

Economic Perspective of Transferability of Mode Choice Models

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Abstract: Economic analysis between the increment of accuracy and the number of small sample size was conducted to the spatial transferability in Ho Chi Minh City. Transfer index generated from the association of small sized samples with naïve method, updating alternative specific constants, Bayesian updating, updating alternative specific constants and scale parameter, and combined transfer estimator were used to represent the accuracy in the analysis. Graphical observation based on marginal transfer index and increment of marginal transfer index was used to produce the optimum range. In general, the economic range produced by the first three methods is between 150 and 360 observations. However, there is no optimum range need to be constructed from the last two methods as the transfer index is relatively established. A sample of 100 observations is recommended as the cost-effective sample size for these two methods. These monetary findings are not in line with the result from previous study.

Key Words: *transferability, small sample optimization, economic value*

1. INTRODUCTION

Transferability of mode choice models has been considered as one of the alternatives to save time and cost in conducting transportation studies. By transferring a model from another area to our study area, we can significantly reduce the number of samples to be collected from travel survey and, at the end, will speed up the time of data collection and reduce cost.

Since disaggregate choice models represent the average behavior of an individual trip maker and it is reasonably accepted to assume that individual travel behavior is the same regardless of location, an appropriately specified model is claimed to be transferable. The parameters of disaggregate models are not dependent on a specific zonal system as the aggregate models, therefore, a model estimated in one area (estimation context) can be applied in another area (new application context).

Transferability should be viewed from the standpoint of the degree to which the existing model could provide information that can improve forecasting in a new context (Gunn *et al.*, 1985). Additionally, due to the limitation in model specification and behavioral differences which may exist between the estimation and application contexts, perfect transferability, where the model specification and parameters of the estimation context are directly used to the application context (naïve method), is considered difficult to be achieved, with exception

the study of Atherton and Ben-Akiva (1976). The behavioral differences in traveling and specification limitations may result in differential transferability of different model components (Koppelman *et al.*, 1985). In anticipation of this problem, methods have been developed and proposed to update the model transferability using sample data from the application context. Therefore, transferring a model is usually associated with updating the parameters of the model to better serve the new application context.

Many transferability studies have been conducted using data of developed countries (Atherton and Ben-Akiva, 1976; Talvitie and Kirshner, 1978; Ben-Akiva, 1981; Galbraith and Hensher, 1982; Koppelman and Wilmot, 1982; McCarthy, 1982; Koppelman *et al.*, 1985; Gunn *et al.*, 1985; Koppelman and Wilmot, 1986; Ben-akiva and Bolduc, 1987; Badoe and Miller, 1995a, 1995b; Karasmaa, 2001) and just recently, some studies used developing countries data in their research works (Santoso and Tsunokawa, 2005a; Santoso and Tsunokawa, 2005b). Among these studies, some tried to develop new updating procedures to solve weaknesses of available updating methods and improve the performance of transferability. Many compared the performances of updating methods applied in transferability analysis. They also evaluated the influence of the size of small samples in the transferability process. Some attempted to recommend the required number of observations to get the optimal updating result. Koppelman, *et al.* (1985) suggested that sample sizes for model updating could be one-fifth or less than the corresponding sample size for full model estimation. In a previous research, Koppelman and Chu (1983) recommended to use data samples in the order of 1000 to 2000 observations, to estimate a disaggregate choice model. A spatial transferability study in Ho Chi Minh City produced a recommendation for sample size not less than 400 observations (Santoso and Tsunokawa, 2005a), which is in line with the Koppelman's finding. However, all of these studies were based their analysis mainly on statistical analysis. To the best of the authors' knowledge, there is no research analyzing and linking the performance of the updating method associated with the size of small sample and the economic perspective, how the trade off between the improved model performance and the cost of conducting transportation study to achieve the performance. Thus, the present study tried to fill this gap by examining the trade off between improved model performance provided by the small sized sample and the cost effectiveness in achieving the performance. It is expected that from this trade-off analysis, optimum range can be drawn to provide guidance in selecting the economic number of small samples.

The data of spatial transferability study for Ho Chi Minh City (HCMC), Vietnam by Santoso and Tsunokawa (2005a) was used in this study. This paper extended their study by examining the economic side of the transferability to determine the financially viable sample size. The evaluation is expected to confirm whether the recommendation to use sample data not less than 400 observations with argument that sample data less than this amount are susceptible to negative effects of the large variance is also economically reasonable and satisfactory.

The next section briefly describes the spatial transferability of HCMC. Information on transferring and updating approaches is provided in section 3. The data and methodology applied in the present study is explained in section 4. Then, section 5 discusses the result of the analysis. Finally, the last section concludes the findings of the study.

