However, in fact, analysts do not know exactly who is the final decision-maker, or who is the decisive person. Sometimes, even for the decision makers themselves, they do not know it exactly. In such cases, applying these models to represent group decision-making mechanisms is problematic, because all these models pre-define one decision maker in order to apply individual-based choice modeling approaches. Therefore, this study attempts to provide an alternative approach in the framework of utility-aggregation models.

Within the utility-aggregation modeling framework, the IE utility function (equation (3)) is still difficult to be estimated in case of discrete choice behavior. Here, we adopt equation (1), i.e., the ML household utility function. Such utility function is similar to the concept of meta-utility, which was initially proposed by Swait et al. (2004) in the development of dynamic discrete choice model to evaluate temporal welfare impacts. They adopted the meta-utility to relate previous utilities to current utility and also simultaneously incorporated initial condition, future expectation, state dependence, and temporally changing scale and taste parameters and covariance. Mother logit model (McFadden et al., 1977) and relative utility based choice model (Zhang et al., 2004b) can be also regarded as the ones derived from meta-utility.

Here, household utility $U_{hj}$ is specified with respect to the alternative $j$ of interest as follows:

$$U_{hj} = \sum_{i=1}^{n} w_{hij} v_{hij} + \lambda_h \sum_{i=1}^{n} \sum_{i' \neq i} \left( w_{hij} w_{hij'} v_{hij} v_{hij'} \right) + \varepsilon_{hj}$$

where $v_{hij}$ is non-stochastic part of member $i$’s utility, $\varepsilon_{hj}$ is error term, weight parameter $w_{hij}$ might be different across households, members and alternatives, and intra-household interaction parameter $\lambda_h$ might be different across households.

It is assumed here that household members share some clearly defined common goal(s) and the household tries to maximize its utility, which is composed of its clearly specified members’ utilities and explicitly incorporates mutual influence of its members (i.e., intra-
household interaction). For example, assuming error terms \( \{ \varepsilon_{hi} \} \) follow an independent and identical Gumbel distribution results in the following logit-type household discrete choice model with group decision-making mechanisms.

\[
P_{hi} = \frac{\exp \left( \sum_{i} w_{hi} v_{hi} + \lambda_{h} \sum_{i} \sum_{j} w_{hi} v_{hij} + \sum_{i} w_{hi} v_{hik} \right)}{\sum_{i} \left( \exp \sum_{i} w_{hik} v_{hik} + \lambda_{h} \sum_{i} \sum_{j} w_{hik} v_{hij} + \sum_{i} w_{hik} v_{hik} \right)}
\]  

(5)

Theoretically, relaxing the assumptions made about the error terms in equation (4) could result in various types of group choice models. In this study, to simplify the discussion about group decision-making mechanisms, we only examine the applicability of equation (5). We name the derived model as G_MNL model. It can be estimated based on conventional maximum likelihood function. One important feature is that any number of household members can be flexibly incorporated in the model. Since the group here can be a household, employer and its employees, car-pooling users, a travel group (e.g., friends or colleagues) and so on, it is expected that the above-derived group choice model could be applied to explain various group decision-making mechanisms.

In equation (5), both the determinant term \( v_{hi} \) of utility and interaction parameter \( \lambda_{h} \) can be non-negative or non-positive. Let us consider the case that a group has two members. Focusing on a particular alternative, if the calculated members’ utilities are all positive and the estimated interaction parameter is also positive, this means that joint decisions of the group further affirm and support both members’ beliefs about their preferences of the alternative. As a result, the group also tends to prefer the same alternative. If the calculated members’ utilities are all negative and the estimated interaction parameter is also negative, this means that as an outcome of joint decisions, the group will follow both members’ preferences and tend to choose other alternatives rather than the alternative of interest. If the two members’ utilities and their interaction parameters have opposite signs, the outcomes of joint decisions will become more complicated. Behaviorally, it might occur that the two members’ utilities are positive, but their interaction parameter is negative. In other words, even if the two members prefer the alternative very much as their personal attitudes, joint decisions might tend to weaken their preferences. This is probably because, for example, joint decisions might call the two members’ potential attentions to the choice constraints (e.g., monetary constraint to buy a car), which are ignored or depreciated in the formation of their personal attitudes to the alternative. It is also possible in behavior that the two members’ utilities are negative and their interaction parameter is positive. Consider the residential choice behavior of a couple that are both working at a city center. They may personally dislike living in the city center. However, the couple might change their attitudes during the process of joint decision. They may become recognizing the risk of the expensive car-dependent life at suburban area and gradually realize how attractive to live in the city center together. In such case, one can expect that the couple might decide to live in the city center. The aforementioned discussion suggests that the derived group choice model could be used to represent more general group behaviors.

