Spatial Transferability of Travel Forecasting Models: A Review and Synthesis

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**Introduction**

Spatial transferability of travel forecasting models is of considerable practical interest. The ability to transfer models from one region to another can help in significant cost and time savings for regions that cannot afford to invest in extensive data-collection and model-development procedures. This issue is particularly important in the context of activity-based models whose development typically involves significant data inputs, skilled staff, and long production times. As several transport planning agencies are moving toward (or considering the shift to) tour-based/activity-based travel models, there is a revival of interest in the issue of model transferability.

This conference paper aims to provide a synthesis of the extant literature on spatial transferability of travel forecasting models. The specific objectives are to review: (1) the theoretical and practical considerations related to model transferability, (2) the approaches and metrics used to assess model transferability, (3) the methods used to enhance model transferability, and (4) the empirical evidence on model transferability. Building on this review, a framework will be laid out for assessing the transferability of operational tour-based/activity-based models of travel.

In the remainder of the paper, we provide a brief discussion of each of the issues we plan to discuss at the conference, and finally present a table with an extensive review of the empirical literature on spatial transferability. At the conference, we plan to present select insights from this review. The goal is to gather empirical evidence and provide guidelines for making decisions on whether (and how) models can be transferred.

**Defining Transferability: Theoretical and Practical Considerations**

Most empirical research takes a restricted view of model transferability – as equivalence of the model parameters between different contexts. However, it is useful to begin with a broader understanding of the concept transferability, in terms of both theoretical and practical aspects.

**Theoretical Considerations**

Theoretical issues related to travel model transferability are best laid out in three resource papers by Ben-Akiva (1981), Hansen (1981), and Louviere (1981) for a conference workshop on *Spatial, Temporal and Cultural Transferability of Travel-Choice Models*. Thus, this section draws from these three papers.

Travel forecasting models for a population are usually developed based on conceptual theories of travel behavior operationalized into empirical relationships between endogenous measures of travel (or, dependent variables) and exogenous factors that influence travel (or, independent variables). The empirical relationships are expressed as mathematical models with unknown parameters relating the dependent and independent variables. Estimates of the unknown parameters are obtained using a sample of the data representing the population. Alternative empirical specifications are compared to arrive at a final empirical model to be used for policy analysis and forecasting. Based on this process of travel model development, Ben-Akiva (1981) and Hansen (1981) suggested the following hierarchy of different levels at which transferability needs to be considered:

- Underlying theory of travel behavior
- Mathematical model
- Empirical model specification
- Parameter values

The above hierarchy transitions from a general and abstract level to a more specific level that involves numerical estimates of the parameters. The first level involves the transferability of broad behavioral postulates (Hansen, 1981) of travel behavior such as utility maximizing or satisficing decision paradigms. The second and third levels involve considerations of the specific model structure (e.g., logit vs. probit, joint vs. sequential choice structures), functional form (e.g., additive vs. non-additive utility forms, linear vs. non-linear specifications) and the specification of explanatory variables and the way they are included in the model. The fourth level considers the transferability of coefficients of explanatory variables and other parameters such as elasticities and value of time measures.
In theory, an empirical model can be considered “perfectly transferable” from one context to another only if its underlying behavioral theory, mathematical structure, variable specification and the parameter estimates are all transferable between the two contexts. However, several factors contribute to the potential failure of transferability at various levels of the hierarchy. Intuition suggests that the potential for transferability decreases from the general, theoretical level to the specific level of parameter estimates. Further, failure of transferability at any level reduces the potential for transferability at the lower level. Thus it is very difficult to develop perfectly transferable models.

