A MODE CHOICE MODEL SEPARATING TASTE VARIATION AND STATED PREFERENCE REPORTING BIAS

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Abstract: The stated preference (SP) approach has proven to be successful in describing and predicting individual preference and choice for not-yet-existing alternatives. Since the SP approach contains more biases than revealed preference (RP) data, SP-based prediction models tend to overestimate the future demand of new alternatives. This paper, therefore, proposes a dynamic travel mode choice model by separating SP reporting bias and taste variation based on the integration of a RP/SP combined logit model and a mass point approach. Furthermore, it also attempts to remove panel-conditioning bias by introducing previous RP choice results into the SP model. Through an empirical analysis based on SP panel survey data collected to predict the future demand of Astram Line (a new transit system) in Hiroshima, it is shown that the proposed model provides a higher goodness-of-fit index (internal validity) and temporal transferability (external validity) than conventional ones.

Key Words: SP reporting bias, taste variation, RP/SP combined logit model, mass point approach, panel-conditioning bias

1. INTRODUCTION

The SP approach, originating in mathematical psychology, has been widely used in transportation (Hensher, 1994), since it can measure how people choose not-yet-existing travel modes, or how people take actions in case of introducing new policies (e.g., road pricing, introduction of intelligent transport systems). This approach examines individual response to a series of experimentally designed choice alternatives, which are typically described in terms of combinations of attributes with several pre-defined levels.

Besides the ability to directly measure the demand/response under not-yet-existing conditions, the SP approach has some other advantages over the RP approach, which is based on observed choice in real situations. These advantages include the ability to control statistical problems such as multi-collinearity and lack of variance in explanatory variables, the increased possibility of including subjective or qualitative factors as explanatory variables and cost-efficiency to develop models from a relatively small size of samples (Kroes and Sheldon, 1988; Oppewal, 1995; Polak and Jones, 1997).

Because of the consideration of hypothetical situations, the SP approach inevitably includes some biases such as reporting bias and non-reporting bias, which have not been treated properly in conventional travel behavior models. Many studies have empirically pointed out that prediction models based on SP data overestimate the future demand for not-yet-existing travel modes (e.g. Couture and Dooley, 1981). Furthermore, since individual preference and choice may change over time, SP panel surveys are needed to capture this kind of dynamic. This makes the SP-based modeling process more complicated.

This paper attempts to correct some of these biases, meanwhile incorporating individual taste variation in the context of mode choice. As a result, a new mode choice model is obtained. This model differs from conventional ones in several ways, as explained later. The internal and external validities of the proposed model is examined by using 5-wave SP/RP panel data, which was collected to predict the future demand of Astram Line in Hiroshima. The survey was conducted almost every year from 1987 to 1994; when Astram Line was opened.

The paper, therefore, is organized as follows. Section 2 summarizes the SP approach in a wider sense. Section 3 describes the biases existing in the SP approach and gives a brief review on existing correction methods. Following that, section 4 outlines the proposed model and section 5 gives the estimation and evaluation results of the related models. Finally, section 6 concludes the study.

2. THE SP APPROACH AS AN ANALYSIS TOOL OF DECISION MAKING

Individuals often have to make a choice among a number of discrete alternatives, such as routes, travel modes and shopping centers, in terms of a bundle of attributes and an evaluation and choice process, as shown in Figure 1.

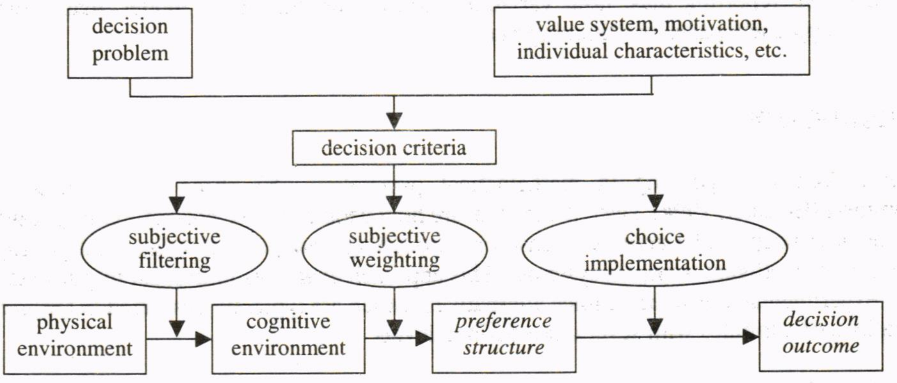

Figure 1. A Conceptual Model of Individual Decisions (after Timmermans, 1982)

The SP approach, called conjoint analysis in marketing science, assumes that the decision-making process described in Figure 1 can be uncovered by presenting respondents experimentally controlled choice alternatives and asking them to express their preferences for these alternatives or to choose the most preferred alternative. The former case refers to conjoint preference analysis, while the latter case refers to conjoint choice analysis.

