Transferability Analysis of Disaggregate Choice Models

FRANK S. KOPPELMAN AND CHESTER G. WILMOT

The transferability of disaggregate choice models is widely assumed in travel demand analysis and forecasting. However, research results are mixed in their assessment of transferability. This paper considers transferability from the perspective of the usefulness of information provided by a model that predicts in a context different from that in which it is estimated. Issues that influence transferability are discussed and methods are formulated to evaluate transferability. These methods are demonstrated by application to spatial transfer between pairs of geographic sectors within a single urban area by using identically specified models. This application provides useful insights into the transferability of choice models. We observe an inconsistency between general measures of error that indicate that transferability in this context is appropriate and statistical analyses that reject hypotheses that support transferability. Model transferability is a property of the estimation and application contexts as well as the specification of the model. Transferability is substantially improved by adjustment of alternative-specific constants. These results indicate the need for additional research to identify the conditions of model specification and context characteristics for which model transfer is effective. Directions for such research are identified.

The transfer of a model is the application of a model formulated and estimated in one context to another context. Transferability implies that the model transferred can provide useful information about the behavior or phenomenon of interest in the application context. The transferability property is commonly invoked implicitly when models are estimated on historic data and used to predict into the future. The transferability property is invoked explicitly when models are estimated in one area and used to predict in another area.

The purpose of this study is to develop an approach to examine the transferability of disaggregate travel choice models. We describe this approach and demonstrate it by application to the intraregional transfer of a disaggregate model of mode choice to work. This application demonstrates the usefulness of the proposed approach when studying the transfer of a specific model specification between different spatial contexts.

ISSUES IN MODEL TRANSFERABILITY

Model transferability has been discussed extensively in the travel demand analysis and prediction literature. Yet, there is little agreement on the definition of transferability or on the circumstances in which it is appropriate. A set of issues that need to be addressed includes the following.

First, we define transfer as the application of a model, information, or theory about behavior developed in one context to describe the corresponding behavior in another context. We further define transferability as the usefulness of the transferred model, information, or theory in the new context.

Second, we identify two general conditions, one theoretical and one practical, for effective model transferability. The theoretical condition for model transferability is that the underlying behavioral process described by the model is the same in the application context as in the context in which the model was estimated. If this condition does not hold (if, for example, people in one context are utility maximizers and people in another context are satisficers), models will not be transferable between the contexts. However, if this condition does hold, a further practical condition for model transferability is that the model be well-specified and that the data used to estimate it are such that the model describes the underlying behavioral process.

Third, transferability is not satisfactorily described as a dichotomous property. Rather, it is appropriate to consider the degree of transferability of a model, theory, or information from one context to another [2]. Thus, we must develop measures that describe transferability in continuous terms.

Fourth, different portions of a model, theory, or data may be more or less transferable than other portions. Thus, it is appropriate to consider the notion of partial transferability [2]. That is, it is appropriate to evaluate separable components or portions of a model for transferability to a new context.

Fifth, we distinguish between prior and posterior analysis of transferability. Prior analysis of transferability is the determination that a model, theory, or data would have been transferable to an application context after observing the formulation and estimation of an analogous model, theory, or data in the application context. Prior analysis of transferability may be used as a basis to make prior inferences about transferability in some new context. All empirical studies undertaken to date have been posterior studies. The study reported in this paper is also a posterior study; however, it is undertaken as a part of an overall effort to develop a capability to make prior inferences about transferability.

Sixth, we consider two distinct classes of tests for model transferability—both applied to posterior studies of transferability. Tests of model parameters are designed to evaluate, either subjectively or statistically, the degree to which the transferred model describes the behavioral process in the application context. Tests of model predictions are designed to evaluate, either subjectively or statistically, the accuracy with which predictions of a transferred model describe travel behavior in an application context.

The work reported here addresses each of the issues. We develop and apply methods to evaluate the transferability of disaggregate travel choice models. We assume the existence of behavior equivalence (i.e., equivalent behavioral processes in each context) and evaluate the transferability of a model that has demonstrated its ability to reproduce travel behavior in other studies. We consider transferability of portions of the model parameters. We examine posterior transferability based on tests of parameter equivalence and prediction usefulness.

