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PREDICTION ACCURACY OF DYNAMIC SP MODELS

AKIMASA FUJIWARA
Hiroshima University
Graduate School for International Development and Cooperation
Kagamiyama 1-5-1, HIGASHI-HIROSHIMA 739-8529, JAPAN

YORIYASU SUGIE
Hiroshima University
Graduate School for International Development and Cooperation
Kagamiyama 1-5-1, HIGASHI-HIROSHIMA 739-8529, JAPAN

Abstract

Dynamic models based on SP panel data include two kinds of biases: SP response biases and the attrition bias of panel data. This study empirically examines the prediction accuracy of dynamic SP models which correct these biases. The models which deal with the effects of state dependence are proposed as a substitute for traditional cross-sectional SP models. It is shown that dynamic SP models which treat the cumulative effects of state dependence are capable of finely tuning the prediction power of SP models for the actual shares observed at a single time point.

INTRODUCTION

A Stated Preference (SP) survey examines an individual's choice intention within a hypothetical situation. It is well known that SP data is useful to predict the future demand for an as yet nonexistent transport system (Hensher, 1994). Revealed Preference data (RP data), which is the traditional travel diary data, is not available in this case. Furthermore, SP data has many advantages in model building, for example, the choice set can be clearly specified; multi-collinearity across explanatory variables can be prevented; attributes are free from measurement errors; qualitative factors such as comfort, reliability and safety can be easily incorporated; and multiple responses can be obtained from a respondent (Morikawa, 1989).

Nevertheless, it is also common knowledge that SP does not always coincide with actual travel behaviour because of biases inherent in SP data (Bonsall, 1985). These SP biases might produce misleading results for travel demand forecasting when the new transport service is introduced. In addition, an individual's SP tends to be variant over time depending on changes not only in observed factors such as travel attributes and socio-demographic characteristics but also in unobserved factors such as the public attitude towards transport policy. Consequently, the travel demand predicted by SP models may not be stable over time. There is no doubt that these disadvantages impair the application of SP data to practical transportation planning in Japan.

Dynamic models based on panel data have the capacity to resolve these problems. Models which incorporate a dynamic aspect have recently been receiving increasing attention (Kitamura, 1990). Panel data which trace back changes in an individual's behaviour are especially powerful in analysing the changes in travel behaviour before and after the introduction of new transport policies. The data is useful in dealing with state dependence, serial correlation and heterogeneity in models (Heckman, 1981; Daganzo, and Sheffi, 1982).

Unfortunately, a further critical unsolved problem still remains in the use of panel data. This is the 'sample attrition' problem, in which the number of samples decreases with additional surveys. If the 'stayers' who successively participate in the repetitive survey have different features of travel behaviour from the 'leavers', an attrition bias will arise in the estimated parameters in SP models. Unless the bias is corrected, the model will predict erroneous future demand. This study aims to develop dynamic models using SP panel data to accurately forecast the future modal share for a newly introduced transport system by correcting SP and attrition biases.

The following models are proposed in this paper:

1. Three types of static models are developed based on cross-sectional SP data obtained at each point in time (cross-sectional SP models). The actual travel behaviour at that point is incorporated into the models as RP information in order to correct the biases inherent in SP data. A model with mixed RP and SP data is also developed.

2. Two types of dynamic models are postulated based on SP panel data (dynamic SP models). The effects of state dependence, or the way in which the individual's past behaviour significantly affects his or her present SP, are incorporated into the dynamic models. One model includes only a previous choice result as an explanatory variable, while another includes the entire past behavioural path.

3. The attrition bias underlying these dynamic models is corrected. A weighting method proposed referring to WESML (Weighted Exogenous Sampling Maximum Likelihood) is expanded into complicated panel data obtained at more than two points in time.

As an empirical study, the share of the transport market for the New Transit System in Hiroshima predicted by these SP models is compared with the actual share reported after its opening. It is believed that the results of this study contribute to enhancing the applicability of SP data to travel demand forecasting.

EXISTING CORRECTING METHODS OF BIASES

Correcting methods of SP biases : SP/RP combined estimation approach

Extensive research has been done to ameliorate the reliability of SP data. These can be divided into two categories. The former concerns the methodology of SP survey. Computer-based SP interviewing has been developed to the level where it can be of practical use (Jones, 1989). The latter is the modelling technology of SP data which deals with RP information. The modelling approaches are essentially a scale factor approach (Wardman, 1991) and an SP/RP combined estimation approach.

An SP/RP combined estimation approach has been developed by Ben-Akiva and Morikawa, in which SP and RP data which have mutually compensatory characteristics are combined by incorporating the scale factor μ (Ben-Akiva and Morikawa, 1990). This approach elaborately expands the theory of the well-known scale factor approach. An important difference between the two approaches is that the SP/RP combined estimation model (SP/RP model) simultaneously estimates two equations (i.e. SP and RP models) which have different dependent variables.

