# REVIEW ON THE ARRANGEMENT OF ALTERNATIVES IN DISCRETE CHOICE MODELS AND COMPARATIVE STUDIES IN THE RECREATIONAL DESTINATION CHOICE BEHAVIOR

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**Abstract**: This study focuses on the applicability of discrete choice models, which relaxes the strong assumption on error term, to recreational destination choice behavior. Particularly, we verify to what extent discrete choice models should be enhanced in order to get the data with enough accuracy for grasping recreational traffic demand. First, we adjust the characteristics of individual's recreational destination choice behavior and identify the points to be considered for applying discrete choice models. Next, we review various discrete choice models that cope with it. Finally, we make comparative studies between some reviewed models by applying to actual recreational destination choice behavior data of one-day car trip. And the fact was confirmed that the relaxation of the strong assumption in multinomial logit models improves the precision of estimates.

## 1. INTRODUCTION

Discrete choice model, especially the one based on disaggregate logit model, is a powerful and efficient tool to describe various individual travel choice behaviors for the purpose of demand forecasting. While there exist many applications to various aspects in travel behavior, it is strongly emphasized that its application to recreational travel behavior is very efficient because it enables analysts to estimate the models with much smaller data than aggregate travel demand models (e.g. Morichi and Yai, 1984).

However, there are only a few applications of discrete choice models particularly in recreational destination choice behavior, such as the choice of large-sized recreational destination zone. It is mainly because there were few recreational travel surveys conducted over a very large area, such as home-based survey, and it was impossible to collect enough data to predict global recreational demand correctly. Also, it is partly because analysts cannot distinguish each traveler's subjective choice sets and that causes some debates on the application to the choice behavior with large choice sets, such as recreational destination choice, residential location choice, and shopping site choice, from the statistical and behavioral point of view. The first problem was resolved by the introduction of large-scaled survey such as Nationwide Recreational Travel Survey (NRTS) in Japan, and some researches have made an attempt to utilize this survey (e.g. Okamoto *et al.*, 1995). However, they do not deal with choice set formation process in detail. On the other hand, some researches developed the methodology of arranging alternatives and models to cope with the second problem. However, most of them use very detailed data of small-scaled survey and are not applicable to global traffic flow prediction.

It is true that the arrangement of choice set has been of theoretical and practical concern in discrete choice modeling, and if possible, it is desirable to apply it to destination choice models so as to get the prediction results with high accuracy. However, at this stage, it is difficult to develop a methodology of recreational destination choice models with both choice set consideration process and applicability to the choice behavior of large-sized destination zone because of the lack of large-scaled and more detailed survey data. Hence, it is now important to pay attention to another problem of previous destination choice models, namely the 'independence of irreverent from alternatives' (IIA) property of multinomial logit model. We think that it is more important problem than the choice set consideration process when we refer to the applicability of discrete choice models to the recreational destination choice behavior.

In this paper, we examine the applicability of improved discrete choice models to recreational destination choice behavior. First, in Chapter 2, we summarize the characteristics of recreational travel behavior and identify the points to be considered for applying discrete choice model. Secondly, we review various procedures and improved discrete choice models that relax the strong assumption of standard multinomial logit model in Chapter 3. Finally, in Chapter 4, we focus only on the problem caused by the strict assumption on error terms of logit model, and make comparative studies of some improved discrete choice models, namely Heteroscedastic extreme value model, Mixed-Logit model, by applying them to revealed preference data on one-day recreational car trip.

## 2. RECREATIONAL DESTINATION CHOICE BEHAVIOR: A BACKGROUND

### 2.1 Characteristics of Recreational Travel Behavior

International Association of Traffic and Safety Sciences (1998) shows in full detail the characteristics of recreational travel behavior. Salient features of recreational travel behavior includes:

A) Non-daily and rare phenomenon
B) It is difficult to practice the large-scale home-based survey efficiently.
C) Travelers can decide freely various aspects of behavior such as trip generation, the means of moving, destination, the pattern of excursion, and duration time.
D) The excursion trip holds the majority in recreational trips.
E) The size of recreational site which individual recognizes as one destination depends on not only the type of activity but also the distance between the site and the residential location.*
F) The attractiveness of recreational sites and transportation facilities has the most influence on recreational travel behavior but is difficult to quantify objectively. One alternative way is to use the number of persons who visited the recreational site during certain period. But, from the viewpoint of demand forecasting, this is not rational at all.

