A DISCRETE CHOICE MODEL WITH TASTE HETEROGENEITY USING SP, RP AND ATTRIBUTE IMPORTANCE RATINGS

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Abstract

The purpose of this study is to improve the discrete choice model incorporating the individual taste heterogeneity using RP, SP and attitudinal data. We tested three methods, a priori segmentation, latent class model and mass point model, on the mode choice context. From the case study of the models, we concluded that the latent class model is more efficient for considering individual taste heterogeneity and that SP data with multiple responses help identify the segments clearly.

INTRODUCTION

Discrete choice model is applied to various areas of transportation planning, because it has some well-known advantages. Recent study of travel behavior with discrete choice model have approached to individual decision making process closely. The consideration of taste heterogeneity of individual is one of main study area for the precious forecasting of individual travel behavior. There are mainly three reasons why considering taste heterogeneity have active area of study. One is the requirement from the transportation planning. There are some developments in transportation planning alternatives like as information services of the route time. Analyzing the effect of those transportation measures requires more precious modeling scheme of travel behavior not only the taste heterogeneity. The other is the developments of new travel behavior modeling and data collection methods, for example, stated preference data or panel data. We thought that these data are superior to the existing data for considering the taste heterogeneity because these data could easily collect multiple data from one person. Another is development of computational data processing capacity. This development has relations to the second reason of data collection. The complicated choice model, like as RP and SP combined model, could be estimated in reasonable time on the personal computers using numerical analysis. These three reasons promote the taste heterogeneity consideration in the discrete choice model. The typical existing method to incorporate the taste heterogeneity into the discrete choice model is a priori segmentation which is characterized by some socioeconomic variables. This modeling scheme assumes several homogenous sub-groups in the population, which is identified some exogenous characters. Introducing the individual these variables into the utility function also varies the alternative specific constants according to those variables, which imply the expectation of unobserved terms. Since the basic assumption of discrete choice model treat the taste heterogeneity as the component of the error term (Ben-Akiva and Lerman (1984)), the alternative specific constants could be regarded as the expectation of unobserved component. As a result, this socioeconomic variable introducing method structurize a portion of the unobserved utility component. This is one of a special case of a priori segmentation especially for the alternative specific constants. It has been discussed that the a priori segmentation methods are not always effective on any situation. Especially on the situation as route choice, leisure trip and so on, the taste variation is more complicated and subjective factor affect that more than exogenous factors. In this study, we applied some modeling scheme that consider the subjective taste heterogeneity explicitly using SP, RP and subjective importance ratings data.

TASTE HETEROGENEITY

As stated in chapter 1, the analyzing situations on which taste heterogeneity takes an important role could be listed below.

1) A assignment analysis of the policy which have effects on the decision maker's lifestyle
   e.g. The policy analysis of the TDM measures
2) Travel demand analysis of high degree of freedom
   e.g. Destination and route choice of sightseeing trip
3) The choice modeling for the subgroups in which choice set is varied
   e.g. Mode choice analysis of aged or disabled person
4) Choice modeling which includes the uncertainty
   e.g. the effect analysis of route time information service

On the other hand, there are many situation on which the taste heterogeneity is not so important (Hensher and Wrigley (1986)).

1) The demand forecasting for long term planning
2) The forecasting of single representative index of transportation
   e.g. Forecasting the household car ownership

On these situations, the difference of forecasting by the individual heterogeneity may be less important than that of social circumstance or socioeconomic situation. Incorporating the taste heterogeneity of individuals into those analyses might make the precision of forecasting worse. The heterogeneity of individual has the deep relation to the omitted variables in the utility function, because the random component involves both effects of individual taste heterogeneity and omitted variables. There are two types in the omitted variables. One is observable variables and another is unobservable or hard to observe one. The observable omitted variable implies that the analyst has made misspecifications in the utility function. Therefore, the bias would be canceled by introducing the factor into the utility function after observing it or making a priori segmentation by the observable factor. This type of omitted variable problem is not consequently so serious. The effect of unobservable omitted variable for the utility function is absorbed in the error component as heterogeneity. To measure the effect these components in random term separately is difficult. If the effect of unobservable omitted variables could be neglected, the I.I.D. property of error term in the utility function of logit model is approved. As a result, estimates in the utility function would be biased. However, another type of omitted variable problem is not easy to solve. Taste, attitude and subjective perception are typical unobserved or hard to observe variable. Besides, the observable factors depending on the time sometime have the same effects as the unobserved factors. Introducing the instrumental variable into the utility function is one of the major existing method to solve this problem. But this method is hard to approve the representativity of the omitted variable. The unobservable factors that affect to the travel behavior could be classified mainly four categories.