Consider a choice model based on random utility theory. The SP/RP model can be defined as follows:

$$U_{in}^{SP} = \beta x_{in}^{SP} + \gamma z_{in}^{SP} + \varepsilon_{in}^{SP} \qquad (1a)$$

$$U_{in}^{RP} = \beta x_{in}^{RP} + \alpha z_{in}^{RP} + \varepsilon_{in}^{RP} \qquad (1b)$$

$$Var(\varepsilon_{in}^{RP}) = \mu^2 Var(\varepsilon_{in}^{SP}) \qquad (2)$$

where U_{in}^{SP} is the utility of individual n for alternative i in the SP model, X is a vector of explanatory variables commonly included in SP and RP data, and Z and W are vectors of explanatory variables obtained from SP and RP data, respectively. α, β and γ are vectors of unknown parameters and ε is an error term in utility function.

The scale factor μ in eqn. (2) adjusts the differences in variance of error terms in the utility functions between the SP and RP models. When $\mu < 1$, the variance of the error term ε_{in}^{SP} in the SP model could be larger than the variance of ε_{in}^{RP} in the RP model, which means that SP data is less reliable than RP.

Ben-Akiva and Morikawa have ascertained that this approach can significantly correct the biases inherent in SP data. Furthermore, Morikawa developed a more sophisticated SP/RP model dealing with the serial correlation between both error terms (Morikawa, 1994).

However, approaches using cross-sectional data cannot controvert the temporal variation of the prediction power of SP models; this paper will therefore propose an alternative approach using a dynamic model.

Correcting methods of panel attrition bias

Attrition bias is caused by the non-random dropping out of survey participants over successive waves of the panel survey. Kitamura and Bovy developed a weighting method by referring to WESML in choice-based samples and examined its effectiveness in the case of two-period panel data (Kitamura and Bovy, 1987). Firstly, probability $A_{n,t-1}$ in which individual n participates consistently in the panel from time (wave) t-1 to t is derived by the attrition model as shown in eqn. (3):

$$A_{n,t-1} = f(\theta, S_{n,t-1}) \tag{3}$$

where θ is a parameter vector to determine the attrition and S is a vector of explanatory variables.

Secondly, probability $A_{n,t}$ from wave t to t+1 is calculated by using the estimated parameters $\hat{\theta}$ in eqn. (3) and the explanatory variables $S_{n,t}$ of individual n at wave t. Then the likelihood function of travel choice model (e.g., mode choice model) is weighted by a reciprocal of $A_{n,t}$. Supposing that the choice probability of alternative i is represented as $P(i|x_{n,t}, \beta)$, the log-likelihood function is given by

$$L^* = \sum_{n \in N} \sum_{i \in J_n} \left[\delta_{in}(1/A_{n,t}) \ln P(i|x_{n,t}, \beta)\right] \tag{4}$$

where N is the number of stayers in the panel, J is the number of alternatives for individual n, x is a vector of explanatory variables in the travel choice model, and β is the parameter vector. δ_{in} is an indicator of travel choice which =1 if the alternative i is chosen, and =0 otherwise. Consequently, information about the eventual travel behaviour of individuals who will leave the panel survey can be highly weighted.

The author is not going to discuss the simultaneous estimation of a model system that consists of an attrition model and travel choice model, because it is beyond the scope of this work. The sequential estimation used in this study will yield consistent but not efficient estimators of the model parameters.

SPECIFICATION OF MODE CHOICE MODEL BASED ON SP PANEL DATA

Cross-sectional SP models

The linear-in-parameters logit model in the context of mode choice will be considered in this paper. The basic form is given as follows:

$$U_{in,t}^{SP} = V_{in,t}^{SP} + \varepsilon_{in,t}^{SP} \tag{5}$$

$$P_{in,t}^{SP} = \exp(V_{in,t}^{SP}) \Big/ \sum_j \exp(V_{jn,t}^{SP}) \tag{6}$$

where $U_{in,t}^{SP}$ is the utility of the SP model, $V_{in,t}^{SP}$ is a measurable (systematic) component $\varepsilon_{in,t}^{SP}$ is an error term of i.i.d. Gumbel and the suffix t indicates the number of waves.

Suppose that SP responses are independent across waves; in that case, cross-sectional SP models can be independently developed at each wave by using maximum likelihood estimation. Three types of cross-sectional models are developed based on cross-sectional SP data.