Practical Considerations
Models are only abstractions of reality. Thus, no model can ever be perfectly specified. Even for a single region (let alone transferability to another region), models can be developed only up to a satisfactory level of performance according to certain statistical and pragmatic criteria (Ben-Akiva, 1981). Further, such criteria are not clearly defined in the profession and vary from one region to another. Besides, the gap between a models’ representation of human travel behavior and reality is likely to be different from one region to another. Thus, it is unrealistic to expect models to be perfectly transferable with same specification and equivalent parameters between different regions. Nevertheless, several regions may have no option but to borrow models or information from other regions due to data and resource constraints. Thus, it might be more constructive to understand if models can be transferred up to certain acceptable practical criteria, rather than expecting perfect transferability. In this context, we would like to use Koppelman and Wilmot’s (1982) definition of transferability as “the usefulness of the transferred model, information or theory in the new context”. To the extent that a “borrowed” model could be used to make appropriate planning and policy decisions, the model could be considered transferable for practical purposes. The tricky part, however, is to determine whether (and to what extent) a transferred model helps in making appropriate decisions.

Assessment of Transferability
Since theoretically perfect spatial transferability is difficult to achieve, empirical assessment of transferability is essential to assess the extent to which models can be transferred. Empirical assessment of model transferability requires data and/or information from at least two different spatial contexts. The context from which an empirical model is transferred is called the base context or the estimation context, and the context to which the model is transferred is called the application context or the local context.

Almost all empirical studies in the literature assume that the underlying theory and mathematical model structure are transferable across spatial contexts. Typically the empirical specification (especially the parameter estimates) has been subject to tests of transferability. Table 1 presents a summary of the metrics widely used for such tests. These metrics can be classified into three categories: (1) Statistical tests of model equivalence, (2) Measures of predictive ability (at disaggregate and aggregate levels), and (3) Policy sensitivity comparisons. Within these categories, one can categorize the metrics into absolute and relative measures of transferability. Absolute measures are used to assess how well a transferred model represents observed behavior in the application context, while relative measures are used to assess the performance of a transferred model relative to a model estimated in the application context. These different categories are briefly discussed next.

Statistical tests: Statistical tests can be used to formally test the null hypothesis of model transferability (e.g., equality of parameters between estimation and application contexts). However, before jumping into conclusions based on these tests, it is worth remembering at least a couple of caveats. First, in the context of discrete choice models, the parameter estimates are confounded with the scale (i.e., variance) of the unobserved components of utility functions. Thus, parameter equivalence implies equality of the ratio of true (but unknown) coefficients to the scale of the unobserved factors; not necessarily the equality of true coefficients. Second, one should be cognizant of the weakness of statistical hypothesis testing. Results of statistical tests (e.g., test of equal parameters hypothesis) depend, in part, on the size of the data samples used (Ben-Akiva, 1981). With small data samples, precision in the estimates may not be sufficient to reject the null hypothesis. However, lack of sufficient evidence to reject the hypothesis does not necessarily mean the analyst can safely conclude that parameters are transferable. Numerical differences in the estimates may be sufficient to result in practically different predictions (Talvite and Krishner, 1983) On the other hand, with large enough data samples, the null hypothesis of parameter
equality is highly likely to be rejected (Gunn et al., 1985). In summary, there is perhaps no need of rigorous statistical tests to reject the hypothesis of "perfect transferability". The role of statistical tests should be to identify significant differences between the estimation and application contexts and to identify weakness in model specifications that could be potentially addressed (Ben-Akiva, 1981). Once statistically significant differences are identified, further tests can be conducted to see if these differences are practically important.

Measures of Predictive Ability: Although a model is not “statistically” transferable, it could closely approximate behavior in the application context for all practical purposes. Measures of predictive ability have been used to make such practical assessments. These metrics measure the predictive accuracy of transferred models in the application context. Disaggregate-level metrics measure the goodness of fit of the transferred model in the application context, while aggregate-level metrics provide a measure of error in the aggregate predictions (e.g., predicted mode shares) of the transferred model. The analyst needs to make assumptions on the level of acceptable error in predictive accuracy to determine whether a model is transferable.

Policy Sensitivity Tests: It is important to note that the ability of a model to reproduce observed behavior does not guarantee the ability to adequately forecast changes in travel demand under different demographic, land-use and transportation system change scenarios. Since a predominant use of travel models is for forecasting and policy analysis, a more robust way to assess model transferability is to see if a transferred model provides similar responses to policies as a locally estimated model. For example, one can compare elasticity values of the transferred and local models with respect to different explanatory variables both at the aggregate and disaggregate levels. Surprisingly, only a handful of empirical studies (Atherton and Ben-Akiva 1976, Karasmaa 2007, Nowrouzian and Srinivasan 2011) use policy sensitivity tests to assess model transferability.