In this way, recreational travel behavior has many characteristics different from regular travel behavior such as the mode choice for commuting. And it is difficult to use the aggregate models which require many sampled data in estimation for the purpose of demand forecasting. It is mainly because of the characteristics A) and B). Hence, disaggregate discrete choice models, particularly the one based on logit model, have been applied to the excursion behavior, mode choice and route choice of recreational trip.

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* For example, in the case of Japan, the travelers from other countries regard Japan as one recreational spot, and the residents in Tokyo regard Hokkaido as one recreational spot, whereas the residents in Hokkaido usually do not recognize the whole Hokkaido as one site. In this way, the size of area which travelers recognize as one destination depends on such difference in spatial recognition of travelers.

## 2.2 A Point to be Considered for Applying Discrete Choice Model

When we try to apply logit models to recreational destination choice behavior, new problems will generally arise. It may be because the destination choice behavior of recreational sites may mostly depend on traveler's discretion in recreational travel behavior. We focus on three major problems here.

(1) Specification of Alternatives

As pointed out in 2.1 F), the size of recreational sites which travelers recognize as one alternative depends on the distance between the place of traveler's residence and recreational sites. Moreover, that may be related to the duration of visiting. Longer distance and duration seem to be related to larger recreational site in traveler's perception. However, most of existing studies arbitrarily provide the units of alternatives (destinations) so that data collection and model estimation can become easier. Most of them have neglected how travelers recognize destinations.

(2) Selection of Alternatives (Choice Set Formation)

Analysts must provide ad-hoc and arbitrary choice set for discrete choice models, unless they can investigate the availability of each alternative and the subjective choice sets are specified. The same thing is true for the recreational destination choice behavior analysis. However, most of such behaviors are very tangled and hard to decide the subjective choice set of each traveler, compared with the case of commuting mode choice. Consequently, the choice model of such behaviors seems to have theoretically very large choice sets, even if any constraints are imposed. This drives us to the question that the converged and stable parameters cannot be obtained in estimation. Moreover, from the viewpoint of behavioral decision theory, it is open to the criticism that the assumption that individual judges so many alternatives together goes against the intuition. According to psychological survey, it is said that human can judge only four or five alternatives together (Tversky, 1972, Mcfadden, 1999).

(3) Similarity between Alternatives

It is likely that analysts have to deal with more similar alternatives, as the number of alternative increases. The logit model is most commonly applied because of its high operationality and efficiency in estimation. However, it has been pointed out that the IIA property of multinomial logit model causes biased choice probabilities in the existence of similar alternatives (Ben-Akiva and Lerman, 1985, and many other studies).

# 3 PARADIGM OF ALTERNATIVE ARRANGEMENT

The problems mentioned in Chapter 2 are common to choice behavior with many alternatives, such as recreational destination, brand and shopping-store, and residential location choice. Fortunately, in the field of econometrics, marketing science and so on, there have been various types of discrete choice models proposed recently, which relax the strong assumption of logit model, and agree with our intuition on decision-making process. It is desirable to describe these issues before moving on to the main objective of our study. We review these related works in this chapter.

## 3.1 Specification of Alternatives

Most existing studies specify each alternative based on geographical characteristics and other relevant factors. For example, Okamoto *et al.* (1995) defines the size of each alternative (recreational destination) so that travelers can drive on a tour through the whole area in a day. Morikawa (1995) provides each destination to be the same area as described in the excursion tickets of train companies or so that the boundary of each destination can agree with the boundary among prefectures. In Train (1998), each fishing site, which contain one or more of the stream segments used in official river information system, is defined as one alternative.

In this way, most studies define the size of each destination on the basis of the convenience for collecting data and the objectives of their studies. However, this definition is arbitrary and the wrong size definition of each alternative sometimes leads to biased results. Parsons and Needelman (1992) points out that defining a group of recreation sites as one alternative has a large influence on parameter and welfare estimates. At this stage, our information on the size of each alternative which travelers regard as single alternative is limited, but in the future, we hope that the methodology of defining rationally the size of each alternative will be developed.

### 3.2 Selection of Alternatives (Choice Set Formation)

Various approaches have been suggested in the context of discrete choice models to tackle the problem of the choice set formation. In most applications of destination choice modeling, analysts assign choice set of each sample on the basis of a few deterministic criteria that reflect available information and *a priori* their beliefs about human behavior (Thill, 1992). The major patterns of their choice set definitions are as follows.