Having mentioned the possible generality of the derived group choice model, we are also recognizing its limitations. One of them is caused by the way to incorporate group members’ influences and their interactions in joint decisions. For example, in the case of the above-mentioned couple, it might occur behaviorally that the two members’ utilities are positive (or negative), but their interaction parameter is negative (positive). If the utilities are not extremely high, the decision outcomes of the group are generally acceptable, as discussed
above. However, if all the group members extremely prefer a particular alternative (i.e., their utility values are extremely high), and the interaction parameter is negative, then the group utility will become extremely low. This means that even if this particular alternative is each member’s most preferred alternative, as an outcome of joint decisions, it could become the least preferred alternative to the group. This is not intuitive. When such extreme cases happen, we can say that the group members are captive to the alternatives. Then we need to adopt other types of choice models. In other words, as long as such extreme cases do not happen, the derived group choice model is practically acceptable. Therefore, when applying equation (5), one needs to check if this kind of unrealistic choice behavior occurs.

In this study, the derived group choice model (G_MNL model) will be applied to the analysis of household car ownership behavior, because it is expected that there might exist clear intra-household interactions when a household makes decision on its car ownership.

4. MODEL ESTIMATION AND DISCUSSION

4.1 Data
To examine the effectiveness of the proposed G_MNL model, we adopt a data collected from a revealed preference survey in October 2004, which was designed to investigate current household car ownership and use behavior in two cities in Japan. The sample households were randomly selected from the residents living in Hiroshima City (population: about 1.12 millions) and its satellite city of Higashi-Hiroshima (population: about 0.12 millions). All the recruited household members over 15 years old were asked to answer the questions about household and individual attributes (e.g., number of household members, number of owned passenger cars, residential characteristics, age, gender, driving license, occupation, car use behavior, and daily activity participation), attributes of currently and previously owned passenger cars (e.g., make, engine displacement, manufacture year, total travel distances). As a result, we collected the questionnaires from 595 households, among which 51% came from Hiroshima City, 49% from Higashi-Hiroshima City. It is observed that 97% households own their passenger cars and 47% have 2 or more cars. This result reveals that people’s mobility in the survey areas is highly dependent on car traffic.

4.2 Dependent and Independent Variables
In this case study, we apply the G_MNL model to represent how a household chooses the types of its first and second passenger cars, defined as the orders in which they were purchased. Up to now, disaggregate choice models are generally used to describe the choice behavior of vehicle type, where household characteristics (e.g., household income, number of household members, and age of household head etc.), characteristics of main users, and vehicle attributes (e.g., body price, operating cost, and seating capacity etc.) are usually used as explanatory variables in the models (e.g., Golob et al., 1996). Existing research has classified vehicle type based on various attributes, for example, vehicle size (e.g., Hayashi et al., 2001), model type (e.g., Choo and Mokhtarian, 2004), fuel type (e.g., Golob et al., 1996; Adler et al., 2003), and automaker (e.g., Koh, 2003). In Japan, vehicle type is usually classified using engine displacement, because tax levels vary with the engine size. Exploring how people choose passenger cars with different engine displacements is important for both marketers and public policy makers, especially considering that more and more people are showing concerns about environmental issues.
The sample used to estimate the household choice model is 211 households for the first car, and 99 for the second car. Note that the samples were selected by excluding missing data related to the variables in this study. We first define the choice alternatives below.

