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Spatial Transferability of Activity-Based Travel Forecasting Models

Sujan Sikder
University of South Florida, ssikder@mail.usf.edu

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by

Sujan Sikder

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Major Professor: Abdul R. Pinjari, Ph.D.
Xuehao Chu, Ph.D.
Jian John Lu, Ph.D.
Yu Zhang, Ph.D.
Sivaramakrishnan Srinivasan, Ph.D.

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DEDICATION

This dissertation is dedicated to my father, Samiran Sikder and my mother, Swapna Sikder for their love, affection and nurturing. I am greatly indebted to them for their support and encouragement throughout my life. I would also like to dedicate this dissertation to my brother, Shuvo Sikder for his warm companionship.

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ABSTRACT

Spatial transferability of travel forecasting models, or the ability to transfer models from one geographical region to another, can potentially help in significant cost and time savings for regions that cannot invest in extensive data-collection and model-development procedures. This issue is particularly important in the context of tour-based/activity-based models whose development typically involves significant data inputs, skilled staff, and long production times. However, most literature on model transferability has been in the context of traditionally used trip-based models, particularly for linear regression-based trip generation and logit-based mode choice models, with little evidence on the transferability of activity-based models and that of emerging model structures.

The overarching goal of this dissertation is to assess the spatial transferability of activity-based travel demand models. To this end, the specific objectives are to:

1. Survey the literature to synthesize: (a) the approaches used to transfer models, (b) the metrics used to assess model transferability, (c) the available evidence on spatial transferability of travel models, and (d) notable gaps in literature;

2. Lay out a framework for assessing the spatial transferability of activity-based travel forecasting model systems, and evaluate alternative methods/metrics used for assessing the transferability of specific model components and their parameters;

3. Conduct empirical assessments of spatial transferability of the following two model components used in today's activity-based model systems: (a) daily activity participation and time-use models, and (b) tour-based time-of-day choice models. Data from the 2009 National Household Travel Survey (NHTS) and the 2000 San Francisco Bay Area Travel Survey (BATS) were used for these empirical assessments;

4. Conduct empirical assessments of model transferability using emerging model structures that have begun to be used in activity-based model systems – specifically the multiple discrete-continuous extreme value (MDCEV) model;

5. Investigate alternate ways of enhancing model transferability; specifically: (a) pooling data from different geographical regions, and (b) improvements to the model structure.

The dissertation provides a framework for assessing the transferability of activity-based models systems, along with empirical evidence on the pros and cons of alternative methods and metrics of transferability assessment. The results suggest the need to consider model sensitivity to changes in explanatory variables as opposed to relying solely on the ability to predict aggregate distributions. Updating the constants of a transferred model using local data (a widely used method to transfer models) was found to help in increasing the model's ability to predict aggregate patterns but not necessarily in enhancing its sensitivity to changes in explanatory variables. Also, transferability assessments ought to consider sampling variance in parameter estimates as opposed to only the point estimates.

Empirical analysis with the daily activity participation and time-use model shed new light on the prediction properties of the MDCEV model structure that have implications for model transferability. This led to the development of a new model structure called the multiple discrete continuous heteroscedastic extreme value (MDCHEV) model that incorporates heteroscedasticity in the model's stochastic distributions and helps in enhancing model transferability. Transferability assessment of the time-of-day choice models show encouraging evidence of transferability of a large proportion of the model coefficients, albeit except important parameters such as the travel time coefficients. Collectively, there is evidence that pooling data from multiple regions may help in building better transferable models than those transferred from a single region.

CHAPTER 1

INTRODUCTION

1.1 Travel Forecasting Models

Travel forecasting models are used to predict future travel characteristics under alternative scenarios of population socio-demographics, land-use patterns, and transportation system characteristics. Transportation planners and policy makers use these models to analyze the effectiveness of various transportation alternative strategies with the intent of arriving at appropriate transportation infrastructure planning decisions. The appropriateness of planning decisions is therefore dependent on the quality of the travel forecasting models used to analyze the effectiveness of various alternative strategies. The quality of these models, in turn, depends on whether or not the individual and household activity and travel behaviors are appropriately incorporated in the models (Bhat and Lawton, 2000). It is now well recognized that the traditionally used "trip-based" four step models do not incorporate realistic representations of activity and travel behavior, and thus fall short in their ability to inform emerging transportation planning and policy questions. These limitations have led to the emergence of the "activity-based" approach to travel demand modeling.

The activity-based approach differs from the trip-based approach in at least three ways. First, the activity-based approach recognizes that travel is a "derived demand" in that it is derived from the need to participate in activities that are dispersed in time and space (Bhat and Koppelman, 1999). Thus, this approach places emphasis on analyzing individuals' activity participation prior to analyzing travel. Second, the trip-based approach represents travel as a mere collection of independent trips, while the activity-based approach attempts to represent travel in a more realistic fashion by recognizing the spatial, temporal, and modal linkages between different trips via trip chains and/or tours (Davidson et al., 2007). Third, the activity-based approach is less fraught with aggregation biases (than that in the trip-based approach) due to analyzing activity participation and travel at a disaggregate, individual and household level as opposed to simply using demographically, spatially, and temporally aggregate measures of travel behavior as a forecasting model.

Given the greater theoretical foundation and behavioral appeal, models built based on the activity-based approach are likely to provide better (than trip based models) information on individual-level responses and aggregate-level changes in travel behavior to transport planning/policy measures. Therefore, several planning agencies in the United States and Europe have already developed (and some others are in the process of developing) activity-based models (ABMs) to serve the emerging planning needs and policy questions.

1.2 Spatial Transferability of Travel Forecasting Models

Spatial transferability of travel forecasting models refers to the appropriateness of using models developed with data and information from one geographical region for travel forecasting purposes in another region. This topic is of considerable interest from both theoretical and practical standpoints. Theoretically, assessment of a model's performance in different contexts provides insights into its ability to provide credible forecasts under different scenarios. From a practical standpoint, 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 procedures. The data required for developing (or updating) travel demand models are generally collected through different surveys. Oftentimes, the cost of collecting data through these surveys is so high that it could easily exceed the annual budget of a planning organization responsible for this task (Wilmot and Stopher, 2001). Therefore, only large metropolitan regions with sizeable budgets are able to manage such extensive data collection procedures. In such situations, the ability to transfer models developed for other regions can save significant resources for many regions. Besides, many small-sized and mid-sized regions do not have an option but transfer models from elsewhere. In addition to potentially saving the data collection costs, transferability of a model can also help reduce the efforts and time required for model development and estimation 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. Hence, this dissertation research focuses on the spatial transferability of activity-based models (ABMs).

As mentioned earlier, compared to the conventional trip based models, the activity-based models provide a much more behaviorally-oriented approach to modeling travel behavior. From the transferability point of view, a natural question is *whether the behavioral realism helps make activity-based travel forecasting models more transferable than the conventional trip-based models*. At this point, there is no easy answer to this question because of a lack of sufficient empirical evidence on the transferability of tour/activity-based models. The increasing need for behaviorally oriented models to address different policy measures has motivated the researchers/practitioners to develop and refine these models instead of focusing on their transferability assessments. Only a handful of studies in literature (see chapter 2 for a detailed review) document the transferability assessment of activity-based model systems to varying degrees (e.g., Arentze, 2002; PB Consult Inc. 2007; Le-Vine, 2010) while some recent efforts are underway (e.g., the SHRP-2 C10 studies, Bowman et al., 2013) and a few studies focus on the transferability of specific components of activity-based model systems (e.g., Nowrouzian and Srinivasan, 2012).