<u>(1) Universal choice set of all chosen alternatives for all individuals</u>

Thill and Horowitz (1991) and many other researches assume that all individuals share the same choice set consisting of all destinations in the geographic area of interest. In many transportation studies, the universal choice set is assumed to consist of all destinations actually chosen by individuals living in the same geographic area. Although many alternatives may be included in the choice set in this procedure, this has been a quite popular because it provides a suitable means for coping with large-size choice sets in spatial alternatives. The most typical way is an "elemental alternatives" (Mcfadden, 1978), which efficiently extracts less alternatives from the choice set. It is applied to not only residential location choice but to the aggregation of recreational sites (Parsons and Needelman, 1992, Parsons and Kealy, 1992).

<u>(2) Pre-specification of the choice set with less alternatives by analyst</u>

Some analysts prespecify the destinations to be included in the choice set. For example, Gautschi (1981) restricts the set of feasible destinations for major non-grocery shopping in suburban of San-Francisco to be four major retail centers only, discarding smaller centers from potential destinations. On the other hand, Parsons and Kealy (1992) employs the actually chosen destination and randomly drawn four destinations to individual's choice set of recreational sites.

<u>(3) Survey questions to identify individual's choice set</u>

The most direct way to determine choice sets is to obtain the information directly from decision makers. Peters *et al.* (1995) uses the survey data, which asked individuals to indicate the destinations they considered. Peters *et al.* forms each traveler's choice set on the basis of it. A method of preference ranking of destinations in the universal choice set is used in Arnold *et al.* (1983), and the individual's choice set contains the highly ranked alternatives only. However, Lerman (1985) points out that people cannot report their choice set correctly and only a small part of the true set is provided.

These methods are convenient for modeling choice behavior because it is generally difficult to get information on individual's real choice set. The question of how to define choice sets, however, provokes a great deal of controversy. For example, Manski (1977) discusses that correct information about choice sets induces correct estimation of parameters in discrete choice models. Williams and Ortuzar (1982) suggests that the consistency of the parameter estimates depends on whether the choice set defined by analysts includes alternatives actually never evaluated by decision makers or not. On the other hand, in the field of marketing science, it is empirically found that consumers have been observed to choose from subsets of the available brands (Gensch, 1987, Silk and Urban, 1978). They are called "Evoked Set" or "Consideration Set" and very important from the viewpoint of marketing, because leading brands may derive large share advantages by entering the consideration sets of more consumers than do their principal competitors (Roberts and Lattin, 1991, Hauser and Wernerfelt, 1990). Such controversy induces various behaviorally based choices set definitions as described below.

(4) Temporal and spatial constraints on choice sets

The time and distance threshold is settled in this approach. In the case of one-day car trip destination choice behavior, recreational sites which are too far to return home in a day are excluded from choice sets. Parsons and Hauber (1998) shows in full detail about the specification of the spatial boundary of recreational trip, based primarily on the researcher's judgment. This temporal and spatial constrained-oriented approach to destination choice was originally discussed in Hägerstand (1970) and later extended to "human activity pattern analysis" later (Kitamura and Kermanshah, 1984, and many other studies).

(5) Probabilistic choice set (PCS) formation model

Most of the discrete choice literature assume that choice sets or consideration sets can be predicted deterministically. However, unless the analysts can have enough information on individual subjective choice sets, they should be specified stochastically. That means two-stage choice should be assumed: (i) simplified rules screen the many alternatives down to a manageable number of alternatives, and (ii) through an elaborate process the most preferable alternative is found. The prototype model of this approach is the Latent Class Choice Models (LCCM) and can be formalized by the following equation (Ben-Akiva *et al.*, 1997):

$$P_n(i) = \sum_{s=1}^{S} P_n(i \mid s) \cdot Q_n(s)$$

where $P_n(i)$ is the probability of individual $n$ choosing alternative $i$; $Q_n(s)$ is the probability of individual $n$ belonging to latent class $s$; $P_n(i|s)$ is the probability of individual $n$ choosing alternative $i$ given $n$ belonging to class $s$; and $S$ is the number of latent classes. If the latent classes are specified more restrictively, LCCM is identical to various types of PCS model, such as Manski's random choice formation model (Manski, 1977), Dogit model (Gaudry and Daganais, 1979), Parameterized Logit Capacity (PLC) model (Swait and Ben-Akiva, 1987). Morikawa (1995) applies PCS model to recreational destination choice behavior by providing random constraint model with non-compensatory nature to the choice set formation process. And many applications of the model can be seen in each subject such as recreational destination choice (Haab and Hicks, 1997), travel mode choice (Ben-Akiva and Boccara, 1995), and brand choice (Gensch, 1987). Thill (1991) suggests that the framework of integrated PCS model has theoretically great potential for use in the context of destination analysis.