In a broad sense, the SP approach can be divided into algebraic (quantitative) and non-algebraic (qualitative) subgroups. The former can be further divided into compositional and decompositional approaches. Instead of algebraic approaches, many non-algebraic ones have also been suggested. These range from production systems to neural networks, decision tables and decision nets (Molin, 1999). Algebraic approaches express the preference or utility function by algebraic equations.

(1) Compositional SP Approach

This approach derives individual preference by measuring separately and explicitly individual evaluation of the attributes of alternatives and the relative importance of each attribute. This information is then combined using some algebraic rule to arrive at an overall preference measurement. The linear additive rule is the most frequently used rule, which assumes that overall preference is a weighted additive function of attribute evaluations (Lindberg et al, 1989).

This approach has the advantages of relatively simple measurement and ease of implementation, however, it suffers the following two problems. The first problem is the ignorance of correlation and trade-off among attributes. The second is that, when the respondents are requested to evaluate attributes separately, it is not clear what they (need to) assume about the other attributes. Accordingly, the measurement task does not reflect the mechanism underlying actual decision-making and choice processes.

(2) Decompositional SP Approach

This approach (also called conjoint approach) measures overall preferences for bundles of attributes, called profiles. Thus, the respondents have to trade-off the attributes to arrive at an overall evaluation of a profile. Because the profiles are constructed based on statistically designed experiments, the overall evaluations can be easily and efficiently decomposed into the part-worth utility contributions of the attribute levels (Fujiwara and Sugie, 1997; Molin, 1999). The SP approach often applied in transportation refers to this decompositional approach, simply called the SP approach.

3. BIASES IN SP PANEL SURVEY AND EXISTING CORRECTION METHODS

Since SP panel data is used to develop mode choice models in this study, biases in both SP and panel surveys are summarized here. After that, the existing correction methods for these biases are briefly reviewed.

3.1 Biases in SP Panel Survey

Biases can arise at any stage and any situation during the course of transport surveys. For instance, respondents cannot answer the questions properly when the purpose of the survey is not clear. They may feel very confused to give answers due to bad wording and ordering of the questions. They may also lose their patience when answering too many questions.

Richardson et al (1995) discussed these matters with regard to every stage in transport surveys (Figure 2). Considering the different definitions of biases in different fields, Groves (1989) systematically classified these biases, as shown in Figure 3. The biases treated in this paper arise in the stage of survey administration, and are related to respondent observational errors. They are shown in bold italic fonts in Figures 2 and 3, respectively.

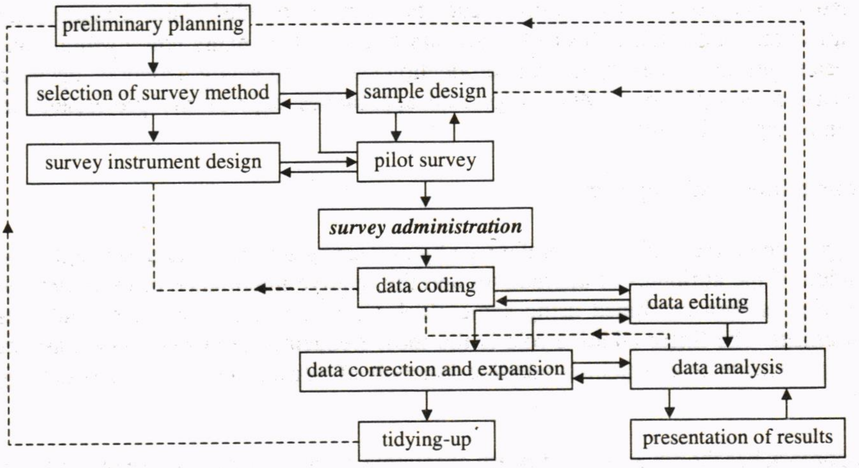

Figure 2. The Transport Survey Process (after Richardson et al, 1995)

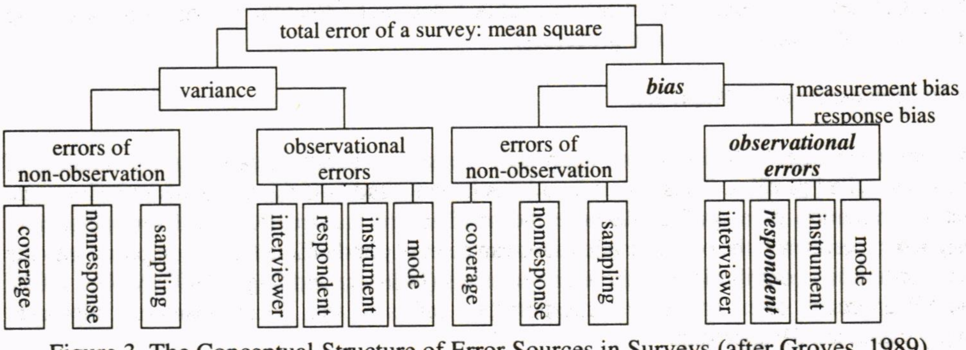

Figure 3. The Conceptual Structure of Error Sources in Surveys (after Groves, 1989)

(1) SP-specific Biases

One of the SP-specific biases is called SP reporting bias, which arises when the respondents do not answer the questions based on the attributes presented in profiles or misunderstand/ignore the trade-off relationships among these attributes. Another is called SP non-reporting bias, which occurs when the respondents do not give answers about the questions.