2. SPATIAL TRANSFERABILITY ANALYSIS OF HCMC

The study on spatial transferability analysis of HCMC was conducted by transferring a work trip mode choice model estimated on the urban area of HCMC to the suburban area. The data used in the study was collected from the HOUTRANS project, which commenced in August 2002. Three dominant modes of the city: walking, bicycles and motorcycles were the modes under investigation in the study. The other modes, including cars and public buses, had an insignificant share which can be ignored. The variables used in the model are tabulated in Table 1 and the utility function of each mode can be expressed as follows:

$$U_{\text{walking}} = -0.0384 \text{ TRAVT}_{\text{walking}} - 0.355 \text{ VEHRAT} \quad (1)$$

$$U_{\text{bicycle}} = -1.9386 - 0.0384 \text{ TRAVT}_{\text{bicycle}} + 0.3939 \text{ BOWN} \quad (2)$$

$$U_{\text{motorcycle}} = -2.2152 - 0.0384 \text{ TRAVT}_{\text{motorcycle}} - 210.6638 \text{ COST/INC} \\ + 3.0116 \text{ MOWN} + 0.141 \text{ MALE} \quad (3)$$

Table 1 Definition of variables used in the model

Variable	Definition
BASC	1 for bicycle mode 0 otherwise
MASC	1 for motorcycle mode 0 otherwise
TRAVT	travel time (minute)
COST/INC	travel cost (vietnamese dong) / worker's monthly income (vietnamese dong) for motorcycle mode 0 otherwise
MOWN	1 if worker owns a motorcycle for motorcycle mode 0 otherwise
BOWN	1 if worker owns a bicycle for bicycle mode 0 otherwise
MALE	1 for male worker for motorcycle mode 0 otherwise
VEHRAT	number of vehicles available in the household / number of workers in the household for walk mode 0 otherwise

Naïve method and four updating approaches: i) updating alternative specific constants, ii) updating alternative specific constants and scale parameter, iii) combined transfer estimator and iv) Bayesian updating were applied in the study associated with small sized samples. Based on analysis of goodness-of-fit index (ρ^2) and transfer index (TI), the study concluded that small sample not less than 400 observations should be used to reduce the possible negative effects of the large variance on the transferability performances. The results also indicated that the first three updating approaches have proved to produce significant improvement (Santoso and Tsunokawa, 2005a).

3. TRANSFERRING AND UPDATING APPROACHES

Application of updating approaches in improving the performance of the model in the new application context has been recommended by many research studies. Generally, naïvely transferring a model is not the preferred option because no model is sufficiently specified,

with the exception of the study by Atherton and Ben-Akiva (1976). Therefore, an assessment of model transferability, only on the basis of the set of model parameters being equal in the two areas, is unlikely to be achieved (Ben-Akiva, 1981; Koppelman and Wilmot, 1986).

Adjustment of parameters of the model to the new application context can be performed by incorporating available information on the new application context. Therefore, small sample data related to the variables being used in the model should be available or collected from the new application context. Many updating approaches have been developed to server this purpose. McFadden (1976); and Westin and Manski (1979) have also identified that there are three types of differences existing in models, between the estimation and application contexts: differences in the alternative specific constants, in the sensitivity or scale of the model parameters, and in the relative values of variable coefficients. To deal with the first differences, we need to update the alternative specific constants, which is the prominent approach in updating. Additionally, the scale parameter could also be adjusted, to further improve the model as suggested in the second type.

A combination of the coefficients of a model, from the estimation context, with those estimated on the small sample data of the new application context could also be used to update the model. This should be done in such a way that all of the coefficients of the model are modified and, at the same time, any unfavorable effects resulting from the small sample from the new context are minimized (Atherton and Ben-Akiva, 1976). There are two updating methods in this line, the Bayesian updating and the combined transfer estimator methods. Atherton and Ben-Akiva (1976) applied the Bayesian theorem in updating the coefficients of the model. Coefficients of the model estimated from the available small sample, were combined with coefficients of the model from the estimation context to yield asymptotically normal updated coefficients. The updated coefficient is, theoretically, a weighted average of the transfer model coefficient and the coefficient estimated from the small sample. The method was used with considerable success in their research study.

The implicit assumption of Bayesian updating that the underlying set of parameters was equal, may be difficult to be justified if a model is transferred to a very different context, including transferring over a long period of time. Solution to this problem was provided by Ben-Akiva and Bolduc (1987). They integrated the presence of transfer bias which is the magnitude of the differences in parameter values between the two contexts, into the Bayesian procedure and produced a method called combined transfer estimator. The method is based on the mean squares error criterion. This approach accounts for a non-zero transfer bias, and yields the minimum mean square error estimate of the updated coefficients achievable from a linear combination of the estimation and application context parameter estimates. Given that the transfer bias is small, this method is expected to produce better estimates of updated coefficients than the Bayesian updating.

4. DATA AND METHODOLOGY

As this paper augments the previous study on spatial transferability of HCMC by analyzing the trade-off between accuracy and cost, it uses the same work trip travel survey data of HCMC. There were 37,217 valid survey data which can be divided into 26,864 observations for the urban area and the rest are for the suburban area. The same four updating approaches and naïve method were adopted in this study, combined with small sized samples of 100, 200, 300, 400, 600, 800 and 1000 observations. The whole sample data for suburban area were also

included in the calculation to provide more rigorous analysis. Each size has three sets of small samples except for 100, 200 and 300 observations which are assigned with five sets to minimize bias in the result due to large variance. All sample sets were generated randomly from the whole sample data of the suburban area.