### 3.3 Similarity between Alternatives

The wrong prediction under the existence of similar alternatives is caused by the restrictive assumption of the standard multinomial logit model that the error terms of the utility functions are independent and identically distributed with the Type 1 extreme value distribution (*i.i.d.* ~*Gumbel*). Although some models to cope with it were proposed, there had been a trade-off between model and behavioral complexity, and model simplicity and ease of estimation. However, this dilemma is recently being resolved by the development of simulation-based method. Some enhanced discrete choice models have been applicable with the use of simulation methods in estimation. Most of them can overcome the IIA property of the standard multinomial logit model.

(1) Nested-Logit (NL) model

NL model is superior to other models described below in ease of estimation and does not keep IIA property between alternatives in different subsets. However, in the recreational destination choice, it seems that there exist too many alternatives to define the nest structures and the subsets of alternatives properly. NL model is a powerful and efficient tool to represent the similarity between alternatives, but what nest structure should be adopted in recreational destination choice is a question which we want to keep beyond the scope of this present discussion.

(2) Heteroscedastic Extreme Value (HEV) model

HEV model is employed to travel mode choice by Bhat (1995) and to the choice of canned tuna of consumers by Allenby and Ginter (1995). Although HEV model cannot express the similarity between alternatives, it relaxes the IIA property by giving heterogeneity to error terms. In addition, this model is superior to others in ease of estimation.

(3) Mixed-Logit (ML) Model

ML is the logit model with random-coefficients, and does not exhibit IIA property. The variation in coefficients can provide taste differences over people and correlation over alternatives (Mcfadden and Train, 1997). For example, Train (1998) applies it to the fishing-site choice behavior of anglers.

(4) Multinomial Probit (MNP) Model

Many discrete choice models used in the literature can be seen as a special case of MNP model. Although the nuisance parameters as well as computation are the main problems in MNP use, structuring covariance matrix of the error terms enables researchers to reduce the number of parameters and specify the interdependencies among alternatives. Recently, applications can be seen in many cases such as the choice of the first practice location by general practitioners (Bolduc *et al*., 1997), and the choice of railway-route by commuters (Yai *et al*., 1997).

### 3.4 Discussions

In this way, many procedures have been applied to cope with each problem. We think 3.1 is the most significant and difficult problem for choice behavior. However, there are no objective procedures for handling this problem at this stage. The same thing is true of the problem 3.2, except for PCS model. All we have to do now is try to overcome the problems 3.3. In next chapter, comparative studies of the models described in 3.3 will be done by using actual data, particularly focusing on the improvement of prediction.

# 4. MODEL SPECIFICATION AND COMPARATIVE STUDIES

In this chapter, we make comparative study of some revised discrete choice model for the purpose of verifying to what extent the accuracy of model will be improved by relaxing IIA property of the standard multinomial logit model. The data, choice set definition and the identification of non-stochastic portion of utility function used in this study are all in conformity to Okamoto *et al.* (1995). We demonstrate the difference in recognition of each destination and the similarity between destinations by applying HEV model and ML model.

## 4.1 Description of the Case

We use the one-day car trip data sampled from The Nationwide Recreation Travel Survey (NRTS) conducted by Ministry of Construction in Japan in 1992. (Refer to Okamoto *et al.*, 1995, for the detail of NRTS). Okamoto *et al.* establishes the maximum size of choice set so that the actually chosen destinations within the cumulative 90% could be included. The variables that enter the non-stochastic portion of utility function are defined in Table 1. All of them are in accordance with Okamoto *et al.* They have already examined the validity of these variables by testing with a standard multinomial logit model. We decide the choice set for each sample according to the activity each traveler involved in. In other words, each destination is included in choice set if it has the recreational resources corresponding to the activity of each sample.

We make comparative studies according to these arrangements. As space is limited, we have concentrated on the two cases: one is the estimation with the sample data who live in Chugoku-Area (maximum 13 destinations, see Figure 1 and Table 2), and another is with the sample from Kanto-Area (maximum 20 destinations, see Figure 2 and Table 3).