METHODS FOR EVALUATING MODEL TRANSFERABILITY

A set of measures that may be used to evaluate model transferability includes the following classes:

1. Tests of model parameter equality,
2. Tests of disaggregate prediction, and
3. Tests of aggregate—zonal level—prediction.

The first set of measures is based on conventional tests of equality between model parameters. These tests are symmetric between contexts. The second and third sets of measures describe the predictive accuracy of the transferred model and can be formulated as absolute tests or relative tests. The
absolute measures are based on some comparison between transfer model prediction and observed behavior. The relative measures adjust these comparisons by the accuracy of prediction that would be obtained by a similarly specified model calibrated in the application context. Aggregate transfer measures differ from disaggregate measures because they are influenced by the distribution of exogenous variables in the aggregate group.

Model Parameter Equality

We hypothesize that the underlying choice process in two or more contexts can be described by a common model, the model equality test statistic (METS). This is defined by

\[
\text{METS}_i = -2(\text{LL}_i(\theta_j) - \text{LL}_i(\hat{\theta}_j) - \text{LL}_i(\theta_j))
\]

where \( \text{LL}_i(\theta_j) \) is the log likelihood that the behavior observed in context \( i \) was generated by the model estimated in context \( j \) and \( \text{LL}_i(\hat{\theta}_j) \) describes the union of contexts \( i \) and \( j \).

This test is analogous to the commonly used test of equality of models between market segments (3). In this case the market segments of interest are the pair of contexts between which transferability is being considered. The resultant statistic is chi-square distributed with degrees of freedom equal to the number of model parameters.

The METS statistic can be used to test the equality of the entire set of model parameters or a subset of model parameters. In particular, we may consider the case where some of the parameters of the model are assumed to be context dependent and others are assumed to be equal across contexts. Atherton and Ben-Akiva (2), McFadden (4), and Ben-Akiva (5) discuss the case of context-specific alternative-specific constants. In this case the hypothesis to be tested is that the underlying model is equal across contexts with respect to a selected subset of parameters. The resultant statistic is chi-square distributed with degrees of freedom equal to the number of parameters tested for transfer.

These tests have been used in earlier studies of transferability (6-9). Unfortunately, these tests have an important deficiency in transferability analysis. This deficiency is the inherent symmetry of the tests, whereas transferability is a directional property. To observe this point, consider two contexts; one is a large urban region with a wide range of population groups and the other is a suburban area of an urban area that has relatively little diversity. Although it might be appropriate to use a model estimated in the first context for prediction in the second, it is unlikely that the reverse transfer will be useful.

Disaggregate Measures of Transferability

We formulate a set of transferability measures based on the ability of a transferred model to describe individual observed choices in the application context. These measures are based on the generally used log-likelihood measure. Specifically, we define the log of the likelihood that the observed data in application context \( i \) were generated by the transferred model estimated in context \( j \) \( \text{LL}_i(\theta_j) \). We examine this log likelihood of the transferred model relative to the log likelihood for a null (equal shares) model \( \text{LL}_i(\theta_i) \); the log likelihood for a market share model \( \text{LL}_i(\text{MS}_j) \); the log likelihood for a model estimated in the application context \( \text{LL}_i(\theta_j) \); and the log likelihood of a perfect model \( \text{LL}_i(\theta) \), which is equal to zero. The relation between these measures is shown in Figure 1.

A natural measure of the transferability of the model estimated in context \( j \) for application in context \( i \) is the difference in likelihood between this model and a corresponding model estimated in context \( i \), \( -[\text{LL}_i(\theta_j) - \text{LL}_i(\theta_i)] \). We use this measure to formulate three specific indices of transferability.

