Center for Multimodal Solutions for Congestion Mitigation
University of Florida

Final Report

to the

CENTER FOR MULTIMODAL SOLUTIONS FOR CONGESTION MITIGATION (CMS)

CMS Project Number: 2009-008

Tour Generation Models for Florida

for period May 2009 – November 2011

from:

Sivaramakrishnan Srinivasan (PI)
Associate Professor
Department of Civil and Coastal Engineering
University of Florida
siva@ce.ufl.edu

Roosbeh Nowrouzian
Graduate Research Assistant
Department of Civil and Coastal Engineering
University of Florida
roosbeh.nowrouzian@gmail.com

Date prepared June 25, 2012

Table of Contents

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Acknowledgment of Sponsorship

This work was sponsored by a grant from the Center for Multimodal Solutions for Congestion Mitigation, a U.S. DOT Tier-1 grant-funded University Transportation Center.

List of Tables

List of Figures

ABSTRACT

Household travel surveys from three regions of Florida (Jacksonville, Tampa, and Miami areas) were examined to understand patterns in travel behavior. Tours were constructed and characterized in terms of purpose, travel party composition, complexity, and flexibility. The empirical findings underscore the need for travel-demand models that incorporate trip-chaining and intra-household interactions. A framework for modeling tour generation was also developed. This comprises a suite of four models applied sequentially. These models were estimated for each of the three regions (a total of 12 multinomial logit models in all). This study also examined the transferability of tour-generation models among three metropolitan regions in Florida. Naïve transfer methods are examined to assess the performance of the transferred models (from two other regions) to that of the locally-estimated model. Transferability is evaluated using multiple measures such as aggregate- and disaggregate predictive ability and the aggregate elasticities to specific socio-economic factors. Overall, while it might be acceptable to use a similar modeling framework, caution must be exercised in borrowing parameters from one area for use in another region. The current study can be significantly extended using the recent Florida add-on samples to the NHTS to guide the efforts to build a standardized activity-based modeling system for Florida.

EXECUTIVE SUMMARY

Given the shortcomings of the conventional, trip-based approach to travel forecasting, there is continued interest in developing activity-based models in the different parts of the country including Florida. As a first step towards building such advanced models for Florida, household travel surveys from three regions of the state (Jacksonville, Tampa, and Miami areas) were examined to understand patterns in travel behavior.

Tours were constructed from the trip-based surveys and were characterized in terms of purpose, travel party composition, complexity, and flexibility. Our analysis underscores the need for travel-demand models that incorporate trip-chaining. Further, strong intra-household inter-dependencies are also observed in the activity-travel patterns in Florida.

A framework for modeling tour generation was also developed. This comprises a suite of four models applied sequentially. Choices about mandatory tours (work) are made first followed by choices about escort tours (if children are present in the household). Choices about joint tours follow and the fourth and final component is on independent tours. The empirical analysis highlights that the three household travel surveys conducted in the state during the last decade to support the current trip-based models do lend themselves to tour-based analysis.

The four tour-generation models were estimated for each of the three regions (a total of 12 multinomial logit models in all). Several socio-economic variables were found to be statistically significant and reasonable predictors of tour-generation patterns. However, the number of explanatory factors included was also limited given the need to retain consistent variables across all models from the three regions.

This study also examined the transferability of tour-generation models among three metropolitan regions in Florida. Naïve transfer methods are examined to assess the performance of the transferred models (from two other regions) to that of the locally-estimated model. Transferability is evaluated using multiple measures such as aggregate- and disaggregate predictive ability and the aggregate elasticities to specific socio-economic factors. Overall, while it might be acceptable to use a similar modeling framework, caution must be exercised in borrowing parameters from one area for use in another region.

The current study can be significantly extended using the recent Florida add-on samples to the NHTS to guide the efforts to build a standardized activity-based modeling system for Florida.

CHAPTER 1. INTRODUCTION

The state-of-the-practice approach to travel-demand modeling (called the "four-step" or the "trip-based" approach) uses individual trips as the unit of analysis. That is, the travel volumes are quantified in terms of the number of trips; and the spatial, temporal, and modal attributes of each trip are determined *independent* of the similar characteristics of other trips made by the same person. The shortcomings of such an approach are well recognized in the literature. For instance, the "trip-based" approach could lead to erroneous predictions of the effects of policy actions. Consider a person who drives to work and on the way back home, stops to pick up his/her child from day care. If transit is improved between the home and work locations of this person, it is possible that the trip-based model predicts a mode shift from auto to transit for the trip to work with no mode changes for the other trips (work to day-care and day-care to home). This is because the mode for each trip is determined independent of the mode for other closely linked trips.

The above discussion highlights some of the issues with the treatment of individual trips as the unit of analysis for travel forecasting. These issues are of particular significance in the current-day transportation-planning context in which there is a critical need to realistically assess the behavioral responses of travelers to congestion-mitigation strategies. Consequently, "tour-based" and "activity-based" approaches have been developed as an alternative to the exiting trip-based approach. These methods recognize the inter-dependencies among the different trips made by the same person and among the trips made by the different members of the same household. In both these methods, "tours" constitute a fundamental unit of analysis – a tour is defined as a journey that starts and ends at the same location and comprises of two or more trips. In tour-based methods, the tours are the fundamental unit of analysis. In activity-based methods, the focus is on time-use and activity-participation patterns. However, all activity-based models do determine the sequencing of activities into tours. In the rest of this document, the term "activity-based model" or ABM is used interchangeably with "tour-based model".

ABMs have already been developed in some of the major metropolitan areas in the United States and are currently in development in other areas. Vovsha et al. (2004), Bradley and Bowman, (2006), Davidson et al. (2007), and Pinjari and Bhat (2011) provide excellent syntheses of the state of the practice in activity-based modeling in the United States. The objective of this study is to contribute towards activity-based modeling efforts in Florida.

One of the first steps in the development of an operational activity-based model system is to identify the important characteristic features of the travel patterns in the region. This can be accomplished by undertaking an empirical analysis of the activity-travel patterns using local travel-survey data. Subsequent to such exploratory analyses, a modeling framework is developed to systematically predict the different components of the travel pattern of all household members ensuring overall consistency.

The focus of this study is on developing a framework for modeling tour-generation, which is one of the first steps in the sequence of models that comprise the activity-based model system for any region. One of the key factors in the development of a framework is the extent to which intra-household interactions (joint participation of household members in activities, escorting of household members, sharing of household maintenance tasks) are incorporated. Inclusion of intra-household interactions adds behavioral realism to the representation and modeling of travel patterns. Models incorporating such interactions are more suitable for evaluating policy actions such as HOV/HOT lanes (see for example, Vovsha et al 2003) and can also capture secondary effects of policy actions (secondary effect is a change in the travel behavior of a person who is not directly exposed to the policy because of the effect of the policy on another household member's travel; see for example, Srinivasan and Bhat, 2006). At the same time, modeling these interdependencies also place additional demands on the data. For instance, travel undertaken by household members jointly may have to be derived based on spatio-temporal matching of the travel records as the household-travel surveys may not directly elicit such data (see Srinivasan and Bhat, 2005). Further, modeling such interactions may also limit the data sample as all the travel records from a household may not be usable even if one piece of information is missing for one trip of one person. In light of these discussions, this research effort will seek to characterize the intra-household interdependencies that can be identified from Florida's household travel surveys. This is very important in deciding the extent of inclusion of household interactions in Florida's ABMs. This study aims to identify and characterize tours and develop tour generation models using data from three regions (Jacksonville, Tampa, and Miami areas) in Florida.