[Model 1]: a base model with SP data only

$$V_{in,t}^{SP} = \beta_t x_{in,t}^{SP} \tag{7}$$

where $x_{in,t}^{SP}$ is a vector of travel attributes set up in an SP experiment, and β_t is a vector of unknown parameters at wave t and is variant over time.

This is a base model treating only the attributes which are set up in the SP experiment as a set of explanatory variables. This model does not correct SP biases.

[Model 2]: a cross-sectional SP model including current RP information

$$V_{in,t}^{SP} = \beta_t x_{in,t}^{SP} + \alpha_t w_{in,t}^{RP} \quad (8)$$

where $w_{in,t}^{RP}$ is a vector of the explanatory variables representing current RP information and α_t is a vector of unknown parameters.

Model 2 is an SP model explicitly incorporating the individual's existent RP information such as an actually chosen travel mode, in addition to the attributes in Model 1. For example, car users generally tend to prefer a private car to public transport. This model corrects one of the SP biases, namely the 'justification bias' which is induced when the individuals' responses in an SP survey tend to justify their actual travel behaviour.

[Model 3]: an SP/RP combined estimation model

Model 3 is the SP/RP model as shown in eqns. (1a), (1b) and (2). The log-likelihood function for the simultaneous estimation of eqns. (1a) and (1b) is rewritten as eqn. (9).

$$L^* = \sum_{n=1}^{N^{SP}} \sum_{i=1}^{J_n^{SP}} \left(\delta_{in}^{SP} \ln P_{in}^{SP}\right) + \sum_{n=1}^{N^{RP}} \sum_{i=1}^{J_n^{RP}} \left(\delta_{in}^{RP} \ln P_{in}^{RP}\right) \quad (9)$$

where N^{SP} and N^{RP} are the sample sizes in SP and RP data respectively.

Dynamic SP models

Dynamic SP models which deal with the effects of state dependence are developed by including the previous choice behaviour rather than the current behaviour as an explanatory variable in addition to the travel attributes set up in the SP experiment.

It is assumed that the temporal independence of error terms in dynamic models exists in the same as in cross-sectional models. The serial correlation of error terms among waves is as crucial a problem as the state dependence in dynamic models. However, for the sake of simplicity, the point of this study will be limited to state dependence of dynamic models. How to tackle the serial correlation is discussed in a previous study concerning unobserved heterogeneity in mode choice (Sugie *et al*, 1996).

According to this assumption, the following two types of dynamic models are postulated based on the samples pooled across waves. The joint probability that individual n has a set of choices over time $C_{in}^{SP} = \left\{y_{in,t}^{SP} \middle| y_{in,t}^{SP} = (0,1); i = 1,\ldots,J_n^{SP}; t = 1,\ldots,T_n^{SP}\right\}$ can be expressed as

$$\Pr(C_{in}^{SP}) = \prod_{t=1}^{T_n} P_{in,t}^{SP} = \prod_{t=1}^{T_n} \exp\left(V_{in,t}^{SP}\right) \Big/ \left[\sum_j \exp\left(V_{jn,t}^{SP}\right)\right] \quad (10)$$

where $y_{in,t}^{SP}$ is an indicator of choice result for mode i at wave t, J_n^{SP} is the number of alternatives and T_n^{SP} is the number of waves in the panel survey.

[Model 4]: a dynamic SP model including past RP information

$$V^{SP}_{in,t} = \beta x^{SP}_{in,t} + \lambda \delta^{RP}_{in,t-1} \tag{11}$$

where $\delta^{RP}_{in,t-1}$ is an indicator of travel mode choice with $\delta^{RP}_{in,t-1}=1$ if individual n chooses a car at wave t-1. The parameter vector β is invariant over time.

Model 4 postulates that an individual's SP responses are significantly affected by the result of his or her last choice in the same manner as the current one in the cross-sectional SP models. Supposing that the effects of state dependence are constant and apart from the length of time (duration) after the initial wave, some SP biases (e.g., justification bias) can be corrected by introducing the effect of state dependence as shown in eqn. (11). Note that for the initial or refreshed samples, the second term on the right-hand side of the equation can be omitted because there is no previous information.

[Model 5]: a dynamic SP model including RP information on the entire past behavioural path

$$V^{SP}_{in,t} = \beta x^{SP}_{in,t} + \lambda_i \sum_{t'=1}^{t-1} \left[\delta^{RP}_{in,t'} \exp(\rho_i d_{t'})\right] \tag{12}$$

where d_t is the duration from wave 1 to t, and ρ_i and λ_i are the shape and scale parameters of the exponential function which represents the temporal variations of the effects of state dependence.