An activity-based model system consists of several model components, each focused on modeling a specific aspect of individuals' daily activity and travel schedule. For example, daily activity pattern models focus on generating the activities an individual participates in a day, along with the number of tours he/she undertakes in a day. Once the activity/travel needs are generated using the daily activity pattern models in the form of activities to be participated and/or tours to be undertaken, the tour level models are used to predict the mode choice, destination choice, and time-of-day choice for each tour. Subsequently, trip-level models are used to predict the mode, destination, and timing of each trip in each tour. It is possible that the transferability of each of these model components may differ from that of the other. Little evidence exists in the literature on which model components in an activity-based model system are more transferable and which are less transferable.

As reviewed in Chapter 2, most literature on travel model transferability has focused on the transferability of specific model components (e.g., mode choice model component, trip generation model component) of trip-based travel model systems. A plausible reason is that the structure and design features of the traditionally used trip-based model systems are very similar across different regions. Thus, transferability of a trip-based model *system* generally boils down to the transferability of its model *components*. With activity-based model systems, however, there is no universally accepted model structure with a unique set of design features. In fact, there is probably no need for a universally accepted modeling framework. The overall model structure, the design features, and the level of disaggregation considered (e.g., in time and space) can very well vary based on the policy and planning needs for which the models are intended to be used, the size of the regions for which the models are developed, and the availability of data and other resources to build, maintain, and use the models. In summary, the transferability of an activity-based model *system* comprises much more than the transferability of the individual model *components*. Thus, assessing the transferability of individual model *components* of an activity-based model *system* is not necessarily the same as assessing the transferability of an entire activity-based model *system*. This warrants the need for a framework that can guide researchers and practitioners in assessing the transferability of activity-based model system across geographical contexts.

1.3 Enhancing Spatial Transferability of Travel Forecasting Models

A variety of methods have been used in literature to transfer models across geographical contexts (see chapter 2 for a detailed discussion on these methods). Among these, the simplest approach is the naïve transfer in which the model estimated in one context is transferred to another context without any modifications. The empirical results suggest that the performance of a naively transferred model is far from a locally estimated model both in terms of data fit as well as aggregate prediction. Thus using available information and data from the application context, the base context model is usually “updated” to better capture behavior in the application context (i.e., to make it more transferable). Despite using different updating techniques, the available evidence on model transferability is still mixed and inconclusive, with much of the empirical research suggesting the difficulty of transferring models. This warrants the need for exploring alternate ways to *enhance* model transferability.

One possible way to enhance model transferability is to estimate the model using data pooled from different geographic regions. In general, different context-specific characteristics such as social, cultural, and spatial structures, urban form, and transport system and network features have a significant influence on travel behavior, but they are not usually represented in the travel models built for a specific region due to limited variation in these characteristics within a region (Brand and Cheslow, 1981). The presence of such context specific characteristics in a model may improve its transferability especially in the situations where these characteristics differ from one region to another. The inclusion of these characteristics, however, depends on the data used for model estimation. Specifically, data with a high degree of variability can ensure the presence of such characteristics in the model, and make the model more transferable. The potential advantages of using such a dataset have been indicated in previous studies as well. For instance, Richards and Ben-Akiva (1975) argued that *if a disaggregate model is truly a behavioral model, and if it has been estimated with data which has a high degree of variability, then it can be expected that the model can be used in different* *geographic locations and for populations with different economic structures without amendment to the coefficients* (Galbraith and Hensher, 1982). Brand & Cheslow (1981) also highlighted the importance of such data variability in model transfer. Despite recognizing such potential advantages of using data with a high degree of variability, it has not been discussed with special attention in literature; neither the impact of data variability on model transfer, nor how to bring this variability in the data has been discussed.

Another possible way to enhance transferability is by improving the mathematical structure of the models being transferred. On one hand, it is likely that improvements to the mathematical structure of a model may enhance its ability to better represent travel behavior, and therefore result in an enhanced transferability. On the other hand, there is also a notion in the field that improvements to the model structure may not lead to considerable improvements in the way the travel behavior is modeled. Perhaps both views hold merit in that some improvements in the model structure may indeed help enhance the transferability of models while other improvements may not. But there is little empirical evidence on what types of model improvements may enhance the spatial transferability of models.

1.4 Research Objectives and Contributions

The broad objectives of this research are five-fold:

1. Conduct an extensive review of literature on spatial transferability of travel forecasting models to summarize and synthesize: (a) the empirical evidence in the literature on spatial transferability, (b) the methods used to transfer models, and (c) the

methods and metrics used to assess model transferability. Based on the findings from this review, lay out an agenda for future research on this topic.

2. Lay out a framework for assessing the transferability of activity-based travel forecasting model system, and evaluate alternative methods/metrics used to assess the transferability of specific model components and their parameters.

3. Conduct empirical assessments of spatial transferability of the following two model components used in today's activity-based model systems: (a) daily activity participation and time-use models, and (b) tour-based time-of-day choice models.

4. Conduct empirical assessments of model transferability using emerging model structures that have begun to be used in activity-based model systems – specifically the multiple discrete-continuous extreme value (MDCEV) model.

5. Investigate alternate ways of enhancing model transferability; specifically: (a) pooling data from different geographical regions, and (b) improvements to the model structure.

The above objectives are pursued in six different chapters in the dissertation, as outlined below. The outline provides the organization along with identifying the contributions of each chapter in the dissertation.

Chapter 2 provides an extensive review and synthesis of the extant literature on spatial transferability of travel forecasting models. Specifically, different theoretical and practical issues related to model transferability, methods used in the literature to transfer models, and metrics used to assess the effectiveness of these transfer methods are discussed in different sections of this chapter. In addition to providing the most up-to-date review and synthesis of the literature on spatial transferability of travel models, the chapter identifies several important avenues of future research addressing which should be of value to the travel modeling community. Of the various gaps in literature identified in this chapter, the notable ones that will be addressed in this dissertation research are summarized at the end of this chapter.

Chapter 3 presents a broad discussion and a guiding framework for assessing the transferability of activity-based model systems that goes beyond the transferability of specific model components.

Chapter 4 investigates the spatial transferability of person-level daily activity generation and time-use models, an important component of activity-based model systems being tested in several regions in the United States (e.g., Los Angeles and Dallas Fort-Worth). A recently emerging model structure known as the Multiple Discrete Continuous Extreme Value (MDCEV) model is used to develop this model component. Since this is the first empirical assessment of the transferability of an MDCEV-based model, prediction properties of this model structure are investigated first, and then transferability is assessed. This investigation helped shed light on some properties and limitations of this model structure that might have implications to model transferability.

On an empirical front, the chapter compares the transferability of activity generation and time-use models between different states (Florida and California) and across different regions within the state of Florida (Tampa, Miami, Orlando, urban regions in District-1, and all rural regions of Florida). Doing so helps in assessing if these models are more transferable within a state than across states. Further, the chapter compares the transferability of the models between different urban regions and between urban and rural regions. This helps in assessing if models developed in large urban regions (for which data and resources are typically available) can be transferred to rural regions (for which data and resources are scarce).