Enhancement of Model Transferability
The simplest approach to transfer a model is naïve transfer, where the model specification and parameter estimates from the base context are applied directly (without any change) to the application context. Empirical evidence suggests that that naïvely transferred models may not adequately represent behavior in the application context. Thus, using available information and data from the application context, the base context model can be “updated” to render it better capture behavior in the application context. The various updating methods used in the literature are discussed next.

Updating alternative specific constants: In general, the alternative specific constants in a discrete choice model capture the average effects of omitted variables (i.e., unobserved factors). Since the influence of unobserved factors can vary between contexts, the alternative specific constants estimated in the one context may not be directly transferrable to another context. Thus, a model transferred from the base context can be improved by updating the alternative specific constants using data from the application context.

Transfer scaling: In this method, it is assumed that the utility function parameters computed in the base context (excluding the alternative constants) are transferrable to the application context up to a certain “scale”. The scale represents the ratio between the influences of unobserved factors in the two contexts. One can use a small sample from the application context to estimate the ‘scale’ by which the base context parameters need to be updated.

Bayesian updating (Atherton and Ben-Akiva, 1979): This approach involves a Bayesian updating of the base context parameter estimates using estimates from a small sample in the application context. In other words, the prior distribution (distribution of the base context coefficients) is combined with the sample distribution (distribution of the coefficients estimated from the small sample) to obtain the posterior distribution (or updated distribution of the coefficients).

Combined transfer estimator (Ben-Akiva and Bolduc 1987): This approach is an extension of the Bayesian technique to take into account the transfer bias between the estimation and application contexts.
Joint context estimation (Bradley and Daley, 1991; Ben-Akiva and Morikawa, 1990): This approach combines data from both the estimation and application contexts to estimate a joint estimation/application context model. Depending on the data availability from the two contexts, common coefficients can be estimated for a subset of variables (combining data from both contexts) while context-specific coefficients can be estimated for other variables. Further, the scale-difference between the two contexts is recognized by estimating a scale parameter.

Empirical Evidence
Table 2 presents an extensive review of the empirical literature on spatial transferability of travel models. The first 13 studies in the table are in the context of mode and/or destination choice model components, studies numbered 14 to 18 are in the context of travel generation model components, and while studies numbered 19-25 are in the context of tour-based/activity-based model systems or model components. Based on this review, a synthesis of the empirical evidence will be presented at the conference, with an emphasis on the following aspects:

1. Strengths and weakness of different transferability assessment methods,
2. The performance of different model updating methods,
3. A framework for assessing the transferability of tour-based/activity-based model systems, and
4. Guidelines for transferring models to a region.

Summary
This paper provides a review and synthesis of the extant literature on spatial transferability of travel forecasting models. More specifically, the theoretical and practical considerations related to model transferability, the metrics used to assess model transferability, and the approaches used to enhance model transferability are reviewed. Further, an extensive amount of empirical evidence is gathered on model transferability. At the conference, we plan to present important insights from this review. Building on these insights, a framework will be laid out for assessing the transferability of operational tour-based/activity-based travel models, and guidelines will be presented for transferring models to a region.

Acknowledgements
This work is based on a research project supported by the Florida Department of Transportation (FDOT). We appreciate the advice and encouragement of Vidya Mysore and Terry Corkery from the Systems Planning office of the FDOT. Of course, any errors are own responsibility.