It was confirmed in an existing RP panel analysis that the effects of state dependence and habit persistence were significant in vehicle choice and use models (Hensher *et al*, 1992). We assume in model 5 that SP responses are influenced not only by the most recent behaviour but also by earlier behaviours and that the effects of state dependence vary in relation to the time intervals between waves. The nearer the past behaviour, the higher the effects of state dependence. Figure 1 illustrates an example in which the temporal variation of the effect for car choice follows an exponential function with a shape parameter ρ_{car} and a scale parameter λ_{car}. The horizontal axis indicates the length of the duration from the initial wave of the panel survey and the vertical axis indicates the effect of state dependence for car choice. By summing up the effects across all waves, the cumulative effects of state dependence can be measured.

Thus, Model 5 can deal with all participants who have different past behavioural paths simultaneously. Moreover, since the second term on the right-hand side of eqn. (12) is a function of the length of duration d_t, panel data sets with irregular intervals can be used in the models. This is an extremely advantageous improvement to the practical design of a panel survey.

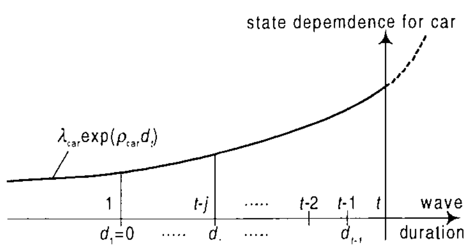


Figure 1 - Temporal variation of the effect of state dependence

Dynamic SP model correcting panel attrition bias

As previously mentioned, a weighting method for attrition bias which has been proposed with two-period panel data is applied to multi-period panel data. It is known that there exists a 'self-selective bias' in SP data. The bias results from the fact that individuals who do not intend to use a newly introduced travel service tend not to cooperate in the survey. This means that SP responses are endogenous to attrition. Therefore, it is reasonable to adopt the weighting method used in the choice-based sample to correct the panel attrition bias.

[Model 6]: a dynamic SP model correcting the panel attrition bias existing in model 5

First, the entire group of respondents is divided into homogeneous groups in terms of the entire past behaviour of participation in the panel. Second, the attrition models (eqn. (3)) from wave t-1 to t are estimated by each group. The binary logit model is given in eqn. (13).

$$A_{nk,t-1} = 1/\left[1+\exp\left(\theta_k S_{nk,t-1}\right)\right] \tag{13}$$

where suffix k represents the group.

Finally, a reciprocal of the attrition probability $A_{nk,t-1}$ for the samples of mode choice models at wave t is used as a weight in the log-likelihood function for the dynamic mode choice models as follows:

$$L^* = \sum_n \sum_t \sum_k \left[\delta_{in}\left(1/A_{nk,t}\right)\ln \Pr\left(C_{in}^{SP}\right)\right] \tag{14}$$

Now, we can correct the attrition bias underlying in the dynamic SP models for all groups simultaneously.

OUTLINE OF SP PANEL DATA IN HIROSHIMA

An SP panel survey was carried out at five different points in time, i.e., 1987, '88, '90, '93 and '94, in order to examine the variations over time in the individual's choice intention for the New Transit System (NTS) in Hiroshima. In addition, an RP survey was carried out to understand actual choice behaviour three months after the opening of the NTS. The objects of the panel survey were commuters and school travellers aged fifteen years or over who lived in a residential area along the NTS line.

The questionnaire for the SP panel survey consisted of two stages: i) details of the present mode choice behaviour (RP) and ii) the SP experiment. An example of the SP cards used in the experiment is drawn in Figure 2. Respondents were asked to rank three travel modes (i.e., car, bus and NTS) in order of their preference according to hypothetical levels of travel attributes (e.g., in-vehicle time, waiting time, access time, cost and crowdedness in the vehicle). The combination of the travel attributes, which had three levels, was selected on the basis of a fractional factorial design. As a result of temporal variations in the actual travel services and the progress of the NTS project, these levels varied across five waves in the panel survey. A more complete description of the SP panel survey is given in our previous paper (Fujiwara and Sugie, 1996).

In the RP survey, which was carried out after the opening of the NTS, the respondents reported their chosen travel modes prior to the opening in addition to the actual mode choice behaviour.

The results of the panel survey are summarised in Figure 3. Respondents who travelled to the centre of Hiroshima by car or bus were selected for this analysis. This criterion can screen out the respondents whose actual mode choice situations are different from the hypothetical situations presented in the SP experiment. The number of responses was calculated by multiplying the number of respondents by three (excluding uncompleted responses), because three SP responses were obtained from each respondent according to the different situations at each wave.

At the second wave or later, the further sampling was carried out to supplement the number of the leavers from the survey, so that a constant level of 300 samples was maintained. A total of 310 responses in the RP survey after the opening was also used in this analysis. Since the bus services bound for the centre of town were abolished at the same time as the beginning of the NTS operation, there is no bus user shown in the last column of Figure 3.