1)	experience:	the personal background
2)	decision rules:	non compensatory decision rule, the heterogeneity of choice set
3)	subjective factors:	such as taste, attitude and perception
4)	perception structure:	perceptional heterogeneity for the same attributes

The situations affected by these four factors are necessary to consider the effect of the individual taste heterogeneity. For example, the route choice behavior when route time information for several route are provided would be affected by the individual confidence for the information. The difference of the confidence may be produced by their experiences, decision rule, subjective factors and perception structure. More over, the destination choice of sightseeing is also affected by the individual experience.

THE METHODS TO INCORPORATE THE INDIVIDUAL HETEROGENEITY INTO THE DISCRETE CHOICE MODEL

In this chapter, we list the several major methods of considering the individual heterogeneity in the disaggregate choice model and comment on the property of the methods. As stated above, the heterogeneity has relation to the observable and unobservable omitted variables. First, we classify the modeling scheme according to this viewpoints. Table-1 shows the classification of the schemes.

Table 1 - the Classification of the Methods Considering the individual Heterogeneity

Observable Omitted Variables	Unobserved Omitted Variables
segmentation the observed exogenous variables	*segmentation* the latent endogenous variables ***probabilistic approach*** random coefficient model mass point model latent class model mixing distribution model

Several case study of mass point model and mixing distribution model could be reviewed in the travel behavior analysis. Random coefficient models was being developed in the early times of disaggregate model (Fischer and Nagin (1981)). The estimation of more generalized form of random coefficient model, which is equal to estimation of multinomial probit model, is not easy up to the present developed the computer circumstance. The structured covariance probit model using monte calro simulation method is one of practical methods with less computational load. In this chapter, we discuss the property of the mass point model, latent class model and mixing distribution model.

Mass Point Model (Nishii et. al (1995))

The mass point of the utility function means the expectation of random term, in more practical words, the alternative specific constant. That express the unobservable individual attitude for each mode. In the mass point model, the alternative specific constants are assumed non-parametricly distributed in the population. Although, this model could be estimated without any additional information of ordinary logit model, this model usually applied to the repeated observed data like as panel data and repeated SP data, which have rich attitudinal information of each sample. The likelihood function of binary logit model, assuming two mass points , is written as below.

$$L^* = \prod_{n=1}^{N}\left[p\prod_{t=1}^{T}\frac{\left[\exp(\beta x_{nt}+m_1)\right]^{(1-\delta_{int})}}{1+\exp(\beta x_{nt}+m_1)} + (1-p)\prod_{t=1}^{T}\frac{\left[\exp(\beta x_{nt}+m_2)\right]^{(1-\delta_{int})}}{1+\exp(\beta x_{nt}+m_2)}\right] \tag{1}$$

$$p = \frac{1}{1+\exp(\alpha)}$$

where

α, β :array of unknown parameters

x_{nt} : vector of explanatory variables for observation n on time t

m_1, m_2: mass points, unobserved attitude for the alternative

δ_{int} : 1; alternative i chosen at time t, 0; otherwise

N: the total number of sample

T: the number of observation repeated

Latent Class Model (Kamakura et. al (1994))

This model assumes that the whole parameter of utility function distributed non-parametricaly, although the mass point model varies only the alternative specific constants. In other word, this model assumes the unobserved classes (segments) of homogenous taste in the population. Each class has the different utility parameter. In this model, each sample belongs to the latent class probabilisticaly and the probability is structured by the instrumental variables that represent the individual heterogeneity. Therefore, the probability means membership for each class. The likelihood function is shown below assuming logit type membership probability.

