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Sanko, Nobuhiro  
Morikawa, Takayuki

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Title:

**Temporal Transferability of Updated Alternative-Specific Constants in Disaggregate Mode Choice Models**

Authors:

Nobuhiro Sanko, Takayuki Morikawa

Affiliations and addresses of authors:

Nobuhiro Sanko:

Graduate School of Business Administration, Kobe University, Japan

2-1 Rokkodai-cho, Nada-ku, Kobe 657-8501 Japan

Takayuki Morikawa:

Graduate School of Environmental Studies, Nagoya University, Japan

Furo-cho, Chikusa-ku, Nagoya 464-8603 Japan

Corresponding author:

Nobuhiro Sanko

e-mail: sanko@kobe-u.ac.jp

**Abstract**

Methods of updating disaggregate discrete choice models have been proposed as a means of obtaining better transferability. However, the temporal transferability of models updated for better spatial transferability has rarely been analysed, and the factors affecting temporal transferability have not been determined. This paper deals with one updating method—the use of disaggregate data to update alternative-specific constants—and investigates the factors affecting the temporal transferability of the updated constants.

In the analysis, repeated cross-section data collected in the Chukyo metropolitan area are divided, efficiently generating many application areas. The analysis showed that the factors can depend on regional characteristics and past travel behaviours (inertia), and are anti-symmetric and path-dependent of changes in the level of service.

**Keywords:** Mode choice, disaggregate model, model updating, transferability

## Introduction

While aggregate models had been used to forecast travel demand, a major turning point was reached in 1970s when a practical disaggregate model was developed (Ben-Akiva and Lerman 1985). The advantages of disaggregate models over aggregate models are widely known. One of the advantages is higher transferability. *Transfer* is defined as “the application of a model, information, or theory about behavior developed in one context to describe the corresponding behavior in another context (Koppelman and Wilmot 1982).” *Transferability* is further defined as “the usefulness of the transferred model, information, or theory in the new context (Koppelman and Wilmot 1982).” The advantages of higher spatial transferability can be summarised as follows. 1) A model estimated in one area can be applied to another area for which survey data have not been obtained so long as the two areas have similar contexts. 2) Using a model developed for another area reduces the sizes of both the survey data and the calculation load. 3) The model for an area that contains a previously introduced transport mode can be applied to another area when the transport mode is introduced. 4) A more efficient survey can be designed at the data-sampling stage (Morichi 1995).

The advantages of higher temporal transferability can be summarised as follows. 1) The results are highly predictable. 2) Older models can be updated and reused. 3) Models containing more than one time point can be compared, and temporal changes in decision-making structures can be analysed (Morichi 1995).

Previous studies support the idea that disaggregate transport mode choice models have higher temporal and spatial transferability than conventional aggregate models (e.g., Harata and Ohta 1982; Morikawa et al. 2004). However, no disaggregate model has been perfectly specified, and no model can be expected to be perfectly transferable. As a result, some researchers have attempted to improve model transferability through updating (Atherton and Ben-Akiva 1976). Proposed updating methods include utilising aggregate or disaggregate data to update either alternative-specific constants or all parameters (Bayesian updating), re-estimating all alternative-specific parameters to a new alternative, and re-estimating all parameters using the same set of explanatory variables (Morichi 1995). Actually, quite a few studies have analysed the transferability of updated models, with the following results.

- 1) The transferability of updated models depends upon the contexts, such as area or time points, and it is difficult to determine whether an updated model can be transferred.
- 2) The relative advantages of each updating method depend upon the contexts, such as area or time points, and it is difficult to determine which method is better.
- 3) Some papers discuss factors affecting the transferability of updated models from the viewpoints of the similarity of the transport conditions in the estimation and application contexts, the number of samples used for updating, the fit to the data in the estimation context, and a set of explanatory variables. (See next section.) However, the similarities in the transport conditions for the estimation and application contexts have received little attention and there has been inadequate investigation into which factors—regional characteristics, their changes over time, etc.—affect transferability.
- 4) Most research has focused on either spatial or temporal transferability. Few studies have looked at both. When predicting future transport conditions, models that have been updated for higher spatial transferability must have higher temporal transferability in the application area. However, the temporal transferability of models that have been updated for higher spatial transferability has rarely been studied.

This study examined one of the many proposed updating methods, specifically, a methodology for updating alternative-specific constants utilising disaggregate data. The goal of this study was to gain insight into the temporal transferability of updated models. We updated the constants in order to obtain higher spatial transferability, and then analysed their temporal transferability. We also analysed the factors affecting the temporal transferability, such as regional characteristics and their changes over time. Thus, this study helps to solve issues 3) and 4) above. This paper does not draw conclusions about the transferability or non-transferability of models that use disaggregate data to update alternative-specific constants, and does not discuss the advantages of this methodology over other methodologies. Besides, one of the most significant reasons for the limited number of

transferability studies is the difficulty of obtaining suitable data for analysis. This study overcomes this problem by proposing a methodology in which repeated cross-section data is divided.

### Using disaggregate data to update alternative-specific constants

In this section, we examine the characteristics of alternative-specific constants in disaggregate models, describe the use of disaggregate data to update alternative-specific constants, and review related studies.

The deterministic components of the utility functions of disaggregate models can be expressed by the level of service, socio-economic variables, and alternative-specific constants. The first two variables can differ between samples, but the last is common to all samples. Alternative-specific constants express an average utility, which is not explained by the other variables but is common to all samples for each alternative. In other words, alternative-specific constants are determined mainly by observed sample shares. It is well known that when estimating multinomial logit models with  $N$  alternatives containing  $N-1$  alternative-specific constants, the share calculated by sample enumeration is identical to the sample share (Ben-Akiva and Lerman 1985).

Atherton and Ben-Akiva (1976) have proposed updating alternative-specific constants utilising disaggregate data in the application context. The reason for updating alternative-specific constants is as follows. (Other studies update the constants inter-spatially and inter-temporally for a similar reason.) “The specification of most models contains constant terms to account for factors not explicitly explained by the model. The presence of these constants indicates that in fact the model has not captured all aspects of the choice process and, because these other factors can vary between areas (or, time points), the value of such a constant estimated in one area (or, time point) may or may not be appropriate for another. Therefore, although there is a theoretical basis for transferring the relationships estimated between time, cost, income, automobile availability, and such, there is no such basis for transferring these constant terms” (Atherton and Ben-Akiva 1976).