Finally, the study also examines the extent to which the tour-generation models are similar across the state. This is accomplished by examining the extent to which models developed in one region are transferable to another. The transferability assessments are undertaken among the three regions for which models are developed. This transferability analysis is the primary contribution of this study as this is an important step towards developing standardized modeling frameworks for the state of Florida.

The rest of this report is organized as follows. Chapter 2 presents the framework for modeling tour generation. Chapter 3 presents a summary of data and the empirical results for the tour generation models. Chapter 4 discusses the extent of transferability of the tour generation models from one region to another. Chapter 5 presents an overall summary of the work done and identifies the major conclusions and the next steps.

CHAPTER 2. A FRAMEWORK FOR MODELING TOUR GENERATION

In activity-based and tour-based travel-demand modeling systems, “tours” constitute a fundamental unit of analysis. A tour is defined as a journey that starts and ends at the same location and comprises of two or more trips. The generation of tours (i.e., the number of tours of various types made by a person during the day) is one of the first choices modeled in activity-based / tour-based approaches. The purpose of the tour (defined as the purpose of the primary activity undertaken during that journey) is often used as a major characterizing feature of tours in implemented ABM structures such as DaySim and CT-RAMP. Other aspects such as joint versus solo travel are also being incorporated.

In this study, we classify tours to reflect the following four dimensions: (1) purpose, (2) complexity, (3) travel-party composition, and (4) flexibility. Tour purpose is defined in terms of the purpose of the primary activity undertaken in the tour. Complexity is related to the number of stops. A simple tour has only one stop (or two trips) whereas a complex tour has multiple stops (three or more trips). Travel-party composition reflects whether the travel is being undertaken solo (Independent) or jointly with other household members. Tour flexibility may depend on both purpose and travel-party composition. A flexible tour is one that has no constrained activities such as work and escort and is undertaken independently. An inflexible tour is defined as either a joint tour or one that has spatially- and/or temporally- constrained activities (work and escort).

The above-discussed dimensions guided the development of the following operational tour-generation framework (Figure 1). If the person is worker, (s)he makes choices about mandatory tours first. The alternatives are none (no work on that day), a simple tour (work is the only stop), a complex work tour with escort (a tour with two stops in which one is work and the other is escort), and a complex work tour without escort (i.e., work travel chained with a non-escort activity leading to a total of two or more stops in the work tour). Non-workers in households with children make choices about escort tours and choose from none (no escort tour), simple tour (escort is the only activity), and complex tour (escort is chained with a non work activity). Note that person makes a work tour, he/she is found (empirically) to predominantly chain any escort activity with this work tour rather than undertake an independent escort tour. Next, decisions about joint tours are made and this applies to only households with two or more persons. The person chooses from none, a single, simple (one stop) joint tour, a single complex (multi-stop) joint tour, or multiple joint tours (either simple or complex). Finally decisions about independent non-mandatory tours are made and the same set of four alternatives as in the case of joint tours applies. Overall, the framework reflects decisions about constrained tours being made prior to the decisions about less-constrained / unconstrained tours. It is important to emphasize that the development of the framework was strongly guided by an extensive empirical analysis of household travel surveys from three regions in Florida (See Chapter 3 for further details on data) in addition to theoretical considerations. Thus, the framework is operational (i.e. such patterns can be analyzed and modeled using the available travel-survey data).

It is useful to re-emphasize that the modeling framework reflects the travel-survey data that was available consistently across the three regions. Therefore, only those facets of activity-travel patterns that could be extracted from the surveys are modeled. Clearly, there are other aspects that characterize travel such as partially joint tours, non-home-based tours (or work-based sub tours), and the substitution of in-home activities for out-of-home travel (such as telecommuting). The modeling framework can be extended to accommodate these subject to data availability.

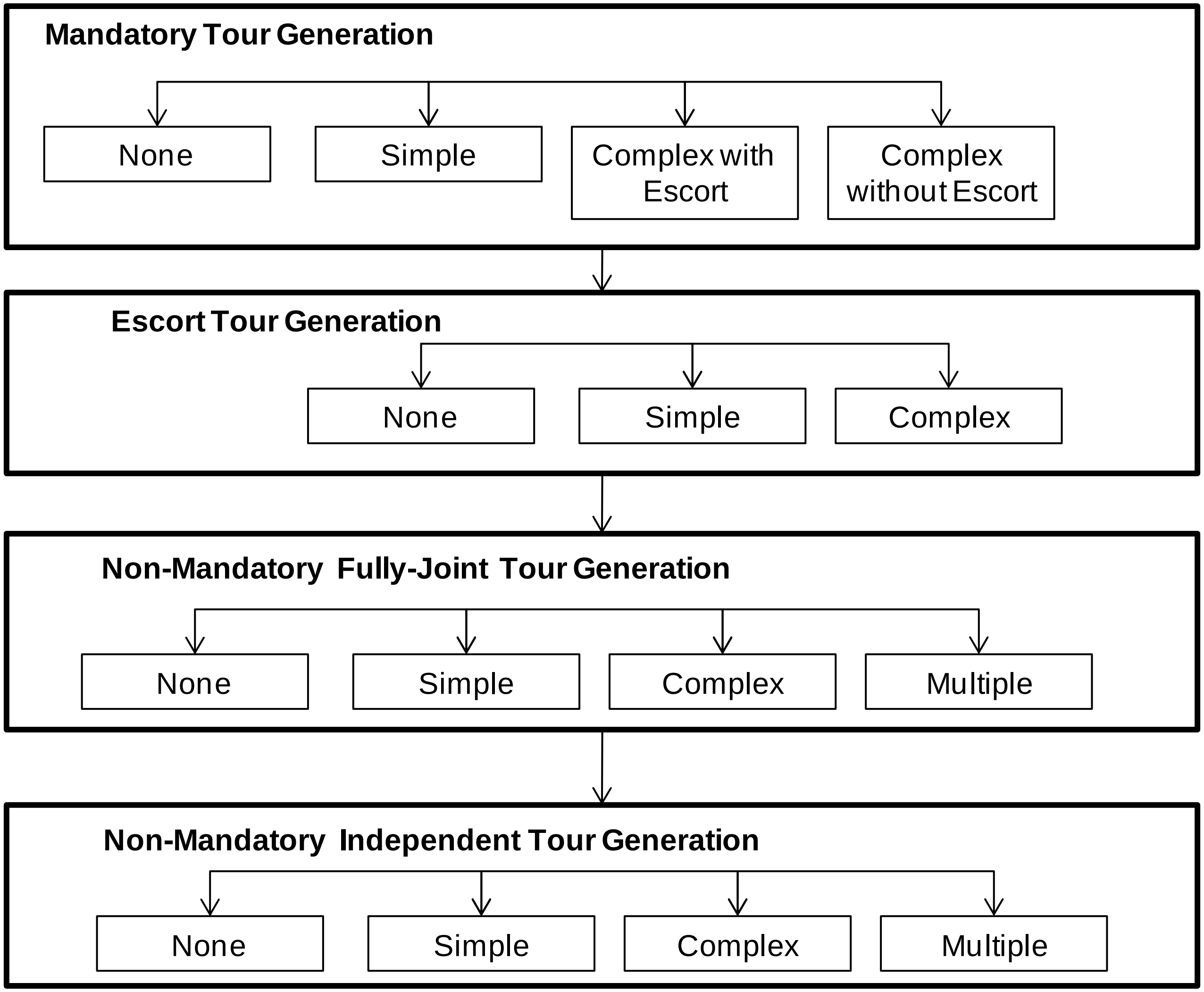

Figure 1. A Framework for Tour Generation

CHAPTER 3. DATA AND MODELS

This study uses data from the following three household-travel surveys conducted in Florida: (1) The 2000 Northeast Florida (NE) Household Travel Survey (28,390 trips from 8036 persons in 3921 households), (2) The 1999 Southeast Florida (SE) Household Travel Survey (33082 trips from 8873 persons in 4603 households), and (3) The 1996 Tampa Bay (TB) Area Household Travel Survey (31277 trips from 8997 persons from 5304 households). The data and documentation are available for download from the following web site: http://www.fsutmsonline.net/Floridatravelsurveys/data%20archive.htm. It is useful to note here that the Florida add-on samples from the 2009 National Household Travel Survey (NHTS) were not available to the researchers during much of the project period.