In addition to the above, this chapter compares the different techniques used in the literature to assess the transferability of travel models and provides recommendations for the same. The influence of updating constants of a transferred model using locally available data (a widely used technique for transferring models) on model transferability is also assessed. Further, the chapter sheds light on the influence of sampling variance of the parameter estimates on the transferability assessment results. Finally, this chapter provides empirical evidence to answer whether (and to what extent) pooling data from multiple regions helps in enhancing the spatial transferability of activity-participation and time-use models.

Chapter 5 addresses the limitations associated with the prediction properties of the MDCEV model, this chapter incorporates heteroscedasticity in the multiple discrete continuous (MDC) model structure, and formulates a new econometric model named the Multiple Discrete Continuous Heteroscedastic Extreme Value (MDCHEV) model. Next, the prediction ability and transferability of this model structure are examined and compared with those of the MDCEV structure. This comparison sheds light on the influence of this improvement in model structure on its prediction properties and transferability across geographical contexts.

Chapter 6 investigates the spatial transferability of tour-based time-of-day choice models among four counties (Alameda, Santa Clara, San Francisco, and San Mateo) in the San Francisco Bay Area of California. This assessment sheds light on what aspects of tour-based time-of-day choice models are transferable and what are not transferable.

Specifically, the chapter addresses the question of what types of parameters in these models are transferable and what types of parameters are not transferable. In addition, the chapter compares different methods of transferability assessment. Furthermore, the chapter examines if models built using data pooled from multiple counties are more transferable than models built using data from a single county.

Chapter 7 concludes the dissertation by summarizing the findings and conclusions from each of the above chapters and providing directions for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Spatial transferability of models has been a subject of much interest since the eighties and nineties. Thus the literature abounds with studies on this topic. These studies lay out theoretical and practical aspects of model transferability, use different methods to transfer models, and assess the effectiveness of these transfers by using different metrics. This chapter aims to provide a synthesis of the extant literature on spatial transferability of travel forecasting models, and positions our research within the overall context of the literature. The specific objectives are to review: (1) the theoretical and practical considerations related to model transferability, (2) the methods used to transfer models, (3) the approaches and metrics used to assess model transferability, (4) the empirical evidence on model transferability, and to identify the notable gaps in literature.

The above review and synthesis is based on an extensive review of the theoretical and empirical literature on the issue of model transferability. Table 2.1(a) and Table 2.1(b) together provide a summary of the empirical studies in literature. Specifically, Table 2.1(a) provides a summary of the model structures, geographical contexts, transfer methods and transferability assessment metrics used in the literature while Table 2.1 (b) summarizes the findings in literature. The first 14 studies in these tables are in the

Table 2.1(a) A Summary of the Empirical Literature on Spatial Transferability of Travel Forecasting Models (model structures, geographical contexts, transfer methods, and transferability assessment metrics)

Paper	Model Structure	Transferred between…	Method of Transfer	Assessment Metrics
1. Watson & Westin (1975)	Mode choice BL model (train & auto) with only LOS variables (BL: Binary Logit)	6 intercity region pairs of Glasgow & Edinburgh divided into central, suburb & periphery regions	Naïve transfer	Transferability test statistic (TTS), Statistical test of equality between the predicted probability distributions of transferred and local models
2. Atherton & Ben-Akiva (1976)	Work trip mode choice MNL model (drive alone, shared ride, transit) with LOS, demographic, and land-use variables (MNL: Multinomial Logit Model)	Washington D.C. to New Bedford, Massachusetts and Los Angeles	Naive transfer, Updating constants, Transfer scaling, Bayesian updating, Full re-estimation	TTS, t-tests of parameter equality, Transferred ρ^2, predicted mode shares compared with observed shares, forecasting ability (changes in mode shares due to policy changes)
3. Talvitie & Kirshner (1978)	Work trip mode choice MNL model (drive alone, shared ride, transit) with LOS, demographic, & land-use variables	Washington DC, Minneapolis-St Paul, San Francisco bay area (pre-BART and post-BART)	Naïve transfer	Model equality test statistic (METS)
4. Stopher et al. (1979)	Work trip mode choice MNL model (car-driver, car-passenger, bicycle, motorcycle ,walk, walk & bus, drive & bus, lift club) with only LOS variables	South Africa and different areas of the U.S.	Coefficients of the model in the estimation context were compared with those of the models in the application context	No tests were performed. (coefficients were directly compared)
5. Galbraith & Hensher (1982)	Work trip mode choice MNL model (car, rail) with only LOS variables	Intra-urban transferability between two regions of Sydney (Northwest Sydney, Southwest Sydney)	Naïve transfer, Transfer scaling, Bayesian updating	TTS, t-tests of parameter equality, transferred ρ^2, predicted mode shares compared with the observed shares
6. Koppelman & Wilmot (1982)	Work trip mode choice model (drive alone, shared ride, transit)	Intra-urban (within different sectors of Washington DC)	Updating constants	TTS, Model equality test statistic, Transfer index (TI), RMSE between predicted and observed shares, aggregate prediction statistic(APS)
7. Koppelman & Wilmot (1985)	Work trip mode choice MNL model (drive alone, shared ride, transit) with LOS and demographic variables	within different sectors of Washington DC (intra-urban transfer)	Updating constants for different specifications: (1) los variables only, (2) los & demographic variables	Transferred ρ^2, Transfer Index (TI)
8. Koppelman et al. (1985)	Work trip mode choice MNL model (drive alone, shared ride, transit) with LOS and demographic variables	within different sectors of Washington DC (intra-urban), & between Washington DC, Minneapolis, & Baltimore (inter-urban)	Naïve transfer Transfer scaling (i.e., updating constants and scale of parameters)	Transferred ρ^2, transfer index (TI), RMSE between predicted and observed shares, relative aggregate transfer error (RATE)

Table 2.1(a) (Contd.)

Paper	Model Structure	Transferred between…	Method of Transfer	Assessment Metrics
9. Gunn et al. (1985)	Joint mode-destination model (MNL) for business and shopping purposes, and trip generation model (linear regression) with LOS, demographic, and land-use variables	Two adjacent regions in Netherlands	Naïve transfer, Transfer scaling, Transfer scaling with two scale parameters (one for demographic variables, other for LOS variables), Complete re-estimation of all parameters	TTS, Transfer ρ^2, Predicted mode shares compared with the observed shares
10. Koppelman & Pass (1986)	Commute mode choice (drive alone, shared ride, transit) and auto ownership. (MNL & NL) with los & demographic variables	within three different sectors of Washington DC (intra-urban)	Updating constants	Transfer index (TI), Transferred ρ^2
11. Abdelwahab (1991)	Intercity mode choice MNL model	Eastern and western CMAs of Canada (eastern region: all CMAs east of thunder bay, western region: all CMAs west of winnipeg)	Updating constants, Bayesian updating	TTS, Transfer ρ^2, Transfer index (TI), RMSE between predicted and observed shares, Relative aggregate transfer error (RATE), aggregate prediction statistic (APS)
12. Santoso and Tsunokawa (2005)	Work trip mode choice MNL model (walking, bicycles and motorcycles)	From urban to suburban areas of Ho Chi Minh City, Vietnam	Naïve transfer, Updating constants, Updating both constants and scale parameter, Bayesian updating, Combined transfer estimator	TTS, t-tests of parameter equality, Transferred ρ2, Transfer Index,
13.Karasmaa (2007)	Home based other trip mode and destination choice NL model (walking, bicycle, car, and public transportation) (NL: Nested Logit model)	Two areas (Helsinki Metropolitan Area and Turku region) in Finland	Transfer scaling, Bayesian updating, Combined transfer estimation, Joint context estimation with different sets of common and data-specific variables	TTS , Transfer index (TI), Value of time comparisons, Elasticity comparison (changes in mode shares due to changes in car cost, public transportation travel time), Value of time comparison
14. Santoso & Tsunokawa (2010)	Work trip mode choice MNL model (walking, bicycles and motorcycles)	Ho Chi Minh city of Vietnam and Phnom Penh city of Cambodia	Naïve transfer, Updating constants, Updating both constants and scale parameter, Bayesian updating, Combined transfer estimator	Transferred ρ^2, Transfer index (TI), Relative error measure (REM)
15. Mahmassani et al. (1979)	Area-wide trip rates, and household-level trip rates (cross-classification)	7 urban areas of population between 50-250K in Indiana	Naive transfer	χ^2 test to compare aggregate trip rates, pair-wise samples t-test to compare predicted & observed household trip rates
16. Caldwell & Demetsky (1980)	Household-level trip rates (regression and cross-classification)	Three cities in Virginia (of population ranging from 14k to155k)	Naïve transfer	χ^2 test to compare predictions (at the aggregate level) from transferred and local models