An example of updating alternative-specific constants for a multinomial logit model is shown in eq. (1), where  $\mu$  and  $\alpha$  are estimated by the maximum likelihood method.

$$P_n(i|C_n) = \frac{\exp\left(\mu\left(\sum_k \beta_k x_{ikn} + \alpha_i\right)\right)}{\sum_{j \in C_n} \exp\left(\mu\left(\sum_k \beta_k x_{jkn} + \alpha_j\right)\right)} \quad (1)$$

where,  $P_n(i|C_n)$  is a probability that individual  $n$  chooses alternative  $i$  from the choice set  $C_n$ ;  $\beta_k$  is a parameter before updating for the  $k$ -th explanatory variable;  $x_{ikn}$  denotes an attribute value of the  $k$ -th explanatory variable of individual  $n$  for alternative  $i$ ;  $\mu$  represents a coefficient to update the scale of utility functions ( $\mu$  can be called *utility scale* and sometimes can be set to one); and  $\alpha$  is alternative specific constants to be updated.

As for existing studies on updating alternative-specific constants to improve spatial transferability, Atherton and Ben-Akiva (1976) updated alternative-specific constants and a utility scale and evaluated the transferability based on likelihood ratio indexes and the share prediction. They argued that when the model had higher transferability before updating, the resulting benefit was smaller. They also discussed the number of samples required for updating. On the other hand, Koppelman and Wilmot (1982) concluded from disaggregate and aggregate measures that model transferability was substantially improved when the alternative-specific constants were updated. Harata and Ohta (1982) updated alternative-specific constants and a utility scale and stated that the updated model was more transferable based on the likelihood ratio indexes. They also reported that, in their case study

areas, the utility scale was not changed significantly. Morichi et al. (1985) suggested the possibility of obtaining higher transferability by updating alternative-specific constants and a utility scale when the estimation and application contexts have similar ratios of parameters. Their suggestion is based on disaggregate and aggregate measures. They also analysed transferability from the viewpoints of the number of samples required for updating and a set of explanatory variables in the model. In summary, many of the above studies show that updating alternative-specific constants and/or a utility scale results in higher spatial transferability. However, these studies do not mention the temporal transferability of the updated models.

As for existing studies that updated alternative-specific constants to improve temporal transferability, Karasmaa and Pursula (1997) updated alternative-specific constants and a utility scale, then used log-likelihood values to analyse the transferability. They concluded that the values were stable over the number of samples used for updating. Badoe and Miller (1995) used disaggregate and aggregate indexes to show that updating alternative-specific constants improved model transferability and that updating both the constants and a utility scale further improved the transferability. This suggests that alternative-specific constants and the utility scale may not be stable inter-temporally. They also developed a number of models that considered a set of explanatory variables and segmentation, and compared the validity of updating the constants and the utility scale. McCarthy (1982) developed a model before the introduction of BART (Bay Area Rapid Transit), then updated the BART-related parameters, including the BART alternative-specific constant, and analysed the temporal transferability of the updated model to the data collected after the updating. Chi-squared tests showed that the transferability of the updated model was not low, but that transferability was better when the alternative-specific constant was updated again using the data collected after the updating above. In addition, the paper pointed out that the model could be transferred to a population with similar alternatives and socio-economic characteristics. In summary, many of the above studies show that updating alternative-specific constants and/or a utility scale results in higher temporal transferability. This implies that alternative-specific constants and a utility scale are not transferable even to the same area. However, it is not clear what kinds of regional characteristics and their changes over time affect temporal transferability, since most transferability studies focus on very limited areas and time points.

As mentioned above, Atherton and Ben-Akiva (1976) and others have pointed out the importance of transferability analysis of alternative-specific constants. If this paper provides insights into the factors affecting the temporal transferability of alternative-specific constants that have been updated to improve spatial transferability, as well as insights into the direction of the changes over time in the alternative-specific constants, then these findings can be useful to both researchers and practitioners.

## Methodology

This study analyses repeated cross-section data collected at two time points, T1 and T2. An original model, in which all parameters other than constants are assumed to be transferable, is estimated using all data collected in the entire study area in T1. Application areas are set as origin-destination (OD) pairs generated by dividing the study area into a number of zones. Accordingly, many application areas are effectively created. Here, the methodology is explained using a binary logit model for simplicity, but the methodology itself can be applied to other models. Fig. 1 shows the steps.

\*\*\*\*\* Fig. 1 \*\*\*\*\*

- 1) Develop a binary logit model (on a trip basis) in which a constant is included in one of two alternatives, using all data collected in the entire study area in T1. The model developed in step 1) is hereinafter called the original model.
- 2) Assuming spatial transferability of all parameters other than the constant, estimate an alternative-specific constant for the original model (on a trip basis) for each OD pair, using the data for the corresponding OD pair in T1.

- 3) Assuming temporal transferability of all parameters other than the constant, estimate an alternative-specific constant for the original model (on a trip basis) for each OD pair, using the data for the corresponding OD pair in T2.
- 4) Investigate the differences in the updated constants (constants updated using T2 data minus constants updated using T1 data) for each OD pair. Conduct regression analysis on an OD pair basis when the dependent variable is the difference and the independent variables are the characteristics of the OD pairs.

When the entire study area is divided into  $n$  zones,  $n(n+1)/2$  OD pairs are generated, and the constants are updated  $n(n+1)/2$  times in steps 2) and 3). The constant estimated in step 1) includes various factors not explained by the other variables for the entire study area. However, the factors can vary across areas. The constants updated in step 2) include factors not explained by the other variables in the corresponding OD pairs if the parameters other than the constant are transferable<sup>1</sup>. If the updated constants have perfect temporal transferability, then the updated constants estimated in steps 2) and 3) must be identical. In other words, an increased constant implies an increase in the factors not explained by the other explanatory variables, thereby promoting the selection of an alternative that includes the constant. On the other hand, a decreased constant discourages the selection of an alternative that includes the constant.