Table 1. Variable Definitions of Utility Function

| Variable Names: | Definitions: |
|---|---|
| Level of Service | |
| (1) Travel Time [minute] | The shortest route time to destination calculated in road network data. |
| (2) Travel Cost / ln(Income) [Yen / ln(Yen)] | The total toll of expressway of the shortest route, divided by the natural log of household income in ten thousands Yen. |
| Attractiveness Index | |
| (3) Sightseeing<br>(4) Seaside & Marine Activity<br>(5) Spa Visitation<br>(6) Field Activity<br>Unit: [ln(# of spots)] | All travelers participate in only one of these four activities. The variable whose activity each traveler participate in is equal to the natural log of attraction resources.<br>The number of attraction resources of each destination were defined as the total number of recreational spots recognized by the Japan Travel Bureau (JTB).<br>Other variables are all equal to zero. |

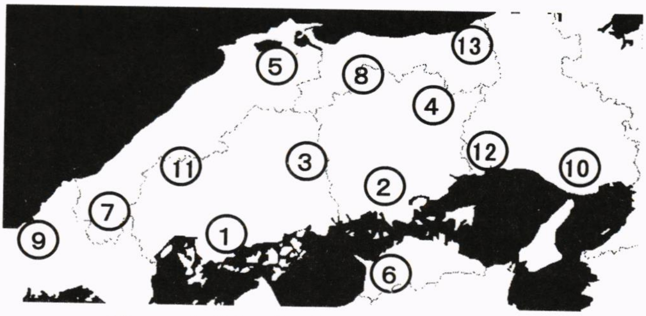


Figure 1. Distribution of Destination in Chugoku Area

Table 2. Recreation Sites of Chugoku Area

| No | Major Recreation Sites |
|---|---|
| ① | Hiroshima & Onomichi |
| ② | Okayama & Kurashiki |
| ③ | Taishaku & Dogo |
| ④ | Tsuyama |
| ⑤ | Matsue & Izumo |
| ⑥ | Sanuki |
| ⑦ | Tsuwano |
| ⑧ | Oyama |
| ⑨ | Hagi |
| ⑩ | Kobe |
| ⑪ | West-Chugoku Region |
| ⑫ | Himeji |
| ⑬ | Tottori |

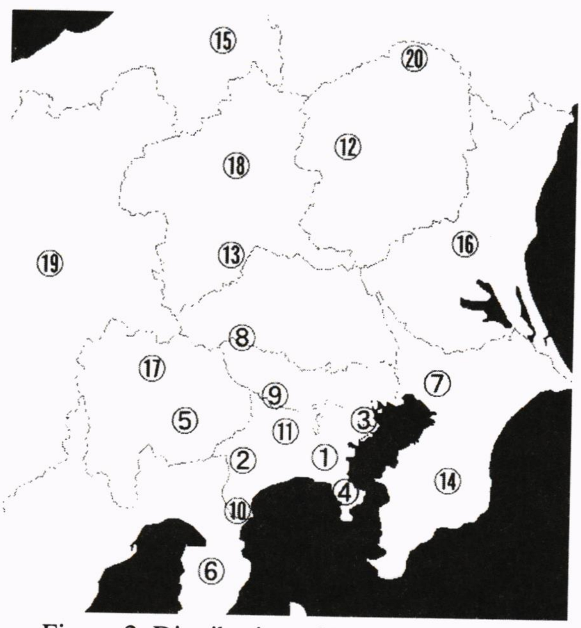


Figure 2. Distribution of Destination in Kanto Area

Table 3. Recreation Sites of Kanto Area

| No | Major Recreation Sites |
|---|---|
| ① | Kamakura & Shonan |
| ② | Hakone |
| ③ | Yokohama City |
| ④ | Miura-Peninsula |
| ⑤ | Mt. Fuji |
| ⑥ | Izu-Peninsula |
| ⑦ | Tokyo Disney Land |
| ⑧ | Okutama |
| ⑨ | Lake Sagamiko |
| ⑩ | Atami & Ito |
| ⑪ | Tanzawa |
| ⑫ | Nikko |
| ⑬ | Chichibu |
| ⑭ | Boso-Peninsula |
| ⑮ | Yuzawa-Ski-Area |
| ⑯ | Tsukuba & Mito |
| ⑰ | Kofu & Japan South Alps |
| ⑱ | Akagi & Haruna |
| ⑲ | Lake Suwa |
| ⑳ | Nasu Highlands |

### 4.2 Model Specification

(1) Heteroscedastic Extreme Value (HEV) Model

HEV model posits that the stochastic portion of utility function ( $\varepsilon_{n,i}$) is independent, but not identically distributed. The CDF for each $\varepsilon_{n,i}$ is the type 1 extreme value distribution with precision parameter $\theta_i$. Hence, the cumulative distribution function of the random error term and choice probability of person $n$ for $i$th alternative are:

$$F(\theta_i \varepsilon_{n,i}) = \exp(-\exp(-\theta_i \varepsilon_{n,i})) \tag{4-1}$$