- Alternative 1 (Small-sized car): engine displacement equal or smaller than 660cc
- Alternative 2 (Middle-sized car): engine displacement larger than 660cc and equal or smaller than 1500cc
- Alternative 3 (Large-sized car): engine displacement larger than 1500cc

Next, to estimate the G_MNL model, we make several assumptions. All household members over 18 years old participate in the household decisions, because driving license can be acquired at the age of 18 in Japan. Due to the data availability, this case study only focuses on the interactions between household head (defined as the member registered at government) and spouse, their parents and their two children: “Child 1” and “Child 2”. The maximum number of household members in this study is five. For the alternatives that are not actually chosen by the households, their attributes (e.g., body price and riding capacity) are defined using the relevant average values in the sample. Some other imputation methods could be applied. However, discussion about such imputation is beyond the scope of this study. Members’ weight parameters might be different according to their characteristics. To incorporate such heterogeneity, weight parameter is defined using a logit-type model. Individual attributes are used as explanatory variables in the weight function. It is also expected that intra-household interaction parameters ($\lambda_k$) are different across households. Since the sign of this parameter can be non-negative or non-positive, we adopted a linear function to define this interaction parameter. We show the utility function, weight parameter function and intra-household interaction parameter function below.

1) Utility function of car alternative

$$v_{hij} = \sum_k \beta_k z_{hik} + \sum_s \gamma_s x_{hij}$$  \hspace{1cm} (6)

2) Weight parameter function

$$w_{hi} = \frac{\exp(\sum_k \beta'_k z'_{hik})}{\sum_i \exp(\sum_k \beta'_k z'_{hik})}$$  \hspace{1cm} (7)

3) Intra-household interaction parameter function

$$\lambda_k = \sum_k \mu_k A_k$$  \hspace{1cm} (8)

where,

- $z_{hik}, z'_{hik}$ are the $k$th attribute of member $i$ in household $h$,
- $\beta_k, \beta'_k$ are the parameter of $z_{hik}, z'_{hik}$,
- $x_{hij}$ is the $s$th attribute of alternative $j$ for member $i$ in household $h$,
- $\gamma_s$ is the parameter of $x_{hij}$,
- $A_k$ is the $k$th attribute of household $h$, and
- $\mu_k$ is the parameter of $A_k$.

For members’ attributes, based on the preliminary analysis results, the following independent variables are adopted: car body price and the categorized household income level per year (1: within 3 million Yens, 2: within 4.5 million Yens, 3: within 7.5 million Yens, 10.5 million
Yens and 5: 12.0 million Yens, seating capacity (legally permitted passengers within a car) and number of household members, driving license (Yes: 1, No: 0), status of employment (employed: 1, unemployed: 0), number of children under 18 years old, dummy variable of residential area (Hiroshima: 0, Higashi-Hiroshima: 1). Since price of purchased car is strongly influenced by household income, a composite variable is defined based on car price and household income level, i.e., “car price/household income”. Seating capacity might be influenced by the number of household members, we define another composite variable “seating capacity/number of household members” to avoid the multicollinearity. Moreover, vehicle type choice of the second car is also significantly affected by the first car’s characteristics or usage (Button et al., 1992; Romilly et al., 1998). We additionally introduced vehicle type dummy and annual travel distance of the first car into the model for the second car. The variables of weight parameter function include each member’s age, status of employment, driving license, gender (male:1, female:0), and the variables of interaction parameter function include “car price/household income”, and number of household members.

4.3 Model Performance

Based on the above-described independent variables, we estimated the G_MNL model using TSP software (Hall, 1998), which results are shown in Tables 1 (for the first car) and 2 (for...
### Table 2 Estimation results of household car size choice model for the second car