Incidentally, if the parameters of the explanatory variables are not transferable, the transferability of the updated constants can be affected. Assuming that the parameters of the explanatory variables other than an alternative-specific constant are transferable does not insure their transferability. However, this study follows a standard methodology for updating alternative-specific constants, assuming transferability of the other parameters, and analyses the transferability of only the constant. Some studies update both the constant and a utility scale, but in this study, in order to emphasise the transferability of the constant, the utility scale was not updated.

## Data

The person-trip survey data (household travel survey data) were collected in the Chukyo metropolitan area in 1971 and 1991 and consisted of two-time-point repeated cross-section data. The Chukyo metropolitan area is the third-largest metropolitan area in Japan and the city of Nagoya is at its centre. The survey covered an area of 4,096 km<sup>2</sup> in 1971 and 5,173 km<sup>2</sup> in 1991. In 1971, the population of the area was 6.11 million. In 1991, it was 8.10 million, 2.16 million of which resided in Nagoya. In this paper, we examined the 1971 area, since the 1971 area is part of the 1991 area. However, the zoning system for 1991 was used since the 1991 system and related information was much easier to access.

The data were constructed according to the procedure shown in the previous section. The study area was divided into 86 zones, 16 of which were in Nagoya. Two alternative transport modes were considered: public transit (rail and bus) and auto. Travel time between each OD pair for each alternative was an average of travel times reported by the trip makers. Only the 1991 cost data are available to authors. The cost data for 1971 were calculated by considering the 1991 cost and price increases between 1971 and 1991<sup>2</sup>. Trips with identical

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<sup>1</sup> Each OD pair is part of the entire study area mentioned in step 1). The spatial transferability described in step 2) is not transferability to a completely different area, but is transferability in the broader sense. When practitioners analyse the transport behaviour of a specific OD pair, they sometimes develop models with samples from a much broader area that includes that OD, and update alternative-specific constants using the data for that OD. From this point of view, the insights described in this study are useful to practitioners.

<sup>2</sup> Price data for transit service in 1991 were set to 400% of those in 1971, by taking into consideration changes in the fare for travelling 10 km and the starting fare. Fares based on reports published by the Japanese government. Price data for automobiles in 1991 were set to 200% of those in 1971, by taking into consideration changes in the petrol price and petrol mileage. Petrol price and mileage based on reports published by the Japanese government.

origins and destinations were excluded due to the low reliability of the travel time and cost data.

### Mode choice model

A binary logit model (the choice between transit and auto) using 1971 data on a trip basis was developed. The results are shown in Table 1. To reduce computation time, 10,000 samples were randomly selected. The cost variable was standardised using the hourly wage published in reports by the Japanese government<sup>3</sup>. Trip purpose information was adjusted: a *returning home trip* after a *commuting trip* was considered a *commuting trip*, while a *returning to office trip* after a *business trip* was considered a *business trip*. All parameter estimates satisfy the 5% level of significance with the expected signs. A rho-squared-bar index shows that the model has a good fit with the data. We also estimated the 1991 model using the same set of explanatory variables as a reference<sup>4</sup>. The results show that all parameter estimates satisfy the 5% level of significance except for “employed person dummy (A).” Since we cannot know in 1971 which parameters will be significant in 1991, it is reasonable to ignore the level of significance of the 1991 model.

\*\*\*\*\* Table 1 \*\*\*\*\*

### Analysis of the temporal transferability of updated constants

Many studies use the following criteria for evaluating transferability: 1) a significance test of parameter equality (*t*-test); 2) disaggregate level criteria based on likelihood-related indexes calculated using log-likelihood; and 3) aggregate level criteria based on share differences (Morichi 1995). This study, however, focused on constant differences, since the goal of the study is to analyse the types of regional characteristics and their changes over time that can cause the constant to increase or decrease. This section analyses: 1) significance differences in updated constants (preliminary analysis before examining constant differences); 2) differences in updated constants, paying attention to specific regional characteristics, and; 3) differences in updated constants using regression analysis.

#### Significance differences in updated constants

This analysis statistically tests the differences in constants updated at two time points. An asymptotical *t*-test is conducted using eq. (2).

$$\frac{\alpha_{od}^{91} - \alpha_{od}^{71}}{\left(Var(\alpha_{od}^{91}) + Var(\alpha_{od}^{71})\right)^{1/2}} \quad (2)$$

where,  $\alpha_{od}^{91}$  and  $\alpha_{od}^{71}$  are the constants updated using 1991 and 1971 data, respectively, for OD pair *od*;  $Var(\alpha_{od}^{91})$  and  $Var(\alpha_{od}^{71})$  are the corresponding variances of the constants. The results are summarised in Table 2, which divides them into the following three ODs: a) both origin and destination are in Nagoya; b) either origin or destination is in Nagoya; and c) neither origin nor destination is in Nagoya.

\*\*\*\*\* Table 2 \*\*\*\*\*

A comparison of updated the constants using 1971 data and those using 1991 data (numbers without square brackets in Table 2) shows that a number of OD pairs have

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Transit cost data were weighted averages based on the number of trip makers using rail and bus. A method for generating 1971 cost data seems less reliable, but the authors introduce it in order to exclude biases that may be included in the constant.

<sup>3</sup> 323.5 JPY/hr in 1971 and 1,605.3 JPY/hr in 1991 are used.

<sup>4</sup> \*\*\*\*\* Appendix Table 1 \*\*\*\*\*



significantly different updated constants. In OD pairs in which the origin or destination or both is in Nagoya (columns a) and b) in Table 2), the 1991 constant is generally larger than the 1971 constant. In other OD pairs in which neither the origin nor the destination is in Nagoya (column c) in the Table 2), the 1991 constant is generally smaller than 1971 constant. These characteristics are analysed in greater detail later in this section.

The constant in the original model was then compared to the constants updated using 1991 data (numbers in square brackets in Table 2) and  $\alpha^{71}$  was used instead of  $\alpha_{od}^{71}$  in eq. (2). The results show that fewer constants are significantly different when the constants are updated using 1971 data, implying that these constants are more transferable than that of the original model.

Although we wish the reader to pay more attention to the constant differences, both disaggregate and aggregate analyses are conducted. Both analyses support that updated constants are more transferable as shown below.