The four-period panel data will be used to develop mode choice models in this analysis. The second wave will be omitted from this analysis, because many respondents dropped out at that wave due to the difference of sampling methods. The prediction accuracy of the SP models will then be examined by comparing the actual RP data in the following sections.

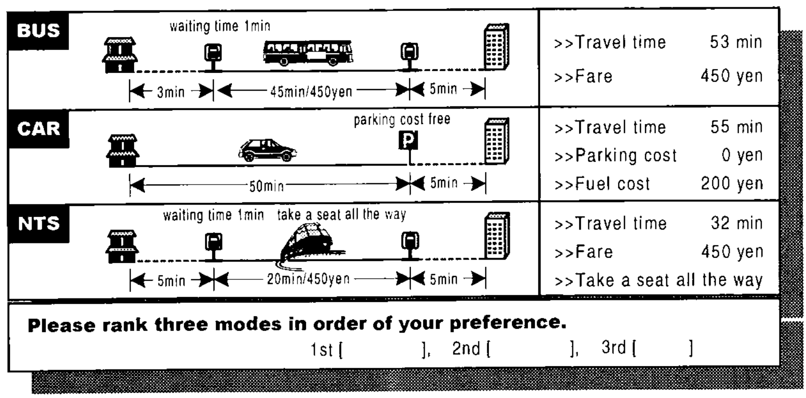
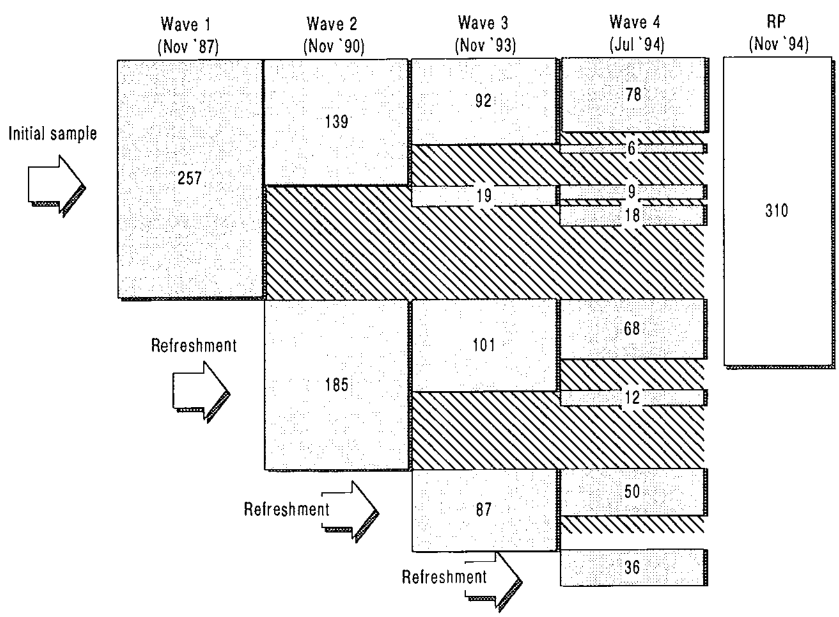


Figure 2 - An example of SP cards



	Wave 1	Wave 2	Wave 3	Wave 4	RP
# of samples	257	324	299	277	310
# of responses	716	925	855	761	310
# of car users	112	156	144	133	139
# of bus users	156	168	155	144	---
# of NTS users	---	---	---	---	171

Figure 3 - SP panel samples used in this study

EMPIRICAL ANALYSIS

Estimation results of SP models

Cross-sectional SP models

The estimation results of models 1, 2 and 3 based on cross-sectional SP data are shown in Tables 1, 2 and 3, respectively. Concerning model 1 in Table 1, the goodness-of-fit indices of models (i.e., $-2\left[L(0)-L(\hat{\beta})\right]$ and adjusted likelihood ratio indices) and the significance levels of the model parameters tend to declining from wave 1 to wave 5. The estimated parameters are variant over time. One probable reason for these variations is the variance in the composition of the sample across waves. Another reason may be that the individuals responded more faithfully to the levels of travel attributes set up in the experiment at the earlier wave. As the opening of the NTS came closer, the respondents might have been affected more significantly by the omitted attributes in the experiment or the unmeasurable biases, e.g., the policy response bias in which some respondents intentionally respond to affect a plan or policy. Further work will be required to examine the other reasons for temporal variation of cross-sectional SP models.

The goodness-of-fit indices of model 2 in Table 2 are higher than those of model 1 at every wave. Incorporating a current travel mode is remarkably effective in improving the goodness-of-fit of SP models.