(2) Panel-specific biases

The definitions of three major panel-specific biases are given here. The first is called attrition bias, which takes place when the statistically selected respondents do not drop out at random in the course of a panel survey. The second is called panel-conditioning bias, which occurs when the respondents' answers are subjectively affected by previous choice results. The last is called panel fatigue bias, which arises when the respondents answer similar questions repeatedly and lose their patience. This kind of fatigue bias also occurs in answering multiple-choice SP questions at the same point in time. More detailed discussions about panel-specific biases can be found in Golob et al (1997) and Kasprzyk et al (1989).

In order to avoid/mitigate the biases described above, the first step is to improve the survey plan and its administration. Prior contact (e.g. by phone or post card), incentives (e.g. gifts) and better questionnaire design (e.g. proper wording and use of graphs or computers) are good examples (Richardson et al, 1995). The second step is to eliminate these biases based on modeling methods. These modeling methods can be used to weight the usable samples if the samples cannot represent the population under consideration on the one hand, as well as remove the erroneous/biased information from the model on the other.

Distinguishing between SP-specific biases and panel-specific biases can be expected to improve the accuracy of SP models, however, its efficiency can only be verified throughout the empirical analysis.

3.2 Existing Correction Methods

Here, we give a brief review of representative methods for correcting SP reporting bias, even though the definition of reporting bias has not been made clear in some literature.

The mode choice model under consideration is based on random utility maximization, which assumes that an individual always chooses the travel mode with the highest utility. Define $U_{ij,t}$ in equation (1) as the utility function of individual i choosing travel mode j at time t, where $V_{ij,t}$ is a non-stochastic component and $\varepsilon_{ij,t}$ is an error component.

$$U_{ij,t} = V_{ij,t} + \varepsilon_{ij,t} \tag{1}$$

Different assumptions on error component $\varepsilon_{ij,t}$ result in different choice models. If errors are assumed to follow an independent and identical Gumbel distribution with respect to i, j, t, then the widely used multinomial logit model (MNL) can be obtained as,

$$P_{ij,t} = \frac{\exp(V_{ij,t})}{\sum_{j'} \exp(V_{ij',t})} \tag{2}$$

where $P_{ij,t}$ indicates the probability of individual i in choosing mode j at time t.

Let $y_{ij,t}$ represents mode choice result, which equals 1 for the chosen mode j, otherwise 0. Then $P_{ij,t}$ can be used to measure $y_{ij,t}$, regardless of RP or SP data. Before discussing in detail we assume,

(1) there does not exist reporting bias in RP data, and
(2) there do not exist measurement errors for explanatory variables in RP data.

Thus, SP reporting bias means that some reported results of $y_{ij,t}^{SP}$ are not correct. For instance, Bonsall (1985) proposes to remove respondents' erroneous SP choice results based on transfer price prior to model estimation.

Since we start the discussion in the context of random utility maximization, if $P_{ij,t}$ is not properly estimated, it means that the non-stochastic component $V_{ij,t}$ or (and) error component $\varepsilon_{ij,t}$ is (are) not properly specified. Based on equation (1), there possibly exist three kinds of methods to correct SP reporting bias: (1) improving the specification of $V_{ij,t}$, (2) assuming a more appropriate structure and/or distribution for $\varepsilon_{ij,t}$, and (3) combining the above two methods.

(1) Improving the Specification of Non-Stochastic Component $V_{ij,t}$

McFadden (1986) introduces a latent variable on SP reporting bias based on the LISREL model. Bates (1988) first calculates elasticity values with respect to relevant explanatory variables based on external data sources and then uses these elasticity values to estimate all the parameters of the model under consideration.

Morikawa (1989) proposes a RP/SP combined logit model by introducing a scale parameter to balance the different variances of RP and SP errors in order to estimate RP and SP models simultaneously. Then he realistically assumes that the stated value of time is equal to the revealed one. Although this model is not developed initially to correct SP biases by distinguishing between SP reporting bias and other biases clearly, it provides one of the most important and practical methodologies and will be discussed in detail later.

Han et al (2001) applies a mixed logit model to explain driver taste variation and repeated choice correlation in hypothetical route choice situations, where taste variation is represented by assuming that the parameters of explanatory variables follow a normal (and lognormal) distribution and empirically confirm its effectiveness.