First, the following example of disaggregate analysis compares the log-likelihood values, which are the bases of the disaggregate transferability measures. Log-likelihood  $L^{91}(\theta^{71})$  is calculated by applying  $\theta^{71}$  to the 1991 data, where  $\theta^{71}$  denotes estimates using the 1971 model. (The constant is estimated in the original model and corresponds to step 1) in the “Methodology” section.) Similarly, log-likelihood  $L^{91}(\theta_{up}^{71})$  is calculated by applying  $\theta_{up}^{71}$  to the 1991 data, where  $\theta_{up}^{71}$  denotes estimates using the 1971 model. (The constants are updated and correspond to step 2) in the “Methodology” section.) The relationships between these two log-likelihoods are shown in Table 3.  $L^{91}(\theta^{71}) < L^{91}(\theta_{up}^{71})$  means that the updated model has better transferability, while  $L^{91}(\theta^{71}) > L^{91}(\theta_{up}^{71})$  means that the updated model has worse transferability. The results show that, in the majority of OD pairs,  $L^{91}(\theta_{up}^{71})$  is greater than  $L^{91}(\theta^{71})$ , implying that models with updated constants are more transferable.

\*\*\*\*\* Table 3 \*\*\*\*\*

Next, the following example of aggregate analysis of the binary choice model compares prediction errors for the transit share.  $S(\theta^{71})$  is a share of the transit and is calculated by applying  $\theta^{71}$  to the 1991 data, where  $\theta^{71}$  denotes estimates using the 1971 model. (The constant is estimated in the original model and corresponds to step 1) in the “Methodology” section.) The prediction error for transit is defined as  $E^{71} = |S(\theta^{71}) - S|$ , where  $S$  represents an actual share of transit in 1991. Similarly,  $S(\theta_{up}^{71})$  is a share of the transit and is calculated by applying  $\theta_{up}^{71}$  to the 1991 data, where  $\theta_{up}^{71}$  denotes estimates using the 1971 model. (The constants are updated and correspond to step 2) in the “Methodology” section.) Again, the prediction error is defined as  $E_{up}^{71} = |S(\theta_{up}^{71}) - S|$ . The relationships between these two prediction errors are shown in Table 4.  $E^{71} > E_{up}^{71}$  means that the updated model has better transferability, while  $E^{71} < E_{up}^{71}$  means that the updated model has worse transferability. The result shows that, in the majority of OD pairs,  $E_{up}^{71}$  is smaller than  $E^{71}$ , implying that models with updated constants are more transferable.

\*\*\*\*\* Table 4 \*\*\*\*\*

Finally, the decision not to update the utility scale can be justified, and the process is

shown in the footnotes<sup>5</sup>.

#### *Differences in updated constants: specific regional characteristics*

This section investigates in greater detail changes in the updated constants, focusing on specific regional characteristics. Two examples of these characteristics are a core metropolitan area with dense public transit infrastructure (Naka ward in Nagoya), and a suburban area with relatively less dense public transit infrastructure (Toyota city centre).

Figs. 2 and 3 depict the updated constants for 1991 minus the updated constants for 1971. OD pairs in which at least 10 samples were obtained in both 1971 and 1991 are coloured in these figures; other ODs are labelled “fewer than 10 samples”<sup>6</sup>. Fig. 2 shows that the updated transit constants have increased in almost all OD pairs, suggesting an increase in the factors promoting transit use that is not explained by the model. The constants have particularly increased to or from zones that are close to railway lines radiating from Nagoya but located a bit far from Nagoya. For the purposes of prediction, transit share can be under-estimated in such OD pairs when constants for 1971 are used. On the other hand, Fig. 3 shows that the updated transit constants have decreased in almost all OD pairs excluding those to or from the Nagoya, suggesting an increase in the factors discouraging transit use that is not explained by the model. For the purposes of prediction, transit share can be over-estimated in OD pairs in which both origin and destination are near each other in suburban areas and constants for 1971 are used.

\*\*\*\*\* Fig. 2 \*\*\*\*\*

\*\*\*\*\* Fig. 3 \*\*\*\*\*

#### *Differences in updated constants: regression analysis*

The analysis in the previous section was limited to two specific areas. In this section, we investigate the factors that have a more general effect on updated constants. In regression analysis of an OD pair, the dependent variable is the updated constants for 1991 minus the

<sup>5</sup> When both the utility scales and the alternative-specific constants are updated, the utility scale is subjected to a following *t*-test using eqs. (A1) and (A2).

$$\frac{\mu_{od}^{91} - \mu_{od}^{71}}{\left(Var(\mu_{od}^{91}) + Var(\mu_{od}^{71})\right)^{1/2}} \quad (A1)$$

$$\frac{\mu_{od}^{91} - 1}{\left(Var(\mu_{od}^{91})\right)^{1/2}} \quad (A2)$$

where,  $\mu_{od}^{91}$  and  $\mu_{od}^{71}$  are the utility scales updated using 1991 and 1971 data, respectively, for OD pair *od*;  $Var(\mu_{od}^{91})$  and  $Var(\mu_{od}^{71})$  are the corresponding variances of the utility scales. The results are summarised in Appendix Table 2, which compares the updated utility scales using 1971 data and 1991 data (numbers without square brackets in Appendix Table 2 using eq. (A1)) and the updated utility scales using 1991 data and the utility scale in the original model (that is, one) (numbers in square brackets in Appendix Table 2 using eq. (A2)). Both results show that the updated utility scales are not rejected in the majority of OD pairs.

\*\*\*\*\* Appendix Table 2 \*\*\*\*\*

<sup>6</sup> Railway network shown in Figs. 2 and 3 for reference purposes includes a few freight-only lines. (Network as of approx. 2002.) The city of Nagoya consists of Naka ward and 15 surrounding zones.

updated constants for 1971, and independent variables are characteristics of the OD pairs. These characteristics can be divided by prediction year (1971) and by the changes from the prediction year to the target year (1991). This analysis shows that the future direction of the constant can be predicted from the prediction year by using the OD characteristics in a prediction year and by assuming the changes in the OD characteristics from the prediction year to the target year. Eq. (3) shows the regression.

$$\alpha_{od}^{91} - \alpha_{od}^{71} = \lambda' \mathbf{z}_{od} + \varepsilon_{od} \quad (3)$$

where,  $\alpha_{od}^{91}$  and  $\alpha_{od}^{71}$  represent updated constants of the OD pair  $od$  in 1991 and 1971, respectively;  $\lambda$  is the unknown parameter vectors to be estimated;  $\mathbf{z}_{od}$  denotes explanatory variable vectors; and  $\varepsilon_{od}$  is an error component.