$$P_n(i) = \int_{-\infty}^{\infty} \prod_{k \neq i} F\left[\theta_k \left(V_{n,i} - V_{n,k} + \varepsilon_{n,i}\right)\right]\theta_i f(\theta_i \varepsilon_{n,i}) d\,\varepsilon_{n,i} \tag{4-2}$$

where $f(\theta_i \varepsilon_{n,i})$ is the CDF and $V_{n,i}$ is the non-stochastic portion of utility function. The scale parameter of error term represents the level of uncertainty, and so this model relaxes the IIA property partially. We can express the difference in recognition of each destination with the difference in each scale parameter. However, we have to estimate not only parameters of $V_{n,i}$ but also scale parameters $\theta_i$ of each error term. Then, Gauss-Laguerre quadrature is used for approximation likelihood function because equation (4-2) is not closed form for integral (Judd, 1998).

(2) Mixed-Logit (ML) Model

ML model is defined as random coefficients logit model with linear utility function. To take the similarity of distance between each alternative into consideration, we specify the utility function below.

$$U_{n,i} = \boldsymbol{\beta}^{t} \cdot \boldsymbol{X}_{n,i} + \boldsymbol{\mu}^{t} \cdot \boldsymbol{Z}_i + \varepsilon_{n,i}, \qquad \varepsilon_{n,i} \sim i.i.d.\ Gumbel \tag{4-3}$$

where $U_{n,i}$ is the utility of $i$th destination, $\boldsymbol{\beta}$ is a $1\times 6$ vector of fixed coefficients, $\boldsymbol{X}_{n,i}$ is a $6\times 1$ vector of observed variables (see Table 1.), $\boldsymbol{\mu}$ is a $1\times N(N\text{-}1)/2$ random vector whose all components have normal distribution with zero mean and same variance $\omega^2$, and $\boldsymbol{Z}_i$ is a $N(N\text{-}1)/2\times 1$ vector of observed data related to $i$th destination. The similar model structure can be seen in Brownstone and Train (1999) and Shimizu *et al.* (1998). The terms in $\boldsymbol{\mu}^{t} \cdot \boldsymbol{Z}_i$ are interpreted as error components that induce similarity and correlation over alternatives. In order for the distance between alternatives to be the index of similarity, we specify $\boldsymbol{Z}_i$ below:

$$\boldsymbol{Z}_i = (d_{12}^{-1}, d_{13}^{-1}, \ldots, d_{1N}^{-1}, d_{23}^{-1}, \ldots, d_{2N}^{-1}, \ldots, d_{N\text{-}1,N}^{-1})^{t} \tag{4-4}$$

where $d_{ij}$ is the distance between centroids of $i$th destination and $j$th destination and calculated in road network data, and $N$ is the total number of destinations included in choice set. Hence, the covariance of utility between $i$th destination and $j$th destination is as follows.

$$\mathrm{E}([\boldsymbol{\mu}^{t} \cdot \boldsymbol{Z}_i + \varepsilon_{n,i}][\boldsymbol{\mu}^{t} \cdot \boldsymbol{Z}_j + \varepsilon_{n,j}]) = d_{ij}^{-2} \cdot \omega^2 \tag{4-5}$$

By this definition of $\boldsymbol{Z}_i$, we can express the distance similarity between destinations easily. In this model, we have to estimate seven parameters –six for fixed coefficients: $\boldsymbol{\beta}$ and one for standard deviation of $\boldsymbol{\mu}:\omega$. Finally, the choice probability of $i$th destination is as follows:

$$P_n(i) = \int \frac{\exp\left(\beta^{t} \cdot \boldsymbol{X}_{n,i} + \mu^{t} \cdot \boldsymbol{Z}_i\right)}{\sum_j \exp\left(\beta^{t} \cdot \boldsymbol{X}_{n,j} + \mu^{t} \cdot \boldsymbol{Z}_j\right)} \cdot f(\mu | \omega) d\mu \tag{4-6}$$

where $f(\boldsymbol{\mu}|\omega)$ is the multivariate normal distribution function. This is also not closed form for integral. So we use simulated log-likelihood function for estimating parameters. (Refer to Hajivassiliou and Ruud, 1994, for simulation methods.)

### 4.3 Empirical Results and Discussions

We estimated the parameters of the models described in 4.2. First, we made comparison among the standard multinomial logit models and these models by applying them to the data samples of Chugoku-Area with 13 destinations. Next, we focus particularly on the difference in recognition of each destination by applying HEV model to the data samples of Kanto-Area with 20 destinations. Table 4 shows the estimation results of former case, and Table 5 and Figure 3 show the latter case.