For the trade-off analysis, the study used transfer index to represent the improvement of the model performance or accuracy, as the higher the transfer index, the higher the predictive accuracy of the model. This index illustrates the degree to which the log likelihood of the transferred or updated model exceeds some base or reference model (usually market share model), relative to the improvement provided by a model developed in the new application context (Koppelman and Wilmot, 1982). Briefly, this index wants to measure the predictive accuracy of the transferred model relative to a locally estimated model. The upper bound is one which is obtained when the transferred model is as accurate as the local one. Negative value means the transferred model is worse than the local reference model. The formula is defined as:

$$TI = \frac{LL_s(\beta_{up}) - LL_s(MS)}{LL_s(\beta_s) - LL_s(MS)} \quad (4)$$

where

$LL_s(MS)$ = the log likelihood of market share model.

$LL_s(\beta_{up})$ = the log likelihood of the transferred or updated model.

$LL_s(\beta_s)$ = the log likelihood of the locally estimated model.

The estimation of cost for the analysis was not as simple as expected. Unavailability of cost data for the travel survey was the major problem. Consequently, we could not calculate the exact optimum cost. Secondly, the cost of conducting travel survey data is not universal, it is case to case basis, which depend on location, labor cost, how detailed the data are, etc. Besides the cost constraints, how accurate we need the model to be is also an important factor need to be considered to represent the value of precision or accuracy. Even though these constraints impede thorough analysis of this trade off, it does not mean that the analysis could not be conducted. An approach based on the optimization principle using the marginal increment of TI value can be applied to generate the optimum range of small sized sample in terms of cost.

In this study, cost for conducting travel survey is assumed to have linear relationship with number of sample collected (as number of observations increase, cost also linearly increases). Assuming that the relationship of number of observations and transfer index is as shown in Figure 1, we can define that the optimum range is between P and Q. The curve representing relationship between number of observations and transfer index begins from point A and as we add a few observations, we get significant improvement of accuracy. This pattern of increment continues until point B when Line X (slope of tangent: marginal accuracy) touches curve ABCD and, after that, the increment of accuracy is not as much as before but still large enough. The rate of accuracy improvement per additional observation is decreasing, as well. Finally, starting from point C (when Line Y touches curve ABCD), when we add more observations which mean increasing cost, we do not get any significant improvement of the accuracy. The additional cost is not valuable compare to the increment of accuracy gains from it. From this explanation, we can reasonably expect that the optimum point should be located between points B and C. Therefore, we can confidently define that the range between P and Q as the optimum range of the curve.

The above approach was applied in this trade-off analysis. The first derivative of the transfer index function (marginal transfer index) was utilized to estimate the location of points B and C.

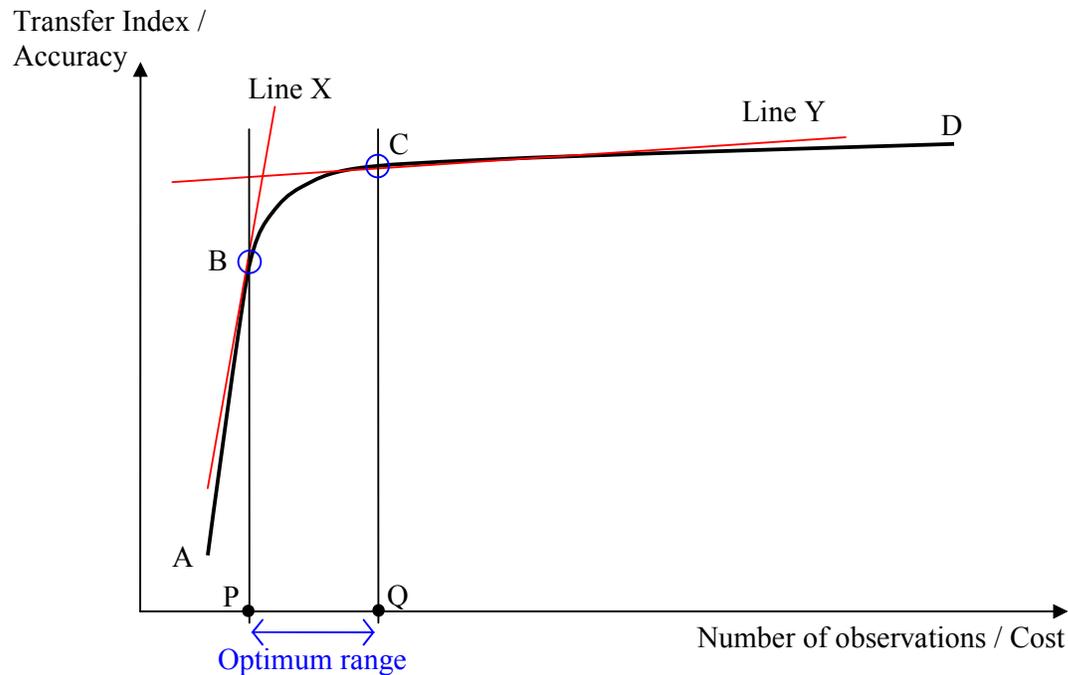


Figure 1 Optimum range of trade-off between cost and accuracy

5. OPTIMALITY ANALYSIS

The optimality analysis between predictive accuracy and cost for conducting the survey was discussed in this section. Transfer index (TI), which represents the predictive accuracy were calculated for each method associated with small sized samples. However, as there are three to five sets of sample for each small sized sample, the average value of transfer index from the sample sets was used in the analysis. The average transfer index values are presented in Table 2. The first column represents the size of small sample used for transferring or updating the model. The other columns represent the average transfer index values for each transfer or updating method.