Table 2.1(a) (Contd.)

Paper	Model Structure	Transferred between…	Method of Transfer	Assessment Metrics
17. Rose & Koppelman (1984)	Household-level Tour generation & intermediate stop generation models (linear regression) with only demographic variables	Intra-regional (within two sectors of Baltimore and Minneapolis) and inter-regional (Baltimore to Minneapolis)	Naïve transfer, Updating model constants using aggregate data from application context w/ disaggregate data)	Transfer R^2, Transfer Index for Regression model (TIR), Root Mean Square Error (RMSE), Relative aggregate transfer error (RATE)
18. Wilmot (1995)	Trip generation models (linear regression) with only demographic variables	Different cities of South Africa	Naïve transfer, Updating constant, Transfers were conducted only within areas with data from the same survey	Transfer R^2, Transfer Index for Regression model (TIR), Transferability test statistics (TTS) for linear regression model
19. Agyemang-Duah and Hall (1997)	Household-level home based shopping trip generation on weekdays (ordered response model with demographic and land use variables)	Different regions within Toronto	Naïve transfer, Transfer scaling (2 scale parameters - one for demographic variables, another for an accessibility variable)	t-test to compare coefficient pairs between two models, Transfer R^2, Measures of aggregate predictive ability (weighted RMSE, APS).
20. Kawamoto (2003)	Person-level home based trip generation model (Liinear regression model)	Two urban areas in Brazil: Sao Paulo and Bauru	Transfer scaling	Wald Test Statistics, Predicted number of trips compared with the observed number of trips, Root Mean Square Error (RMSE)
21. Cotrus et al. (2005)	Person-level trip generation model (Linear regression and Tobit models)	Tel Aviv and Haifa Metropolitan area in Israel	Naïve transfer	Z-test, Chow test, Chi square test, Predicted trip rates were compared with the observed trip rates
22. Everett, (2009)	Person-level trip generation model (cross-classification)	11 Metropolitan areas in Ohio and Tennessee	Naïve transfer	Q-statistic
23. Gunn & Pol (1986)	A model system of (1) tour-level joint mode-destination choice models for different tour purposes, (2) tour generation, (3) household-level driving license status, and (4) household car ownership models (all logit models) with LOS and demographic variables	Disaggregate	Naïve transfer, Transfer scaling, Transfer scaling with two scale parameters (one for demographic variables, other for LOS variables), Complete re-estimation of all parameters	TTS, t-statistics of the scale factors, Transferred ρ^2, Predicted mode shares compared with the observed shares
24. Arentze et al. (2002)	Albatross Model System (Rule based activity based model system)	3 different regions in Netherlands	Model structure	Prediction ability of the transferred model at the aggregate (such frequency distribution of activity type and mode choice) and disaggregate level (number of activities, average duration of activities)

Table 2.1(a) (Contd.)

Paper	Model Structure	Transferred between…	Method of Transfer	Assessment Metrics
25. PB Consult Inc. (2007)	MORPC tour-based model system	Columbus OH to Lake Tahoe	Updating alternative constants and adding some special terms (such as dummy for external zones) for location choice models	Predicted shares (e.g., mode shares and distribution of maintenance tours) were compared with the observed data
26. Picado, (2013)	CT-RAMP ABM system	SANDAG (San Diego) region to Southeast Florida/SEF (Miami) region	Same overall Structure and submodels. Updated certain model parameters to reflect SEF conditions.	Aggregate level predictions compared with available observed patterns/validation targets
27. Le Vine et al. (2010)	TASHA Model System (Rule based activity based model system)	From Toronto , Canada to London, UK	Empirical activity scheduling rules and algorithm (based on the empirical data from Toronto) were transferred	Predicted temporal distribution of different activities and trips per day were compared with the observed data.
28. Nowrouzian & Srinivasan (2012)	Tour generation models (MNL) for different tour purposes	Tampa bay, Jacksonville, and Miami regions in Florida	Naïve transfer	RMSE between predicted and observed shares, Elasticity comparisons
29. Vovsha et al. (2010)	Work location choice model	4 different cities in the US	No transfer was performed	Simple comparison of parameter estimates between different contexts
30. Bowman et al. (2013)	All 15 model components of the DaySim ABM system	4 regions in California (San Diego, Sacramento, Fresno, San Joaquin valley) and 2 regions in Florida (Jacksonville and Tampa)	Joint context estimation (by pooling data from different regions)	TTS, t-statistics of difference variables capturing parameter differences between different counties

Table 2.1(b) A Summary of the Empirical Literature on Spatial Transferability of Travel Forecasting Models (findings)

Paper	Findings
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 naïvely transferred models matched well with estimated distributions only if the parameter estimates were equivalent between the estimation 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)	• Most model comparisons suggested parameter inequality (or inequality of models) across different regions. The authors argued that differences in how data are collected (including how network travel times and costs are coded) may potentially confound transferability analysis results. • It was pointed that most explanatory power is in mode-specific constants (unobserved factors) making it difficult to transfer models. Better transferability can be achieved by improving the mode choice theory and model specification.
4. Stopher et al. (1979)	• 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. Comparison results suggest that 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.
5. 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. • From an aggregate predictive ability standpoint, 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 sound specifications (e.g., models with mode-specific LOS parameters showed better fit to base context data but poorer transferability). • Bayesian updating using a subset of local data better improved the model performance (based on transferred ρ^2) compared to a naïvely transferred model or a scale-updated model.
6. Koppelman & Wilmot (1982)	• Statistical tests (at both disaggregate and aggregate levels) suggest that updating constants did not result in models that were statistically equivalent to a local model. • Non-statistical tests of transfer errors (e.g., RMSE and TI) suggest that updating constants of the base specification results reasonably transferable models with tolerable errors relative to locally estimated models (80% TI and 20% aggregate prediction error). • Goodness of fit may not be the best measure to select the base context (if there are identically specified models from different base context regions) from which to transfer a model. • Transferability is asymmetric, with significant dependence on the direction of transfer.
7. Koppelman & Wilmot (1985)	• 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.