First, we define the transferability test statistic (TTS) as twice the difference in log likelihoods identified above:

\[
\text{TTS}_i(\theta_j) = -2(\text{LL}_i(\theta_j) - \text{LL}_i(\theta_i))
\]

This statistic is chi-square distributed with degrees of freedom equal to the number of model parameters under the assumption that the parameter vector of the transferred model is fixed. This test is used by McFadden and others (10) in their conditional choice set tests of the IIA property and by Atherton and Ben-Akiva (2) in their tests of transferability between Washington, D.C., and New Bedford, Massachusetts.

This statistic tests the hypothesis that the underlying parameter values in context \( i \) are equal to the estimated values in context \( j \). It is equivalent to the model equality test statistic when there is no error in the transferred parameter estimates. Otherwise, it will have larger values than the model equality test statistic and thus will be more likely to reject the equality hypothesis. The transferability test statistic for model \( j \) applied to context \( i \) is, in general, not equivalent to the corresponding statistic for model \( i \) applied to context \( j \). Thus, it is possible and reasonable to accept transferability in one direction between a pair of contexts but reject it in the other.

Second, the transfer index (TI) describes the degree to which the log likelihood of the transferred model exceeds some base or reference model (we use the market shares model) relative to the

![Figure 1. Sample log-likelihood for alternative local and transferred models.](image-url)
improvement provided by a model developed in the application context. We define TI by
\[ TI(\theta) = \frac{[LL(\theta) - LL(MS)]}{[LL(\theta) - LL(MS)]]} \] (3)

This index measures the predictive accuracy of the transferred model relative to a locally estimated model. TI has an upper bound of one, which it obtains when the transferred model is as accurate as a locally estimated model. This index does not have any lower bound. Negative values imply that the transferred model is worse than the local base model.

Third, the transfer rho-square ($\rho^2$) describes the degree to which the log likelihood of the transferred model exceeds that of the base model relative to the degree of improvement in log likelihood achieved with a perfect (predicts all choice correctly) local model. This measure is analogous to the commonly used rho-square measure (3). We define the transfer rho-square measure by
\[ \rho^2(\theta) = \frac{[LL(\theta) - LL(MS)]}{[LL(\theta) - LL(MS)]} \] (4)

This measure is related to TI by
\[ \rho^2(\theta) = TI(\theta) \] (5)

Accordingly, it is upper bounded by the local rho-square measure, has no lower bound, and negative values are interpreted as for the transfer index.

The three measures defined above are interrelated by their dependence on the difference in log likelihood between the transferred and local models. However, they provide different perspectives on model transferability. The transfer rho-square provides an absolute measure of disaggregate transferability, the transfer index provides a relative measure, and the transfer test statistic provides a statistical test measure.

Each of these measures may be applied to tests of partial model transferability by substitution of the log likelihood for the partly transferred model (a model with some transferred parameters and some locally estimated parameters) in place of the log likelihood for the transferred model in Equations 2, 3, and 4. The partial transfer log likelihood will always lie between the transfer model log likelihood and the local model log likelihood in Figure 1.

Aggregate Measures of Transferability

The planning process is primarily concerned with the prediction of aggregate rather than disaggregate travel flows. Thus, it is appropriate to consider transferability in terms of the accuracy of aggregate predictions. We define the error in aggregate prediction and examine ways in which these errors can be summarized across alternatives and aggregate groups.

We choose the following relative error measure for prediction of alternative choice frequency in some aggregate group:
\[ REM_{mg} = \frac{N_{mg} - N_{mg}}{\sqrt{N_{mg}}} \] (6)

where

- $REM_{mg}$ = relative error measure in prediction of alternative m for group g,
- $N_{mg}$ = number of persons observed to choose alternative m from group g, and
- $N_{mg}$ = number of persons observed to choose alternative m from group g.

In order to evaluate the aggregate predictive accuracy of a choice model we summarize this measure over alternatives and groups by means of the weighted root mean square error (RMSE) measure, defined by
\[ RMSE = \left( \frac{\sum N_{mg} REM_{mg}^2}{\sum N_{mg}} \right)^{1/2} \] (7)

This measure is an index of the average relative error in prediction weighted by the size of the prediction element and structured to place emphasis on large relative errors. RMSE can be disaggregated into alternative-specific error measures and into average and variational components to aid error analysis. These properties and their use in transportation error analysis are described by Koppelman (11-13).