The values in Table 2 were plotted in graphical form for each method as shown in Figures 2 – 6. Please be noted that in the figures, the values of the whole sample data of suburban area (10,353 observations) were also included in the estimation of the curves. However, the values are not showed in the chart for clarity only. The power function was used to generate the curve in analyzing the optimum range. The R^2 values of all figures are high enough to justify that the curves can appropriately represent the data. From the figures, it can be observed that the curves for updating ASC and scale parameter, and combined transfer estimator (Figures 4 and 6) are relatively flat which indicates that the increment of small sample contributed not so much in the increment of accuracy. This is mainly due to the consideration of transfer bias in the calculation of these two methods (please refer to Santoso and Tsunokawa, 2005a for detailed discussion). Meanwhile, Figures 2, 3 and 5 have the same pattern.

As the cost data of the travel survey is not available, marginal analysis could not be conducted. We estimated the optimum range of small sample by considering the marginal TI (MTI) and increment of marginal TI (Δ MTI) in every additional five samples (data is not presented due to space limitation). Because there is no previous reference in deciding the suitable value of MTI or Δ MTI to determine the optimum range, the values of MTI and Δ MTI were graphically plotted to generate ideas as shown in Figures 7 and 8.

Table 2 Average transfer index values

Small Sized Sample	Naïve Method	Updating Alternative Specific Constants (ASC)	Updating ASC and Scale Parameter	Bayesian Updating	Combined Transfer Estimator
100	0.680	0.752	0.956	0.682	0.928
200	0.721	0.801	0.965	0.732	0.972
300	0.754	0.809	0.998	0.764	0.989
400	0.873	0.927	0.993	0.877	0.978
600	0.838	0.928	0.999	0.847	0.977
800	0.853	0.926	0.999	0.859	0.988
1,000	0.860	0.926	0.999	0.867	0.987
10,353	0.914	0.966	0.999	0.951	1.000