The explanatory variables for regression analysis are listed in Table 5. The explanatory variables are limited to those that are related to the independent variables in the mode choice model, since the mode choice model is designed to include as many variables as possible<sup>7</sup>. As stated above, the variables include both the OD characteristics in a prediction year and the changes in the OD characteristics from the prediction year to the target year. For the driver's license dummy, male dummy, business dummy, employed person dummy, student dummy, elderly dummy (aged 60 or over), and commuting dummy, *the average of trip makers in 1971* and *the average of trip makers in 1991 – the average of trip makers in 1971* are considered. Regarding travel time, *travel time in 1971* is taken into account. For travel time changes, *real values*, *dummies*, and *ratios* are considered; some variables related to *the relative superiority of travel time between transit and auto* are also examined. Regarding travel cost, *travel cost in 1971* and *travel cost in 1991 – travel cost in 1971* are considered. (The list contains fewer variables related to travel cost than to travel time, since the travel cost in 1971 is calculated based on the cost in 1991 and the price increase rate.) Finally, *trip to and/or from Nagoya dummy* is evaluated.

\*\*\*\*\* Table 5 \*\*\*\*\*

Table 6 shows the results of the regression analysis. The regression was conducted using OD pairs in which at least 50 samples, 100 samples, and 200 samples were obtained in both 1971 and 1991 for validation checks. The results reported here include a set of variables that gives a reasonable outcome in all 50-, 100-, and 200-sample cases. Adjusted  $R^2$  indicates that analysis using OD pairs with more samples produces a better fit to the data<sup>8</sup>.

<sup>7</sup> Mode choice models in this paper describe the cross-sectional state of the travel behaviours in 1971 and 1991. In the regression analysis, a dependent variable is the difference in the updated constants that are estimated in the model describing the cross-sectional state. Therefore, the inclusion of variables related to mode choice models does not pose any problems in the regression.

<sup>8</sup> The regression analysis was conducted stepwise.

1) One of the variables listed in Table 5 is included as an explanatory variable. Models are generated for three cases—50, 100, and 200 samples—and the model that provides the best adjusted  $R^2$  is named the best model for each sample case. (The coefficient estimate for a variable must satisfy a 5% level of significance.) When the best models for the three cases are identical, that model is selected as the overall best model. When the best models for two of the three cases are identical, that model is selected as the overall best model. When the best models for the three cases all differ, an overall best model is not selected.

2) The variable selected in the first step and one of the variables listed in Table 5 are included as explanatory variables. The best model for each case and the overall best model are selected in the same manner described in the first step. This process continues until the three cases have different best models.

\*\*\*\*\* Table 6 \*\*\*\*\*

Interpreting the analysis is summarised. The constant differences are the changes in the factors not explained by the model. However, the constant is highly related to the sample share (usage ratio) as noted in the section, “Using disaggregate data to update alternative-specific constants.” Accordingly, the usage ratio is included in the following interpretation.

1. The updated constants are increased where the auto travel time in 1971 is longer. OD pairs with longer auto travel times (relatively long distances) can increase the factors not explained by the model, thereby promoting transit usage. This suggests that OD pairs with longer auto travel times (relatively long distances) have the potential to increase transit use if adequate transit service is provided.
2. OD pairs that include Nagoya can increase the factors not explained by the model, thereby promoting transit usage. These factors can be the effects of investment in subway lines and arterial railroads, especially in Nagoya from 1971 to 1991. Some of the effects can be explained by the explanatory variables, such as travel time, but other effects, such as the synergy of the transit networks and the difficulty of expanding roadway networks in Nagoya at that time, can be included in the trip to and/or from the Nagoya dummy. These first and second interpretations are consistent with the results in Figs. 2 and 3.
3. The higher ratio for the superiority of auto travel time in 1971 leads to an increase in the factors not explained by the model, thereby discouraging transit usage. This suggests that inertia exists by which the level of service in the past (1971) can affect behaviour in the future (1991).
4. The higher transit travel cost in 1971 causes an increase in the factors not explained by the model, thereby discouraging transit use. This also implies the existence of inertia.
5. OD pairs in which the auto travel time in 1971 minus the auto travel time in 1991 is greater than 5 min. receive an increase of factors not explained by the model, thereby discouraging transit usage. This means that even if the current level of service is identical, the behaviours will depend on whether the current level of service is obtained by improving the level or by worsening it from 1971 to 1991. In addition, increases in auto travel time and decreases in transit travel time are not considered significant. This indicates that travel behaviours are anti-symmetric regarding the transport mode. In other words, changes in travel behaviour can depend on the transport mode if the level of service changes. This also shows that travel behaviours are path dependent; that is, the changes in travel behaviour are dependent on the direction of change in the level of service.
6. Variables related to individual characteristics are not included in the regression result, showing that the mode choice model adequately explains individual characteristics. Hence, the variables in the regression are those that can be manipulated by policy planners relatively easily. They can also predict future constants easily.
7. The appearance of trip to and/or from the Nagoya dummy can mean that the trip to and/or from the Nagoya dummy estimate in the mode choice model has changed since 1971. In other words, the utility functions of the mode choice model have changed. This study follows a standard methodology for updating alternative-specific constants and assumes the transferability of other parameters. Transferability analysis of other variables can be utilised for additional research.
8. For example, as shown in Table 2, transferability differs when a) both origin and destination are in Nagoya, b) either origin or destination is in Nagoya, and c) neither origin nor destination is in Nagoya. Understanding the cause of the differences would help us to

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3) After the second step, another variable from Table 5 is included as an explanatory variable. If the coefficient estimates for the variables satisfy the 5% level of significance for all three cases, then this model is selected as the overall best model. This process continues until the additional variable does not satisfy the 5% level of significance for the three cases.

define a better zone classification for model transferability in the future. We believe this regression analysis provides some insights into defining a better zone classification.