An alternative measure of the accuracy of aggregate prediction tests the hypothesis that the observed frequencies of choice in each group are, collectively, generated by the prediction model. We formulate the aggregate prediction statistic (APS) as
\[ APS = \sum N_{mg} REM_{mg}^2 = \sum (N_{mg} - N_{mg})^2 / N_{mg} \] (8)

This statistic, which is equivalent to the chi-square one sample test (14), is chi-square distributed under the assumption the $N_{mg}$ is predicted without sampling error. This is equivalent to the assumption adopted in formulating the transferability test statistic.

APS is more likely to reject the hypothesis that all frequencies come from the candidate model than would a statistic that takes account of sampling variation. The degrees of freedom for the APS for full model transfer are (number of alternatives - 1) x (number of groups). However, when applied for local prediction or with locally adjusted alternative-specific constants, the degrees of freedom need to be reduced by the number of alternatives less one to (number of alternatives - 1) x (number of groups - 1).

A relative measure of aggregate prediction accuracy is useful. We define the relative aggregate transfer error (RATE) measure as the ratio between the transfer RMSE and local RMSE measures,
\[ RATE = \frac{RMSE(\theta)}{RMSE(\theta)} \] (9)

These measures are interrelated by their dependence on the relative error measure defined in Equation 6. However, they offer different perspectives on model transferability at the aggregate level. RMSE provides an absolute measure of aggregate transferability, RATE provides a relative measure, and APS provides a statistical test measure.

APPLICATION OF METHODOLOGY

We demonstrate the use of the transferability measures by their application to the transfer of mode choice to work models for the Washington, D.C., area. These models describe the choice among drive alone, shared ride, and transit alternatives for breadwinners who work in the central business district (CBD). There are a total of 2654 such breadwinners, 2088 of whom have all three alternatives available and 566 of whom do not have drive alone available due to lack of a driver's license or lack of available cars in the household. We divide the population into three groups by geographic sector as shown in Figure 2.
The demographics of these CBD-based breadwinners in sectors one and three are similar. Those in sector two are generally younger and come from households that have more persons, more workers, lower household income, fewer cars, and fewer licensed drivers. Average travel service characteristics are similar across sectors for drive alone and shared ride. Transit service is most expensive in sectors one and three and most time consuming in sector three.

### Method of Analysis, Model Specification, and Parameter Estimates

We study the various transferability measures and tests in application to the transferability of workmode-choice-to-CBD models between pairs of sectors depicted in Figure 2. We estimate models by using the specification employed by Koppelman (7,12,13) in his analysis of aggregation error in prediction of disaggregate choice models.