The purpose of each trip was first classified into one of return-home, work, non-work from the disaggregate classification schemes adopted in the surveys (ensuring that only employed persons made work trips). While it might be generally desirable to classify non-work trips into further categories such as shopping, recreation, and meals, inconsistencies in the disaggregate trip purpose classifications across the surveys and the small sample sizes limited pursuing such an approach. To accommodate intra-household inter-dependencies, trips were classified as either joint or solo based on a space-time matching of trip records across household members. Similarly, stops were also classified as joint or solo. Non-work trips made by persons in households with children were classified as escort trips (pick up or drop off) if they had the same start- and end- location and timing (with a five-minute tolerance) as a trip of a household child to/from school. It was also ensured that there was a change in the occupancy of the vehicle used for the trip relative to the previous/next trip. Thus, each trip can be classified into one of the following purposes: solo return home, joint return home, work, escort, solo non-work, and joint non-work (There were too few joint work trips and so this was not considered a separate category).

The next major step in the data assembly procedure was to identify and characterize the tours. A tour is defined as a sequence of trips such that the first trip begins at home, the last trip ends at home, and all the intermediate trips start and end at non-home locations. A tour file was created for each region by grouping the appropriate trips. For each tour, the total number of intermediate stops and the purpose of each leg/trip of the tour were also determined. Based on these details, each tour was classified into one of the categories as identified in the modeling framework presented in Figure 1. The reader will note that the classification reflects possible space-time constraints of the activity pursued in the tour, the tour complexity (single stop versus multi stop), and household interactions (joint travel of household members and escort of children). Joint tour, is defined as a tour which the whole tour is made with at least another household member.

Table 1 presents the sample shares of tours by type from each of the three survey regions. In general there are clear differences in the travel patterns across these regions. In the case of mandatory (work) tours, about one-half of all workers make simple work tours. The proportion of employed persons not making work tours is higher is SE region. Escort tours are generally limited with over 80% of non workers in households with children not making such tours. The escort behavior of TB residents (both workers and non workers) appears to be significantly different (i.e., extremely low) from those of other regions. This is primarily because the data-matching algorithm identified only few escort trips for this region potentially reflecting differences in the internal (i.e., within household) consistency of data across the surveys. To be sure, it is acknowledged in the profession that the escort tours are perhaps not captured in a consistent manner across travel surveys. Therefore, one may need to employ different processing techniques to infer escort tours from different surveys. However, for this analysis, we chose to retain the same procedure for generating the tours across the three surveys to ensure consistency. The patterns for joint tours are more comparable across the regions, although the SE residents appear to me more likely to make joint tours than those of the other regions. On looking at the independent tours, TB residents make most of such tours and SE Florida residents make least of such tours. Overall, the significant prevalence of multi-stop (complex) tours verifies existence of trip chaining behavior in all these Florida regions. Further, strong intra-household inter-dependencies (escort and joint tours) are estimated to exist.

Table 1. Sample Shares of Tours by Type and Region

Tour type	Definition	Region		
		NE	SE	TB
Work Tours				
None	No work tours	9.1	16.0	11.2
Simple	Tour with single stop, and the stop is for the work	43.5	54.0	49.2
Complex without Escort	Tour with more than one stop, without any escort taken place in the tour, the primary stop is work	43.2	25.2	38.8
Complex With Escort	Tour with multiple stops, with escort taken place in the tour, the primary stop is work	4.2	4.8	0.8
Escort Tours				
None	No escort tour	88.1	80.3	97.6
Simple	Tour with single stop, and the stop is for the escort	6.4	12.1	1.8
Complex	Tour with multi stop, and the primary stop is for the escort	5.4	7.7	0.6
Non Mandatory Fully-Joint Tours				
None	No joint tours	89.6	85.7	91.2
Simple	One joint tour with at least one of household members with single stop	6.4	8.0	4.8
Complex	One joint tour with at least one of household members with multi stop	2.8	4.6	2.8
Multiple	Two more joint tours with household members	1.2	1.7	1.2
Non Mandatory Independent Tours				
None	No independent tours	56.0	62.0	45.6
Simple	A solo tour with one stop	22.0	17.2	26.8
Complex	A solo tour with multi stop	10.4	9.6	12.4
Multiple	Two or more solo tours	11.6	11.2	15.2

The next step in the data assembly procedure was to create a consistent set of explanatory factors across the three surveys. Table 2 presents these variables and the sample shares across the regions. The reader will note that the common explanatory variables include age, employment status, household size, presence of children, vehicle ownership, and housing-unit type. The employment status of the person and household size were interacted to create new variables to describe the role of the person in the household (worker in the single worker household, worker in a multi-worker household, etc.). Interestingly, data on gender are not available from the Florida household travel surveys. The TB region has the highest proportion of the elderly and non-employed persons. The NE Florida region has the least number of households with children. In terms of car ownership, the proportion of households with 0 cars is less than 3%; however, the SE Florida region has a higher proportion of car-sharing households. It is useful to emphasize that these reflect the characteristics of the survey samples from the three regions and not necessarily the true demographic profiles.

Table 2. Explanatory variable sample shares

Variable	**Region**		
	NE	SE	TB
Age 16- 21	7.8	10.1	7.0
Age 21- 64	74.7	73.6	63.2
Age 65+	17.5	16.3	29.8
Employed	62.4	71.3	51.7
Full Time Employed	52.0	60.6	43.2
Worker in a single-worker household	23.0	32.0	18.4
Worker in a multi-worker household	41.6	40.4	35.5
Non worker in a 0-worker household	23.0	16.9	37.3
Non worker in a single-worker household	10.2	8.1	7.6
Non worker in a multi-worker household	2.2	2.6	1.2
No children in household	75.0	39.2	57.1
One child in household	15.7	26.6	28.6
Multiple children in household	9.3	34.2	14.3
No car household	1.6	2.4	3.1
Car sharing household (cars < adults)	12.5	21.1	13.0
Non-car sharing (cars >= adults)	85.9	76.5	83.9
Single-family housing unit	67.4	64.3	77.0
Multi-family housing unit	18.5	33.3	8.6
Other housing unit	14.1	2.4	14.4

Multinomial-logit models were estimated for the four tour types for each of the three regions resulting in a total of twelve models. For each tour purpose, the best empirical specification was determined for each region. All models were estimated using 85% of the data samples with the remaining 15% set aside for transferability assessments. For each region, the models for the four tour purposes were estimated independently (i.e., choice outcomes from upper level models do not feed into lower levels models and “logsums” from lower level models do not feed up to the upper level models). This enables assessing the transferability of the models for each tour type independently. Assessment of the transferability of integrated model systems is clearly an important avenue for future research.

To avoid the clutter of presenting twelve multinomial-logit models in detail (i.e., the parameter estimates and “t” statistics for each utility function), a summary of the results is presented in Table 3 (The full set of 12 models are included in the Appendix). A “*” indicates that the corresponding variable was significant in at least one of the utility functions in the corresponding model. Broadly, the model results are intuitively reasonable. The same factors are often found to influence the choices across the three regions (or at least two of the three regions), and in almost all the cases the directionality of impact is found to be the same.