Table 2.1(b) (Contd.)

Paper	Findings
8. Koppelman et al. (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 strong but less significant improvement (TI = 81%). • The transfer index for intra-urban transfer was better than that for inter-urban transfer.
9. Gunn 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 the results from a completely re-estimated model. • Partial transfer models did not provide practically discernible improvements over the transfer scale models.
10. Koppelman & Pass (1986)	• Compared the spatial transferability of two different multidimensional model structures (multinomial logit (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.
11. Abdelwahab (1991)	• Disaggregate 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. • The 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.
12. Santoso and Tsunokawa (2005)	• TTS and t-tests of individual parameter differences suggest that the urban mode choice model cannot be naively transferred to suburban areas. • Transferred $\rho 2$ and TI values suggested poor performance of the Bayesian updating technique in improving the model transferability. The other three updating techniques (updating only constants, updating both the constants and scale, and combined transfer estimator) improved model transferability as long as the sample size used for updating was 400 or more. For the cases with sample size less than 400, only two techniques (updating both the constants and scale, and combined transfer estimator) were recommended.
13. Karasmaa (2007)	• 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 true market shares.

Table 2.1(b) (Contd.)

Paper	Findings
14. Santoso & Tsunokawa (2010)	• Naïve 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). • ρ^2 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 combined transfer estimator does not perform well when the transfer bias exceeds a critical value, say, due to large variability in application data. • Depending on the updating procedure used, a minimum sample size of 200 is recommended for updating the transferred model. Sample sizes smaller than 100 or lower were not recommended due to large variance issues.
15. Mahmassani et al. (1979)	• 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).
16. Caldwell & Demetsky (1980)	• 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.
17. Rose & Koppelman (1984)	• 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 naïve 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.
18. Wilmot (1995)	• Poor transferability was observed between areas with poor data quality, highlighting the importance of good data quality for transferability. Errors in data collection/measurement can lead to masking of 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.
19. Agyemang-Duah and Hall (1997)	• 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 naïvely 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.
20. Kawamoto (2003)	• Compared the spatial transferability of two types of regression models: conventional and standardized. Wald test statistics suggest that the standardized regression models are transferable between these two urban areas in Brazil, but not the conventional regression models. • RMSE values support the results from the wald test statistics. For all transfers, the transferred standardized regression models were found to perform almost equivalent to the locally estimated standardized regression models.
21. Cotrus et al. (2005)	• Z-test and Chow test rejected the hypothesis of the equality of transferred and locally estimated parameters. • But the transferred models were found to perform well in predicting the observed trip rates in the application context.

Table 2.1(b) (Contd.)

Paper	Findings
22. Everett, (2009)	• Results from the Q statistic indicated that the transferability of a trip generation model can be improved significantly (80% of the initially rejected models became acceptable) only by including a context specific variable 'area type' (developed by using a slightly modified procedure of that followed by the Claritas for area classification in the NPTS data). Transfer effectiveness can be further improved by using a more disaggregate area type classification but careful attention is required on the sample size.
23. Gunn & Pol (1986)	• Mode-destination choice: Each successive improvement over the naively transferred model offered statistically significant improvement (log-likelihood improvement). However, from an aggregate prediction ability standpoint, transfer scaling (updating constants and a single scale for all other parameters) offered the most significant improvement over naïve transfer. Updating two scale parameters for two sets of variables offered only marginal improvement. While none of the transfer method is statistically equivalent to complete re-estimation of all parameters, updating constants and scale of coefficients may suffice from an aggregate predictive ability stand point. • Tour generation models: Transfer scaling significantly improved the model fit to the application data (over the naïve 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.
24. Arentze et al. (2002)	• The prediction ability of the transferred model at both the aggregate and disaggregate levels support spatial transferability of the "Albatross" model system (except for mode choice model).
25. PB Consult Inc. (2007)	• Predicted shares (obtained from the transferred models) were reported to have match closely with the observed survey data for certain model components.
26. Picado, (2013)	• For most models, calibration via updating constants helped in getting reasonable aggregate predictions. • Largest differences observed between transferred model predictions and observed patterns for non-mandatory tour destinations and daily activity travel patterns and frequencies for college students, part-time workers and pre-school children. • Did not observe transferability at high levels of disaggregation, probably because updating constants helped in getting reasonable aggregate predictions but not necessarily in adequately capturing local behavior.
27. Le Vine et al. (2010)	• Predicted temporal distribution of activity start time and trips per day were found to be different from that in the local survey data.
28 Nowrouzian & Srinivasan (2012)	• Aggregate prediction supports the concept of transferability while elasticity measures do not. • Transferability depends on tour purpose and the direction of transfer.
29. Vovsha et al. (2010)	• Parameter estimates of location choice models were found to be quite different between different cities. Specifically, the parameter estimates of distance functions, an important determinant of the resulting home-work trip length distribution, were found to be considerably different among the 4 cities. This suggests the difficulty of transferring location choice models.
30. Bowman et al. (2013)	• While TTS rejected the transferability of any model (as a whole), a large proportion of individual coefficients are not significantly different from one region to the next. • It is better to transfer models built using larger estimation samples from a comparable region than to estimate new models using small sample sizes from the local region. • Coefficients of variables that are for specific population segments (that attempt to capture demographic heterogeneity) are more transferable than coefficients generic/common for the entire population. • Models for activity generation and scheduling are more transferable than those of mode choice and location choice. • Greater transferability was found between different regions in a state than across different states, with the exception that Jacksonville was more transferable to regions in California than to Tampa. Tampa was found to be most different from all other regions.

context of mode and/or destination choice model components, studies numbered 15-22 are in the context of travel generation model components, and studies numbered 23-30 are in the context of tour-based/activity-based model systems or model components. The discussion in this chapter draws from these tables and other theoretical studies.

The next section provides an overview of theoretical and practical issues related to model transferability. Discussions on different transferability assessment metrics and transfer methods used in the literature are provided in sections 2.3 and 2.4 respectively. Section 2.5 discusses the transferability of tour/activity based models (and, model system). Along with the discussion, the related gaps in the literature are identified in each of these sections. Of these gaps, the notable ones that will be addressed in this dissertation research are summarized in Section 2.6. Section 2.7 concludes the chapter.

2.2 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.

2.2.1 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 (and builds on) these three papers.

As described by Ben-Akiva (1981), 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:

1. Underlying theory of travel behavior
2. Mathematical model structure
3. Empirical specification
4. Model parameter estimates

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: (1) broad behavioral postulates (Hansen, 1981) of travel behavior such as utility maximizing or satisficing decision paradigms, and (2) theories of travel behavior (e.g., trip based vs. activity-based), including representation of travel (e.g., trips vs. tours). The *second level* involves the transferability of model structure, which includes the mathematical model structure (e.g., logit vs. nested logit to model mode choice). The *third level* involves the transferability of empirical model specification, including the explanatory variables in the model, the specification of heterogeneity in behavior across demographic segments and the way in which variables enter the model (e.g., linear vs. non-linear specifications). 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 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, as discussed below.