The α, β and γ in the first column of Table 3 correspond to the parameter vectors in eqns. (1a) and (1b) of the SP/RP models. In order to compare the parameter estimates in model 3 with those in model 2 (Table 2), the parameter estimates $\hat{\beta}$ and $\hat{\gamma}$ in the SP model must be multiplied by a scale factor $\hat{\mu}$. The differences between the two models are significant in a few parameters $\hat{\beta}$, while insignificant in $\hat{\gamma}$. The estimated scale factors $\hat{\mu}$ are variant over time. The value at wave 3 is somewhat larger than 1.0, in contrast to those at other waves. This implies that the variance of the error term in the SP model is slightly less than that in the RP model at wave 3. Thus, the estimated parameters in the cross-sectional SP models are not temporally stable. This fact leads to a serious disadvantage in the use of models in forecasting travel demand.

Dynamic SP models

Dynamic models are developed by improving model 2 which is the best of all cross-sectional SP models in terms of goodness-of-fit.

Table 4 presents the estimation results of dynamic SP models, i.e., models 4, 5 and 6. The adjusted likelihood ratio index for model 5 into which the cumulative effects of state dependence are incorporated is somewhat higher than that for model 4. Both the shape and scale parameters in model 5 have the expected signs as assumed in Figure 1. The respondents tend to prefer the modes actually chosen at previous waves. The result that the estimated parameter $\hat{\lambda}_{car}$ is larger than $\hat{\lambda}_{bus}$ indicates that the degree of preference of bus users for a bus is higher than that of car users for a car. The estimated parameter $\hat{\rho}_{car}$ is lower than $\hat{\rho}_{bus}$, which means that the slope of the exponential curve for car choice drawn in Figure 1 is not as sharp as that for bus choice. In the case of car choice therefore, the effects of state dependence of the further past behaviour are still more significant with regard to the current SP responses.

The entire group of respondents is divided into seven different groups by the entire past behaviour of participation in the panel survey as follows:

Table 1 - Estimation results of model 1

Variable		Wave 1	Wave 3	Wave 4	Wave 5
Constant	[C]	0.807**	-0.003	0.056	0.241
Constant	[N]	1.977**	0.556	0.428	-0.114
In-vehicle time (min)	[G]	-0.036**	-0.032**	-0.026**	-0.037**
Cost (100 yen)	[G]	-0.200**	-0.262**	-0.217**	-0.229**
Access time (min)	[G]	-0.159**	-0.083**	-0.043	-0.027
Initial likelihood $L(0)$		-786.6	-1016.2	-939.3	-836.0
Maximum likelihood $L(\hat{\beta})$		-661.6	-877.1	-850.3	-768.7
$-2[L(0)-L(\hat{\beta})]$		250.0	278.2	178.0	134.6
Adjusted likelihood ratio		0.156	0.135	0.091	0.078
Number of samples		716	925	855	761

Notes: [C]: Car specific variable, [N]: NTS specific variable, [G]: Generic variable, **: significant at 99% level

Table 2 - Estimation results of model 2

Variable		Wave 1	Wave 3	Wave 4	Wave 5
Constant	[C]	-0.760**	-1.254**	-1.152**	-1.083**
Constant	[N]	1.704**	0.366	0.422	-0.208
In-vehicle time (min)	[G]	-0.047**	-0.036**	-0.028**	-0.039**
Cost (100 yen)	[G]	-0.250**	-0.252**	-0.237**	-0.234**
Access time (min)	[G]	-0.155**	-0.080**	-0.051	-0.024
Current travel mode	[C]	2.878**	2.179**	2.034**	2.374**
Initial likelihood $L(0)$		-786.6	-1016.2	-939.3	-836.0
Maximum likelihood $L(\hat{\beta})$		-567.9	-797.1	-775.5	-674.8
$-2[L(0)-L(\hat{\beta})]$		427.4	438.2	327.6	322.4
Adjusted likelihood ratio		0.275	0.213	0.172	0.190
Number of samples		716	925	855	761

Notes: see Table 1

Table 3 - Estimation results of model 3

Variable		Wave 1	Wave 3	Wave 4	Wave 5
α RP-Constant	[C]	-0.086	0.062	0.176	0.100
γ SP-Constant	[C]	-2.288*	-1.518**	-2.090*	-1.366**
γ SP-Constant	[N]	4.427*	0.601	0.790	-0.115
β In-vehicle time (min)	[G]	-0.042*	-0.031**	-0.072**	-0.039**
β Cost (100 yen)	[G]	-0.533**	-0.332**	-0.356**	-0.298**
γ Access time (min)	[G]	-0.298**	-0.078	-0.114	-0.028
γ Current travel mode	[C]	5.584**	5.150**	4.767**	2.652**
μ Scale factor		0.509**	1.008**	0.425**	0.896**
Initial likelihood $L(0)$		-338.9	-429.9	-396.9	-363.9
Maximum likelihood $L(\hat{\beta})$		-232.3	-327.2	-290.1	-273.4
$-2[L(0)-L(\hat{\beta})]$		213.2	205.4	213.6	181.0
Adjusted likelihood ratio		0.311	0.236	0.266	0.242
Number of samples		973	1249	1154	1038