Efforts were undertaken to incorporate land-use variables into tour generation models in the context of the SE Florida region (Parcel-level land use variables were available only for this region). However, statistically significant and intuitively reasonable effects were not obtained. It is possible that choices about work and escort tours are not really dictated by land-use. Rather, it is the discretionary activities which are more strongly influenced by land-use patterns. However, in this study, all non-work / non-escort activities were lumped into aggregate categories of joint and independent “other” tours. Disaggregating these by purpose could be beneficial in capturing the effects of land use patterns.

Table 3. Summary of Empirical Model Results

Explanatory Variables	Work Tours			Escort Tours			Joint Other Tours			Independent Other Tours		
	NE	SE	TB	NE	SE	TB	NE	SE	TB	NE	SE	TB
Age 21- 64	*	*	*		*	*	*	*	*		*	*
Age 65+	*	*	*				*		*	*	*	*
Employed												
Full Time Employed	*	*	*							*	*	*
Worker in a single-worker household with non-worker adults	*	*					*			*	*	*
Worker in a multi-worker household		*	*				*	*		*	*	*
Non worker in a single-worker household					*	*		*				
Non worker in a multi-worker household						*		*				
One child in household	*	*						*	*	*		
Multiple children in household	*	*	*	*	*	*	*	*	*	*		
Car sharing household (cars < adults)		*	*					*	*	*	*	*
Non-car sharing (cars >= adults)	*	*					*	*	*	*	*	
Single-family housing unit			*					*	*	*		
Other housing unit												
Number of observations	3033	4717	3178	312	665	1176	3598	5598	5148	4201	6203	5842
Log-likelihood at convergence	-3134.7	-5106.5	-3117.8	-133.4	-427.4	-112.2	-1447.5	-2757.9	-1722.7	-4275.5	-6088.5	-6292.1
Rho-squared wrt equal-shares model	0.25	0.22	0.29	0.61	0.41	0.91	0.71	0.64	0.76	0.26	0.29	0.22
Rho-squared wrt market-shares model	0.04	0.03	0.02	0.04	0.02	0.24	0.06	0.1	0.12	0.11	0.08	0.14

CHAPTER 4. ASSESSMENT OF TRANSFERABILITY

One of the characteristic features of Florida’s current trip-based travel modeling system is its statewide standard called the FSUTMS. Clearly, there are several practical benefits of having standardized models for future tour-based or activity-based modeling systems as well. These benefits include development of standardized training programs, sharing of modeling experiences across the state via user groups, and software customizations. In this context, it would be important to assess whether similar model structures are appropriate for the different parts of the state. In this study, this issue was examined via a set of transferability tests among the tour-generation models developed for the three regions. For each tour type, the model estimated for each of the regions was applied to the validation samples (15% of the data) for each of the three regions and the choice probabilities were computed. Thus, the analysis broadly involves comparing the predictions of the locally-estimated model to those from transferred models (from two other regions).

The rest of this chapter is organized as follows. Section 4.1 presents a brief outline of the literature on spatial transferability of travel models. Section 4.2 summarizes results from tests of aggregate comparisons. Section 4.3 presents results from tests of disaggregate comparisons and Section 4.4 examines the similarity of model elasticities. Finally Section 4.5 summarizes the findings on model transferability based on the three types of analyses.

4.1 Literature on Spatial Transferability

The issue of spatial transferability of travel-demand models is of considerable practical interest. This is because transferring the parameters of a model instead of local estimations can result in significant cost- and resource- savings. This issue is of greater concern in the context of activity-based models as these require richer (quantity and quality) data which is costly to obtain.

Consistent with the practical interest on spatial transferability, there has been significant research aimed at developing systematic procedures for assessing whether a model is transferable or not. Some of the earliest efforts include studies by Artherton and Ben-Akiva (1976) and Koppelman and Wilmont (1982) which outlined systematic procedures, presented metrics for assessing transferability, and provided empirical demonstrations. The methods used in literature to assess model transferability can be classified into two categories: (1) statistical tests for parameter equality (or equivalently transferability) across contexts and (2) predictive accuracy of models in the transferred context.

The statistical tests include metrics such as the Transferability Test Statistic (TTS) and the Aggregate Prediction Statistic (APS). TTS (Artherton and Ben-Akiva, 1976) is a (disaggregate) chi-squared-distributed measure and is computed based on the difference between the log-likelihoods of the locally-estimated- and the transferred- models. APS (Koppelman and Wilmont, 1982) is an aggregate measure (also chi-squared distributed) and is computed based on the predicted- and observed- shares of the different choice alternatives. The second category of transferability measures examines the predictive accuracy of models in the transferred context. Unlike the statistical tests, this approach does not examine the equality of model parameters; rather the focus is on assessing whether the overall predictions are close enough to the observed choices. Various "error" measures have been used to calculate the net difference between the predicted- and observed- shares. These include Relative Error Measure (REM), Root Mean Square Error (RMSE) (Koppelman and Wilmont, 1982), Mean Absolute Error (MAE) (Karasmaa and Pursula, 1997), Relative Aggregate Transfer Error (RATE) (Walid, 1991), Transfer Index (TI) (Koppelman and Wilmot, 1985), and Transferred rho-squared (Gunn, Ben-Akiva, and Bradley, 1985).

It is useful to note that the approaches based on the statistical tests provide crisp, "yes or no" answers to the question on whether a model is transferable whereas the second approach only provides a measure of transfer error. Assumptions on levels of acceptable errors are required to ultimately determine whether the model is indeed transferable. Researchers have argued that "perfect" transferability is impossible and that the general aim should be to obtain a model that closely approximates (tolerable error) the behavior in the application context. Therefore, determining a degree of transferability on a continuous scale rather than binary (yes/no) outcome based on statistical tests should be considered (see for example, Ben-Akiva, 1981 and Lerman, 1981). Further, Koppelman and Wilmot (1982) observed that predictive accuracy of a transferred model can be reasonable even when the statistical tests reject transferability. All these issues highlight the value of the transferability-assessment methods based on predictive-accuracy over those based on statistical tests.

At the same time, methods based on predictive assessments rely primarily on the ability of the model to replicate aggregate shares in the transferred context, often under a "base" condition. This does not guarantee that the marginal sensitivities of the model to specific explanatory variables as estimated are also reasonable in the transferred context. This is because the equality of the individual model coefficients (between the estimation and transfer contexts) is not explicitly tested as in the case of the statistically-oriented approaches. However, having appropriate marginal sensitivities (or elasticity) is also important as models are often used to make predictions under alternate scenarios with varying values of explanatory variables. In this context, it would also be useful to compare the elasticities (see for example, Atherton and Ben-Akiva 1976, and Karasmaa, 2007) of the transferred model to key explanatory variables of interest to those of the locally estimated model. In light of the above discussions, the intent of this study is to examine spatial transferability of models using both predictive accuracy and elasticity measures.

It is also useful to note that a substantial body of literature focus on transferring logit-based mode-choice models. Applications in the context of other model structures and other travel choices are much fewer. The applications of transferability assessments in the context of tour-generation models / activity-based models appear to be very minimal (Arentze et al., 2002). This study contributes empirically to the transferability literature by examining logit-based tour-generation models.