References
Keeping in view the word limit, a list of references is not provided (but available from the authors).
Table 1: A Summary of the Metrics used to Assess Model Transferability

<table>
<thead>
<tr>
<th>Name of the Test</th>
<th>Type of the Test</th>
<th>Expression</th>
<th>Description</th>
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<tbody>
<tr>
<td>Model Equality Test Statistic (METS)</td>
<td>Statistical test of model equivalence</td>
<td>$-2[L_i(\beta_j) - L_i(\beta_j')]$</td>
<td>$\chi^2$ distributed. Used to test if the model parameters (or a subset of parameters) in the base and application contexts are equal (i.e., the hypothesis that the behavioral process in the two contexts can be described by a common model). Can be used to test the transferability of a subset of parameters while allowing for other parameters to be different. Requires estimation data from both contexts so a model with a combined dataset can be estimated.</td>
</tr>
<tr>
<td>Transferability Test Statistic (TTS) Atherton &amp; Ben-Akiva (1976)</td>
<td>Statistical test of model equivalence</td>
<td>$-2[L_i(\beta_i) - L_j(\beta_i)]$</td>
<td>$\chi^2$ distributed. Used to test if the transferred model parameters are equal to the parameters in the application context. Does not require estimation data from the base context. Recognizes the possibility of asymmetric transferability between the two contexts. TTS value for transferring a model from one context to another is not necessarily equal to the TTS for transfer in the other direction.</td>
</tr>
<tr>
<td>t-tests of individual parameter equivalence</td>
<td>Statistical test of individual parameter equivalence</td>
<td>Ratio of the difference in parameters to standard error of the difference</td>
<td>Used to compare the parameter estimates of specific variables (e.g., coefficients on travel time variable) between two contexts using standard t-tests (based on parameter estimates and their standard errors)</td>
</tr>
<tr>
<td>Transfer rho-square ($\rho^2_T$) Koppelman &amp; Wilmot (1985)</td>
<td>Measure of disaggregate-level predictive ability</td>
<td>$\frac{1}{L_i(\beta_j) - L_i(C_i)}$</td>
<td>Analogous to the rho-square metric commonly used to measure goodness of fit in model estimation. Describes how well a transferred model fits the data observed in the application context, relative to a reference model such as a market shares model (i.e., a constants only model).</td>
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<tr>
<td>Transfer Index (TI) Koppelman &amp; Wilmot (1982)</td>
<td>Measure of disaggregate-level predictive ability</td>
<td>$\frac{L_i(\beta_j) - L_i(C_i)}{L_i(\beta_j) - L_i(C_j)}$</td>
<td>Measures the goodness-of-fit of a transferred model relative to an identically specified model estimated in the application context. Ratio of a transferred model’s rho-square ($\rho^2_T$) to the locally estimated model’s rho-square ($\rho^2$). The closer the value of TI is to 1, the closer is the transferred models’ performance to a locally estimated model. Can be used to compare the transferability of different models to a region with a same locally estimated model as the reference.</td>
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<tr>
<td>Relative Error Measure (REM)</td>
<td>Measure of aggregate-level predictive ability</td>
<td>$(PS_i - OS_i) / OS_i$</td>
<td>An error measure of the aggregate-level prediction for a choice alternative</td>
</tr>
<tr>
<td>Root-Mean-Square Error (RMSE)</td>
<td>Measure of aggregate-level predictive ability</td>
<td>$\sqrt{\frac{\sum PS_i \times REM^2_i}{\sum PS_i}}$</td>
<td>Measures the aggregate-level predictive ability of the model, when compared to aggregate observed shares in the data.</td>
</tr>
<tr>
<td>Relative Aggregate Transfer error (RATE)</td>
<td>Measure of aggregate-level predictive ability</td>
<td>$\frac{RMSE(\beta_i)}{RMSE(\beta_j)}$</td>
<td>Ratio of the RMSE value of a transferred model with that of a locally estimated model. Used to assess the aggregate-level prediction performance of a transferred model relative to a locally estimated model.</td>
</tr>
<tr>
<td>Aggregate Prediction Statistic (APS)</td>
<td>Measure of aggregate-level predictive ability</td>
<td>$\sum_i (PS_i - OS_i)^2 / PS_i$</td>
<td>$\chi^2$ distributed. Used to test the hypothesis that the alternative shares predicted by the transferred model are equal to the observed shares in the application context.</td>
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*Notation:

$L$ stands for log-likelihood and $\beta$ for a vector of parameters, while $j,i$ are subscripts for transferred and locally estimated models, respectively.