$$L^* = \prod_{n=1}^{N}\left[\sum_{s=1}^{S}\left\{\frac{\prod_i[\exp(\boldsymbol{\beta}_s x_{in})]^{\delta_{in}}}{\sum_j \exp(\boldsymbol{\beta}_s x_{jn})} \times \frac{\exp(\boldsymbol{\Gamma} w_{ns})}{\sum_{s=1}^{S}\exp(\boldsymbol{\Gamma} w_{ns})}\right\}\right] \qquad (2)$$

where

$\boldsymbol{\beta}_s$: a unknown parameter vector of utility function for latent class s

x_{in} : a vector of explanatory variable of utility function for individual n and alternative i

$\boldsymbol{\Gamma}$: a unknown parameter vector of membership function

w_{in} : a vector of instrumental variables for membership function

δ_{in} : 1; individual n choose alternative i, 0; otherwise

N: the total number of sample

T: the number of observation repeated

Mixing Distribution Model (Hensher and Wringly (1986))

Both the mass point model and the latent class model assume the utility parameter distribute nonparametricaly. This mixing distribution model assumes a parametric distribution of the utility parameter, especially for the alternative specific constant. If all the parameter is parametricly distributed, the mixing distribution model is essentially equal to the random coefficient model. The likelihood of the binary mixing distribution model for repeated data is shown below.

$$L^* = \prod_{n=1}^{N}\int_{\eta}\prod_{t=1}^{T}\left[\left(\frac{1}{1+\exp(\boldsymbol{\beta x}_{nt}+\eta)}\right)^{\delta_{1n}} \times \left(\frac{\exp(\boldsymbol{\beta x}_{nt}+\eta)}{1+\exp(\boldsymbol{\beta x}_{nt}+\eta)}\right)^{(1-\delta_{n})}\right] f(\eta)d\eta \qquad (3)$$

where

η : the distributing component of heterogeneity

the others are followed in the mass point model.

Serial correlation model (Morikawa (1994)) has developed for the panel or SP, RP combined data. This model is originally developed to consider the serial correlation of the error component of the same individual. The serial correlation of error term is also brought by the omitted variable partially. Therefore, the serial correlation has similar character to the heterogeneity. The likelihood function of the serial correlation model for SP and RP combined data is shown below.

$$L^* = \prod_{n=1}^{N}\int_{\eta}\left[\left(\frac{\prod_i\left\{\exp(\boldsymbol{\beta x}_{niRP}+\boldsymbol{\lambda})^{\delta_{niRP}}\right\}}{\sum_k \exp(\boldsymbol{\beta x}_{nkRP}+\boldsymbol{\lambda})}\right) \times \left(\frac{\prod_j\left\{\exp(\boldsymbol{\beta x}_{njSP}+\boldsymbol{\lambda})^{\delta_{njSP}}\right\}}{\sum_k \exp(\boldsymbol{\beta x}_{nkSP}+\boldsymbol{\lambda})}\right)\right] f(\boldsymbol{\lambda})d\boldsymbol{\lambda} \qquad (4)$$

$\boldsymbol{\lambda}$: a vector of alternative specific serial correlation term

x_{niRP}, x_{niSP} : a vector of explanatory variables for individual n and alternative i, for SP and RP data respectively

$\delta_{niRP}, \delta_{niSP}$: 1; if alternative i is chosen on RP SP data respectively, 0; otherwise

This model is essentially equal to the mixing distribution model when the serial correlation term defied as common to each alternative.

CASE STUDY

We estimate the models shown in chapter 3 with the existing SP, RP and subjective importance rating data and compare the estimation result of each model.

Description of the Survey Data

The survey was conducted in 1992 for measuring the intention of the virtual new high-speeded ferry between Yokosuka, residential area and Tateyama resort area in Tokyo Bay. This data includes several types of data, SP and importance rating of the attributes of alternatives, additional to the ordinary RP data. Each sample was shown six different cost and frequency conditions of the new ferry and asked their intention of making use of the ferry. The importance ratings of attributes are categorical data as important or not important. These six attributes. congestion, number of transfer, comfort, ease with heavy luggage, silence, cost, travel time, reliability of arrival time are asked for each sample.