At the *theoretical level*, there is an increasing recognition that the widely held assumption of a rational, utility-maximizing behavior assumed to model travel choices may not be valid in several contexts. For example, it is possible that individuals make several travel-related choices based on decision-making heuristics such as satisficing (Simon, 1955), and lexicographic (Tversky, 1969) rules, as opposed to the utility-maximizing rule. Similarly, the classical expected utility theory may not necessarily be the most appropriate theory to explain several travel choices (see Kahneman and Tversky, 1979; and Li and Hensher, 2011). To the extent that the appropriate theories decision-making heuristics needed to model travel behavior are different across different contexts, it becomes difficult to transfer models. Although the utility theory can be used to accommodate a range of behaviors outside the purview of rationality, operationalizing the concept may need simplifying assumptions that may not hold across a wide range of contexts (Ben-Akiva, 1981). At this point, no empirical evidence exists on the influence of assumptions on a choice theory and decision-making rules on model transferability.

At the *second level*, the choice of a specific model class from a variety of plausible model structures (e.g., porbit vs. logit vs. nested logit vs. mixed-logit) and the functional form can introduce additional approximations (Ben-Akiva 1981). For instance, using linear regression to model trip generation introduces errors due to ignoring the discrete and integer nature of the outcome variable. To the extent that these errors vary across different contexts, model transferability gets affected. Similarly, ignoring unobserved heterogeneity in response to level-of-service variables in mode choice models can introduce errors that vary across spatial contexts and reduce model transferability. Like-wise the choice between additive and non-additive utility forms can influence transferability. The choice of the model structure is generally guided by the underlying theory of the travel behavior being modeled and considerations of simplicity. While significant research exists on advancing the model structures used to model travel choices, little evidence exists on what advances/improvements to the model structure made the models more transferable. Further research is needed to examine the effect of model structure on transferability.

At the *third level*, different aspects related to model specification can influence transferability. Such errors include: (1) the omission of influential explanatory variables (Koppelman and Wilmot 1985), (2) neglect of socio-demographic heterogeneity and unobserved variation in travel behavior, and (3) the use of inappropriate transformation of variables (Ben-Akiva 1981). Inadequate model specification is perhaps one of the most important reasons behind the difficulty of transferring models. Koppelman and Wilmot (1985) provide a theoretical discussion to describe how omitting influential explanatory variables influences model transferability. Omitted explanatory variables in travel demand models cause the econometric problem of endogeneity when they are correlated to the variables included in the model (Koppelman and Wilmot, 1985). To the extent that the errors introduced by omitted variables vary across contexts, model transferability becomes difficult. Empirical specifications of travel demand omit several variables that explain the variation in travel behavior across different regions. In this context, Louviere (1981) argued strongly that several issues related to variable specification need to be addressed before even considering transferability. He highlighted that several context-specific characteristics – social, cultural, physical environment and spatial structures and urban form and transport system and network features – have a significant influence on travel behavior but are usually not represented in travel models built for a specific region due to limited variation in these characteristics within a region. Thus, it would be difficult to successfully transfer a model where these characteristics differ from one region to another.

At the *fourth level*, there can be several reasons why the parameter estimates may not be transferable, including the sampling errors in estimating the parameters and differences in the way variables are measured (and in the measurement errors) between different contexts (Louviere 1981). Simple issues such as differences in the way variables are defined and created (e.g., network coding procedures for creating level of service variables) can lead to differences in the estimated coefficients of the variables between the two contexts (Louviere 1981). He argued that lack of commensuration of variables across different contexts makes it difficult to even test transferability of the estimated coefficients of those variables. Further, differences in the survey methods, instruments, and administration procedures can influence transferability.

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 difficult to achieve perfect transferability while transferring models across different geographical contexts.

2.2.2 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. 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. Taking these issues into consideration, Koppelman and Wilmot (1982) define 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. The tricky part, however, is to determine whether (and to what extent) a transferred model helps in making appropriate decisions. Thus, a more operational definition of transferability could be as follows: *if a transferred model performs better than (or as good as) a model that can be built using locally available data and resources, then the* *model could be considered transferable for practical purposes*. This definition uses a locally built model as a yardstick against which a transferred model is assessed. However, it is useful to note that a transferred model that performs better than a locally built model may not necessarily be theoretically transferable in that it may not capture behavioral relationships that are invariant across geographical contexts; especially in situations with a poorly performing locally built model.

2.3 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. In this section, we first discuss the approaches and metrics used in the literature to assess model transferability. Subsequently, we identify several issues that need to be considered while assessing the transferability of travel forecasting models.

2.3.1 Transferability Assessment Metrics

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. As discussed earlier, no empirical evidence exists on the influence of assumptions on choice theory and model structure on transferability. The empirical assessment of transferability has largely focused on transferring empirical specification with a corresponding set of parameters, implicitly assuming that the underlying theory and mathematical model structure are transferable.

Table 2.2 presents a summary of the metrics used in the literature for model transferability assessment. These metrics can be classified into three categories: (1) Statistical tests of equivalence of parameters, (2) Measures of predictive ability (at disaggregate and aggregate levels), and (3) Policy sensitivity/elasticity 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 (or behavioral changes) 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.

2.3.1.1 Statistical Tests of Equivalence of Parameters

Statistical tests can be used to formally test the null hypothesis of model transferability (e.g., equality of parameters between estimation and application contexts), and make a determination of whether a model is transferable or not. The commonly used statistical tests in the literature are model equality tests statistic (METS), transferability tests statistics (TTS), and t-tests. Among these, METS and TTS are log-likelihood based measures that are used to test the statistical equivalence of models (i.e., the entire set of parameters) in the base and application contexts, while t-tests are used to compare the parameter estimates of specific variables between two 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 parameters estimates are confounded

Table 2.2 A Summary of the Metrics Used in the Literature to Assess Model Transferability

Name of the Test	Type of the Test	Expression	Description
Model Equality Test Statistic (METS)	Statistical tests of equivalence of parameters	$-2[L_{ij}(\beta_{ij}) - L_i(\beta_i) - L_j(\beta_j)]$	• χ^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.
Transferability Test Statistic (TTS) Atherton & Ben-Akiva (1976)	Statistical tests of equivalence of parameters	$-2[L_i(\beta_j) - L_i(\beta_i)]$	• χ^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.
t-tests of individual parameter equivalence	Statistical test of individual parameter equivalence	Ratio of the difference in parameters to standard error of the difference	• 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).
Transfer rho-square (ρ_T^2) Koppelman & Wilmot (1985)	Measure of disaggregate-level predictive ability	$\rho_T^2 = 1 - \frac{L_i(\beta_j)}{L_i(C_i)}$	• 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).
Transfer Index (TI) Koppelman & Wilmot (1982)	Measure of disaggregate-level predictive ability	$\frac{L_i(\beta_j) - L_i(C_i)}{L_i(\beta_i) - L_i(C_i)}$	• Measures goodness-of-fit of a transferred model relative to an identical specification estimated in the application context. • Ratio of a transferred model's rho-square (ρ_T^2) to the locally estimated model's rho-square (ρ^2). • The closer the value of TI is to 1, the closer is the transferred models' performance to a locally estimated model.
Relative Error Measure (REM)	Measure of aggregate-level predictive ability	$(PS_k - OS_k) / OS_k$	• An error measure of the aggregate-level prediction for a choice alternative.
Root-Mean-Square Error (RMSE)	Measure of aggregate-level predictive ability	$\left(\frac{\sum_k PS_k \times REM_k^2}{\sum_k PS_k} \right)^{1/2}$	• Measures the aggregate-level predictive ability of the model, when compared to aggregate observed shares in the data.
Relative Aggregate Transfer error (RATE)	Measure of aggregate-level predictive ability	$\frac{RMSE_i(\beta_j)}{RMSE_i(\beta_i)}$	• 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.
Aggregate Prediction Statistic (APS)	Measure of aggregate-level predictive ability	$\sum_k \frac{(PS_k - OS_k)^2}{PS_k}$	• χ^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 .