$L_i(\beta_j)$ = log-likelihood of the transferred model applied to the application context data

$L_i(\beta_i)$ = log-likelihood of the local model applied to the application context data

$L_i(C_i)$ = log-likelihood of a constants only model for the application context data

$PS_i$ and $OS_i$ = Predicted shares and observed shares, respectively, for a choice alternative $k$
<table>
<thead>
<tr>
<th>Authors</th>
<th>Findings</th>
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| 1. Watson & Westin (1975)     | • TTS test of parameter equality suggests that most models (between different inter-city regional pairs) showed significantly different parameters from each other.  
• Predicted probability distributions of naively transferred models matched well with estimated distributions only if the parameter estimates were equivalent between the base and application contexts. |
| 2. Atherton & Ben-Akiva (1976)| • TTS test of parameter equality suggests that the model parameter estimates for the Washington D.C. region were statistically similar to those in the New Bedford and Los Angeles areas. t-tests of individual parameter differences suggested that level-of-service (los) coefficients were not significantly different across the three regions. This result supports naïve transfer. The authors attribute the result to good specification and performance of the base context model in the base context.  
• Bayesian parameter updating method was concluded to have performed best (among other updating procedures). But there was no significant difference between a naively transferred model and the Bayesian updated model. The naively transferred model was itself as good as a locally estimated model (i.e., there was no transfer bias). |
| 3. Talvitie & Kirshner (1978) | • Statistical tests for most model comparisons did not support parameter inequality (or inequality of models) across different regions.  
• Most explanatory power was in mode-specific constants (unobserved factors) making it difficult to transfer models. |
| 4. Galbraith & Hensher (1982) | • Statistical tests (TTS, and t-tests) rejected the hypothesis of the equality of naively transferred and locally estimated parameters. This may be because the rail modes in the two regions were very different in terms of unmeasured service attributes.  
• Transferred models were unable to closely predict the observed rail mode shares, perhaps due to the absence of socio-demographics and unmeasured level of service attributes in the specification.  
• Model specifications with higher rho-square did not transfer well if they were not theoretically/conceptually sound specifications.  
• Bayesian updating using a subset of local data better improved the model performance (based on transferred $r^2$) compared to a naively transferred model or a scale-updated model. |
| 5. Koppelmann & Wilmot (1982) | • Investigated the effect of omitted demographic variables on spatial transferability.  
• A minimum adequate specification was necessary to enable reasonable model transfer (i.e., at least 75% TI). Specification with only los variables did not satisfy this minimum requirement.  
• Each successive improvement of the model specification (with additional variables) lead to improvement in absolute transfer effectiveness (goodness of fit to observed data) although the transfer effectiveness relative to locally estimated model remained unaffected beyond a minimum adequate specification. |
| 6. Koppelmann & Wilmot (1985) | • Naively transferred model was substantially deficient compared to a model estimated with local data (with an average transfer index of only 53% for interurban transfer).  
• Updating constants and scale using a subset of local data (i.e., 20% of the local data available for full re-estimation) helped significantly improve the performance of the transferred model (resulting in an average transfer index of 81% for interurban transfer).  
• Updating constants lead to significant improvement of the transferred model (TI = 76%) while updating the parameter scale lead to considerable but less significant improvement (TI = 81%).  