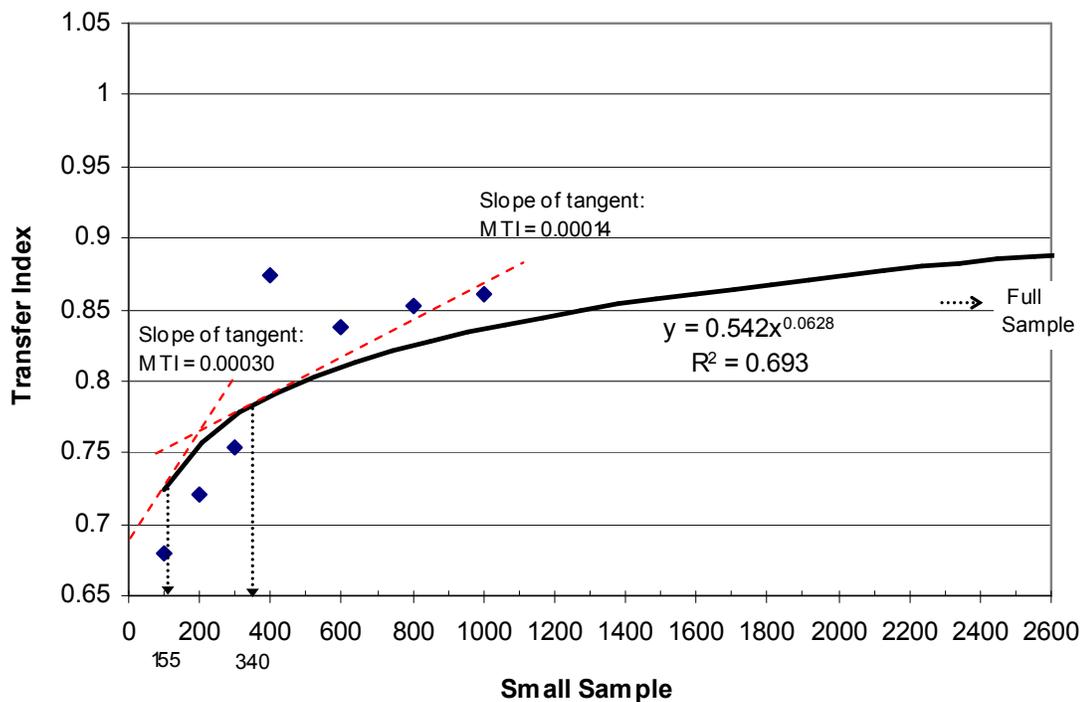


Figure 2 Small sample optimization for naïve method

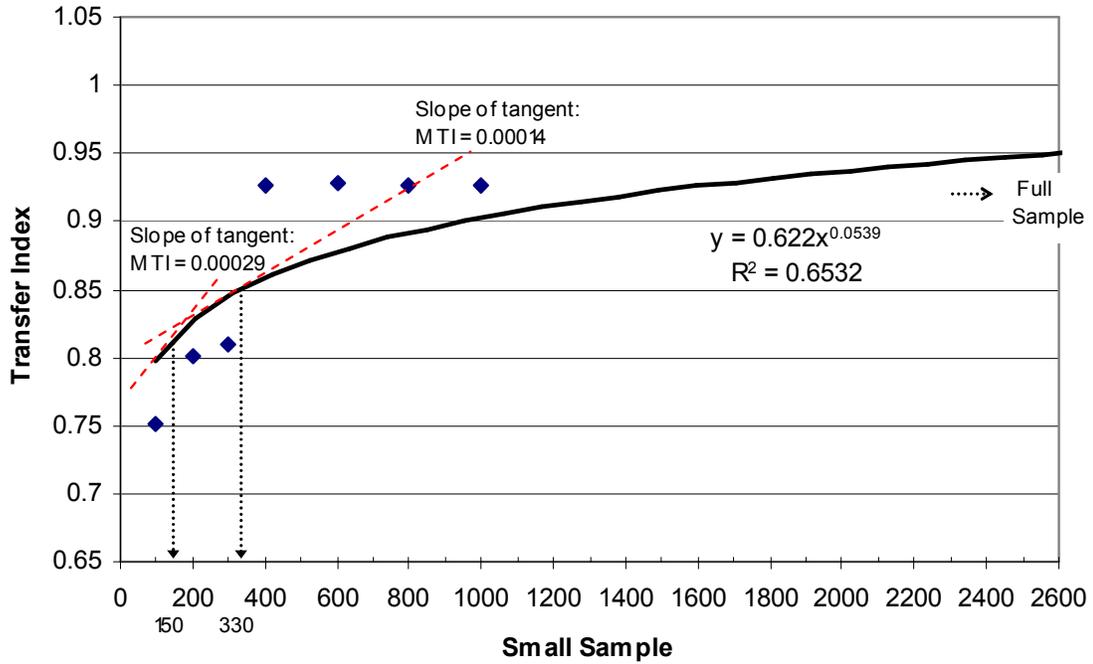


Figure 3 Small sample optimization for updating alternative specific constants

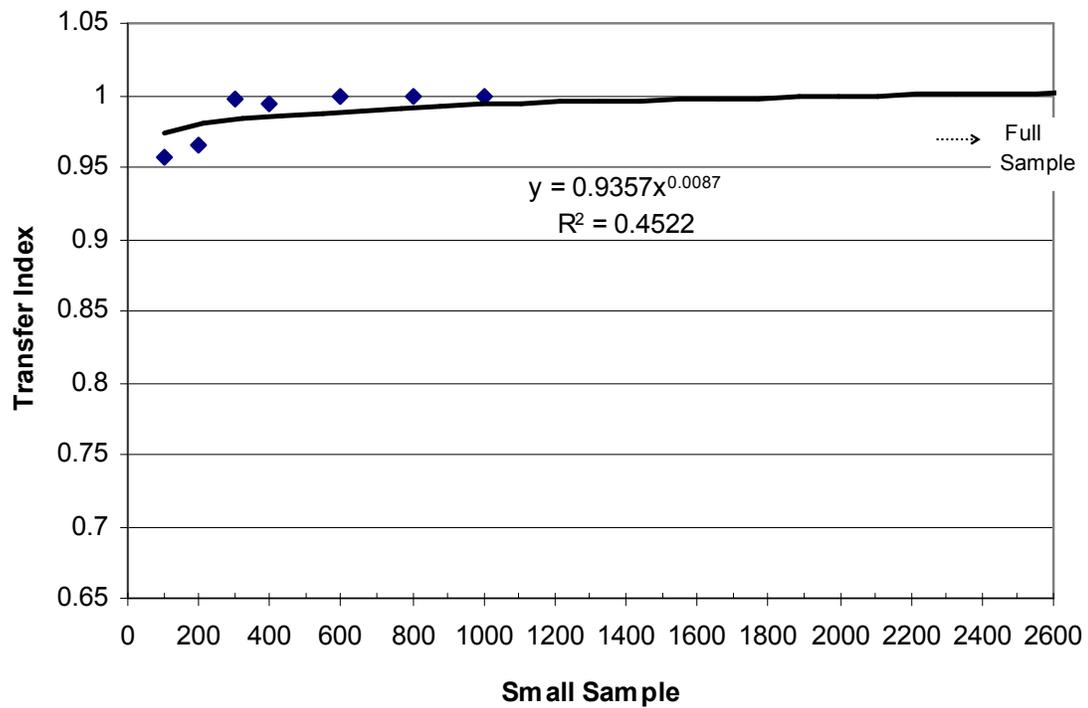


Figure 4 Small sample optimization for updating ASC and scale parameter

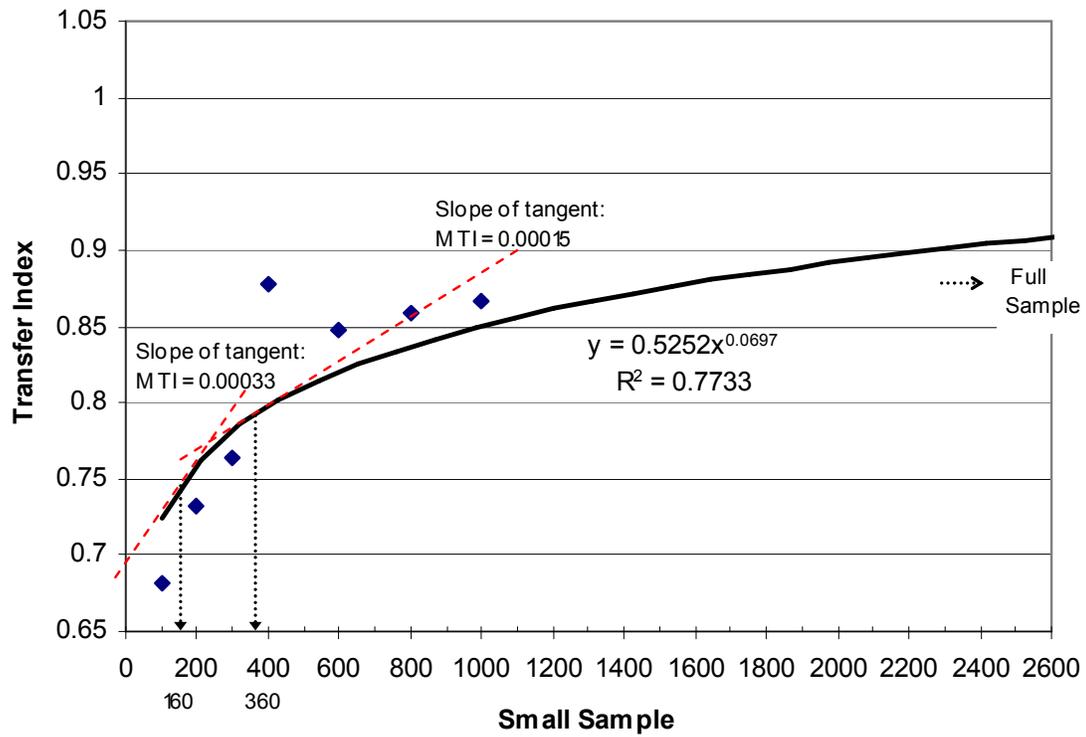