(1) Comparison among Models (Table. 4)

Table 4 presents the application of enhanced discrete choice models to the case of Chugoku-Area samples. Each coefficient comes out with the expected sign and is significantly different from zero at the 5% level, except for the standard deviation of $\mu$. Although the log likelihood function values at convergence are relatively close to each other, the values of HEV and ML are better than that of Standard Logit. This result shows that the prediction with high accuracy can be accomplished by relaxing the assumption of the error terms. Particularly, it follows that ML is the best one judging from the value of AIC.

There are remarkable differences in the parameters of six exploratory variables in the standard logit, HEV, and ML. Although the parameters of Travel Time and Travel Cost are indispensable for welfare estimates, these values are fairly different in these three models. It should be noted that the difference in the assumption of the error term might bring about enormous difference in demand forecasting and welfare estimatess.

A comparison of the standard logit and HEV by using the six exploratory variables indicates that the figure of Travel Time and Travel Cost / ln(Income) are not close to each other, compared to those in the standard logit and ML. The main reason may be their dependence on the difference of variance of error term for each destination in HEV model. The variance of the $i$th destination's error term is equal to $\pi^2 / 6\theta_i^2$. Although it is not shown in Table 4, the values range between 0.46 and 3.65 in destinations. That means the heteroscedasity for the variance of each destination is the superior factor to the other parameter in the formulation of utility function. So, another factor should be considered as exploratory variable in future studies.

A comparison of the standard logit and ML suggests that the estimates can be fairly improved by the introduction of distance similarity of each destination to the model. In addition, the $t$-static value of the standard deviation of $\mu$ is not so wrong and is significantly different from zero at the 0.1 level. At this point, it seems meaningful to express the similarity in the distance as the form of equation (4-5).

(2) Difference in the Variances of Each Destination (Table. 5 and Figure. 3)

Next, we examine the difference in recognition for each destination by applying HEV model to Kanto-Area data. We can see in Table 5 that the sings of all parameters are consistent with *a priori* expectations. Most of them are significantly different from zero at 99% confidence, including all scale parameters of error terms.

Although Table 5 does not exhibit the scale parameters of error terms, instead, the standard deviations of each error distribution are shown in Figure 3. The standard deviation of $i$th destination is expressed by the following equation.

$$\sigma_i = \frac{\pi}{\sqrt{6}\theta_i} \qquad (4\text{-}7)$$

The values of Yuzawa-Ski-Area and Tokyo Disney Land are smaller than others. We attempt to interpret from the behavioral point of view that the destination with less activity menu has smaller value of standard deviation and travelers recognize such destinations more clearly than others. Of course, the error term represents all factors which are not included in the exploratory variables and that assumption is statistically not reliable.

However, through this discussion, we could reconfirmed that the assumption of *i.i.d.* ~ *Gumbel* for error terms in disaggregate logit model is very restrictive.

Table 4. Estimation Results for the Case of Chugoku-Area

| Variable (*t*-static) | Standard Logit | HEV[1)] | ML[2)] |
|---|---|---|---|
| Travel Time | $-9.54\times10^{-3}$ (-20.12) | $-11.41\times10^{-3}$ (-14.47) | $-9.61\times10^{-3}$ (-17.92) |
| Travel Cost / ln(Income) | $-5.55\times10^{-4}$ (-3.81) | $-7.53\times10^{-4}$ (-3.25) | $-6.89\times10^{-4}$ (-3.99) |
| Sightseeing | $7.76\times10^{-1}$ (10.42) | $9.65\times10^{-1}$ (4.93) | $3.64\times10^{-1}$ (4.29) |
| Seaside & Marine Activity | $14.69\times10^{-1}$ (7.09) | $12.94\times10^{-1}$ (6.52) | $12.93\times10^{-1}$ (7.26) |
| Spa Visitation | $5.06\times10^{-1}$ (2.65) | $8.26\times10^{-1}$ (3.08) | $3.98\times10^{-1}$ (1.71) |
| Field Activity | $8.59\times10^{-1}$ (6.85) | $11.7\times10^{-1}$ (5.75) | $7.69\times10^{-1}$ (5.93) |
| Scale Parameters for 1st Destination $\theta_1$ | — — | 0.560 (11.98) | — — |
| 2nd Destination $\theta_2$ | — — | 1.061 (9.18) | — — |
| ⋮ | ⋮ | ⋮ | ⋮ |
| 13th Destination $\theta_{13}$ | — — | 1.00 (Fixed)[3)] | — — |
| Standard Deviation of $\mu$ | — — | — — | $10.8\times10^{-4}$ (1.12) |

| Statistics | Standard Logit | HEV | ML |
|---|---|---|---|
| Log Likelihood at Convergence | -2296.6 | -2173.3 | -2060.5 |
| Adjusted Likelihood Ratio Index | 0.227 | 0.268 | 0.306 |
| AIC | 4605.2 | 4382.6 | 4135.0 |
| Sample Size | 1158 | | |
| Number of Destinations | 13 | | |
| Log likelihood value at zero | -2970.2 | | |