(2) Assuming More Appropriate Error Structure and/or Distribution for Error $\varepsilon_{ij,t}$

Since SP surveys ask each respondent to answer several hypothetical choice questions, this might increase respondent burden and cause fatigue bias. Nishi et al (1995) attempts to apply the mass point approach and mixing distribution approach to correct this SP fatigue bias. They first treat SP multiple-choice results from the same respondent at a given point of time as repeated cross-sectional data, and then subdivide error $\varepsilon_{ij,t}$ into two parts, where the first part is correlated over alternatives and the second part is independently and identically distributed. The mass point approach and mixing distribution approach are separately used to represent the first part (called unobserved heterogeneity), and the mixing distribution approach is confirmed to be superior to the mass point approach. The mixing distribution approach, however, suffers the problem of different assumptions on unobserved heterogeneity sensitively leading to different estimated parameters (Heckman and Singer, 1984).

Wang (1999) applies the multinomial probit model to describe the choice issues of destination and stop pattern simultaneously by assuming the error components follow a multivariate normal distribution in the context of activity-based conjoint analysis.

(3) Improving both { $V_{ij,t}$ } and { $\varepsilon_{ij,t}$ }

Morikawa (1994) incorporates state dependence and serial correlation into his original RP/SP combined model, where the former can improve the specification of $V_{ij,t}$ and the latter redefines error $\varepsilon_{ij,t}$. Polydoropoulou and Ben-Akiva (2001) propose a RP/SP combined nested logit model to represent the choice issues of multiple mass transit systems. Sakano and Benjamin (2001) suggest a structural equation model to combine RP and SP data for explaining travel mode and activity choices. Their approach can also reveal various unobserved traveler attitudes and perceptions, which affect their activity and mode choices.

Brownstone et al (2000) applies a joint mixed logit model of stated and revealed preferences for alternative-fuel vehicles. However, it is computationally difficult to further incorporate taste variation due to additional error components.

4. FORMULATION OF MODELS SEPARATING SP REPORTING BIAS AND TASTE VARIATION

4.1 Longitudinal RP/SP Combined Logit Model

As an extension of Morikawa's (1989) original RP/SP combined model for cross-sectional data, the scale parameter μ for balancing variances $\mathrm{Var}(\varepsilon_{ij,t}^{RP})$ and $\mathrm{Var}(\varepsilon_{ij,t}^{SP})$ of RP and SP errors is assumed to be invariable over time to describe temporal choice issues.

$$\mathrm{Var}(\varepsilon_{ij,t}^{RP}) = \mu \mathrm{Var}(\varepsilon_{ij,t}^{SP}) \tag{3}$$

Thus, a longitudinal RP/SP combined logit model can be derived as follows:

$$P_{ij} = \prod_t \left\{ \left[\frac{\Pi_j \exp(V_{ij,t}^{RP})}{\sum_{j'} \exp(V_{ij',t}^{RP})} \right]^{y_{ij,t}^{RP}} \right\} \cdot \prod_t \left\{ \left[\frac{\Pi_j \exp(\mu V_{ij,t}^{SP})}{\sum_{j'} \exp(\mu V_{ij',t}^{SP})} \right]^{y_{ij,t}^{SP}} \right\} \tag{4}$$

$$V_{ij,t}^{RP} = \pi_{j,t}^{RP} + \sum_h \beta_{jh,t} X_{ijh,t}^{RP} + \sum_g \gamma_{jg,t} W_{ijg,t}^{RP} \tag{5}$$

$$V_{ij,t}^{SP} = \pi_{j,t}^{SP} + \sum_h \beta_{jh,t} X_{ijh,t}^{SP} + \sum_k \varphi_{jk,t} Z_{ijk,t}^{SP} \tag{6}$$

where $y_{ij,t}^{RP}$ and $y_{ij,t}^{SP}$ are RP and SP choice results, $\pi_{j,t}^{RP}$ and $\pi_{j,t}^{SP}$ are constants for the RP and SP utility functions, $X_{ijh,t}^{RP}$ and $X_{ijh,t}^{SP}$ are the h'th common explanatory variables for $V_{ij,t}^{RP}$ and $V_{ij,t}^{SP}$, $W_{ijg,t}^{RP}$ is the g'th RP-specific explanatory variable, $Z_{ijk,t}^{SP}$ is the k'th SP-specific explanatory variable, and $\beta_{jh,t}, \gamma_{jg,t}, \varphi_{jk,t}$ are parameters to be estimated.

With respect to explanatory variables for mode choice, the RP/SP combined model usually adopts level-of-service variables as common variables for different travel modes, such as travel time and travel cost. Since the value of time from SP data is assumed to be the same as the one from RP data, unrealistic estimation of SP parameters can be avoided.