Notes: *: significant at 95% level, α,β,γ,μ: parameters in eqns. (1a) and (1b), Others: see Table 1

Group A: participated
Group B: participated -> participated
Group C: participated -> participated -> participated
Group D: participated -> participated -> dropped out
Group E: participated -> dropped out
Group F: participated -> dropped out -> participated
Group G: participated -> dropped out -> dropped out

The attrition models of binary logit type are estimated by each group. The explanatory variables consist of four socio-demographic characteristics, namely sex, age, driver licence holder and household size. Table 5 presents the sample size, attrition probability and adjusted likelihood ratio of each model. The goodness-of-fit indices (i.e. adjusted likelihood ratio) of models are higher in group C, E and G, whereas are lower in group A and B. It seems necessary to introduce some other variables to discriminate the participant behaviour in the latter groups.

The estimation result of model 6 which corrects the attrition bias is shown in the last column of Table 4. By comparing it with the result of the uncorrected model 5, the relative ratio of the estimated parameters $\hat{\lambda}_{car}$ to $\hat{\lambda}_{bus}$ (=0.85) in model 6 is higher than that (=0.49) in model 5. The positive high value of the parameter λ_{car} increases the choice probability of car users for a car. Accordingly, the result of these parameters reveals that the under-prediction for a car share, that is the excessive prediction of the NTS share, can be corrected by the weighting in model 6, even if all travel attributes for car and bus are equal to each other.

Table 4 - Estimation results of dynamic SP models

Variable		Model 4	Model 5	Model 6
Constant	[C]	-0.059	0.245**	0.170**
Constant	[N]	0.891**	0.822**	0.528**
In-vehicle time (min)	[G]	-0.028**	-0.028**	-0.031**
Cost (100 yen)	[G]	-0.173**	-0.192**	-0.201**
Access time (min)	[G]	-0.085**	-0.081**	-0.071**
Previous travel mode λ	[C]	1.356**		
λ_{car}	[C]		0.743**	0.709**
ρ_{car}	[C]		0.012**	0.036**
λ_{bus}	[B]		1.507**	0.836**
ρ_{bus}	[B]		0.131**	0.357**
Initial likelihood $L(0)$		-3578.2	-3578.2	-5403.4
Maximum likelihood $L(\hat{\beta})$		-3071.6	-3035.4	-4606.3
$-2[L(0) - L(\hat{\beta})]$		1013.2	1085.6	1594.2
Adjusted likelihood ratio		0.141	0.151	0.145
Number of samples		3257	3257	3257

Notes: [B]: Bus specific variable, Others: see Table 1

Table 5 - Attrition probability and goodness-of-fit of attrition models

Group	Sample size	Attrition pro.	Likelihood ratio
A	526	44.9%	0.030
B	240	33.3	0.085
C	92	15.2	0.421
D	47	87.2	0.501
E	202	84.7	0.400
F	19	52.6	0.093
G	99	81.8	0.343

Prediction accuracy of SP models

Cross-sectional SP models

The hypothetical context of mode choice in the SP experiment is a tri-modal choice, whereas the actual context after the opening is a binary choice between car and NTS. If the property of IIA (independence from irrelevant alternatives) holds in the multinomial logit model (eqn. (6)) for three alternatives, then the model ought to apply to the binary choice context in RP data after the opening. According to the result of the statistical test (Ben-Akiva, and Lerman, 1985), the IIA assumption was not rejected. Consequently, the choice probability for car and NTS will be predicted by using multinomial logit models based on SP panel data in the rest of this paper.

The future choice probability $\widetilde{P}_{in}$ after the opening of the NTS is predicted by using the expected levels of attributes after the opening and their estimated parameters in cross-sectional SP models. For example, the probability predicted by model 1 is expressed as eqn. (15).

$$\widetilde{P}_{in} = \exp\left(\hat{\beta}_t \widetilde{x}_{in}\right) / \left[\sum_i \exp\left(\hat{\beta}_t \widetilde{x}_{in}\right)\right] \qquad (15)$$

where $\hat{\beta}_t$ is the vector of the estimated parameter at wave t and $\widetilde{x}_{in}$ is the vector of the expected levels of travel attributes.

In this section, the actual levels of attributes obtained from RP data after the opening are substituted for the expected ones. Therefore, the prediction error of the attributes is exactly zero and the differences between the predicted and observed modal shares merely reflect the prediction errors caused by the model parameters or model structure.

