Transfer Model Updating with Disaggregate Data

FRANK S. KOPPELMAN, GEOK-KOON KUAH, and CHESTER G. WILMOT

ABSTRACT

Model transfer provides an alternative to undertaking complete data collection and model development in every planning context. The effectiveness of the transferred model in the application context can be improved by updating selected model parameters by using limited data from the application context. The effect of model updating on the transferability of disaggregate travel choice models both within and between urban areas is examined. It is found that transfer effectiveness improves with updating alternative specific constants and improves further with updating the parameter scale for both intraurban and interurban transfers. Further, the sample size necessary to obtain a substantial improvement in model transferability is a small fraction of that needed to estimate a complete model in the application context. Thus, it appears that model transfer with updating may be preferable to either full model transfer or new model estimation in situations of constrained resources.

The transfer of a previously estimated model to a new application context can reduce or eliminate the need for a large data collection and model development effort in the application context. However, the usefulness of a transferred model depends on the degree to which it can provide useful information about the behavior or phenomenon of interest in the application context.

Models are not perfectly transferable between contexts. Thus, the general objective of model transfer is to obtain a model that reasonably approximates the behavior in the application context. The quality of this approximation can be improved by using available information about the application context to modify or update some or all of the model parameters. A wide range of updating procedures can be employed depending on the type of information available in the application context. Schultz and colleagues have employed updating by using transit corridor volumes and screen-line counts in Houston, Seattle, and New Orleans (1-3).

This study examines the effect of updating alternative specific constants and the scale of the model parameters on the transferability of disaggregate mode-choice models that use disaggregate data. This approach may be employed to facilitate the analysis process when a small sample of disaggregate data has been collected. Such an updating sample can be considerably smaller than the sample that would be necessary to calibrate a new model system. The approach is demonstrated and evaluated for both intraregional and interregional transfer of disaggregate models of mode choice to work.

This paper is organized as follows. The sources of differential transferability of model components are identified and the procedure is described that is used for the adjustment of alternative specific constants and the scale of the transferred parameters. The research approach, including the data used, model specifications, and the model estimation results, is described next. Then the effect of model updating on intraregional and interregional model transferability is evaluated, and the final section sets forth conclusions and implications.

PARTIAL TRANSFERABILITY AND MODEL ADJUSTMENT

Model transfer is expected to be effective when the underlying individual travel choice decision process is the same in both the estimation and application contexts and the model specification is appropriate (4). Perfect transferability of models cannot be achieved because of behavioral differences between contexts and limitations in model specification. The behavioral differences and specification limitations may result in differential transferability of different model components. Updating procedures can be used to modify selected parameters of transferred models by incorporating available information about the application context.

Sources of Differential Transferability of Model Components

McFadden (5) and Westin and Manski (6) identify three types of differences that may exist in models between estimation and application contexts. These are differences in the alternative specific constants, in the sensitivity or scale of the model parameters, and in the relative values of variable coefficients. These differences in expected transferability result from the differential effect of model specification errors on these classes of model parameters.

The impact of model specification error for the multinomial logit model can be seen from a review of the model derivation (similar results can be obtained for the multinomial probit model). Consider a decision maker faced with the problem of selecting one of a set of available alternatives. It is assumed that the decision maker will select that alternative which has the highest utility to him or her. The utility U_{it} of an alternative i to an individual t includes deterministic (V_{it}) and random (ε_{it}) components:

$$U_{it} = V_{it} + \varepsilon_{it} \qquad (1)$$

The derivation of the multinomial logit model is based on the assumption that the random components (ε_{it}) are independently and identically Gumbel distributed over individuals and alternatives. Further, the systematic or deterministic portion of the utility function is generally assumed to be linear in parameters so that

$$V_{it} = X_{it}\beta \qquad (2)$$

where X_{it} is a row vector of variables describing individual t and alternative i, and β is a column vector of parameters. Under these assumptions, the multinomial logit model has the form

$$P_{it} = \exp\,[(\eta_i + X_{it}\beta)/\omega] / \sum_j \exp\,[(\eta_j + X_{jt}\beta)/\omega] \quad (3)$$

This model has location parameters (η_i), which represent the mode of the distribution of errors for each alternative; a scale parameter (ω), which represents the variance of the distribution of the error terms; and attribute importance parameters (β), which represent the attribute weighting that the individual employs in evaluating alternatives.