Further, starting with Naïve transfer approaches which involve simply applying the model parameters estimated in one region directly to another (without making any updates using local data) methods for "updating" the model parameters with small-samples from the target region have also been developed and demonstrated. These methods include transfer scaling, updating alternative constants, bayesian approach, combined transfer estimation and joint context estimation. (see for example, McCoomb (1986), Gunn et al., (1985) for Naïve transfer; Koppelman et al (1985), Santoso and Tsunokawa (2005) for updating alternative constants method; Ben-Akiva and Buldoc (1987) for combined transfer estimation; Walid (1991) for bayesian approach; Badoe and Miller (1995), Karasmaa, and Pursula (1997), Karasmaa (2007) for transfer scaling, and joint context estimation approach. This study is, however, focused on the Naïve transfer. It is reasonable to expect that a naively transferred model can be further improved using local data.

4.2 Aggregate Predictions

The following methodology is adopted to assess the transferability of the models in terms of the accuracy of the aggregate predictions. For each tour type (Work, Escort, Joint Other, and Independent Other) and model application region (NE, SE, and TB), each of the three models is applied to predict the average predicted probability of each alternative in the validation sample. The predicted shares are then compared the observed shares in the validation sample using the following two measures: Mean Absolute Relative Error Measure (MA-REM), Root-Mean-Square Error (RMSE). These measures are calculated as:

$$\mathrm{REM_m} = \frac{\mathrm{P_m} - \mathrm{O_m}}{\mathrm{P_m}}$$

$$\mathrm{MA - REM} = \frac{1}{\mathrm{n}}\sum_{\mathrm{m}} |\mathrm{REM_m}|$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{\mathrm{m}} \mathrm{P_m} * \mathrm{REM_m^2}}{\sum_{\mathrm{m}} \mathrm{P_m}}}$$

Where, $\mathrm{P_m}$ is number of predicted share choosing alternative $\mathrm{m}, \mathrm{O_m}$ is the observed share choosing alternative m, and n is number of alternatives.

The reader will note that the REM value is defined for each alternative and is the percentage error in the aggregate prediction of that alternative. Both the MA-REM and the RMSE measures aggregate the REM values across all alternatives into a single measure (the former is a simple average whereas the latter is a weighted average based on the predicted shares of the different alternatives). Both MA-REM and RMSE are absolute measures (i.e., these measures are independent of the performance of a locally estimated model).

The MA-REM values are summarized in Table 4(a). Note that the major rows represent the model application regions and the three columns represent the regions the models were estimated on. Therefore, the work-tour models estimated using SE data when applied to the validation sample data of NE region results MA-REM of 0.4 (SE model transferred to NE). Similarly, the work-tour model estimated on NE when applied to the NE region yields an MA-REM value of 0.16 (application of a locally-estimated NE model). The RMSE values are summarized in Table 4(b) which has the same structure as Table 4(a).

In general, the application of locally estimated models results in lower errors than the application of transferred models, as would be expected. It is useful to note that given the small shares of some of the alternatives, the estimation (85%) and validation (15%) samples for the same region do not have exactly the same distribution across the choice alternatives. The errors are the highest in the case of TB escort models applied to the other two regions. Similarly, the TB work-tour models when applied to the other regions also result in significant errors. This is primarily because of data issues. As already discussed, much fewer escort trips were identified in TB relative to either SE or NE regions. In the case of the other two tour purposes (joint and independent non-mandatory), the errors are much lesser, although the TB model for joint tours is not quite transferable to the SE region as is indicated by the large error. Further, the errors on transferring models between SE and NE regions also appear lesser when compared to models transferred to/from TB region.

To assess whether the models are transferable or not, one needs to make assumptions about acceptable thresholds on RMSE values. If an RMSE value of no more than 0.3 is deemed acceptable (many studies such as Koppelman and Wilmot 1982, Pas and Koppelman, 1984, consider this level of error as acceptable for the transferability of mode-choice models), then 15 out of the 24 total transfers (4 tour types * 3 regions * 2 transfers per region) are acceptable. Models for independent- and joint- tours applied to other regions seem to be more transferable compared to models for other tour purposes. For each of these tour purpose 5 out of 6 total transfers (3 regions * 2 transfers per region) have RMSE values less than 0.3. Models estimated in SE and NE are more transferable (6 out of 8 in each, 4 tour types * 2 regions) compared to those estimated in TB region (3 out of 8).

Table 4(a). Comparison of Aggregate Predictions MA-REM Values

Measure	Tour type	Predicted on	Estimated based on		
			NE	SE	TB
MA-REM	Work tours	NE	**0.16**	0.4	1.38
		SE	0.4	**0.14**	1.12
		TB	0.38	0.31	**0.12**
	Escort tours	NE	**0.19**	0.15	2.14
		SE	0.42	**0.03**	2.13
		TB	0.61	0.66	**0.23**
	Joint tours	NE	**0.13**	0.43	0.27
		SE	0.14	**0.23**	2.97
		TB	0.18	0.36	**0.06**
	Independent tours	NE	**0.16**	0.13	0.27
		SE	0.08	**0.06**	0.22
		TB	0.29	0.29	**0.35**

Table 4(b). Comparison of Aggregate Predictions RMSE Values

Measure	Tour Type	Predicted on	Estimated based on		
			NE	SE	TB
RMSE	Work tours	NE	**0.14**	0.28	0.47
		SE	0.41	**0.11**	0.47
		TB	0.28	0.24	**0.05**
	Escort tours	NE	**0.10**	0.14	0.63
		SE	0.28	**0.09**	0.71
		TB	0.31	0.39	**0.08**
	Joint tours	NE	**0.08**	0.21	0.15
		SE	0.06	**0.13**	0.57
		TB	0.12	0.22	**0.02**
	Independent tours	NE	**0.16**	0.13	0.23
		SE	0.08	**0.05**	0.2
		TB	0.26	0.31	**0.33**

4.3 Disaggregate Predictions

The following methodology is adopted to assess the transferability of the models in terms of the accuracy of the disaggregate predictions. For each tour type (Work, Escort, Joint Other, and Independent Other) and model application region (NE, SE, and TB), each of the three models is applied to calculate the log-likelihood value on the validation sample. This assesses the ability of the model to assign high probabilities to the alternative observed to be chosen, and hence, is considered a disaggregate analysis. These values are summarized in Table 5. The values represented in parenthesis represent the ratio of the log-likelihood value of the local model to the transferred model. For example, when the SE model for work tours was applied on the NE region, the estimated log-likelihood value was -595.55 which is 5% less than the corresponding value (-568.89) based on the local model.

These disaggregate results essentially reinforce the aggregate prediction results. The errors are estimated to be large when the SE and NE models for escort are applied to the TB region. This is because the TB region has too few escort tours but the NE and SE models predict a significantly lower probability of not making escort tours. As in the case of the aggregate analysis, transferring the TB joint tour model to the SE and NE regions is also questioned by the disaggregate analysis.

Once again, to assess whether the models are transferable or not, one needs to make some assumptions about acceptable levels of error. If no more than 10% error in likelihood is acceptable, then 20 out of the 24 total transfers (4 tour types * 3 regions * 2 transfers per region) are acceptable. Models for independent- -and work- tours applied to other regions are more transferable (6 out of 6 in each case total transfers have less than 10% error in likelihood, 3 regions * 2 transfers per region) compared to models for other tour purposes. Models estimated in SE and NE are more transferable than models estimated for Tampa with models for all tour purposes from SE being transferable to NE and vice versa.