4.2 Separation of SP Reporting Bias and Taste Variation

The following assumptions are added to separate SP reporting bias and taste variation.

(3) there do not exist any statistically or behaviorally significant objective explanatory variables except ones in the model,
(4) parameters of each explanatory variable does not change over time,
(5) individual taste variation does not change over time, and
(6) parameters of each explanatory variable do not change according to alternatives.

Assumptions (1), (2) and (3) imply that constant $\pi_{j,t}^{RP}$ only indicates the influence of omitted subjective variables, which cannot be quantitatively measured. Assumptions 4, 5 and 6 are made since temporal change cannot be captured properly with short-term panel data used in this study. Henceforth, τ_{ij} is used to replace $\pi_{j,t}^{RP}$ and represent individual i's taste variation with respect to alternative j. Accordingly, the utility functions for RP and SP models are rewritten as follows:

(1) Utility function for existing travel mode

$$U_{ij,t}^{RP} = \tau_{ij} + \sum_h \beta_h X_{ijh,t}^{RP} + \sum_g \gamma_g W_{ijg,t}^{RP} + \varepsilon_{ij,t}^{RP} \tag{7}$$

$$U_{ij,t}^{SP} = \tau_{ij} + \phi_j^{SP} + \sum_h \beta_h X_{ijh,t}^{SP} + \sum_k \varphi_k Z_{ijk,t}^{SP} + \varepsilon_{ij,t}^{SP} \tag{8}$$

(2) Utility function for not-yet-existing travel mode

$$U_{ij,t}^{SP} = \psi_j^{SP} + \sum_h \beta_h X_{ijh,t}^{SP} + \sum_k \varphi_k Z_{ijk,t}^{SP} + \varepsilon_{ij,t}^{SP} \tag{9}$$

The original SP constant $\pi_{j,t}^{SP}$ is rewritten as $\tau_{ij} + \phi_j^{SP}$ with regard to existing travel modes, where ϕ_j^{SP} indicates SP reporting bias. Uniqueness of the solutions for τ_{ij} and ϕ_j^{SP} based on the maximum likelihood method can be easily proved. The parameter ψ_j^{SP} indicates a constant of a non-yet-existing travel mode and may include both SP reporting bias and taste variation, which cannot be separated due to a lack of available RP information. In other words, SP reporting bias and taste variation can only be separated for existing travel modes.

Thus, elimination of SP reporting bias and introduction of taste variation can avoid underestimation for existing travel modes and indirectly alleviate overestimation for not-yet-existing modes.

4.3 Removal of Panel-Conditioning Bias from SP Data

Since panel-conditioning bias is caused by the influence of previous SP choice results and stated preference hinges largely upon revealed preference, we propose to remove panel-conditioning bias by introducing previous RP choice results into the SP model, as shown in

Figure 4. The utility functions for existing travel modes are rewritten as equation (10), where the previous choice result $y_{ij,t-1}$ is called state dependence with parameter λ.

$$U^{SP}_{ij,t} = \tau_{ij} + \phi^{SP}_{j} + \lambda y_{ij,t-1} + \sum_h \beta_h X^{SP}_{ijh,t} + \sum_k \varphi_k Z^{SP}_{ijk,t} + \varepsilon^{SP}_{ij,t} \tag{10}$$

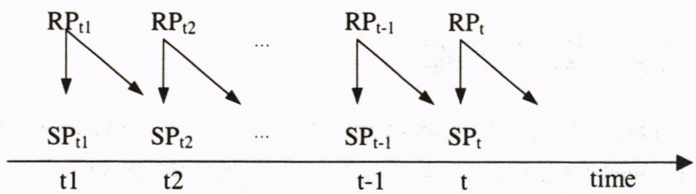

Figure 4. Conceptual Structure of Travel Mode Choice Model based on RP/SP Panel Data

4.4 Representing Taste Variation based on the Mass Point Approach

There exist two approaches to incorporate τ_{ij} into the model (Chamberlain, 1980; Lindsay, 1981, 1983a, b; Heckman and Singer, 1984). The first one is called the fixed-effects approach assuming that τ_{ij} is a non-stochastic variable. The second one is called the random-effects approach assuming that τ_{ij} is a stochastic variable. The second approach can be further classified into the parametric approach and the mass point approach.

The fixed-effects approach imposes several strict restrictions on model structure, and the parametric approach has the problem that the estimated values of parameters change sensitively according to different assumptions on the distribution of τ_{ij}. In contrast, the mass point approach does not have such a problem and needs only a few mass points to reach the convergence of model estimation. Sugie et al (1999) confirmed the effectiveness of the mass point approach in the context of mode choice.