Tardiff (7) shows that the omission of explanatory variables will shift the mean of the error distribution represented in the model by η_i, increase the variance of the error distribution represented by ω, and bias the estimates of parameters associated with included variables. When different contexts are compared that have similar behavior but incompletely specified models, it is expected that the differences in the mean values of the error distribution will be relatively large, the differences in the error distribution variance will be smaller, and the differences in behavioral parameters will be the smallest. Thus, efforts to improve the transferability of a model to a specific application environment should emphasize adjustment of alternative specific constants first, parameter scale second, and relative parameter values last. Empirical results confirm the importance of adjusting alternative specific constants by using disaggregate data to improve the transferability of disaggregate choice models (8,9,4). However, there is no reported study of the effect of scale adjustment on model transferability.

Analytic Formulation of Updating Procedures

The parameters in Equation 3 are not uniquely identified and therefore cannot all be estimated. First, the η parameters can only be identified up to an additive constant. This limitation is dealt with by imposing an arbitrary constraint on one of these parameters (e.g., set $\eta_k = 0$). Second, it is not possible to estimate ω but only to estimate the ratios η/ω and β/ω. Defining ratios of these parameters by $\mu_j = \eta_j/\omega$, and $\theta = \beta/\omega$ and restating the multinomial logit model in terms of these new parameters obtains

$$P_{it} = \exp\,[\mu_i + X_{it}\theta] / \sum_j \exp\,[\mu_j + X_{jt}\theta] \quad (4)$$

where one of the μ_j is constrained to zero.

Updating procedures can be used to modify or replace selected parameters in this model. In this study, the effectiveness is examined of updating the location parameters (μ) and the scale of the remaining parameters by using a sample of individual observations from the application context.

Parameter estimates for a choice model are obtained with disaggregate data by maximizing a log likelihood expression of the form

$$L = \sum_t \sum_i \delta_{it} \ln P_{it}\,(X_t, \mu, \theta) \quad (5)$$

where

δ_{it} = indicator variable set to 1 if individual t chooses alternative i and to 0 otherwise,

$P_{it}(X_t,\mu,\theta)$ = probability that individual t chooses alternative i, and

μ = vector of alternative specific constants.

Embedded in the probability function in Equation 5 are expressions for the deterministic component of utility for each alternative formulated as

$$V_{it} = \mu_i + X_{it}\,\theta \quad (6)$$

The transfer of the parameters describing the effect of time, cost, and other variables on travel choice is based on some expected generality of these factors across estimation and application contexts. There is no comparable basis for transferring the constant terms because average differences in the excluded factors between contexts are expected. Therefore, it is appropriate to consider transferring the θ parameters in Equation 6 to the application context while obtaining a local estimate of the alternative specific constants. In this case, the θ-parameters transferred to the application context are denoted with a subscript T (θ_T) and the transferred portion of the utility function is defined as

$$Z^A_{it} = X^A_{it}\,\theta_T \quad (7)$$

where X^A_{it} is a vector of attributes of alternative i for individual t in the application context. The updating of the alternative specific constants is accomplished by modifying the utility function in Equation 6 for the application context to

$$V^A_{it} = \mu^A_i + Z^A_{it} \quad (8)$$

where

V^A_{it} = deterministic component of utility for alternative i in the application context,

μ^A_i = updated alternative specific constant for alternative i in the application context, and

Z^A_{it} = transferred portion of the utility function defined in Equation 7.

The estimate of the updated alternative specific constants (μ^A_i) consists of those values that maximize the log likelihood function:

$$L = \sum_t \sum_i \delta_{it} \ln P_{it}\,(Z^A_t, \mu^A) \quad (9)$$

where Z^A_t is a vector of variables defined in Equation 7 for individual t in the application context for all alternatives and μ^A is a vector of alternative specific constants. The final utility function employed for transfer prediction becomes

$$V^A_{it} = \mu^A_i + X^A_{it}\,\theta_T \quad (10)$$

which includes all the transferred slope parameters (θ_T) and locally estimated alternative specific constants (μ^A_i).