• The transfer index for intra-urban transfer was better than that for inter-urban transfer. |
| 7. Koppelmann et al. (1985)   | • The base case model specification was taken and several transfer models were estimated with updated constants and different scale parameters (such as one per variable (transfer scaling), one per group of variables (partial transfer), one for all variables (complete re-estimation), using data from application context.  
• None of the transfer methods resulted in models that were statistically equivalent to that from a completely re-estimated model (in terms of log-likelihood).  
• From an aggregate predictive ability standpoint, transfer scaling provided the most significant improvement over the naively transferred model and sufficient approximation to a local model.  
• Partial transfer models did not provide practically discernible improvements over the transfer scale models. |
| 8. Gunn et al. (1985)         | • Compared the spatial transferability of two different multidimensional model structures (MNL and nested logit(NL)) for modeling mode choice and auto ownership.  
• Both model structures were almost equally transferable (with a transfer index of 0.85). This may be because the model estimation results and the model fit were almost similar between the two models. Specifically, the nesting parameter in the nested logit model was not statistically different from 1, suggesting the two models are equivalent in the current empirical context. |
| 9. Koppelmann & Pass (1986)   | • Disagregate transferability measures (TTS, TI) suggest that the models cannot be naively transferred from one region to another. Statistical measures of predictive accuracy (APS) suggest that the transferred models are capable of reproducing the observed model share in the application context at an aggregate spatial level but not at a finer, Census Metropolitan Area level.  
• Poor transferability in this empirical context was attributed to the poor performance of the models in their local areas (i.e., in the base contexts).  
• Updating only the constants of the transferred models lead to 18-23% less accuracy in predicting mode shares (when compared to locally estimated model). Bayesian updating of all parameters lead to transferred models that were 8-13% less accurate.  
• Transferability depended on the direction of transfer between two regions. |
| 10. Abdelwahab (1991)         | • Transferred models did not perform better than a locally estimated model with a large sample, but updating the transferred model using a smaller sample of the application context significantly improved the transferred model performance.  
• Transferred models updated with a small sample performed much better than locally estimated models with a small sample, indicating the usefulness of transferred model updating methods when there is no sufficient data to estimate models in application context.  
• Value of time and elasticity comparisons suggested that the performances of different updating techniques improve (relative to the local model) with the increase of sample size. Among the different updating methods, joint context estimation was found to have the best prediction performance. Bayesian updating was found to be very risky due to potential transfer bias.  
• No concrete recommendation was made on the sample size. This is because the sample size depends on the method of transfer and also on the model structure and specification used in the analysis. A major problem, however, is the difficulty of small data samples from application context to accurately reflect the true market shares. |
| 11. Karasmaa (2007)           | • Disaggregated transferability measures (TTS, TI) suggest that the models cannot be naively transferred from one region to another. Statistical measures of predictive accuracy (APS) suggest that the transferred models are capable of reproducing the observed model share in the application context at an aggregate spatial level but not at a finer, Census Metropolitan Area level.  
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• Transferability depended on the direction of transfer between two regions. |