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Parameter</th>
<th>t-score</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Household member-specific attribute</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Car price / household income ((1,2,3))</td>
<td>-7.202</td>
<td>-1.708 *</td>
</tr>
<tr>
<td>Riding capacity / number of household members ((1,2,3))</td>
<td>-8.009</td>
<td>-2.199 **</td>
</tr>
<tr>
<td>Driving license (yes: 1, no: 0) ((2,3))</td>
<td>4.116</td>
<td>1.692 *</td>
</tr>
<tr>
<td>Status of employment (employed: 1, unemployed: 0) ((2,3))</td>
<td>-4.117</td>
<td>-1.692 *</td>
</tr>
<tr>
<td>Number of children under 18 years old ((2,3))</td>
<td>-0.329</td>
<td>-0.620</td>
</tr>
<tr>
<td>Residential area (Hiroshima: 0, Higashi-hiroshima:1) ((2,3))</td>
<td>-1.166</td>
<td>-1.260</td>
</tr>
<tr>
<td>If the first car is light car or not (yes:1, no:0) ((2,3))</td>
<td>0.461</td>
<td>0.359</td>
</tr>
<tr>
<td>Annual travel distance of the first car ((2,3))</td>
<td>-1.700</td>
<td>-1.438</td>
</tr>
<tr>
<td><strong>Alternative-specific constant term</strong> ((2))</td>
<td>6.312</td>
<td>2.197 **</td>
</tr>
<tr>
<td><strong>Alternative-specific constant term</strong> ((3))</td>
<td>4.994</td>
<td>1.436</td>
</tr>
<tr>
<td><strong>Weight parameter</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.024</td>
<td>1.237</td>
</tr>
<tr>
<td>Status of employment (employed: 1, unemployed: 0)</td>
<td>-0.459</td>
<td>-1.036</td>
</tr>
<tr>
<td>Driving license (yes: 1, no: 0)</td>
<td>0.100</td>
<td>0.326</td>
</tr>
<tr>
<td>Gender (male: 1, female: 0)</td>
<td>0.336</td>
<td>1.051</td>
</tr>
<tr>
<td>Main user dummy variable of the first car</td>
<td>1.299</td>
<td>2.121 **</td>
</tr>
<tr>
<td><strong>Intra-household interaction parameter</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Car price / household income</td>
<td>0.463</td>
<td>1.047</td>
</tr>
<tr>
<td>Number of household members</td>
<td>0.051</td>
<td>1.666 *</td>
</tr>
<tr>
<td>Constant term</td>
<td>-0.222</td>
<td>-0.975</td>
</tr>
</tbody>
</table>

Additional parameters:

- Initial logarithm likelihood: -108.763
- Converged logarithm likelihood: -59.597
- McFadden’s Rho-squared: 0.452
- Adjusted McFadden’s Rho-squared: 0.277
- Hit ratio: 78.79%
- Sample size (number of households): 99

* * Numbers in parentheses indicate alternatives associated with this variable: (1)~660cc, (2)661~2000cc, (3) 2001cc~.
* * Significant at the 10% level; **: Significant at the 5% level.

the second car). Focusing on the model accuracy, the adjusted McFadden’s Rho-squared are 0.387 for the first car and 0.227 for the second car, respectively. Most of the explanatory variables are statistically significant. This means that the developed group choice model (G_MNL) is good enough to represent household joint choice behavior about vehicle type.

To check if all the household members have the same extreme utilities, as mentioned in section 3, we calculated all the members’ utilities of alternatives. Due to the limitation of pages, we only showed the results of two and three household members for the first car in Figures 1 and 2. One can see that there does not exist any extreme values of utilities in this case study in the sense that all the members’ utilities range between -2.0 and +2.0 for all the alternatives. On average, all the members show the least preferences to “small-sized car”, the highest preferences to “middle-sized car”. Households with different members seem to show clearly different preferences on the “large-sized car”. In the households with three members,
most of the members relatively prefer the “large-sized car”, while in the two-member households, there are large variations among members’ preferences for the “large-sized car”. Households with different members also show different patterns of intra-household interactions. In the households with two members, range of intra-household interactions is largest with respect to “small-sized car”. In contrast, the three-member households show the largest intra-household interactions for the “middle-sized car”. Large range of intra-household interactions suggests large influence of intra-household interactions on joint decisions.

4.4 Household Decision-Making Mechanisms

Focusing on the parameters related to the size choice of the first car, the composite variable “car price/household income” has a negative value. This result seems logical, because people usually prefer low price and high income. Another composite variable “seating capacity/number of household members” also has a negative value. This result means that people prefer the cars with small seating capacity. Driving license and number of children less than 18 years old are also influential factors.

Concerning weight parameters, elderly people and non-license holders show larger influences
in joint decisions. This means that households select their cars by giving a high priority to the influences of elderly people and non-license holders in the households. Next, significant parameter of “car price/household income” for intra-household interaction shows that low-income households do not prefer mutual influence during joint decision-making process.