The methodology just outlined can be extended to adjust the scale of the transferred parameters as well as the alternative specific constants. The coefficient of Z^A_{it} in Equation 8 was restricted to 1 in the preceding approach. When the parameter scale is updated, that restriction is relaxed and a coefficient is estimated for Z^A_{it}. The deterministic component of utility becomes

$$V^A_{it} = \mu^A_i + \lambda^A Z^A_{it} \quad (11)$$

where λ^A is the scaling parameter for the application context relative to the estimation context.

Updating the alternative specific constants and the parameter scale amounts to selecting values of μ^A and λ^A that maximize the log likelihood function:

$$L = \sum_t \sum_i \delta_{it} \ln P_{it} (Z_t^A, \mu^A, \lambda^A) \tag{12}$$

The scaling parameter (λ^A) adjusts the scale of the explanatory variables but does not affect their relative importance. The adjusted expression for alternative utility becomes

$$V_{it} = \mu_i^A + \lambda^A X_{it}^A \theta_T \tag{13}$$

which differs from Equation 10 only by inclusion of the scaling constant (λ^A).

Practical Application of Updating Procedures

The updating procedures described can be readily implemented in standard packages for logit model estimation. The common application of such procedures includes the selection of variables to be included in the choice model. To use the same package for model updating, it is necessary to formulate the composite variable Z_{it}^A by means of Equation 7 and estimate the new model with a full set of alternative specific constants. For updating alternative specific constants only, the parameter of the composite variable (Z_{it}^A) must be restricted to 1. For updating the alternative specific constants and the parameter scale, the parameter is unrestricted. This procedure can be employed with a disaggregate data set of any size for the application context. The same data can be used both to estimate parameter scale adjustment and to update the alternative specific constants. It is expected, and this empirical study confirms, that a substantially smaller data set can be used to obtain satisfactory estimates of these parameters than would be necessary to estimate the complete model in the application context.

RESEARCH DESIGN

The analysis undertaken in the previous section suggests that transferability will be enhanced by adjustment of alternative specific constants and parameter scale and describes procedures for making such adjustments. However, the qualitative analysis does not provide information about the importance of these adjustments on transferability. An empirical exploration of these impacts is undertaken to increase the understanding of the effectiveness of these adjustments.

The research approach is to evaluate the transferability of models of mode choice to work within a single urban region and between urban regions. The intraregional transfers are among sectors in the Washington, D.C., metropolitan area. The interregional transfers are among the metropolitan areas of Minneapolis-St. Paul, Baltimore, and Washington, D.C. Model transfer effectiveness is evaluated for full model transfer, model transfer with updating of alternative specific constants, and model transfer with updating of alternative specific constants and parameter scale.

Data

The intraregional transferability analysis is undertaken by using Washington, D.C., data for those who reported traveling to work in the central business district (CBD) by driving alone, shared ride, or transit. These records are grouped into three geographic sectors between which model transferability is evaluated. The interregional transferability analysis is undertaken among the regions of Minneapolis-St. Paul, Baltimore, and Washington, D.C. Differences among sectors in Washington represent real differences in sociodemographic characteristics and transportation service attributes. Differences among the three regions include these real differences as well as apparent differences due to inconsistencies in data collection procedures. Thus, the analysis of transferability within Washington and between regions provides some insight into the additional limits on transferability that may be attributable to differences in data collection and other conventions between study areas.

Model Specification

The specification employed in the Washington, D.C., intraregional transferability analysis includes three level-of-service variables, a car-per-driver variable applied separately to the drive-alone and shared-ride alternatives, and alternative specific constants. This model is in the mid-range of specifications analyzed for transfer effectiveness by Koppelman and Wilmot (10).

The specification employed in the three-city interregional transferability analysis includes all the variables used in the intraregional transfer study with the addition of a variable that measures automobile access time to transit for zones in which automobile must be used to reach transit. The variables included in each transferability analysis are identified and defined in Table 1.