Notation: L stands for log-likelihood and β 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 application context data, $L_i(\beta_i)$ = log-likelihood of the local model applied to application context data, $L_{ij}(\beta_{ij})$ = log-likelihood of the model estimated on a combined dataset i and j , $L_i(C_i)$ = log-likelihood of a constants only model for application context data, PS_k and OS_k = Predicted shares and observed shares, respectively for alternative k.

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 imply 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), but that doesn't imply that the differences are practically important. As can be observed from column 5 of Table 2.1(a), several studies (e.g., Watson & Westin, 1975 and Atherton & Ben-Akiva, 1976) in the literature used statistical tests to assess model transferability. Results from these tests have rejected the hypothesis of transferability in almost all the cases (see Table 2.1 (b) for details). Thus, statistical tests of model (in)equality should be considered in light of practical differences between the models (Koppelman and Wilmot, 1982). The tricky part, however, is in determining whether the statistical differences are practically important.

2.3.1.2 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 and can be classified into two categories: (1) aggregate prediction based transferability metrics (such as relative error measure and root-mean-square error), and (2) log-likelihood based transferability metrics (such as transfer rho-square and transfer index).

Aggregate-level prediction based transferability metrics such as the Root Mean Square Error (RMSE) 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. A cautionary note is in order here regarding the use of aggregate-level prediction metrics for transferability assessments. These metrics measure how well a transferred model reproduces aggregate-level behavior (e.g., mode shares) in the application context, but not necessarily the ability to adequately forecast changes in travel demand under different demographic, land-use and transportation system change scenarios. Thus, models deemed transferable based on aggregate prediction metrics may not necessarily be transferable in terms of policy predictions.

Among the log-likelihood based transferability metrics, transfer rho-square (ρ_T^2) describes how well a transferred model fits the data observed in the application context, relative to a reference model (e.g., a constants only model). The transfer index (TI) is a derived measure from transfer rho-square in that it is the ratio of a transferred model's rho-square to the locally estimated model's rho square. Thus, TI measures the goodness of fit of a transferred model *relative* to a locally estimated model (the closer the TI value is to 1, the more transferable is the model considered to be). Introduced by Koppelman and Wilmot (1982), TI is a widely used measure to assess transferability, partly because of its simplicity and primarily because it provides valuable information on the extent of transferability even if a model is deemed not transferable by statistically rigorous tests. TI is also a valuable measure to assess the influence of model improvements (e.g., specification improvements) on model transferability. Further, the TI can be used to compare the transferability of different models to a region with a same locally estimated model as the reference. For example, one can compare models transferred from different regions to see which model predicts observed behavior closest to the locally estimated model. However, no consensus exists in the literature on the minimum threshold value of TI needed for a model to be transferable.

Log-likelihood based metrics in the table are generally viewed to measure how well a transferred model predicts the disaggregate-level behavior in the application context. In a stricter sense, however, they measure the aggregate-level goodness of fit of the transferred model in the application context. It is not clear, if this necessarily provides an assessment of the ability to adequately forecast changes in travel demand under different demographic, land-use and transportation system change scenarios. For example, the transferability test statistic (TTS) measure, as discussed in Table 2.2, assesses if the transferred model has a similar likelihood of predicting the observed choices as a locally estimated model. It is possible that two models have similar likelihood of predicting the observed choices but different sets of coefficients (see Atherton and Ben-Akiva, 1976 for such a result)[1]. Similarly, it is not clear what should be

[1] Atherton and Ben-Akiva (1976) report that TTS supports transferability of a mode choice model, while comparing the parameter estimates suggest that the coefficients of only the level of service variables are equivalent between the base and application contexts. Consequently, the two models may differ in the way they respond to changes in demographic makeup of the regions.

the minimum TI value threshold for which the analyst can confidently declare a model to be transferable (in terms of its ability to respond to changes in explanatory variables).

2.3.1.3 Policy Sensitivity/Elasticity Comparisons

Assessment of model transferability has traditionally been on the basis of how well transferred models reproduce existing behavior rather than on their ability to adequately forecast changes in travel demand (Karasmaa 2007). This is in part due to the obsession in the field toward expecting travel models to accurately predict the observed patterns. Even when models developed for a single region are validated for that same region (let alone transferring to another region), the typical yardstick for model assessment is prediction of observed travel patterns rather than appropriate policy sensitivity. This same tendency appears in the way transferability is assessed as well.

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. An advantage of comparing elasticities or policy sensitivities is that, unlike the parameter estimates in discrete choice models, such measures are not confounded with the scale of the unobserved factors. Surprisingly, however, only a handful of empirical studies (e.g., Atherton and Ben-Akiva

1976, Karasmaa 2007, Nowrouzian and Srinivasan 2012) use policy sensitivity tests to assess model transferability.

2.3.2 What are Acceptable Levels of Errors?

As discussed earlier, perfect transferability is very difficult to achieve. Thus, the yardsticks used to measure transferability also ought to allow for errors. That is, the analysts need to make assumptions on the level of acceptable error (or differences in the transferred and local models; either in predictive accuracy or in policy sensitivity) to determine whether a model is transferable. For example, Karasmaa (2007) uses “25% error” in the prediction accuracy of a transferred model as a maximum acceptable threshold. Nowrouzian & Srinivasan (2012) report that 20 out of the 24 models they considered become “transferable” if no more than 10% error in the predictive likelihood on a validation sample is considered acceptable. No guidelines exist on what are acceptable levels of errors. Thus, further empirical research on transferability should focus on arriving at robust thresholds (Nowrouzian and Srinivasan, 2012) for errors in predictive measures and policy sensitivity measures. For example, what is the minimum threshold value of transfer index (TI) needed for a model to be considered transferable?

2.3.3 Relationships among Different Metrics of Transferability

As can be observed from column 5 of Table 2.1(a), a variety of metrics have been used to assess model transferability. A closer look at the findings in last column of this table suggests that the transferability results and findings are mixed and vary based on the metrics used to assess transferability. This makes it difficult to make conclusions on the conditions under which (and the procedures using which) models can be transferred.

As discussed earlier, similarity of log-likelihood based predictive measures between the transferred and locally estimated models does not necessarily imply equality of parameter estimates between the models. Similarly, different models which provide similar aggregate predictions do not necessarily provide similar policy responses (e.g., elasticity values). Empirical research toward understanding the relationship between the outcomes from different metrics of transferability will be useful. A few questions to be addressed are listed below:

1. Are similarity of log-likelihood based measures and aggregate predictions necessary but not sufficient conditions for model transferability?

2. Does similarity of log-likelihood based measures imply the similarity of aggregate predictions from a transferred model to that of a locally estimated model?

3. What is the minimum value for transfer index (TI) which the analyst can confidently declare that the transferred model can provide policy predictions as good as a locally estimated model?

2.3.4 Factors Influencing Transferability Assessment

Although model transferability is viewed as the transferability of the travel behavior relationships reflected in model equations, as discussed earlier several factors other than differences in travel behavior influence the transferability of models. They are discussed here, along with relevant directions for further research.