1) The number of support points for quadrature formula is set to 20.
2) The number of random draws used in simulating the probabilities is set to 50.
3) One of the scale parameters for HEV is to be fixed to 1.00 for identification. Hence, twelve scale parameters should be estimated in this case. (3rd~12th parameters are not shown in this table for convenience.)

Table 5. Estimation Results of HEV model for the Case of Kanto-Area

| Variable ($t$-static) | HEV |
|---|---|
| Travel Time | $-4.81 \times 10^{-3}$ (-7.96) |
| Travel Cost / ln(Income) | $-3.17 \times 10^{-4}$ (-2.55) |
| Sightseeing | $8.98 \times 10^{-1}$ (19.98) |
| Seaside & Marine Activity | $7.58 \times 10^{-1}$ (18.13) |
| Spa Visitation | $7.30 \times 10^{-1}$ (10.47) |
| Field Activity | $10.10 \times 10^{-1}$ (21.65) |
| Log Likelihood at Convergence | -5474.25 |
| Adjusted Likelihood Ratio Index | 0.258 |
| Sample Size | 2464 |
| Number of Destinations | 20 |
| Log likelihood value at zero | -7381.48 |

Note) The number of support points for quadrature formula is set to 20.
Nineteen scale parameters should be estimated in this case.
These are not shown in the table. Instead, the standard deviation defined by e.q.(4-7) are displayed in Figure 3.

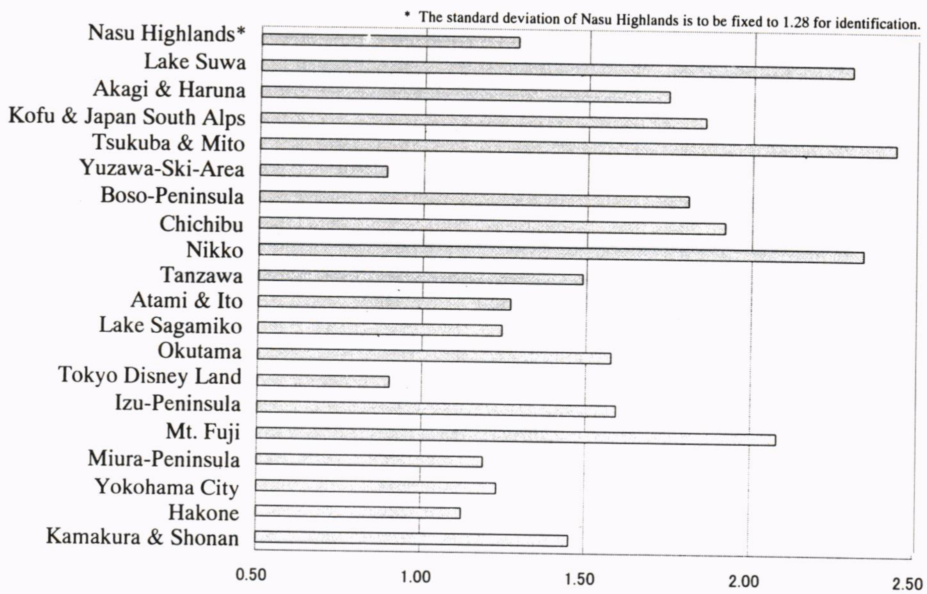


Figure 3. Standard Deviation of Error Terms for Each Destination (Kanto Area)

## 5. CONCLUSION

The outcomes brought out by this study described above are as follows:

First, we summarized the problems in the case of applying discrete choice models to the behavior which has spatial and large choice sets, such as recreational destination choice behavior, and reviewed the approaches for tackling these problems.
Secondly, we focused on the difference in recognition of each destination and the distance similarity between alternatives, and made comparative studies of proposed approaches by using revealed preference data on one-day recreational car trip. In this comparative study, we used the closeness of each destination as a simple index of similarity. And we investigated the difference in the perception for destinations judging from the difference in the variances of each destination's error term

Finally, we demonstrated that the heteroscedasity of error terms and the introduction of similarity index has brought some improvement0. in estimates. For the further studies, we are trying to include other factors in the similarity index. For example, the difference in recreational resources will have more effects on the similarity between recreational sites.

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