## Conclusions

This study reviewed prior studies aimed at improving the model transferability and identified problems. The study analysed the temporal transferability of alternative-specific constants that have been updated using disaggregate data in order to obtain higher spatial transferability. In the analysis, in order to remove the restrictions on the number of application contexts, a method of dividing the study area into many OD pairs was proposed. A regression analysis was also conducted in which the dependent variable is *the updated constants in 1991 minus the updated constants in 1971*. The results show that the constants have better temporal transferability after updating. The results also show that the transferability of updated constants can depend on regional characteristics, travel behaviours in the past (inertia), and anti-symmetric and path-dependent changes in the level of service. Practitioners who apply models with updated constants will find these insights useful because they can help them determine in which OD pairs the share is over-estimated (the constant has a chance to decrease) or under-estimated (the constant has a chance to increase) in a prediction year. The insights may also be useful when applied to models with a constant estimated in the original model, which can have lower transferability.

The paper also discusses additional research and draws several conclusions. First, the transferability of parameters other than constants can be analysed, although in this paper, they are assumed to be transferable. Second, the transferability of mode choice models developed on a segmentation basis can be useful. In the segmentation, variables found in the regression can be useful. Examples include auto travel time ranges, such as OD pairs in 0-30 min., 30-60 min., and so on; OD pairs to and/or from Nagoya and other OD pairs; OD pairs in which auto travel time is superior and other OD pairs; the range of transit travel costs such as OD pairs in 0-100 JPY, 100-200 JPY, and so on. Third, another area for further research is the analysis of models that update both utility scale and alternative-specific constants. Analysing observed changes in the values of constants over time would produce greater confidence in the results. The change in utility scale is also of fundamental interest. These analyses can be accumulated and used to build models with adequately high transferability. Finally, using more than two-time-point data and evaluating the universality of the regression results can improve the accuracy of the demand forecast.

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## References

- Atherton TJ, Ben-Akiva ME (1976) Transferability and updating of disaggregate travel demand models. *Transportation Research Record* 610:12-18
- Badoe DA, Miller EJ (1995) Analysis of the temporal transferability of disaggregate work trip mode choice models. *Transportation Research Record* 1493:1-11
- Ben-Akiva M, Lerman SR (1985) *Discrete choice analysis: theory and application to travel demand*. MIT Press, Cambridge, Massachusetts
- Harata N, Ohta K (1982) Hishuukei rojitto moderu no tekiyousei ni kansuru kenkyuu – Tsuukin koutsuu shudan sentaku no baai – [A study on the application of disaggregate logit models – The case of commuting mode choice –], *Traffic engineering*, Vol. 17 No. 2:15-23 (in Japanese)
- Karasmaa N, Pursula M (1997) Empirical studies of transferability of Helsinki metropolitan area travel forecasting models. *Transportation Research Record* 1607:38-44
- Koppelman FS, Wilmot CG (1982) Transferability analysis of disaggregate choice models. *Transportation Research Record* 895:18-24

- McCarthy PS (1982) Further evidence on the temporal stability of disaggregate travel demand models. *Transportation Research* 16B (4):263-278
- Morichi S (1995) Hishuukei koudou moderu ni yoru yosoku [Forecasting using disaggregate behaviour models]. In Doboku gakkai doboku keikakugaku kenkyuu iinkai (ed) [The infrastructure planning committee, Japan society of civil engineers (ed)] Hishuukei koudou moderu no riron to jissai [Theory and practice of disaggregate behaviour models], Maruzen, Tokyo (in Japanese)
- Morichi S, Yai T, Tamura T (1985) Spatial transferability of disaggregate mode-choice models, *Journal of infrastructure and management*, No. 359/IV-3:107-115 (in Japanese)
- Morikawa T, Nagamatsu Y, Sanko N (2004) Post-project evaluation of the demand forecast for a new transit system, *Transport Policy Studies' Review*, Vo. 7, No. 2:20-29 (in Japanese)

Table 1 Results of estimations using mode choice model

Variables	Est.	t-stat.
Constant (T)	1.37	12.0
Time [60 min.]	-1.40	-8.2
Cost/hourly wage [JPY/(JPY/hr)]	-1.17	-10.2
Driver's license dummy (A)	2.54	38.5
Male dummy (A)	0.833	11.0
Business dummy (A)	1.21	10.9
Employed person dummy (A)	0.562	4.5
Student dummy (T)	1.42	10.1
Trip to and/or from Nagoya dummy (T)	0.680	10.8
Elderly dummy (Aged 60 or over) (T)	0.294	2.1
Commuting dummy (T)	1.24	14.0
N (randomly drawn)	10,000	
Rho-squared-bar	0.449	

Note: (T) and (A) notations refer to alternative-specific for transit and auto, respectively. Variables without notations are generic.

Table 2 Significance test of constant differences

	a) Both origin and destination are in Nagoya	b) Either origin or destination is in Nagoya	c) Neither origin nor destination is in Nagoya	Total
Rejected (1991 constant is larger than 1971 constant)	39 [41]	89 [100]	3 [9]	131 [150]
Rejected (1991 constant is smaller than 1971 constant)	9 [22]	22 [37]	138 [150]	169 [209]
Not rejected	63 [48]	79 [53]	73 [55]	215 [156]

Note: Table includes OD pairs where at least 50 samples were obtained in both 1971 and 1991. Numbers without square brackets are results of an analysis of updated constants using 1971 data and 1991 data. Numbers with square brackets are results of an analysis between constants from the original model and constants updated using 1991 data. Significance for level of rejection is 5% and a two-sided test is applied.

Table 3 Disaggregate analysis of model transferability

	a) Both origin and destination are in Nagoya	b) Either origin or destination is in Nagoya	c) Neither origin nor destination is in Nagoya	Total
$L^{91}(\theta^{71}) < L^{91}(\theta_{up}^{71})$	80	124	128	332
$L^{91}(\theta^{71}) > L^{91}(\theta_{up}^{71})$	31	66	86	183

Note: Table includes OD pairs in which at least 50 samples were obtained in both 1971 and 1991.