Table 2: A Summary of the Empirical Literature on Spatial Transferability of Travel Models
<table>
<thead>
<tr>
<th>Reference</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>12. Stopher &amp; Wilmot (1979)</td>
<td>A mode choice model was developed in South Africa and the coefficients of this model were compared with those of the models developed in 10 different areas of the United States. Coefficients of in-vehicle travel time and total travel time variables are similar in value to the range of the coefficients of the models developed in the United States. However, as the authors recognize, such direct comparisons of coefficient values does not consider the differences in model specification, variable definitions and measurement, and model scale parameters.</td>
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<tr>
<td>13. Santos &amp; Tsunokawa (2010)</td>
<td>Naive transfer and Bayesian updating techniques were substantially deficient compared to a locally estimated model in predicting observed behavior (based on rho square, TI and REM). The p² and TI values suggest that either updating constants and scale or applying the combined transfer technique using a reasonable sample (of at least 200) provide the maximum improvement toward a locally estimated model with full sample. But combining transfer estimator does not perform well when the transfer bias exceeds a critical value, say, due to large variability in application data. Joint context estimation was not explored in this study. Sample sizes smaller than 100 were not recommended for updating purposes due to large variance.</td>
</tr>
<tr>
<td>14. Mahmassani et al. (1979)</td>
<td>Aggregate level (area wide) trip rates are not transferable across different regions. Household level trip rates computed for an urban area of population in the 50,000 – 250,000 could be transferred to another urban area of similar size (based on the t-test).</td>
</tr>
<tr>
<td>15. Caldwell &amp; Demetsky (1980)</td>
<td>Household-level trip generation models applied at the household level are more transferable (for predicting aggregate trip rates) than the same model applied at an aggregate, zonal level. Transferability of cross-classification model is better between areas with similar cities.</td>
</tr>
<tr>
<td>16. Rose &amp; Koppelman (1984)</td>
<td>For both inter and intra regional transfer, the transfer index metric suggested that a significant level of accuracy (a minimum transfer index of 85%) could be obtained from the naive transfer. Updating the constant (using aggregate data from application context) further improved the transfer index. Non-statistical tests (RMSE, RATE) indicated better transferability for models with updated constants than naively transferred models. Transfer effectiveness is better for intra-regional transfer than for inter-regional transfer, suggesting that context similarity may be an important determinant of model transferability.</td>
</tr>
<tr>
<td>17. Wilmot (1995)</td>
<td>Poor transferability was observed between areas with poor data quality, highlighting the importance of good data quality for transferability. The average transfer index value (TIR) improved from 57% for naively transferred models to 87% for models with updated constants. After controlling for confounding effects (i.e., updating constants with local data and working with good quality data), models with better specification (as measured by R²) transferred better than those with low values. The influence of model specification obscured without updating constants and with poor data. Models transferred better between areas of similar income levels. Including income as explanatory variable would’ve helped improve transferability between areas with different income levels.</td>
</tr>
<tr>
<td>18. Agyemang-Duah &amp; Hall (1997)</td>
<td>Asymptotic t-test suggests that in almost all cases the coefficients of the models estimated for different regions of Toronto are statistically similar. Measures of aggregate predictive accuracy suggest that naively transferred models performed acceptably in predicting aggregate shares of trip frequency (although with some over-prediction of the share of zero trips), except when the models are transferred between dissimilar areas (CBD to urban fringe). Updating constants and parameters (using one scale parameter for all socio-demographic variables, and another for an accessibility variable) improved the aggregate prediction ability when at least 10% (1000 samples) of the application data was used for updating.</td>
</tr>
<tr>
<td>19. Gunn &amp; Pol (1986)</td>
<td>Mode-destination choice: Each successive improvement over the naively transferred model offered statistically significant improvement (log-likelihood improvement). However, from an aggregate prediction standpoint, an initial scaling transfer significantly improved the model fit to the application data (over the naive transfer) and aggregate prediction ability, but complete re-estimation did not improve the model fit in a significant way. Household driving license status and Car ownership models: Fully re-estimated models were statistically superior, but transferred scaling models (with updated constant and a scale parameter) would suffice to capture the practical differences. Overall: Transfer scaling provided the most improvement per additional parameter to be estimated, while partial transfer and complete re-estimation provide quickly diminishing (although statistically superior) returns per additional parameter.</td>
</tr>
<tr>
<td>20. Arentze et al. (2002)</td>
<td>Prediction performance at both the aggregate and disaggregate levels supported the transferability of the “Albatross” activity-based model system (except for the mode choice model component).</td>
</tr>
<tr>
<td>21. PB Consult Inc. (2007)</td>
<td>Predicted shares (of the CT-RAMP tour-based model system transferred from the MORPC region to Lake Tahoe) were reported to have matched closely with the observed survey data for certain model components. More information to be gathered before conference.</td>
</tr>
<tr>
<td>22. Vine et al. (2010)</td>
<td>Predicted temporal distributions of activity and travel participation (obtained from a rule-based activity-travel model system, TASHA, transferred from Toronto to London) were found to be different from that in the local survey data. More information to be gathered before conference.</td>
</tr>
<tr>
<td>23. RSG, Bradley, Bowman (2011)</td>
<td>Transferred the DaySim activity-based model system from Sacramento to Jacksonville. More information to be gathered before conference.</td>
</tr>
<tr>
<td>24. Nowrouzian &amp; Srinivasan (2011)</td>
<td>Aggregate prediction supports the concept of transferability of tour generation models while elasticity measures do not. Transferability of a tour generation model depends on tour purpose, direction of transfer, as well as the region from which the model is transferred.</td>
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</tbody>
</table>