Latent Attitudinal Variables

We first estimated LISREL type model (Joreskog and Sorbom (1986)) to confirm the structure between attitudinal importance ratings and socioeconomic variables. The specification is shown below.

structural equation $w = \mathbf{B}s + \varsigma$

$$\begin{bmatrix} w_1^* \\ w_2^* \end{bmatrix} = \begin{bmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 & \beta_5 & \beta_6 \\ \beta_7 & \beta_8 & \beta_9 & \beta_{10} & \beta_{11} & \beta_{12} \end{bmatrix} \begin{bmatrix} female \\ age20 \\ age50 \\ job \\ sightseeing \\ sports \end{bmatrix} + \begin{bmatrix} \varsigma_1 \\ \varsigma_2 \end{bmatrix} \qquad (5)$$

measurement equation $\mathbf{Y} = \Lambda w + \varepsilon$

$$\begin{bmatrix} y_1(congestion) \\ y_2(transfer) \\ y_3(comfort) \\ y_4(ease) \\ y_5(silent) \\ y_6(lowcost) \\ y_7(lesstime) \\ y_8(reliability) \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ \lambda_2 & \lambda_5 \\ 0 & 0 \\ 0 & \lambda_6 \\ 0 & \lambda_7 \\ \lambda_3 & \lambda_8 \\ 1 & 0 \\ \lambda_4 & 0 \end{bmatrix} \begin{bmatrix} w_1^* \\ w_2^* \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \\ \varepsilon_7 \\ \varepsilon_8 \end{bmatrix} \qquad (6)$$

where
female: 1; if female, 0; otherwise
age20: 1; if under 30 years old, 0; otherwise
age50: 1; if under 60 years old and over 30 years old, 0; otherwise
job: 1; having regular job, 0; otherwise
sightseeing: 1; sightseeing tour, 0; otherwise
sports: 1; trip for sports, 0; otherwise
ς, ε : random term

To estimate the unknown parameter in the eqn (5) and (6), we first use PRELIS to make covariance matrices from categorical data which have some options to estimate the covariance of categorical data. Next, we estimate the unknown parameters in eqn (5) and (6) simultaneously using LINCS. The estimation result of this model is shown in the Table-1

Table 1 - The estimation results of LISREL model ( ): t-value

$$\hat{\mathbf{B}} = \begin{array}{c} \left[\begin{array}{cccccc} -0.0326 & -0.104 & -0.0313 & -0.0071 & 0.0223 & 0.0915 \\ (-0.7) & (2.2) & (-0.7) & (-0.2) & (0.5) & (1.9) \\ 0.0343 & 0.0572 & 0.0321 & -0.0164 & -0.648 & -0.0800 \\ (0.8) & (1.3) & (0.8) & (-0.4) & (-1.4) & (-1.8) \end{array}\right] \begin{array}{c} w_1^* \\ \\ w_2^* \\ \\ \end{array} \\ \begin{array}{cccccc} \text{female} & \text{age20} & \text{age50} & \text{job} & \text{sightseeing} & \text{sports} \end{array} \end{array}$$

$$\hat{\Lambda}' = \begin{array}{c} \left[\begin{array}{cccccccc} \begin{array}{c}0.854\\(4.1)\end{array} & \begin{array}{c}0.487\\(2.0)\end{array} & 0 & & 0 & \begin{array}{c}0.459\\(1.6)\end{array} & 1 & \begin{array}{c}0.962\\(4.3)\end{array} \\ 0 & \begin{array}{c}0.685\\(2.4)\end{array} & 1 & \begin{array}{c}1.13\\(4.1)\end{array} & \begin{array}{c}0.541\\(2.7)\end{array} & \begin{array}{c}1.00\\(3.2)\end{array} & 0 & 0 \end{array}\right] \begin{array}{c} w_1^* \\ \\ w_2^* \end{array} \\ \begin{array}{cccccccc} \text{congestion} & \text{transfer} & \text{comfort} & \text{ease} & \text{silent} & \text{lowcost} & \text{lesstime} & \text{reliability} \end{array} \end{array}$$