Table 4 Aggregate analysis of model transferability

	a) Both origin and destination are in Nagoya	b) Either origin or destination is in Nagoya	c) Neither origin nor destination is in Nagoya	Total
$E^{71} > E_{up}^{71}$	80	123	128	331
$E^{71} < E_{up}^{71}$	31	67	86	184

Note: Table includes OD pairs in which at least 50 samples were obtained in both 1971 and 1991.

Table 5 List of explanatory variables for a regression analysis

**<Driver's license dummy, male dummy, business dummy, employed person dummy, student dummy, elderly dummy, commuting dummy>**

- Average of trip makers in 1971
- Average of trip makers in 1991 – average of trip makers in 1971

**<Travel time for transit, travel time for auto>**

- Travel time in 1971 (min.)
- Travel time reduction (min.): travel time in 1971 – travel time in 1991
- Travel time reduction by more than x min. dummy (x=1, 5):  
travel time in 1971 – travel time in 1991 > x (min.)
- Travel time increase by more than x min. dummy (x=1, 5):  
travel time in 1991 – travel time in 1971 > x (min.)
- Travel time reduction ratio: (travel time in 1971 – travel time in 1991)/(travel time in 1971)

**<Relative superiority of travel time: transit and auto>**

- Superiority of auto travel time in 1971 by more than x min. dummy (x=1, 5):  
transit travel time in 1971 – auto travel time in 1971 > x (min.)
- Superiority of transit travel time in 1971 by more than x min. dummy (x=1, 5):  
auto travel time in 1971 – transit travel time in 1971 > x (min.)
- Superiority of auto travel time in both 1971 and 1991 by more than x min. dummy (x=1, 5)
- Superiority of transit travel time in both 1971 and 1991 by more than x min. dummy (x=1, 5)
- Superiority of auto travel time in 1971 by more than x min. and that of transit travel time in 1991 by more than x min. dummy (x=1, 5)
- Superiority of transit travel time in 1971 by more than x min. and that of auto travel time in 1991 by more than x min. dummy (x=1, 5)
- Ratio of superiority of auto travel time in 1971:  
(transit travel time in 1971 – auto travel time in 1971)/(transit travel time in 1971)
- Changes in ratio of superiority of auto travel time:  
ratio of superiority of auto travel time in 1991 – ratio of superiority of auto travel time in 1971

**<Travel cost of transit, and travel cost of auto>**

- Travel cost in 1971
- Travel cost in 1991 – travel cost in 1971

**<Trip to and/or from Nagoya dummy>**

- Trip to and/or from Nagoya dummy



Table 6 Regression analysis of differences in updated constants

	At least 50 samples		At least 100 samples		At least 200 samples	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Constant	-0.614	-2.7	-0.618	-2.4	-0.139	-0.4
Auto travel time in 1971 (min.)	0.0281	6.3	0.0366	6.6	0.0336	4.0
Trip to and/or from Nagoya dummy	0.806	11.5	0.842	11.5	0.871	9.9
Ratio of superiority of auto travel time in 1971	-1.91	-6.0	-1.99	-5.2	-2.75	-5.3
Transit travel cost in 1971 (JPY)	-0.00304	-3.5	-0.00521	-4.7	-0.00613	-3.0
Auto travel time reduction by more than 5 min. dummy	-0.299	-2.4	-0.349	-2.4	-0.806	-2.2
N		515		312		170
Adjusted R <sup>2</sup>		0.632		0.723		0.745

Appendix Table 1 Results of estimations using mode choice model (Yr 1991)

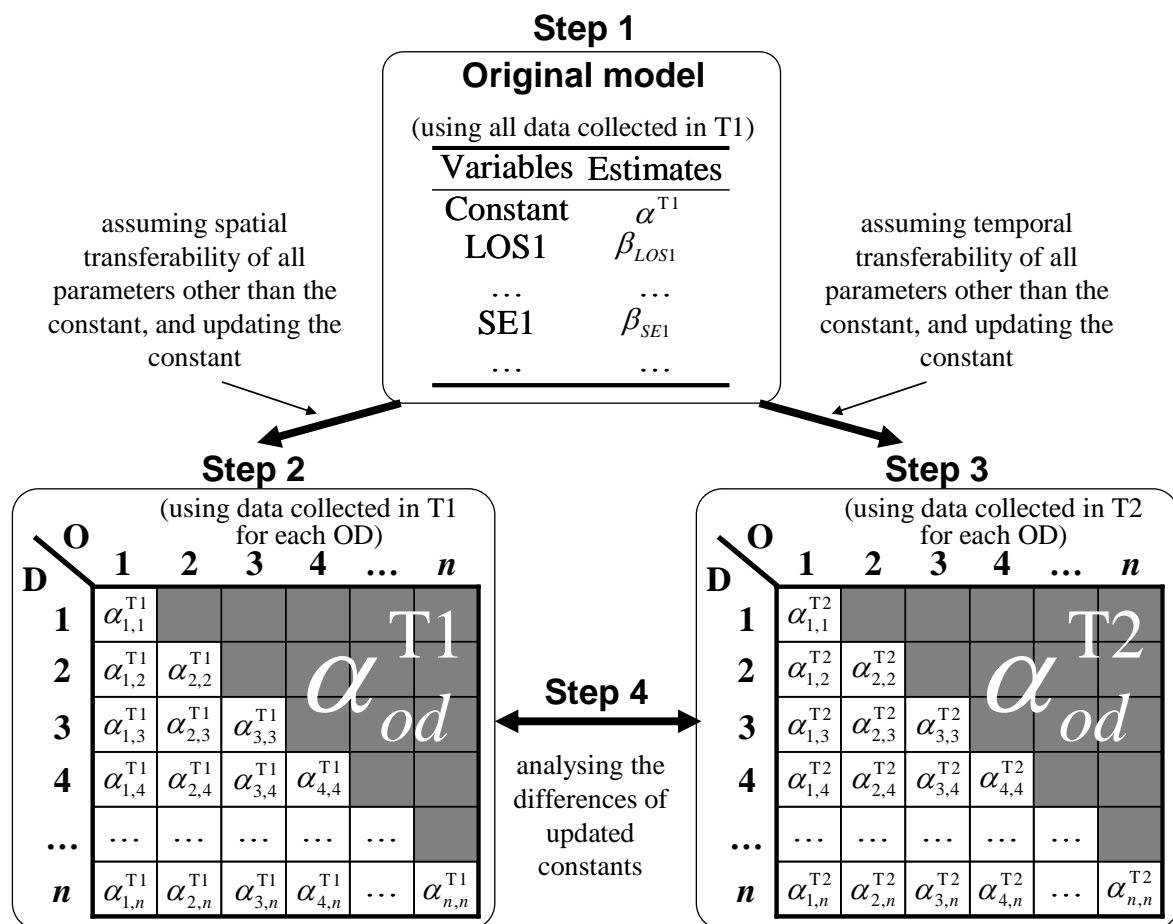
Variables	Est.	t-stat.
Constant (T)	0.556	4.2
Time [60 min.]	-3.22	-19.0
Cost/hourly wage [JPY/(JPY/hr)]	-3.14	-10.1
Driver's license dummy (A)	2.14	25.1
Male dummy (A)	0.765	11.7
Business dummy (A)	0.927	6.9
Employed person dummy (A)	0.177	1.3
Student dummy (T)	2.03	15.1
Trip to and/or from Nagoya dummy (T)	1.58	23.3
Elderly dummy (Aged 60 or over) (T)	0.225	2.0
Commuting dummy (T)	1.26	13.0
N (randomly drawn)		10,000
Rho-squared-bar		0.455