Table 5. Comparison of Disaggregate Predictions: Log-likelihood Values

	Predicted on	Estimated based on		
		NE	SE	TB
Work tours	NE	-568.89(1)	-595.55(1.05)	-610.82(1.07)
	SE	-935.28(1.09)	-859.56(1)	-944.86(1.09)
	TB	-587.67(1.04)	-582.21(1.03)	-562.3(1)
Escort tours	Predicted on	Estimated based on		
		NE	SE	TB
	NE	-26.68(1)	-26.69(1)	-35.49(1.33)
	SE	-74.96(1.03)	-72.68(1)	-70.26(.97)
	TB	-29.86(2.56)	-37.25(3.19)	-11.68(1)
Joint tours	Predicted on	Estimated based on		
		NE	SE	TB
	NE	-296.04(1)	-322.36(1.09)	-314.73(1.06)
	SE	-539.07(1.09)	-494.84(1)	-712.01(1.44)
	TB	-342.39(1.06)	-355.17(1.1)	-322.2(1)
Independent tours	Predicted on	Estimated based on		
		NE	SE	TB
	NE	-764.55(1)	-767.03(1)	-818.56(1.07)
	SE	-1092.5(1.04)	-1053.9(1)	-1157.99(1.1)
	TB	-1166.82(1.01)	-1193.29(1.03)	-1153.93(1)

4.4 Elasticities

To assess the elasticity of models to specific explanatory factors, two scenarios were examined. In the first scenario all car-sharing household in the validation sample were re-classified as non-car sharing (reflecting an increase of car ownership). In the second scenario, single-child households were re-classified as multi-children household (reflecting an increase in household size and children). Note that the car ownership was not statistically significant for escort tour models and hence scenario 1 does not apply for that model. Similarly, children were found to be insignificant in predicting independent tours for SE and TB regions and hence scenario 2 does not apply here.

For each tour type (Work, Escort, Joint Other, and Independent Other) and model application region (NE, SE, and TB), each of the three models is applied to determine the average predicted probability of each alternative in the adjusted validation samples (two scenarios). Next, the predicted aggregate change in the shares of the different alternatives as a consequence of the scenario was calculated. Finally, the mean absolute change was calculated as the average (over the alternatives) of the absolute values of the change for each alternative. The mean absolute change values are listed in Table 6. For example when the SE model for work-tour generation was locally applied to assess the impact of car-ownership changes, the mean absolute change in the distribution of the work-tour alternatives was estimated to be 2.24. The same value was 2.42 when the NE model was applied to SE and 2.94 when the TB model was applied to SE. The values in parenthesis reflect the mean absolute change of the transferred model relative to the local model (2.42 / 2.24 = 1.08 for the NE transferred model and 2.94/2.24 = 1.31) for the TB model. This indicates that the aggregate average change predicted by the NE model is more comparable (than TB model) to what is predicted by the local model. In general, if the values in parentheses are closer to 1, this implies that the transferred model predicts a similar change as the local model.

For any region, model type, and scenario the elasticities of the two transferred models are generally different. Further, if the model transferred from one region performs better for a scenario, it is not guaranteed that it performs the best for the other scenario as well. For instance, for the joint tours model for the SE region, the NE performs better under Scenario 1 but TB performs better under scenario 2. These results reflect the impacts of specific model parameters on the predictive ability as opposed to the overall effect of all parameters as indicated by the aggregate and disaggregate analyses.

Table 6. Elasticity Assessments: Mean Absolute Change

Predicted on	Estimated based on					
	Scenario 1			Scenario 2		
	NE	SE	TB	NE	SE	TB
Work tours						
NE	**1.04(1)**	2.12(2.04)	1.64(1.57)	**2.60(1)**	0.90(.34)	0.66(.25)
SE	2.42(1.08)	**2.24(1)**	2.94(1.31)	4.16(3.04)	**1.37(1)**	0.95(.69)
TB	1.00(1.08)	1.32(1.43)	**0.92(1)**	4.07(4.11)	1.45(1.46)	**0.99(1)**
Escort tours						
NE				**12.15(1)**	5.62(.46)	7.82(.64)
SE				5.15(2.28)	**2.26(1)**	3.40(1.5)
TB				14.15(3.93)	6.12(1.7)	**3.60(1)**
Joint tours						
NE	**2.17(1)**	4.08(1.88)	3.71(1.71)	**1.74(1)**	3.01(1.72)	1.64(.94)
SE	5.26(.65)	**7.99(1)**	4.04(.5)	6.52(3.16)	**2.06(1)**	1.64(.79)
TB	3.60(.6)	6.02(1)	**6.02(1)**	7.58(2.56)	2.08(.7)	**2.96(1)**
Independent tours						
NE	**2.18(1)**	3.54(1.62)	3.15(1.44)	**1.59**		
SE	2.91(.54)	**5.36(1)**	4.40(.82)	2.91		
TB	1.95(.64)	4.33(1.41)	**3.06(1)**	3.58		

4.5 Overall Assessments

An overall summary of transferability for each of the tour purposes, for all three regions, and based on all metrics is summarized in Table 7. The major rows represent the considered tour type and region and columns represent spatial transferability criteria considered. In this table, an entry such as "NE > SE" indicates that NE model is more transferable than SE model under that metric for that tour purpose. Similarly, "NE ~ SE" indicates that model models are about equally transferable and "NE >> SE" indicates that NE model is significantly better than SE model for transferability. It is useful to note that these classifications were derived from the numerical results presented in Tables 4, 5, and 6 using rather arbitrary thresholds. The intent is to draw broad qualitative conclusions from all the comparative analyses performed.

Several interesting patterns emerge. First, for any tour type and region, a transferred model that does best in terms of aggregate predictions is not guaranteed to give an equally good performance in terms of elasticities with respect to specific factors. For example, the NE model for joint tours transfers well the SE region in terms of aggregate predictions; however, the TB model performs much better in terms of elacticities to household composition. Second, for any pair of regions, and for a given metric for assessing transferability, the models for all tour purposes are not equally transferable. For example, based on aggregate predictions, the SE model for joint tours is transferable to NE, however, the SE model for independent tours does not appear to be very transferable. Finally, transferability is not symmetric. For example, the work tour model of NE is transferable to TB, but the TB model for work tours is not necessarily transferable to NE. This is perhaps because the TB region (surveys) is limited in escort activities which are more prevalent in the NE surveys.

Table 7. Overall Spatial Transferability Assessment

	Aggregate (RMSE)	Disaggregate	Elasticity	
Work tours			Scenario1	Scenario2
NE	SE >> TB	SE~TB	TB > SE	SE > TB
SE	NE~TB	NE~TB	NE>TB	TB>>NE
TB	NE~SE	SE~NE	NE>SE	SE>>NE
Escort tours				
NE	SE>>TB	SE>TB		TB > SE
SE	NE>>TB	TB~NE		TB > NE
TB	NE~SE	SE~NE		SE >> NE
Joint tours				
NE	TB~SE	TB~SE	TB~SE	TB>SE
SE	NE>TB	NE >> TB	NE > TB	TB >> NE
TB	NE>SE	NE,SE	SE>NE	SE >> NE
Independent tours				
NE	TB>SE	SE~TB	TB>SE	
SE	NE>TB	NE~TB	TB > NE	
TB	NE~SE	NE~SE	NE~SE	

CHAPTER 5. SUMMARY AND CONCLUSIONS

Given the shortcomings of the conventional, trip-based approach to travel forecasting, there is continued interest in developing activity-based models in the different parts of the country including Florida. As a first step towards building such advanced models for Florida, household travel surveys from three regions of the state (Jacksonville, Tampa, and Miami areas) were examined to understand patterns in travel behavior. Tours were constructed from the trip-based surveys and were characterized in terms of purpose, travel party composition, complexity, and flexibility.