### Variable Name

<table>
<thead>
<tr>
<th>Item</th>
<th>Sector 1 (n = 944)</th>
<th></th>
<th>Sector 2 (n = 964)</th>
<th></th>
<th>Sector 3 (n = 746)</th>
<th></th>
<th>Region (n = 2654)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Parameter</td>
<td>t-Value</td>
<td>Parameter</td>
<td>t-Value</td>
<td>Parameter</td>
<td>t-Value</td>
<td>Parameter</td>
<td>t-Value</td>
</tr>
<tr>
<td>DAD</td>
<td>-3.39</td>
<td>-9.2</td>
<td>-1.84</td>
<td>-5.3</td>
<td>-2.73</td>
<td>-6.8</td>
<td>-2.59</td>
<td>-12.4</td>
</tr>
<tr>
<td>SRD</td>
<td>-2.46</td>
<td>-8.8</td>
<td>-2.10</td>
<td>-8.5</td>
<td>-2.52</td>
<td>-7.3</td>
<td>-2.35</td>
<td>-16.8</td>
</tr>
<tr>
<td>CPDDA</td>
<td>4.13</td>
<td>11.1</td>
<td>3.07</td>
<td>8.8</td>
<td>3.58</td>
<td>9.0</td>
<td>3.59</td>
<td>17.0</td>
</tr>
<tr>
<td>CPDSR</td>
<td>2.05</td>
<td>7.3</td>
<td>1.77</td>
<td>8.2</td>
<td>1.59</td>
<td>5.0</td>
<td>1.83</td>
<td>12.4</td>
</tr>
<tr>
<td>OPTCINC</td>
<td>-0.0069</td>
<td>-0.5</td>
<td>-0.0242</td>
<td>-2.1</td>
<td>-0.0380</td>
<td>-1.7</td>
<td>-0.0232</td>
<td>-3.2</td>
</tr>
<tr>
<td>TVTT</td>
<td>-0.0418</td>
<td>-6.9</td>
<td>-0.0151</td>
<td>-3.2</td>
<td>-0.0223</td>
<td>4.6</td>
<td>-0.0243</td>
<td>-8.3</td>
</tr>
<tr>
<td>OVTVD</td>
<td>0.0258</td>
<td>0.4</td>
<td>-0.105</td>
<td>-1.8</td>
<td>-0.0421</td>
<td>0.5</td>
<td>-0.0667</td>
<td>-1.85</td>
</tr>
<tr>
<td>GWSR</td>
<td>0.746</td>
<td>4.8</td>
<td>0.526</td>
<td>2.6</td>
<td>0.680</td>
<td>4.2</td>
<td>0.653</td>
<td>7.4</td>
</tr>
<tr>
<td>NWORKSR</td>
<td>0.096</td>
<td>0.9</td>
<td>0.264</td>
<td>2.7</td>
<td>0.502</td>
<td>4.1</td>
<td>0.369</td>
<td>4.4</td>
</tr>
</tbody>
</table>

Log likelihood
- At zero: -962.5, -933.8, -790.0, -2686
- At market share: -904.4, -898.5, -771.6, -2587
- At convergence: -754.4, -803.4, -203.4, 840.8

Likelihood ratio: 416.2, 260.7
Likelihood ratio index
- $\rho^2 (0)$: 0.216, 0.140, 0.129, 0.157
- $\rho^2$ (market share): 0.166, 0.106, 0.108, 0.124

The estimated models for each sector and for the region are reported in Table 1. All models are highly significant overall and the parameters for all models are significant at the 0.01 level, except for OPTCINC and OVTVD for all sectors and NWORKSR for sector one.

The overall goodness of fit as measured by the rho-square evaluated at zero or market share is low for disaggregate choice models. However, studies by various researchers have found this general specification to be satisfactory for analysis of this data set and similar specifications have been employed for many of the disaggregate work mode choice studies reported in recent years (2,5,11).
Model Parameter Equality

The model equality test statistics for the complete model and for the partial model (all parameters except alternative-specific constants) between pairs of sectors and for all sectors jointly reject the equality hypothesis at the 0.05 level for two of three sector pairs (except sectors 2 and 3) and for the set of three sectors jointly. Based on this result we would reject the hypothesis of model equality. By implication, this would suggest the rejection of model transferability.

Disaggregate Measures of Transferability

The transferability test statistics (Equation 3) for full and partial model transfer are reported in Table 2. The reported values for the transfer of the full and partial models are all significant at the 0.01 level except for the partial model transfer from sector 2 to sector 3. These results reject strongly the hypothesis of intraurban transferability for the model used in this application.

There are other interesting observations to be made from the results in Table 2. First, as expected, the transferability test results are not symmetric. In fact, the transfer directionality is quite large. Second, improvements in the TTS value when moving from transfer of the total to partial model transfer are large in almost every case. Table 2. Transfer index. The transfer index values in- crease dramatically when moving from transfer of the total model to transfer of the partial model for all transfers except sector two to sector one, which already had a high value. These results indicate that, when alternative-specific constants are adjusted to match application choice shares, the transfer model can provide a high proportion of the information that would be obtained by estimation of a model in the application context. The transfer rho-square market share measure and TI (Table 3) by Equation 5 are not reported here. They can be obtained from the model rho-square market share measure and TI (Table 3) by Equation 5.