Figure 5 Small sample optimization for Bayesian updating

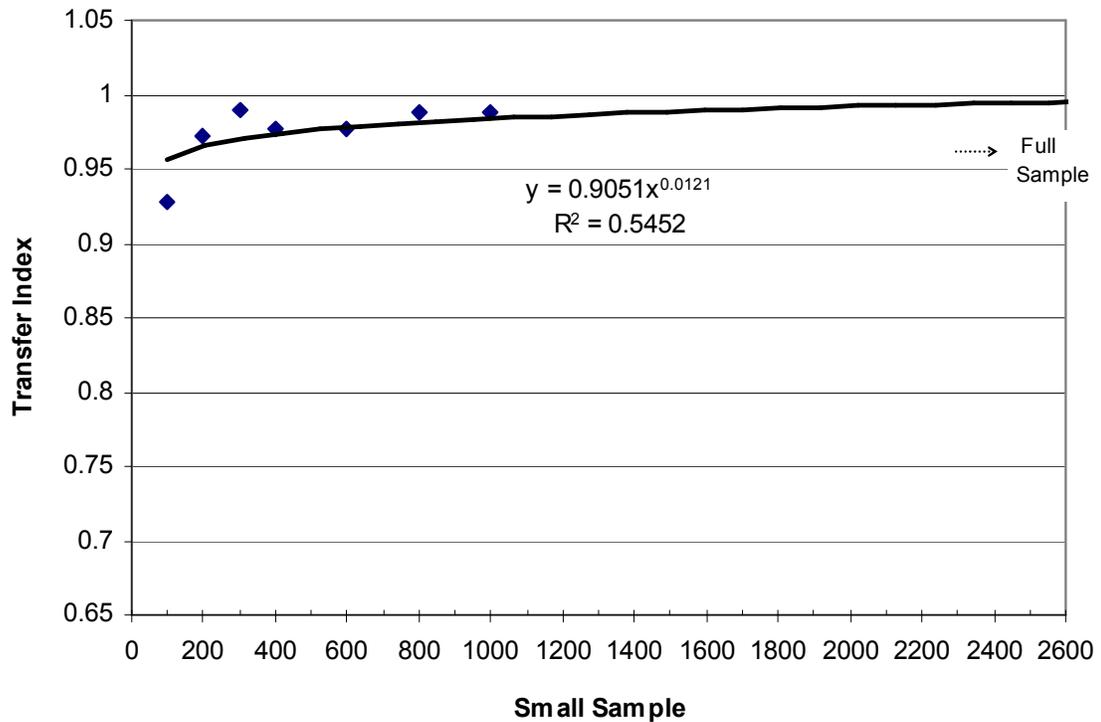


Figure 6 Small sample optimization for combined transfer estimator

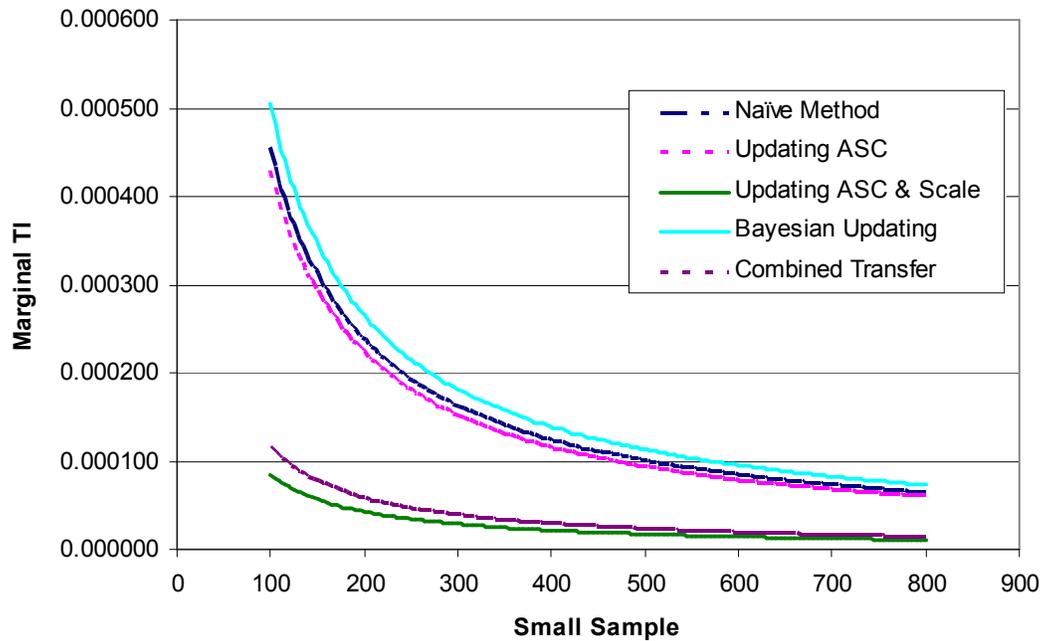


Figure 7 Marginal transfer index (MTI) and sample size

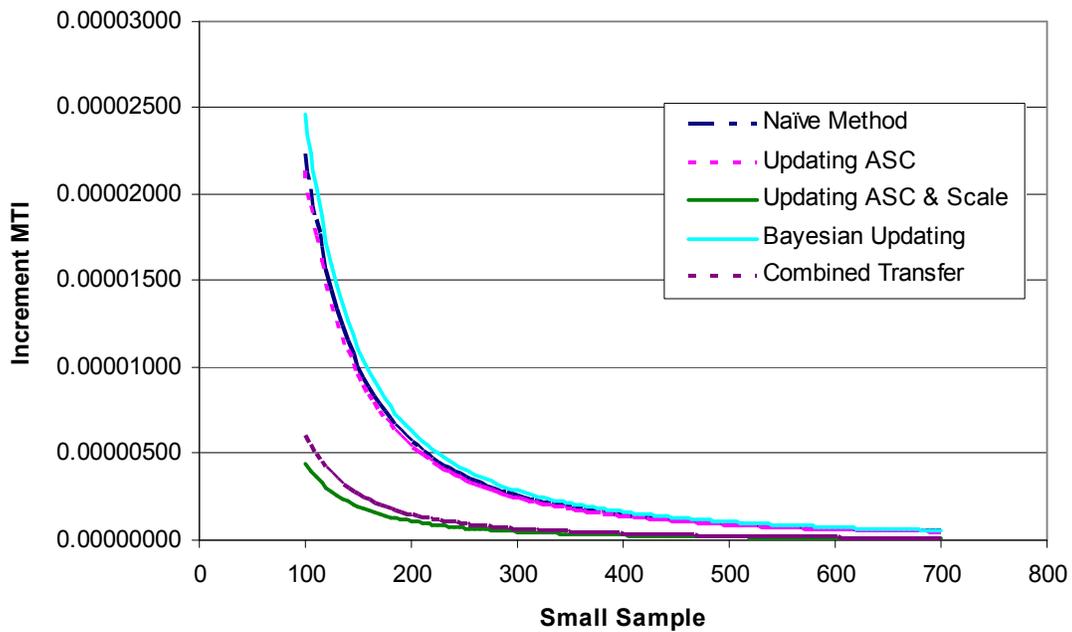


Figure 8 Increment of marginal transfer index (Δ MTI) and sample size

From Figures 7 and 8, especially Figure 8, it can be observed that, for naïve method, updating ASC, and Bayesian updating, the MTI and Δ MTI tend to get less starting approximately from 150 observations, and the MTI and Δ MTI are starting to get flatten for sample size more or less 350 observations. This range is used as a guidance to estimate the optimum range in having economically feasible sample size for transferability analysis. Based on the above