By incorporating all the factors discussed above in the same model structure, the following new RP/SP combined choice model (called SEP_DMP henceforth) can be obtained and its parameters can be estimated by the maximum likelihood method.

$$\begin{aligned} P_{ij} = \sum_m \Bigg\{ & \left[\prod_{t=1} \left(\frac{\prod_j \exp\left(V^{RP}_{ij,t} + \xi_{jm}\right)}{\sum_{j'} \exp\left(V^{RP}_{ij',t} + \xi_{j'm}\right)} \right)^{y^{RP}_{ij,t}} \right] \cdot \left[\left(\frac{\prod_j \exp\left(\mu(V^{SP}_{ij,1} + \xi_{jm})\right)}{\sum_{j'} \exp\left(\mu(V^{SP}_{ij',1} + \xi_{j'm})\right)} \right)^{y^{SP}_{ij,1}} \right] \\ & \cdot \left[\prod_{t=2} \left(\frac{\prod_j \exp\left(\mu(V^{SP}_{ij,t} + \lambda y_{ij,t-1} + \xi_{jm})\right)}{\sum_{j'} \exp\left(\mu(V^{SP}_{ij',t} + \lambda y_{ij',t-1} + \xi_{j'm})\right)} \right)^{y^{SP}_{ij,t}} \right] \rho_m \Bigg\} \end{aligned} \tag{11}$$

$$V^{RP}_{ij,t} = \tau_{ij} + \sum_h \beta_h X^{RP}_{ijh,t} + \sum_g \gamma_g W^{RP}_{ijg,t} \tag{12}$$

(1) $V_{ij,t}^{SP}$ for existing travel mode

$$V_{ij,t}^{SP} = \tau_{ij} + \phi_j^{SP} + \sum_h \beta_h X_{ijh,t}^{SP} + \sum_k \varphi_k Z_{ijk,t}^{SP} \tag{13}$$

(2) $V_{ij,t}^{SP}$ for not-yet-existing travel mode

$$V_{ij,t}^{SP} = \psi_j^{SP} + \sum_h \beta_h X_{ijh,t}^{SP} + \sum_k \varphi_k Z_{ijk,t}^{SP} \tag{14}$$

Taste variation parameter τ_{ij} follows a non-parametric distribution with location parameter ξ_{jm} and weight parameter ρ_m (ρ_m>0, $\Sigma_m(\rho_m)$=1), where subscript m indicates the m'th mass point. Since the mass point approach is only used to represent individual taste variation, ϕ_j^{SP} and ψ_j^{SP} are assumed to be invariable independent of the number of mass points.

SEP_DMP differs from conventional models in several ways. The first and the most distinguished feature is that it accommodates an alternative-specific constant into individual taste variation and unobserved SP reporting bias based on SP/RP panel data. In this sense, SEP_DMP is an extension of Morikawa's (1989) original SP/RP combined model. The second is that it adopts the mass point approach to represent individual taste variation. Finally, it introduces previous RP choice results into the SP model to correct panel-conditioning bias, which is another major bias existing in panel surveys.

5. MODEL ESTIMATION AND DISCUSSION

5.1 Summary of SP Panel Data

In order to predict commuter demand for Astram Line, opened at the time of the 12^{th} Asian Game in 1994, the Transport Studies Group of Hiroshima University conducted a 5-wave SP panel survey (i.e., the years of 1987, 88, 90, 93, 94). The SP panel survey considers passenger car and bus as the alternative modes of Astram Line. Each respondent was requested to participate in the panel as much as possible. Sample refreshment was also done to cover for samples dropped out during the course of the panel survey.

In the survey conducted before the opening of Astram Line, the respondents were asked to answer several hypothetical choice questions, meanwhile, report their actual choice modes for commuting. After its opening, these panel respondents were asked again to report their actual travel modes including Astram Line. Although multiple SP choice results were obtained in the survey from most of the respondents, they are regarded as single-choice results from different respondents without loss of generality.

The effectiveness of SEP_DMP is examined in terms of internal and external validities. The internal validity (i.e. goodness-of-fit index) is examined based on pre-opening data. The external validity (i.e. temporal transferability) is examined by using the parameters estimated based on pre-opening data to predict post-opening choice behavior. The data collected in 1988 was excluded because its sampling method differed from that of other waves. As a result, 904 SP mode choice cases from 226 panel respondents were obtained for this study.

5.2 Model Estimation

The following conventional models are also estimated for the sake of comparison.

(1) SP model: a multinomial logit model based on only SP panel data
(2) SP_D: SP model incorporating previous RP choice results $y_{ij,t-1}$
(3) RP/SP: equation (4)
(4) RP/SP_D: RP/SP model incorporating previous RP choice results $y_{ij,t-1}$
(5) SEP_RP/SP: RP/SP model introducing equations (7), (8) and (9)
(6) SEP_RP/SP_D: SEP_RP/SP incorporating previous RP choice results $y_{ij,t-1}$
(7) SEP_MP: SEP_DMP model without previous RP choice results $y_{ij,t-1}$

The model estimation results are given in Table 1. Since models (3) and (5), or models (4) and (6) have the same estimation results (parameters and Rho-bar squared) except for the constants, only the results of models (5) and (6) are shown in Table 1. Summing taste variation and SP reporting bias from model (5) or (6), one can obtain the constant for model (3) or (4). These two constants are not statistically significant.