TABLE 1 Variables Included in Analysis of Intraregional and Interregional Transferability

Variable	Study Type	
	Intraregional	Interregional
Dummy for drive-alone alternative (DAD)	X	X
Dummy for shared-ride alternative (SRD)	X	X
Cars per driver for drive-alone alternative (CPDDA)	X	X
Cars per driver for shared-ride alternative (CPDSR)	X	X
Out-of-pocket cost divided by income[a] (OPTCINC)	X	X
Total travel time[a] (TVTT)	X	X
Out-of-vehicle travel time divided by distance[a] (OVTTD)	X	X
Automobile access time to transit for zones not served by transit (AATR)	–	X

[a]Level-of-service variables (OPTCINC, TVTT, and OVTTD) are based on the simple home-work-home tour for the Washington, D.C., intraregional analysis and on the one-way home-work trip for the interregional analysis. This difference in variable definition will modify the scale of these parameters by a factor of 2 but will have no other impact on estimation and transferability results.

Disaggregate updating for both intraregional and interregional transfers is undertaken by using all available disaggregate data in the application environment. The earlier study by Atherton and Ben-Akiva (8) used a subsample of the available data for updating the alternative specific constants. Koppelman and Chu (11) show that the use of the full sample rather than a subsample will improve the precision of the obtained estimators but will not affect their consistency.

Evaluation of Transferability With and Without Parameter Updating

Transfer effectiveness is evaluated by the degree to which the transferred model with or without updating predicts the observed behavior in the application environment. Four measures, formulated by Koppelman and Wilmot (4), are used to evaluate transfer predictive accuracy. The transfer likelihood ratio index, analogous to the commonly used likelihood ratio index (12) for evaluating model goodness of fit, describes the extent to which the transferred model explains observed individual behavior in the application environment. The transfer index, a ratio of the transfer likelihood ratio index and the local likelihood ratio index, describes the degree to which the transferred model describes observed behavior relative to an identically specified local model. The root-mean-square-error measure is an index of the average proportional error in prediction of aggregate travel shares by any alternative. The relative root-mean-square error is the ratio between this measure and the corresponding measure for an identically specified local model.

Each of these measures describes the transfer effectiveness of a single estimated model applied in another context. These measures can be pooled across multiple transfers (13) to provide an overall indication of the effectiveness of a specific type of transfer over multiple applications.

Estimation Results

The estimation results for the Washington, D.C., sectors and for three urban regions are reported in Tables 2 and 3, respectively, and the supporting statistics for Tables 2 and 3 are given in Tables 4 and 5, respectively. The signs of all the estimated parameters are consistent with a priori expectations. The parameters for cars per driver and total travel time are significant in all cases. The other level-of-service parameters are significant in some, but not all, cases.

There are important differences in goodness of fit among sectors in the Washington region and among regions measured by the likelihood ratio index with either the equal-share or market-share reference. That is, models of identical specification are more able to explain the travel choices made in some contexts than in others.

EVALUATION OF MODEL TRANSFERABILITY WITH DISAGGREGATE UPDATING

The transferability of the estimated models within the Washington, D.C., region and among the selected regions is evaluated by using the four measures described previously. These measures are pooled over the full sets of intraregional and interregional transfers to provide an average index of the effect of differences in updating procedures.

Disaggregate Transferability Measures

The pooled transfer likelihood ratio index values for intraregional and interregional transfers are as follows:

	Pooled Transfer Index Values	
Adjustment	Intraregional Transfers	Interregional Transfers
None	.092	.089
Constants	.101	.128
Constants and scale	.106	.136
Local estimation	.113	.167

These values indicate that the adjustment of alternative specific constants and the additional adjustment of scale produce a substantial improvement in model transferability. These adjustments result in transfer model goodness-of-fit values that are much closer to the corresponding local goodness-of-fit values than those for full model transfer without adjustment. The magnitude of improvement due to scale adjustment is somewhat smaller than that at-