Our analysis underscores the need for tour-based travel-demand models that explicitly incorporate trip-chaining. A significant volume of overall travel in Florida involves multi-stop tours and consequently includes several "non-home-based (NHB) trips". It has been well recognized that the current trip-based travel modeling methods are inadequate in analyzing these NHB trips. Specifically, the characteristics of these trips (such as mode and time of day) are strongly linked to those of preceding and/or succeeding home-based trips and ignoring these linkages could lead to biased predictions of travel demand. Further, our analysis also indicates strong intra-household inter-dependencies in the activity-travel patterns in Florida. A significant number of tours are made along with other household members, either adults or children. Failure to recognize joint activity/travel participation choices could lead to an over estimation of vehicle trips whereas ignoring the space/time constraints imposed by parents' travel to escort children to/from school can lead to biases predictions on their response to transportation policy actions (people with such constrained travel may not be able to change their behavior easily in response to, say, demand management strategies). Overall, the empirical findings have substantive implications for advancing the travel-modeling practice in Florida.

A framework for modeling tour generation was also developed. This comprises a suite of four models applied sequentially. Choices about mandatory tours (work) are made first followed by choices about escort tours (if children are present in the household). Choices about joint tours follow and the fourth and final component is on independent tours. The three household travel surveys conducted in the state during the last decade to support the current trip-based models do lend themselves to tour-based analysis. While joint travel between adults could be identified by the same space-time-purpose matching algorithms in all three surveys, issues were encountered (Tampa survey) in matching travel patterns of adults to children to determine escort tours.

Future analysis of the Florida add-on samples of the National Household Travel Surveys would be useful in refining these characterizations of tours and for developing consistent definitions of tours and intra-household interactions across the state. Further, separating out the independent "other" tours by purpose such as shopping, leisure, and personal business would be of significant value. Creating such disaggregate tour purpose types consistently across the three surveys was not possible in the current study due to issues such as differences in trip purpose classification and sample size considerations.

The four tour-generation models were estimated for each of the three regions (a total of 12 multinomial logit models in all). Several socio-economic variables were found to be statistically significant and reasonable predictors of tour-generation patterns. However, the number of explanatory factors included was also limited given the need to retain consistent variables across all models from the three regions. Future analysis of the NHTS add-on samples would also be valuable from the standpoint of having an extensive set of consistent explanatory factors across the models. In addition, future studies should seek to incorporate the effects of land use variables on tour generation choices. This is critical as the travel outcomes are a consequence both needs (reflected by the socio-economic variables) and the opportunities and constraints (reflected by land use and network variables).

This study also examined the transferability of tour-generation models among three metropolitan regions in Florida. Naïve transfer methods are examined to assess the performance of the transferred models (from two other regions) to that of the locally-estimated model. The assessment is done in the context of the generation of four different tour purposes. Transferability is evaluated using multiple measures such as aggregate- and disaggregate predictive ability and the aggregate elasticities to specific socio-economic factors. The empirical analyses reveal several interesting and intuitive findings. <u>First</u>, ability to replicate aggregate predictions alone is not an adequate measure of transferability. The sensitivities of the transferred model to parameters on key socio-economic variables of interest are also critical. <u>Second</u>, for any pair of regions, models for all tour purposes are not equally transferable. Thus, in transferring a travel-demand model system, it might be worthwhile to look at parameters from multiple regions (if available) rather than simply choosing to transfer an entire model system from one region. <u>Finally</u>, the results also indicate that transferability is not symmetric. In this context, it would be useful to look for regions, which is inclusive of the behaviors observed/expected in the "home" location for transferring in the parameters. Overall, while it might be acceptable to use a similar modeling framework, caution must be exercised in borrowing parameters from one area for use in another region. Heterogeneity in overall travel patterns, local biases in the surveys, and differences in sensitivities to specific explanatory factors can all affect the performance of the transferred model. It is useful to acknowledge that that the results presented here are from one study and based on a limited set of data. Further empirical studies on the transferability of activity-travel patterns are needed to develop robust thresholds for acceptable levels of error.

REFERENCES

1. Atherton, T., Ben-Akiva, M.E. (1976) Transferability and Updating of Disaggregate Travel Demand Models. Transportation Research Record, 610. pp. 12–18.
2. Bradley, M.A. and Bowman, J.L. “A Summary of Design Features of Activity-Based Microsimulation Models for U.S. MPOs”, White paper presented at the TRB Conference on Innovations in Travel Demand Modeling, May 21-23, 2006, Austin, Texas, 2006. http://www.jbowman.net/papers/Model%20design%20feature%20white%20paper.pdf
3. Davidson, W. Donnelly, R., Vovsha, P. Freedman, J., Ruegg, S., Hicks, J., Castiglione, J., and Picado, R. (2007) “Synthesis of first practices and operational research approaches in activity-based travel demand modeling,” *Transportation Research Part A* (41) pp. 464-488
4. Koppelman FS, Wilmot CG. (1982) Transferability analysis of disaggregate choice models. Transportation Research Record 895, pp18–24.
5. Karasmaa, N., and M. Pursula (1997) Empirical Studies of Transferability of Helsinki Metropolitan Area Travel Forecasting Models. Transportation Research Record, 1607. pp. 38-44.
6. Walid M. Abdelwahab (1991) Transferability of intercity disaggregate mode choice models in Canada. Canadian Journal of Civil Engineering, vol 18(1), 20-26.
7. Koppelman FS, Kuah GK, Wilmot CG. (1985) Transfer model updating with disaggregate data. Transportation Research Record 1037, pp102–107.
8. Gunn, H. F., Ben-Akiva, M. E., and Bradley, M. A. (1985). ‘‘Tests of the scaling approach to transferring disaggregate travel demand models.’’ *Transportation Research Record.* 1037, 21–30.
9. Ben-Akiva, M. (1981) Issues in Transferring and Updating Travel-Behavior Models. In *New Horizons in Travel-Behavior Research* (A.M. Stopher, A.H. Meyburg, and W. Brog, eds.), Lexington Books, Lanham, Md., pp. 665-686.
10. Lerman, R. (1981) A comment on Interspatial, Intraspatial, and Temporal Transferability. In *New Horizons in Travel-Behavior Research* (A.M. Stopher, A.H. Meyburg, and W. Brog, eds.), Lexington Books, Lanham, Md., pp. 628-632.
11. Karasmaa, N. (2007) Evaluation of Transfer Methods for Spatial Travel Demand Models. Transportation Research, Part A, vol 41, pp. 411–427.
12. Arentze, T., Hofman, F., Mourik, H., Timmermans, H (2002) Spatial Transferability of the Albatross Model System: Empirical Evidence from Two Case Studies, Transportation Research Record, Vol 1805, pp. 1-7.
13. McCoomb L.A. (1986) Analysis of the Transferability of Disaggregate Demand Models among Ten Canadian Cities, Transportation Forum, Vol 3(1), 1986, pp. 19-28.
14. Santoso and Tsunokawa (2005). Transferability and updating of model choice models between two developing countries – predictive performance point of view, Journal of the Eastern Asia Society for Transportation Studies, Vol. 6, pp. 173 – 185.
15. Ben-Akiva, M., Bolduc, D., 1987. Approaches to Model Transferability and Updating: the Combined Transfer Estimator. Transportation Research Record, 1139, pp. 1–7.
16. Badoe, D.A., Miller, E.J., 1995. Comparison of Alternative Methods for Updating Disaggregate Logit Mode Choice Models. Transportation Research Record, 1493. pp. 90–100.