5.3 Interpretations of Estimated Parameters

Most of the estimated parameters have the expected behavioral signs and are statistically significant.

(1) The absolute values of individual attributes and level-of-service parameters from models (5) and (6) are larger than the ones from models (1) and (2). This implies that pooling taste variation and SP reporting bias may underestimate the influence of explanatory variables.

(2) The parameters for taste variation in models (7) and (8) are statistically significant, while those of models (5) and (6) are not. This implies that average taste variation cannot reflect individual unobserved heterogeneity, thereby leading to erroneous evaluation.

(3) Positive parameters for state dependence suggest that individuals tend not to choose the new travel mode without delay. Ignoring this behavioral inertia is one of the main reasons for panel-conditioning bias. Inversely speaking, introducing state dependence (i.e. reliable RP choice results in the past) can correct this bias.

(4) Scale parameters become smaller in order of models (5), (6), (7) and (8). This means that conventional models underestimate variance of error for the SP utility function, and consequently overestimate the demand for the new travel mode.

(5) The absolute values of parameters for gender and age in models (7) and (8) are larger, inversely, and the one for employment status is smaller than the ones from other models. This implies that introducing individual unobserved heterogeneity based on the mass point approach results in considering the effect of individual attributes.

Table 1. Model Estimation and Evaluation Results

	SP (1)	SP_D (2)	SEP_RP/SP (5)	SEP_RP/SP_D (6)	SEP_MP (7)	SEP_DMP (8)
Individuals' attributes for Astram and bus:						
Gender (male=1, female=0)	-1.193(5.76)**	-0.804(3.50)**	-2.054(9.45)**	-1.924(8.67)**	-5.319(8.86)**	-10.93(4.84)**
Age (years)	0.052 (6.26)**	0.041(4.66)**	0.081(8.72)**	0.077(8.02)**	0.236(10.4)**	0.204(5.65)**
Employment status (employed=1, non=0)	-0.090(0.15)	0.032(1.39)	-2.119(3.42)**	-2.170(3.41)**	-1.156(1.63)	0.905(0.47)
Level-of-service:						
Travel time for three modes (min)	-0.003(3.16)**	-0.003(3.21)**	-0.012(3.83)**	-0.014(3.34)**	-0.016(3.05)**	-0.016(4.10)**
Travel cost for three modes (yen)	-0.001(3.74)**	-0.001(4.78)**	-0.004(13.4)**	-0.004(13.8)**	-0.007(12.9)**	-0.007(11.6)**
(SP) access time for Astram (min)	-0.003(3.37)**	-0.003(3.53)**	-0.010(3.64)**	-0.010(3.08)**	-0.016(4.05)**	-0.017(3.81)**
State dependence (λ)		0.953(15.8)**		3.129(3.77)**		2.668(3.94)**
Taste variation for car:						
Weight parameter for mass point 1: ρ_1					0.125(4.53)**	0.376(7.55)**
Position parameter for mass point 1: ξ_1			0.086(0.14)	-0.079(0.12)	14.45(13.4)**	-2.845(1.38)**
ρ_2					0.526(13.6)**	0.418(6.34)**
ξ_2					1.937(2.36)**	1.054(0.64)
ρ_3					0.349(10.2)**	0.207(6.32)**
ξ_3					7.750(8.85)**	10.37(3.42)**
SP reporting bias for car(ϕ_{car}^{SP} in equations (8),(13))			0.111(0.35)	0.630(1.31)	-0.592(1.07)	0.267(0.93)
SP constant for car (π_{car}^{SP} in equation (6))	1.463(2.44)*	1.456(4.56)**				
SP constant for Astram (π_{Astram}^{SP} in equation (6))	0.760(8.32)**	1.250(18.1)**				
SP constant for Astram (Ψ_{Astram}^{SP} in equation (9))			1.965(4.20)**	3.995(3.77)**	3.234(6.16)**	5.432(5.65)**
Scale parameter (μ)			0.363(5.33)**	0.308(4.24)**	0.226(12.7)**	0.187(8.43)**
Internal validity:						
Initial log likelihood	-993.15	-993.15	-1619.80	-1619.80	-1619.80	-1619.80
Final log likelihood	-899.01	-861.21	-1295.16	-1253.68	-1100.73	-1083.17
Adjusted Rho-bar squared	0.091	0.129	0.197	0.223	0.317	0.328
External validity:						
Absolute prediction error (%)	23.4	21.6	7.6	5.7	4.4	0.6
Sample size	904		1808			

(t scores in parentheses; *: significant at 5 %; **: 1 %)

5.4 Internal Validity

Comparing models (3) and (5), or models (4) and (6), it is clear that separating taste variation and SP reporting bias does not improve the internal validity of models. However, introducing state dependence, unobserved heterogeneity and combining RP and SP data tend to improve model accuracy (combining RP and SP data is particularly suitable). The other way is to introduce unobserved heterogeneity and state dependence in order. Therefore, SEP_DMP is superior to other models in terms of internal validity.