range and the observation from the Δ MTI, the optimum range was set to have the Δ MTI less than 1.10^{-5} and higher than 2.10^{-6} ($2.10^{-6} < \Delta$ MTI $< 1.10^{-5}$). For all three methods, at the Δ MTI less than 1.10^{-5} , the MTI is at the order of 2.10^{-4} for more than 14 increments (one increment is for five samples). Whilst for Δ MTI larger than 1.10^{-5} , the MTI is at the order 3.10^{-4} only for less than 10 increments before the MTI value move to the higher order of 4.10^{-4} . Thus, based on this observation, Δ MTI at 1.10^{-5} , which is around 150 observations for all three methods, is set as a turning point where the increment of sample size starts to produces less increment to the value of transfer index. The other end of the range is set at Δ MTI = 2.10^{-6} because after this, when we increase the sample, the increment of transfer index is significantly low which is indicated by the order of Δ MTI at 1.10^{-6} per increment for more than 20 increments. With this benchmark, the correspondent values of TI were plotted in Figures 2, 3 and 5 and the optimum ranges for naïve method, updating ASC, and Bayesian updating are shown in the figures. Thus, we can confidently conclude that the optimum range of small sample to economically transfer a mode choice model from another area is between 150 and 360 samples. Meanwhile, for updating ASC and scale parameter, and combined transfer estimator, the optimum range is not necessary to be established as the value of TI depicted in Figures 4 and 6 are not significantly difference, especially for small sample more than 200 observations. This can be clearly seen in Figures 7 and 8 where there is no significant increment of accuracy can be expected by increasing the sample size after 100 observations.

6. CONCLUSIONS AND RECOMMENDATIONS

This study analyzed transferability of mode choice models in terms of monetary value. The trade-off between the improved accuracy performed by the updating methods, associated with small sized samples and the price in achieving the improved performance was analyzed. An economic and optimum range of the size of small samples is expected to be generated from the study.

This study examined the result of transferability analysis conducted by Santoso and Tsunokawa (2005a) using Ho Chi Minh City data from the financial perspective. The cost and accuracy trade-off of spatial transferability from a model estimated in the urban area to the suburban area was examined. The analysis included the application and economic examination of naïve method and four updating approaches: updating alternative specific constants, updating alternative specific constants and scale parameter, Bayesian updating and combined transfer estimator, associated with small sized samples of 100, 200, 300, 400, 600, 800 and 1000 observations. Three sets of samples were allocated to each size, except for 100, 200 and 300 observations which were assigned with five sets to minimize bias in the results due to large variance of small sample. The whole suburban data was also incorporated in the analysis to provide more rigorous results. The average value of transfer index is used to represent the accuracy of the model. For each method, the relationship between the transfer index and small sized sample was graphically marked and a curve was estimated from the relationship in power function with acceptable R^2 value.

The cost of conducting travel survey, which, in this case, was assumed to be linearly correlated with the number of samples, was not available. Therefore, optimization principle based on the marginal analysis was applied to generate the optimum range for the trade-off. Marginal transfer index (MTI) and increment of marginal transfer index (Δ MTI) were used to produce the appropriate optimum range for each transferability method.

Naïve method, updating alternative specific constants and Bayesian updating are in the same trend for the curve produced from the relationship between transfer index and size of small sample. The optimum ranges for these three methods are close to each other. The difference is only 5 to 20 samples. In general, the optimum range can be set between 150 and 360 samples. The range is less than the recommended minimum sample size of 400 samples for transferability (Santoso and Tsunokawa, 2005a). However, it should be noted that this finding is solely based on monetary value.

The optimum range for the last two updating approaches: updating alternative specific constants and scale parameter and combined transfer estimator was not necessary to be derived as the curve relationship between sample size and accuracy for these two methods is almost a straight line, especially for sample larger than 200 observations. These two methods significantly improved the model with high values of transfer index in the range of 0.93 to 1. There is little significant increment in accuracy can be expected by using big size of samples. Therefore, from the economic perspective, regardless issues related to large variance of small sample, 100 samples should be more than economically sufficient to update a model using these two approaches.

These two findings from the financial analysis of transferability could not support the recommendation from previous study where small sized sample less than 400 observations in the transferability of mode choice model. On the contrary, this study suggested that economical sample size for transferability should be less than 400 observations.

This study has shown that the size of small sample to technically produce reliable transferability process is not necessary the economical one. Even this study is conducted using data from one city, it is expected that the results will not vary much for general or other application in different location as long as the same transferability methods are used. Further study related to this paper with factual cost data in conducting travel survey would be beneficial for the development of the research in this field, particularly in the context of developing countries where they normally face financial constraints to carry out transportation study.

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