Concerning type choice of the second car, composite variables “car price/household income” and “seating capacity/number of household members” are all negative, which is consistent with the results for the first car. Focusing on the members’ weight parameters, only main user dummy is statistically significant. Among the variables to explain intra-household interaction, only number of household members is significant and its value is positive (0.051). This means that, if both husband and wife have positive (or negative) utilities with respect to some alternative at individual level before joint decision, then after joint decisions, total household utility will increase more in the households with more members than those with few members.

Table 3 shows the average weight parameters of each member in the joint decisions about the first and second cars. One can see that the relative influence of parent is the largest and children over 18 years old have the smallest relative influence in both models. In contrast, the
influence of children became larger in the joint decisions about the second car size. We also show the distributions of intra-household interaction parameters in Figure 3. It is observed

<table>
<thead>
<tr>
<th>Table 3 Average weights of household members</th>
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<tbody>
<tr>
<td>(a) The first car</td>
</tr>
<tr>
<td>Household members over 18</td>
</tr>
<tr>
<td>1 member</td>
</tr>
<tr>
<td>2 members</td>
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<tr>
<td>0.293</td>
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<tr>
<td>3 members</td>
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<tr>
<td>0.771</td>
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<tr>
<td>0.952</td>
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<tr>
<td>4 members</td>
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<tr>
<td>0.662</td>
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<tr>
<td>5 members</td>
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<tr>
<td>(b) The second car</td>
</tr>
<tr>
<td>Household members over 18</td>
</tr>
<tr>
<td>1 member</td>
</tr>
<tr>
<td>2 members</td>
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<tr>
<td>0.281</td>
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<tr>
<td>0.461</td>
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<tr>
<td>0.500</td>
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<td>4 members</td>
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<tr>
<td>0.215</td>
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<tr>
<td>0.350</td>
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<tr>
<td>5 members</td>
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</tbody>
</table>

Figure 3 Distributions of intra-household interaction parameters
that the distribution of the interaction parameter for the first car shows a larger variation and
the absolute values are also high. In contrast, the interaction parameters of the second car are
narrowly distributed around the average value and the absolute values are smaller than that for
the first car.

5. CONCLUSIONS

Especially in the multi-member household, its behavior is usually characterized by intra-
household interaction. Household members play different roles and show different influences
in joint decision-making process. Such group decision-making mechanisms have been widely
examined in the fields such as social psychology, marketing research and economics. In
transportation, even though group decision-making mechanisms can be observed at various
decision situations, the relevant studies are still limited. To represent the choice behavior of
multiple-member households, this paper developed an alternative household choice model by
integrating random utility maximization theory and group decision-making theory. A multi-
linear utility function is adopted to define the household utility, and it has some attractive
features. One of these features is that it can explicitly and flexibly incorporate each member’s
relative influence and intra-household interaction. It can also include several different types of
decision-making rules as special cases. In the developed household choice model (i.e.,
G_MNL model), heterogeneous group decision-making mechanisms are represented by
defining weight parameter of each member as a function of member’s attributes and intra-
household interaction parameter as a function of household’s attributes. Furthermore, the
households with different members can be incorporated in the same modeling framework. It
should be emphasized that theoretically, the model can be applied to any types of groups as
long as set of group members involved in joint decision can be clearly identified, but it is not
necessary to identify who is the decision maker among these involved members.

Even though the G_MNL model is derived by assuming that the error terms of utility
functions with respect to different alternatives follows an independent and identical
distribution, the case study, using a data about household car ownership behavior collected in
two Japanese cities in 2004, shows that the model accuracy is sufficiently high. The model
applicability to the analysis of household car ownership behavior is also confirmed. It is
found that in the case study, the household decision-making mechanisms are very
complicated, and the influence of intra-household interaction is stronger in the vehicle type
choice of the first car than that of the second car. In addition, in the choice of the second car,
the interaction has smaller influence on household joint decisions.

Future research should include a more theoretical examination about the derived group choice
model and incorporate a more general error structure in the group choice model. Comparing
different types of group models could contribute to the understanding of household travel
behavior and much more proper evaluation of transport policies. To explore how to
incorporate different types of group decision-making rules in the same modeling framework
seems also important. In addition, the estimated weights of household members in joint
decision also need to be justified from the viewpoint of social science.
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REFERENCES