5.5 External Validity

Since service to the city center by bus was terminated with the opening of Astram Line, actual choice results for buses in 1994 are not available. In order to examine the temporal transferability of SEP_DMP, an extremely low level-of-service is pre-defined for buses. Besides that, all separated SP reporting biases are eliminated from the models. Pooled values (i.e. constants) of taste variations and SP reporting biases without the separation are adopted for the models in predicting the demand of Astram Line.

The external validity is evaluated based on an absolute prediction error index as follows:

$$\text{Absolute prediction error (\%)} = \sum_{m} \text{abs}\{AS_m - ES_m\} \tag{15}$$

where AS_m and ES_m are actual and estimated shares for travel mode m, respectively.

The smaller the index, the better the external validity of the model. The index for each model is given at the bottom of Table 1. The indices for models (3) and (4) are 20.8% and 16.1%, respectively. The estimated shares by each prediction model and actual shares are compared in Figure 5.

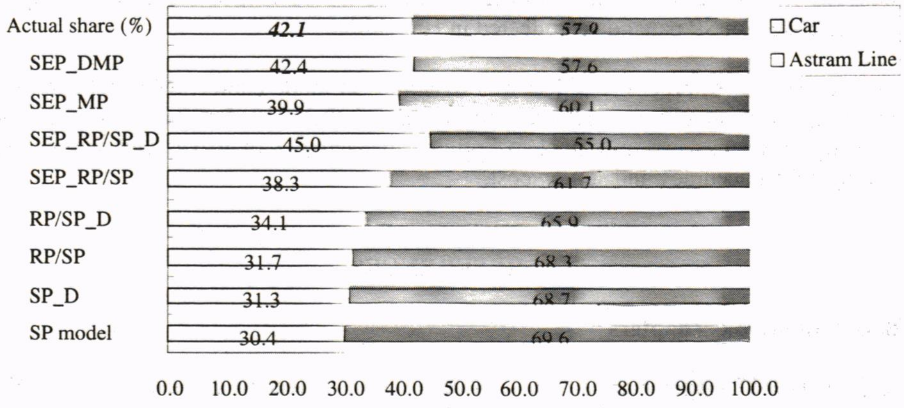

Figure 5. Estimated and Actual Shares (%)

Separating taste variation and SP reporting bias can improve the prediction accuracy of models by more than 10%, while other methods can only improve it by about 3~5%. In other words, the separation of these two factors is the best way to improve the prediction accuracy of a model, unlike the case of internal validity. For the mot part, introducing state dependence to remove panel-conditioning bias has a lower influence on prediction than other factors. This probably results from the fact that SP reporting bias is larger than panel-conditioning bias. Combining RP and SP data can improve the external validity of a model almost as effectively as the introduction of taste variation. Furthermore, the prediction error for SEP_DMP is 22.8% smaller than the SP model, which is a basic prediction model based on SP data. Therefore, it can be concluded that SEP_DMP is superior to any other model in terms of external validity.

6. CONCLUSIONS

Policy makers and analysts often confront issues such as how to predict the future demand of an alternative with new attributes for which there is no RP history and/or for which one cannot safely forecast by analogy to existing alternatives, as well as how to measure user behavioral change when new attributes are introduced to influence the choice of existing alternatives (e.g., the provision of route guidance information based on ITS technologies). Unlike the RP approach, the SP approach can measure human preference and choice under such not-yet-existing conditions.

However, since the SP approach deals with hypothetical situations, it includes more biases than the RP approach. Even more biases arise when a SP panel survey is conducted. Due to these biases, SP-based prediction models tend to overestimate the future demand of not-yet-existing alternatives. Up to now, several methods for correcting these biases have been proposed from different perspectives.

This paper developed a new dynamic mode choice model (i.e. SEP_DMP) by, (a) extending Morikawa's (1989) original SP/RP combined model to separate taste variation and SP reporting bias, (b) introducing previous RP choice results to represent state dependence and accordingly correct panel-conditioning bias, and (c) applying the mass point approach to represent individual taste variation. Furthermore, SP reporting bias was removed from the prediction model. The internal and external validities of the newly developed model were empirically confirmed based on SP panel data collected in Hiroshima.

On the other hand, to precisely reflect true dynamics in mode choice, SP panel surveys with much more waves should be conducted. Since collecting this kind of panel data is, however, very costly, it seems very important to optimize the number of waves and sample size by balancing model accuracy and survey cost.

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