Note: (T) and (A) notations refer to alternative-specific for transit and auto, respectively. Variables without notations are generic.

Appendix Table 2 Significance test of utility scale differences

	a) Both origin and destination are in Nagoya	b) Either origin or destination is in Nagoya	c) Neither origin nor destination is in Nagoya	Total
Rejected (1991 utility scale is larger than 1971 utility scale)	3 [4]	9 [10]	20 [37]	32 [51]
Rejected (1991 utility scale is smaller than 1971 utility scale)	33 [23]	14 [18]	11 [20]	58 [61]
Not rejected	75 [84]	167 [162]	182 [156]	424 [402]

Note: Table includes OD pairs where at least 50 samples were obtained in both 1971 and 1991. Numbers without square brackets are results of an analysis of updated utility scales using 1971 data and 1991 data. Numbers with square brackets are results of an analysis between utility scales from the original model and utility scales updated using 1991 data. Significance for level of rejection is 5% and a two-sided test is applied. Table 2 includes a total of 515 OD pairs; however, this Table includes only 514 OD pairs, since the model in one OD pair produces a poor estimate when both utility scale and constant are updated.



Note: LOS (level of service); SE (socio-economic)  
 Fig. 1 Steps of the analysis

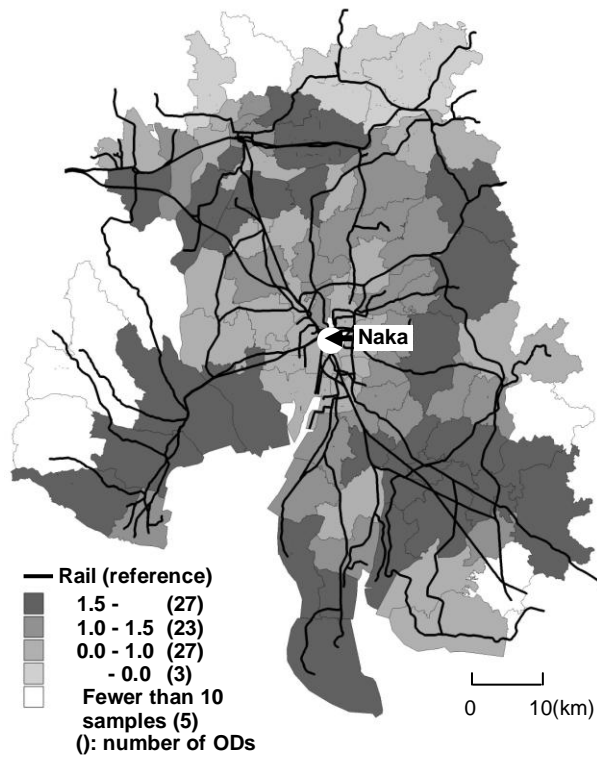


Fig. 2 Changes in updated constants in OD pairs including Naka ward

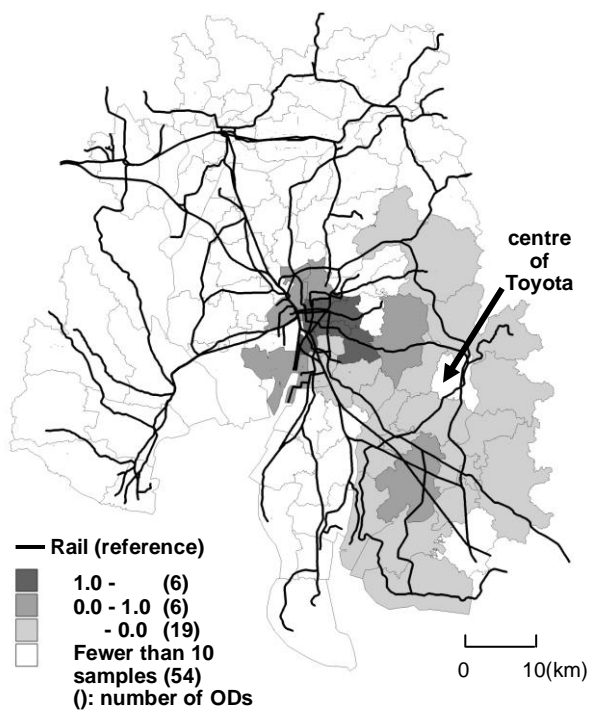


Fig. 3 Changes in updated constants in OD pairs including the centre of Toyota city

## **Author biographies**

**Nobuhiro Sanko** is an associate professor at the Graduate School of Business Administration, Kobe University. He holds Doctor of Engineering and Master of Engineering degrees from Nagoya University, and an MBA from Ecole Nationale des Ponts et Chaussées. His research interests include travel behaviour analysis, stated preference, and transport planning.

**Takayuki Morikawa** is a professor at the Graduate School of Environmental Studies, Nagoya University. He holds a PhD from Massachusetts Institute of Technology. His research interests include travel behaviour, transport demand analysis, transport policies, and ITS. He is also an editorial advisory board member for Transportation Research Part A.