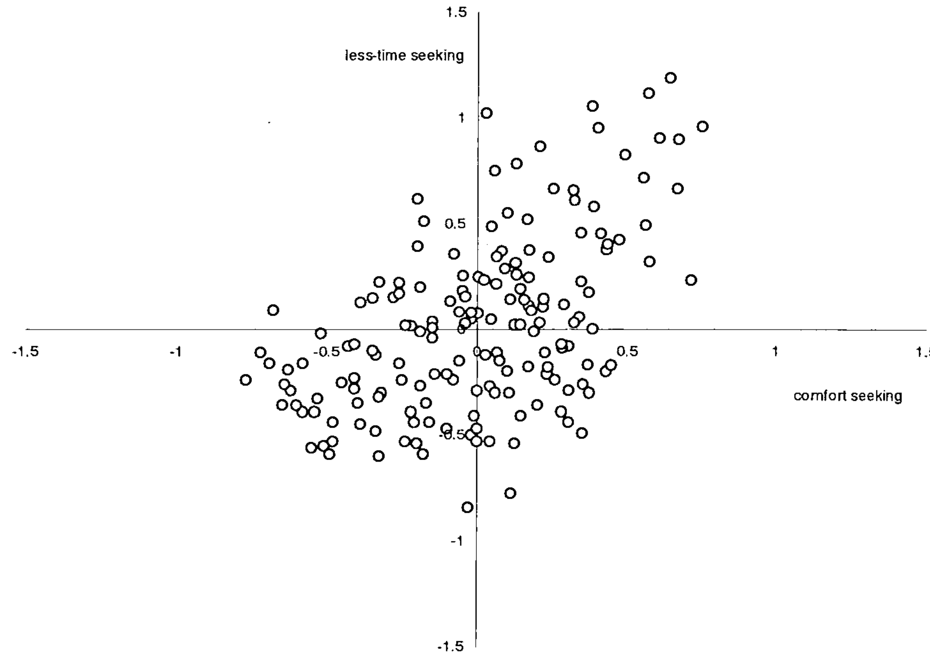

Figure1 - The spraying graph of the fitted value of latent variables

From the estimates of each parameter, we named each latent variable, w_1 and w_2, as "less-time seeking" and "comfort seeking", respectively. The fitted value of each latent variable is calculated from the estimates according to the equation.

$$\hat{w}_n^* = \hat{\mathbf{B}}s_n + \mathbf{Y}_n\hat{\Lambda}'(\hat{\Lambda}\hat{\Psi}\hat{\Lambda}'+\hat{\Theta})(\mathbf{Y}_n - \hat{\Lambda}\hat{\mathbf{B}}s_n) \text{ (Morikawa and Sasaki 1993)} \qquad (7)$$

where

Ψ : the covariance matrix of ς

Θ : the covariance matrix of ε

The spraying graph of the fitted value of the latent attitudinal variables of each sample is shown in Figure-1.The mean of fitted value are normalized to 0 and the scales of the variables, w_1 and w_2 are measured by the scales of the indicators, comfort and less-time seeking, respectively.

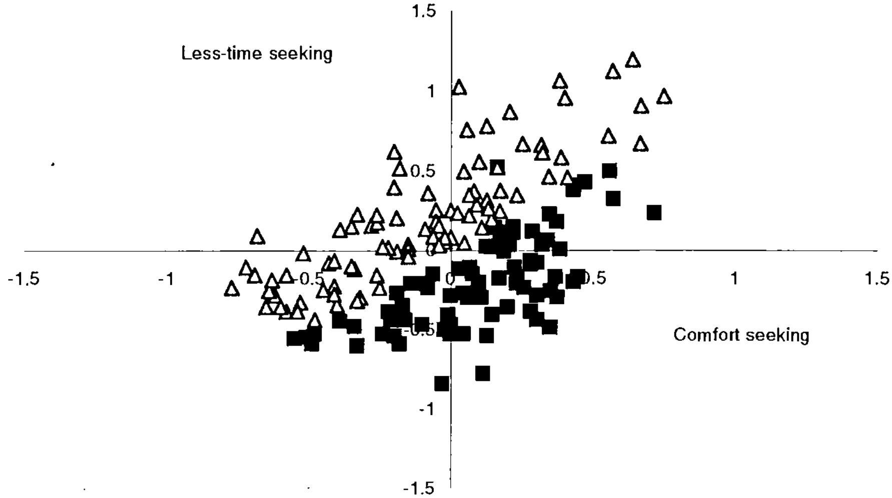

Figure 2 - Spraying Graph of the Two Segments Comfort Seeking■ and Less-time Seeking△