TABLE 2 Mode-Choice Model Estimates for Washington, D.C., Sectors

	Sector 1		Sector 2		Sector 3	
Variable	Parameter Value	t-Statistic	Parameter Value	t-Statistic	Parameter Value	t-Statistic
DAD	−3.455	9.4	−2.018	5.9	−2.875	7.2
SRD	−1.937	9.6	−1.401	8.2	−1.382	5.3
CPDDA	4.181	11.3	3.191	9.2	3.647	5.0
CPDSR	1.964	7.1	1.743	8.3	1.544	5.0
OPTCINC	−0.0055	0.4	−0.0168	1.5	−0.0196	1.2
TVTT	−0.0423	7.0	−0.0148	3.2	−0.0229	4.7
OVTTD	−0.0276	0.5	−0.1029	1.7	−0.0281	0.4

TABLE 3 Mode-Choice Model Estimates for Three Urban Regions

	Minneapolis-St. Paul		Baltimore		Washington, D.C.	
Variable	Parameter Value	t-Statistic	Parameter Value	t-Statistic	Parameter Value	t-Statistic
DAD	−2.387	8.0	−0.815	2.5	−2.799	11.5
SRD	−1.351	4.9	−1.776	6.5	−1.688	12.5
CPDDA	3.017	9.9	2.313	6.3	3.478	14.4
CPDSR	1.048	3.8	2.004	6.4	1.694	10.1
OPTCINC	−0.0967	6.7	−0.0313	1.1	−0.0345	2.1
TVTT	−0.0595	9.1	−0.0159	2.3	−0.0558	8.0
OVTTD	−0.0961	4.7	−0.102	4.0	−0.130	1.6
AATR	−0.0701	1.2	−2.24	2.2	−0.129	3.8

TABLE 4 Supporting Statistics for Table 2

	Sector 1	Sector 2	Sector 3
No. of cases	944	964	746
No. of observations	2,648	2,583	2,165
Log likelihood			
At zero	–962	–933	–790
At market shares	–904	–898	–771
At convergence	–766	–813	–705
Likelihood ratio index (ρ^2)			
Equal-shares base	0.204	0.129	0.108
Market-shares base	0.153	0.095	0.086

TABLE 5 Supporting Statistics for Table 3

	Sector 1	Sector 2	Sector 3
No. of cases	2,000	785	2,000
No. of observations	5,814	2,416	5,568
Log likelihood			
At zero	–1,976	–767.4	–2,022
At market shares	–1,772	–713.4	–1,957
At convergence	–1,416	–556.6	–1,731
Likelihood ratio index (ρ^2)			
Equal-shares base	0.285	0.275	0.135
Market-shares base	0.202	0.220	0.116

tributable to the adjustment of alternative specific constants.

The values for the pooled transfer index for full model transfer and for partial model transfer with adjustment of alternative specific constants without and with scaling factors for both intraregional and interregional transfers are as follows:

	Pooled Transfer Index Values	
Adjustment	Intraregional Transfers	Interregional Transfers
None	.805	.533
Constants	.890	.767
Constants and scale	.948	.814

Both the adjustments in constants and parameter scale substantially improve transferability. The differences in transfer effectiveness between intraregional and interregional transfers presumably reflect regional differences in context similarity and in measurement procedures.

Both pooled disaggregate measures of transferability give a strong indication of the effectiveness of model updating. The pooled values indicate strong improvement obtained by adjustment of alternative specific constants and strong but smaller improvements by the further adjustment of parameter scale in both intraregional and interregional transfer. Examination of the context pair transfer measures (not reported here) indicates some variability in transfer effectiveness. However, those results still support the overall interpretation obtained by analysis of the pooled values. Disaggregate transfer effectiveness can be substantially improved by adoption of these adjustment procedures.

Aggregate Transferability Measures

The pooled root-mean-square errors for local estimation and transfer prediction are as follows for both types of transfer:

	Pooled Root-Mean-Square Errors	
Adjustment	Intraregional Transfers	Interregional Transfers
None	.277	.460
Constants	.248	.369
Constants and scale	.242	.340
Local estimation	.231	.321

The adjustment of the alternative specific constants substantially reduces the pooled values of root-mean-square error for both intraregional and interregional transfers. The additional adjustment of parameter scale produces a small additional reduction in the root-mean-square error in both cases.