Aggregate Measures of Transferability

We now examine the aggregate prediction capability of transferred models. The sectors described in Figure 1 are subdivided into residence zones (16 in sector 1, 19 in sector 2, and 16 in sector 3). Aggregate predictions for mode choice in each residence zone are obtained by summing individual prediction probabilities for each alternative (13). These predictions are compared with the observed travel mode choices to compute the relative error measure (REM) defined in Equation 6 for each mode and zone. These error measures are combined over modes and zones to obtain the aggregate error measures.

The aggregate error in applying each sector model (with and without alternative-specific constants) to each sector by using RMSE is reported in Table 4. Based on RMSE, all of the predictions give reasonably accurate estimates of aggregate mode share. The errors for transfer models are not dramatically greater than those for local models, especially when alternative-specific constants are adjusted to match local data.

Next, we use APS, defined in Equation 8, to test the hypothesis that the aggregate choice frequencies by mode for the zones in each sector are generated by the models estimated in each sector (Table 5). The hypothesis that the observed choice frequencies are generated by the models tested is rejected at the 0.01 level for model transfer in five of six cases for the full model and three of six cases for the partial model. Thus, the APS analysis rejects the hypothesis of model transferability.

We do not report RATE. These measures can be obtained from RMSE for transfer prediction and local model prediction by Equation 9.

SUMMARY AND CONCLUSIONS

This paper develops a methodology and related measures to be used in the analysis of transferability effectiveness. The measures developed include both indices and statistical tests applicable at either the disaggregate or aggregate level. The measures
developed are applied to the analysis of intraregional transferability of disaggregate CBD-work mode choice models estimated on geographic portions of a common data set by using identical specifications. The application illustrates the differences in substantive interpretations and conclusions that can be obtained by use of different measures. It also identifies the variability in transfer effectiveness that exists even within this relatively narrow range of estimation and application contexts.

Conclusions from Relative Transfer Measures

The relative transfer measures indicate that transferred models have relatively small error compared with that incurred by use of local models. This indicates that transferred models provide at least 80 percent of the information provided by local models in four of six full model transfers and five of six partial model transfers. RATE (ratio of transfer and local RMSSE) indicates that the use of transferred models incurs less aggregate error by 20 percent or less for four of six full model transfers and 10 percent or less for four of six partial model transfers. These results suggest that it is reasonable to conclude that models are transferable between these geographic sectors.

Conclusions from Statistical Tests

The statistical tests generally reject hypotheses that are consistent with transferability. The METS test rejects model equality at the 0.05 level for two of three sector pairs. The TTS test rejects model transfer at the 0.01 level for all full model transfers and five of six partial model transfers. The APS test rejects model transfer at the 0.01 level for five of six full model transfers and three of six partial model transfers. These results suggest that transferability between these geographic sectors should be rejected.

Transfer Error Importance Versus Significance

The results of magnitude of transfer error tests and those of transfer significance tests lead to different conclusions about transfer effectiveness. That is, the transfer errors are deemed to be unimportant in magnitude; however, hypotheses that support transferability are significantly rejected. This apparent inconsistency results from confusion in the literature between the observed magnitude of differences incurred by use of local models and the statistical significance of such differences that reflect both the magnitude and the precision of the estimates and predictions obtained. Although statistical tests can be used to alert the planner or analyst to differences between models, they must be considered with reference to the magnitude of errors that are acceptable in each application context. Although the magnitude of prediction error attributable to either a local or transferred model depends on the distribution of explanatory variables in the application context, our experience suggests that the apparent inconsistency between statistical rejection and practically small differences is commonly observed.

Transfer Measures Sensitivity

The transfer measures formulated are highly sensitive to differences in sector pair transfer effectiveness. For example, the TI that measures transferability relative to the local model ranges from 0.61 to 0.89 for full model transfer and from 0.76 to 0.92 for partial model transfer. Thus, these measures appear to be able to discriminate among levels of transferability.