Table-2 The Estimation Result of Segmentation Approach by Attitudinal Variables **( ): t-value**

	Pooled Sample	**Comfort Seeking**	**Less-time Seeking**
Ferry Constant	-0.684 (-2.3)	-0.469 (-1.2)	-0.781 (-1.7)
Cost	-0.426 (-8.7)	-0.380 (-6.7)	-0.512 (5.7)
Frequency	1.39 (9.2)	1.11 (5.9)	1.75 (7.4)
Time	-0.0753 (-3.1)	-0.0262 (-0.8)	-0.126 (-3.7)
RP dummy	-0.827 (-3.0)	-0.975 (-2.5)	-1.02 (-2.4)
Observation	819	422	397
$\bar{\rho}^2$	0.273	0.275	
χ^2	1.	χ^2 =12.56 $\chi^2_{0.05}$(5)=11.07	

Endogenous Segmentation Approach

We first divide this sample into two subgroups and estimate logit models separately. The criterion of the segmentation is the ratio of two attitudinal variables. Figure-2 shows the spraying graph after the segmentation. The estimated result of logit model on segmented sample with SP data are shown in Table-2. The null hypothesis that the two segments have the same utility parameters is rejected by χ^2 test to 5% hazard, though the goodness-of-fit measure does not improved so much. The characteristics of each segment is reasonable because the absolute value of the estimate of time and frequency in the less-time seeking segment is larger than that of the comfort segment.

Latent Class Approach

Next, we applied the attitudinal variables as the explanatory variable for the latent class membership function. The choice model is binary logit model with the latent class model. The estimation result of the model is shown in Table-2. We assume the number of latent classes as two because the dimensions of space that was made by latent variables are two. The estimation result of the latent class model with SP data is shown in Table-3.

Table 3 - The estimation Result of the Latent Class Model with SP data ( ): t-value

Model	Variable	Constraint Model (Normal Model)	Logit Model with Latent Class Latent Class 1	Latent Class 2
Choice Model	Ferry Constant	-0.684 (-2.3)	-1.96 (-4.2)	7.62 (4.6)
	Cost	-0.426 (-8.7)	-0.160 (-3.4)	-3.09 (-5.8)
	Frequency	1.39 (9.2)	1.96 (8.1)	0.949 (2.2)
	Time	-0.0753 (-3.1)	-0.0729 (-1.6)	-0.819 (-4.2)
	RP Dummy	-0.827 (-3.0)	-1.10 (2.3)	-0.993 (-1.0)
Membership Function	Less-time Seeking		-1.04 (-1.6)	
	Comfort Seeking		-0.0647 (-0.1)	
The Number of Observation		819	819	
	$\bar{\rho}^2$	0.273	0.282	
	χ^2		χ^2 =265	$\chi^2_{0.05}$ =20.28

Comparing to the result of Table-2, the goodness-of-fit measure improved and χ^2 is much larger than that of Table-2. The characteristics of each class are as expected judging from the comparison of the estimate of the parameter of time, though the parameter estimates in membership function is not significant. The significant difference between the two latent classes is shown in the estimates of ferry constant. The utility parameter of each person is expectation of two latent class according to the membership probability. In other word the interior division of the parameter vectors of each class. After applying to the only SP data, we estimated the same latent class model with SP and RP data. The likelihood function shown in equation (2) is transformed as below.

$$L^* = \prod_{n=1}^{N}\left[\sum_{s=1}^{S}\left\{\frac{\prod_i\left[\exp(\beta_s x_{inRP})\right]^{\delta_{inRP}}}{\sum_j \exp(\beta_s x_{jnRP})}\times\frac{\exp(\Gamma w_{ns})}{\sum_{s=1}^{S}\exp(\Gamma w_{ns})}\right\}\right.$$
$$\left.\times\sum_{s=1}^{S}\left\{\frac{\prod_i\left[\exp(\mu\beta_s x_{inSP})\right]^{\delta_{inSP}}}{\sum_j \exp(\mu\beta_s x_{jnSP})}\times\frac{\exp(\Gamma w_{ns})}{\sum_{s=1}^{S}\exp(\Gamma w_{ns})}\right\}\right] \tag{8}$$

where

x_{inRP}, x_{inSP} : a vector of explanatory variable of utility function of individual n for alternative i, on SP and RP data, respectively

$\delta_{inRP}, \delta_{inSP}$: 1; individual n choose alternative i, 0; otherwise, on RP and SP data, respectively

μ : scale parameter to adjust the difference of the random term scales between SP and RP model

The others are same as eqn (2).