17. Pas EI, Koppelman FS. (1984) Comparative Analysis of the Transferability of Disaggregate Automobile-Ownership and Mode-Choice Models. Transportation Research Record, 987. pp. 40-48
18. Pinjari, A.R., and C.R. Bhat (2011), "Activity Based Travel Demand Analysis," *A Handbook of Transport Economics*, Chapter 10, pp. 213-248, edited by A. de Palma, R. Lindsey, E. Quinet, and R. Vickerman, Edward Elgar Publishing Ltd.
19. Srinivasan, S., and Bhat, C.R. (2006) "A Multiple Discrete-Continuous Model for Independent- and Joint- Discretionary-Activity Participation Decisions," *Transportation*, 2006 TRB Special Issue, Vol. 33, No. 5, pp. 497-515
20. Srinivasan, S. and Bhat, C.R. (2005) "Modeling Household Interactions in Daily In-Home and Out-of-Home Maintenance Activity Participation", *Transportation*, Vol. 32, No. 5, pp. 523-544.
21. Vovsha, P., Bradley, M., and Bowman, J (2004) "Activity-based travel forecasting models in the United States: Progress since 1995 and Prospects for the Future" Presented at the *EIRASS Conference on Progress in Activity-Based Analysis*, Vaeshartelt Castle, Maastricht, The Netherlands. http://jbowman.net/papers/VBB04.pdf
22. Vovsha, P., Peterson, E., and Donnelly, R. (2003) "Explicit Modeling of Joint Travel by Household Members, Statistical Evidence and Applied Research", *Transportation Research Record* 1831, pp. 1-10.

APPENDIX

Table A1 Models for Mandatory Tour Generation

	Model for NE			Model for SE			Model for TB		
	Simple	Complex w/o P/D	Complex with P/D	Simple	Complex w/o P/D	Complex with P/D	Simple	Complex w/o P/D	Complex with P/D
Explanatory Variables									
Age 16- 21									
Age 21- 64	-0.52		1.33	-0.87	-0.59		-1.79	-1.45	
Age 65+	-1.46	-1.16		-0.94	-1	-1.52	-2.26	-2.53	
Employed									
Full Time Employed	0.39	0.51	0.66	0.8	0.73	0.5	0.75	0.97	
Worker in a single-worker household with non-worker adults	0.24			-0.21	-0.42	1.75			
Worker in a multi-worker household					-0.28	2.34	0.33	0.27	0.71
Non worker in a 0-worker household									
Non worker in a single-worker household									
Non worker in a multi-worker household									
No children in household									
One child in household			2.09		-0.32	1.38			
Multiple children in household	-0.28		2.68		-0.49	1.48			1.83
No car household									
Car sharing household (cars < adults)				-0.74	-0.62			-0.31	
Non-car sharing (cars >= adults)			-0.99	-0.52					
Single-family housing unit								0.18	
Multi-family housing unit									
Other housing unit									
Constant	1.81	1.28	-2.89	2	1.07	-4.71	2.43	1.64	-3.64
Number of observations	3033.00			4717.00			3178.00		
Log-likelihood at convergence	-3134.72			-5106.54			-3117.86		
Rho-squared wrt equal-shares model	0.25			0.22			0.29		
Rho-squared wrt sample-shares model	0.04			0.03			0.02		

Table A2 Models for Escort Tour Generation

	Model for NE		Model for SE		Model for TB	
	Simple	Complex	Simple	Complex	Simple	Complex
Explanatory Variables						
Age 16- 21						
Age 21- 64				0.52	2.84	
Age 65+						
Employed						
Full Time Employed						
Worker in a single-worker household						
Worker in a multi-worker household						
Non worker in a 0-worker household						
Non worker in a single-worker household			0.85		1.26	1.79
Non worker in a multi-worker household			0.85			
No children in household						
One child in household						
Multiple children in household		1.74		0.61	1.24	2.54
No car household						
Car sharing household (cars < adults)						
Non-car sharing (cars >= adults)						
Single-family housing unit						
Multi-family housing unit						
Other housing unit						
Constant	-2.62	-3.66	-2.45	-2.92	-7.11	-7.21
Number of observations	312		665		1176	
Log-likelihood at convergence	-133.39		-427.42		-112.23	
Rho-squared wrt equal-shares model	.61		.41		.91	
Rho-squared wrt sample-shares model	.04		.02		.24	

Table A3 Models for Joint Other Tour Generation

	Model for NE			Model for SE			Model for TB		
	1Simple	1Complex	2 or more	1Simple	1Complex	2 or more	1Simple	1Complex	2 or more
Explanatory Variables									
Age 16- 21									
Age 21- 64	0.5	1.76	1.77	0.6			0.99	1.63	
Age 65+	0.78	2.27	1.99				0.97	1.91	
Employed									
Full Time Employed									
Worker in a single-worker household with non-working adult	-0.93	-0.62	-2.65						
Worker in a multi-worker household	-0.87	-0.6	-2.02	-1.05	-1.1	-1.4			
Non worker in a 0-worker household									
Non worker in a single-worker household with non-worker adults				-1.23	-0.78	-1.3			
Non worker in a multi-worker household					-1.1				
No children in household									
One child in household				-0.73	-1.61	-1.15		-2	
Multiple children in household	0.97	0.81	1.23	-0.47	-0.98	-0.81	0.56		
No car household									
Car sharing household (cars < adults)					1.16		1.71		1.64
Non-car sharing (cars >= adults)	-0.68	-0.98	-1.03	-0.89		-0.79		-1.07	
Single-family housing unit					-0.23			0.73	
Multi-family housing unit									
Other housing unit									
Constant	-2.28	-4.19	-4.69	-1.35	-1.86	-2.08	-4.07	-3. 6	-4.7
Number of observations	3598.00			5598.00			5148.00		
Log-likelihood at convergence	-1447.54			-2757.91			-1722.73		
Rho-squared wrt equal-shares model	0.71			0.64			0.76		
Rho-squared wrt sample-shares model	0.06			0.10			0.12		

Table A4 Models for Independent Other Tour Generation

	Model for NE			Model for SE			Model for TB		
	1Simple	1Complex	2 or more	1Simple	1Complex	2 or more	1Simple	1Complex	2 or more
Explanatory Variables									
Age 16- 21									
Age 21- 64				0.33	0.88	0.96	0.97	1.79	2.64
Age 65+	1.23	1.37	1.16	0.61	1.13	1.16	1.79	2.53	3.42
Employed									
Full Time Employed	-0.62	-1.16	-1.24	-0.9	-1.24	-1.7	-1.04	-1.73	-2.07
Worker in a single-worker household with non-working adults	-0.95	-1.31	-0.97	-0.54	-0.71	-0.54	-0.54	-0.79	-1.05
Worker in a multi-worker household	-0.64	-0.55	-1.03	-0.65	-0.72	-0.83	-0.57	-1.05	-1.29
Non worker in a 0-worker household									
Non worker in a single-worker household									
Non worker in a multi-worker household									
No children in household									
One child in household		-0.33							
Multiple children in household	-0.3	-0.62	-0.42						
No car household									
Car sharing household (cars < adults)	-0.37	-0.48		-0.89	-1.1		-0.43	-1.01	-0.87
Non-car sharing (cars >= adults)			0.41	-0.61		0.96			
Single-family housing unit			0.49						
Multi-family housing unit									
Other housing unit									
Constant	-0.34	-0.9	-1.41	-0.07	-1.42	-2.14	-0.78	-1.98	-2.57
Number of observations	4201.00			6203.00			5842.00		
Log-likelihood at convergence	-4275.53			-6088.48			-6292.1		
Rho-squared wrt equal-shares model	0.26			0.29			0.22		
Rho-squared wrt sample-shares model	0.11			0.08			0.14		