Differences in the magnitude of the root-mean-square error values for both types of transfer are largely attributable to the size of the prediction sample in the aggregate groups used in the two studies. Specifically, the use of large groupings in the intraregional analyses results in smaller errors in aggregate prediction (14). Thus, these measures are not directly comparable.

The pooled relative aggregate transfer errors for intraregional and interregional transfers are as follows:

	Pooled Aggregate Root-Mean-Square Errors	
Adjustment	Intraregional Transfers	Interregional Transfers
None	1.186	1.433
Constants	1.074	1.149
Constants and scale	1.048	1.059

The aggregate prediction errors using transferred models are not substantially larger than those using local models for intraregional transfers but are much larger for interregional transfers. In both cases, the relative error is substantially reduced by adjustment of alternative specific constants with or without parameter scale adjustment.

Thus, the pooled aggregate measures of transferability are consistent with the disaggregate measures. However, in this case, the individual context pair transfers (not reported here) show greater variability in the effectiveness of the updating procedure. Nevertheless, updating of alternative specific constants consistently reduced the aggregate transfer error. However, the additional updating of parameter scale does, on some occasions, produce a small increase in aggregate transfer error.

Sample Size for Transfer Model Updating

It is useful to obtain some estimate of the sample size required for model updating relative to that which would be required for full model estimation. An initial estimate can be obtained by comparison between the standard errors of estimate of the alternative specific constants for full model estimation and those for model updating. The average estimation variance for both alternative specific constants over the three Washington, D.C., sector estimations and the six Washington, D.C., sector transfers is as follows:

Alternative Specific Constant	Full Model Estimation	Transfer Model Updating
Drive alone	0.132	0.010
Shared ride	0.046	0.009

These values indicate that when the full available sample is used, estimation precision is increased by a factor of 13.2 for the drive-alone constant and 5.1 for the shared-ride constant. This suggests that sample sizes for model updating could be one-fifth or less than the corresponding sample size for full model estimation.

Interpretation of Transfer Updating Tests

The updating of alternative specific constants produces a substantial improvement in model transferability for both intraregional and interregional applications with respect to all four pooled measures and for each context pair transfer. Thus, adjustment of alternative specific constants appears to be a universally desirable procedure. The additional updating of model scale produces a smaller average improvement in all four pooled measures but results in a small increase in the aggregate, but not disaggregate, error measures in some cases. Thus, although parameter scale updating appears to be generally desirable, it may result in poorer model performance in some contexts. Further, the sample size required for model updating appears to be substantially smaller than that required for full estimation of a model in the application context.

CONCLUSIONS

This study examines the effectiveness of updating procedures to enhance model transferability. The study is undertaken in contexts where adequate data are available to estimate local models. The results obtained are used here to make inferences about the use of updating procedures in the application of these or other models to new contexts in which there are limitations on the availability of survey data.

The results of this study indicate that full model transfer provides a substantial improvement over using market-share information only but is quite deficient relative to the estimation of a local model (average transfer indices of 0.53 for interregional transfer). The use of updating procedures substantially improves the expected level of model effectiveness (adjustment of alternative specific constants explains almost half of the deficiency with respect to local models and adjustment of parameter scale provides a small incremental increase in model effectiveness). Although there is some variability in the improvement attributable to model updating, every case examined showed a substantial improvement in transferability due to model updating.

It is useful to think about the effectiveness of model updating relative to the extreme options of full model transfer without updating and estimation of new models in the application context. The advantage of full model transfer is the elimination of the need to collect any data on traveler behavior. The advantage of new data collection and model development is to obtain the best possible model estimation results. There is a clear trade-off between cost savings and model effectiveness. Adding the option of model updating offers the potential for obtaining a large portion of the potential improvement in model effectiveness for a small portion of the increased cost. These results indicate that almost one-half of the difference between full transfer and local estimation can be obtained by updating alternative specific constants and more can be obtained by updating constants and parameter scale. However, the amount of data needed for updating is less than one-fifth of that needed for full model development. Thus, it appears that model updating is a desirable alternative to either full model transfer or new model development.

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