The estimation result applying SP and RP data is shown below.

Table-4 The estimation result of logit model with two latent class ( ): t-value

Model	Variable	Constraint model (Normal Model)	Logit Model with Latent Class: Latent Class 1	Latent Class 2
Choice Model	Ferry Constant	0.177 (1.44)	0.157 (1.7)	4.38 (5.2)
	Cost	-0.215 (-6.8)	0.0919 (2.7)	-2.11 (7.3)
	Time	0.103 (4.6)	0.150 (4.6)	-0.230 (-3.1)
	Frequency	0.986 (7.5)	2.70 (7.2)	1.96 (6.6)
	Scale Parameter	1.61 (7.8)	3.84 (7.3)	
Membership Function	Less-time Seeking		-0.566 (-1.0)	
	Comfort Seeking		-1.14 (-2.1)	
The Number of Observation		1030	1030	
$\bar{\rho}^2$		0.156	0.280	
χ^2 value			χ^2 =189	$\chi^2_{0.05}$ =20.3

Table-4 also shows the estimation result of ordinary logit model (constraint model) for comparing. The null hypotheses that the parameter vectors of two latent classes are not significantly different is rejected by 5% hazard by χ^2 test. The parameter estimates in membership function, "less-time seeking" and "comfort seeking" implies that the membership probability of each latent class depends on the ratio of the "less-time seeking" and "comfort seeking" . If the value of less-time seeking minus comfort seeking is positive, his or her membership of latent class 2 becomes large. If negative, the membership of latent class 1 get lager. The parameter estimate of time on the ordinary logit model is significantly positive, though that of the latent class 2 is significantly negative. This implies that the parameter of time is varying in the sample, as a result, the estimate of ordinary model results in positive. Judging from the estimates, latent class 2 is frequency sensitive class and latent class 1 is the cost and time sensitive class.

Table-5 The Estimates of the Mass Point Model ( ): t-value

Model	Variable	Constraint Model (Normal Model)	Mass Point Model: Mass Point 1	Mass Point 2
Choice Model	Ferry Constant	0.177 (1.44)	0.605 (7.3)	-0.181 (-1.4)
	Cost	-0.215 (-6.8)	-0.222 (-6.2)	
	Time	0.103 (4.6)	0.0966 (4.7)	
	Frequency	0.986 (7.5)	1.02 (9.7)	
	Scale Parameter	1.61 (7.8)	1.71 (7.8)	
Membership Function	Less-time Seeking		-21.9 (-190.0)	
	Comfort Seeking		-17.1 (-61.5)	
The Number of Observation		1030	1030	
$\bar{\rho}^2$		0.156	0.160	

Structural Mass Point Approach

Last, we estimate the mass point model. We modeled the mass point membership structured by the attitudinal latent variable to test whether this latent variables affect only the ferry constant or not, because the unobserved attitudinal difference is revealed in the alternative specific constant. The estimates are shown in Table-5. It could be said that his result is not so good comparing the goodness-of-fit measure with that of the ordinary model. The structured mass point model is not suitable for these latent attitudinal variables to consider the heterogeneity.

CONCLUDING REMARKS

In this study, we estimated the four types of choice models considering the heterogeneity of individual. The a priori segment by the attitudinal variable which is estimated using attribute importance rating could not improved the fit of SP model. However, latent class model significantly improves the fit of SP model. In addition, RP mode dummy on SP model become not significant with latent class model. This implies that the RP mode dummy is no longer needed with considering latent classes. When RP data is combined to the SP data, the goodness-of-fit measure of ordinary logit model changed for worse. But, applying the latent class model, the goodness-of-fit measure was dramatically improved, while that of the attitudinal structured mass point model was not so. Although the mass point model is not usually structured, the latent class model is better than mass point model for this data. This result may be caused by the mismatch of attitudinal variable and constant (mass point). After all, we concluded that the latent class model with attitudinal variables are very useful and superior to other models tested in this study.

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