The predicted share $\hat{S}_i$ for alternative i is estimated by the sample enumeration method as follows:

$$\hat{S}_i = \frac{1}{N^{RP}} \sum_{n=1} \widetilde{P}_{in} \qquad (16)$$

where N^{RP} is the number of samples in RP data.

The modal shares predicted by cross-sectional SP models are compared with the shares S_i actually observed after the opening of the NTS in Table 6 (i.e., 55.2% for the NTS and 44.8% for cars). The shares of the NTS are over predicted by approximately 20% by the base model 1 at each wave. As a result of the temporal instability of the estimated parameters, the absolute errors (AE) of the modal shares predicted by model 1 range between 34% and 44% across waves.

In predicting $\widetilde{P}_{in}$ by using model 2, the actual mode choice results at each wave are used as the expected values of current RP information $w_{in,t}^{RP}$. The NTS shares predicted by model 2 decrease by around 5% compared with those predicted by model 1. It is clear that the prediction accuracy of SP model can be improved by incorporating current RP information into the model.

In the case of model 3, the shares are predicted by using the estimated parameters in the SP model (eqn. (1a)). It can be inferred from the results of model 3 that the SP/RP combined estimation model is not superior to model 2 with respect to the prediction accuracy, regardless of its sophisticated model structure. Judging from the above results and the simplicity in model estimation, it would be more practical to use model 2 rather than model 3 in travel demand forecasting.

Dynamic SP models

Dynamic models, by their nature, have the capacity to predict future changes in travel behaviour. Specifically, the models can be used to forecast the future demand at a certain time point in the special case of $T_n = 1$. The dynamic SP models shown in Table 4 are employed to predict the modal shares after the opening of the NTS in this section in the same way as the cross-sectional models.

As evident from Table 7, the modal shares predicted by the dynamic SP models (i.e., models 4 and 5) are closer to the actual shares than those predicted by the cross-sectional models (i.e., models 1, 2 and 3) given in Table 6. It is found that the effects of state dependence contribute to correcting SP biases. Moreover, the future share for the nonexistent travel mode is more accurately predicted by model 5 than by model 4. However, because an actual mode at only one time point before the opening was collected from each respondent in the RP survey carried out after the openning, the effectiveness of the cumulative effects of state dependence could not appear in this case study.

The share for the NTS predicted by model 6 declines by 1.5% from that predicted by model 5. It is evinced that the correction of the attrition bias is additionally effective on the future prediction of modal shares.

Table 6 - Prediction accuracy of cross-sectional SP models

	Wave	NTS	Car	*AE*
Predicted shares by model 1	1	74.9%	25.1%	39.4%
	3	76.8	23.2	43.2
	4	77.1	22.9	43.8
	5	72.0	28.0	33.6
Predicted shares by model 2	1	69.1	30.9	27.8
	3	71.2	28.8	32.0
	4	73.2	26.8	36.0
	5	67.5	32.5	24.6
Predicted shares by model 3	1	74.2	25.8	38.0
	3	76.5	23.5	42.6
	4	67.5	32.5	24.6
	5	69.5	30.5	28.6
Actual shares after the opening		55.2	44.8	0.0

Note: $AE = \sum_i |S_i - \tilde{S}_i|$

Table 7 - Prediction accuracy of dynamic SP models

	NTS	Car	*AE*
Predicted shares by model 4	66.0%	34.0%	21.6%
Predicted shares by model 5	63.7	36.3	17.0
Predicted shares by model 6	62.2	37.8	14.0
Actual shares after the opening	55.2	44.8	0.0

Note: see Table 5

CONCLUSIONS

Some remarkable results were obtained through this analysis. Part of the biases inherent in SP data can be corrected by incorporating current RP information into cross-sectional SP models. However, the prediction accuracy of cross-sectional SP models is not stable over time. This result means that they may produce misleading predictions of future travel demand.

Therefore, the temporal variations of the effects of state dependence on SP responses is specified by a simple exponential function. A dynamic SP model which treats the cumulative effects of state dependence is capable of finely tuning the prediction power of SP models. Although dynamic SP models have been applied to predict the modal shares at a single time point in this study, the power of the models would even more appear in the case of the prediction of changes in travel behaviour over time.

A correction of attrition bias is required in introducing dynamic SP models to forecasting. The weighting of the log-likelihood of mode choice models using the estimated attrition probability is an intelligible and useful method. It is believed that the results given in this study contribute to enhancing the practical availability of the SP approach.

However, further investigation is necessary to develop correction methods for the attrition bias of panel data. In addition, the reasons why some parameters of cross-sectional SP models are variant still remain unsolved.

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