Asymmetry of Transferability Measures

The measures of transferability developed are consistently different, in some cases dramatically different, between the same pairs of sectors, depending on the direction of transfer. This indicates that transferability is not determined solely by differences between sectors but also by the identity of the estimation and application contexts.

Adjustment of Alternative-Specific Constants

The transfer effectiveness measures improve substantially when alternative-specific constants are updated to match choice shares in the application context. These results emphasize the importance of updating alternative-specific constants to take account of differences in the average effect of excluded variables between estimation and application contexts.

Model Goodness-of-Fit and Transfer Effectiveness

The order of models with respect to goodness-of-fit is sector one, sector two, and sector three. However, the sector-one model is not consistently the most-effective model for transfer. Specifically, the sector-two model transfers to sector three better than does the sector-one model by most of the measures employed.

Although it is generally recognized that models that have high goodness-of-fit are not necessarily well-specified and thus are not necessarily effective in transfer, goodness-of-fit measures are commonly used to guide the selection of model specification and the selection of models for application. In this case, all the models have identical specification. Our results indicate that selection of the context from which to draw an identically specified model for transfer application cannot be based on estimation context goodness-of-fit. This result motivates the need to identify characteristics of estimation and application contexts between which models may be effectively transferred.

Contextual Determinants of Transfer Effectiveness

Characteristics of the estimation and application contexts have an important influence on transferability. Research is needed to identify the degree to which contextual characteristics determine transfer effectiveness and the specific contextual characteristics that are important.

Specification and Transfer Effectiveness

It is argued in the literature that transferability improves with improved model specification (1, 5, 15). Although this view is reasonable, it has not been validated empirically. The understanding of transfer effectiveness will be enhanced by research into the relation between model specification and transfer effectiveness. Additional research is being undertaken to explore this relation.

Prior Prediction of Transfer Effectiveness

The transfer analysis reported here and in all previous research on the transferability of travel models is based on posterior analysis. That is, these studies examine the question, "Would it have been appropriate to transfer a specific model from a specific context to another specific context?"
comparison of transfer results to results obtained by application of a local model. The objective for the future is to use an understanding of the relation between model specification and characteristics of both estimation and application contexts to provide prior guidance about the probable transferability of different models estimated in different contexts for use in the application context of interest. This will be the focus of future research.

ACKNOWLEDGMENT

The work reported in this paper was supported by the Office of University Research, U.S. Department of Transportation. James Ryan of the Urban Mass Transportation Administration, who is contact technical monitor, provided technical advice in the development of this work. We also acknowledge the contributions of Eric I. Pas to the refinement of ideas in this paper. Comments by Joel Horowitz and Moshe Ben-Akiva contributed to refinements of certain statistical tests.

REFERENCES


Wisconsin Work Mode-Choice Models Based on Functional Measurement and Disaggregate Behavioral Data

GEORGE KOCUR, WILLIAM HYMAN, AND BRUCE AUNET

This paper describes a series of mode-choice models developed by the Wisconsin Department of Transportation to assess transportation policy issues consistently across four sets of urban areas in the state. The models were developed by using a combination of functional measurement (or by asking respondents their likely mode choice in a series of situations) and disaggregate demand modeling (to calibrate the models and provide a test of the correspondence between stated and actual behavior). Bus, walk, bicycle, ridesharing, and drive-alone modes are included. Key variables include gasoline availability, gasoline price, queuing time to purchase gasoline, bicycle lanes, ridesharing programs, and transit service improvements. The models are being used in statewide policy analysis, for local planning, and for quick-response analysis. They represent an approach to demand analysis and may be an efficient and effective tool for examining other demand issues.

In a single statewide modeling study, the Wisconsin Department of Transportation (WisDOT) has developed work trip mode-choice models for four sets of urban areas of different character: one large city, one medium city, and two sets of small cities. These models permit WisDOT to address key policy issues by incorporating the effects of gasoline availability,