2.3.4.1 Sampling Errors in Parameter Estimates

Most of the above approaches/metrics to assess transferability use point estimates of the parameters (hence, point estimates of the model predictions and elasticity values). However, numerical differences in the point estimates may be sufficient to result in significantly different probability values, aggregate predictions (e.g., mode shares), and elasticity estimates (Talvite and Krishner, 1978). To avoid such situations, it is useful to account for the sampling variance in the parameter estimates. One way to do so is to bootstrap. That is, instead of relying on point estimates of predictions and elasticities, one can arrive at a range of predictions and elasticity values using both the parameter estimates and their standard errors. Another way is to construct sampling distributions (of parameter estimates and implied predictions and elasticities) by repeatedly drawing different samples from the population (see Karasmaa, 2007). Comparing ranges or confidence intervals (of predictions and elasticities) implied by the transferred model with those of the application context model can potentially pave way for a more useful assessment of transferability. For example, one can examine the extent to which the two confidence intervals overlap. Such information allows the analyst to measure the *extent* of model transferability (say, there is an 85% overlap between the two confidence intervals), which is an attractive alternative to searching for a "crisp" *yes/no* answer on transferability.

It is our conjecture that ignoring sampling variance is a reason for rejecting model transferability in many situations, simply because numerical differences in point estimates lead to seemingly practically different predictions.[2] It is possible that the models that provide seemingly different forecasts based on the point estimates might actually provide closely overlapping confidence intervals for those same forecasts. Empirical evidence is needed to either confirm or contest this hypothesis.

[2] Of course, if the sizes of the samples used for estimating either the estimation context model or the application context model are small, the imprecision (or standard error) in the resulting parameter estimates can potentially be too small to make reliable assessments. Thus, first and foremost, it is important to work with sufficient sample sizes in both the estimation and applications contexts to be able to make credible inferences on model transferability.

2.3.4.2 Differences in the Definitions and Measurement of Variables

Contextual differences in the measurement of variables can make it difficult to assess transferability across different contexts. Simple issues such as differences in the way variables are defined and created can potentially lead to differences in the estimated coefficients of the variables between the two contexts (Louviere 1981). Since it is difficult to quantify and disentangle such measurement errors, it becomes difficult to test the transferability of the true influence of the corresponding variables. As Louviere (1981) argued, it will be useful to implement common measurement schemes for important explanatory variables to facilitate model transferability. In addition to measurement errors in explanatory variables, reporting errors (by the survey respondents) in the dependent variables of interest can influence transferability. For instance, rounding-off errors in continuous variables such as activity durations and departure times can influence the transferability of models estimated for such variables. Efforts to disentangle *errors in variables* from the parameter estimates can help in better assessments of model transferability. Further, as Talvite and Krishner (1978) indicated, data cleaning mechanisms and treatment of outliners can also influence the transferability of estimated parameters.

Differences in survey methods, instruments and administration can also get confounded with the differences in the parameter estimates between two regions. Differences in the wording of questions can also cause differences in the elicited responses. Although little empirical evidence exists on the influence of using different survey data sets on transferability results, conducting transferability assessments using data from a same survey/source helps in avoiding potential confounding effects due to differences in survey methods. In this context, it would be useful to understand the extent to which survey differences can influence model transferability assessments.

2.4 Enhancement of Model Transferability (Transfer Methods)

The simplest method to transfer a model is called naïve transfer, where the model specification and parameter estimates from one context are transferred directly (i.e., without any modifications) to another context. When making a naïve transfer, it is assumed that the model is perfectly transferable in that it captures behavioral relationships that do not vary across contexts and that the variability in travel behavior is solely due to the differences in the values of the explanatory variables in the model. As can be observed from column 4 of Table 2.1(a), naïve transfer was used in several studies in the literature. Except in a few cases (e.g., Atherton and Ben-Akiva, 1976), most of these studies suggest that the performance of a naively transferred model was far from a locally estimated model both in terms of data fit as well as aggregate prediction (see Table 2.2 for details). Thus using available information and data from the application context, the base context model is usually "updated" to render it better capture behavior in the application context (i.e., to make it better transferable). The various model updating methods are discussed next (these generally reflect increasing levels of data needs from the application context). Consider the following notation to describe different updating methods used to enhance model transferability.

Let i and j be the subscripts for the base and application contexts.

U_t = utility specification in context t (t = i and j)

C_t = vector of alternative-specific constants in context t (t = i and j)

β_t = true parameter vector (excluding alternative constants) in context t (t = i and j)

$\hat{\beta}_t$ = estimated parameter vector (excluding alternative constants) in context t (t = i and j)

ε_t = vector of unobserved factors in context t (t = i and j)

σ_t = scale of the unobserved factors in context t (t = i and j)

X = vector of explanatory variables

r = vector of context-specific variables in the combined data set (from the base and application contexts)

s = vector of common variables in the combined data set

θ = vector of scales to update the base context parameters

$\hat{\beta}_{updated}$ = updated parameter vector in the application context

$\sum_t$ = covariance matrices of estimated parameters in context t (t = i and j)

$\sum_{updated}$ = covariance matrices of the updated parameters in the application context

$\Delta = \beta_i - \beta_j$ = transfer bias (i.e., difference in the true parameters between the two contexts), which is usually estimated as $\hat{\Delta} = \hat{\beta}_i - \hat{\beta}_j$.

2.4.1 Updating Constants

In this approach, it is assumed that the parameters other than the constants in a model are transferable across areas; only the constants need to be updated. The constants can be either an intercept in a linear regression model, intercept of the propensity function in an ordered response models, or alternative-specific constants of the utility functions in a discrete choice model. For discrete choice models, the constants can be updated using either aggregate level information on the market shares from the application context or a disaggregate sample from the application context.

In general, the constants in a model capture the average effects of unobserved factors on the travel choices being modeled as well as the influence of measurement errors in the explanatory variables. To the extent that the above influences (of unobserved factors and measurement errors) vary across different contexts, the constants can be expected to be different across the contexts. It is not uncommon that constants explain a large share of the variation in the choices being modeled (due to the presence of influential unobservable and un-measurable factors). Thus, updating the constants of a transferred model using information from the application context can help in capturing the differences in the average effects of the unobserved factors between the two contexts.

As can be observed from Column 4 of Table 2.1(a), updating constants is a widely used method in practice to transfer models from one region to another. Empirical evidence in the literature (see column 6 of Table 2.1(a)) suggests that updating the constants in the model can significantly improve the performance of a transferred model in terms of improved log-likelihood based measures (e.g., transfer index) and improved aggregate-level predictions (Koppelman and Wilmot 1982; Koppelman et al., 1985; Abdelwahab, 1991). For example, Koppelman and Wilmot (1982) report that updating the constants of a transferred mode choice model helped in achieving as much as 80% transfer index and containing the aggregate prediction errors (RMSE) to less than 20%. Abdelwahab (1991) reports an 80% accuracy of aggregate predictions after updating the constants of a transferred mode choice model using local data. The important question, however, is to what extent does updating constants help in capturing the behavior in the application context? In other words, does the improvement (due to updating constants) in the log-likelihood based measures (e.g., TI) and aggregate predictions translate to improvements in the ability of the transferred model to predict appropriate responses to policies? For instance, it is possible that a naively transferred model that performs rather poorly can be improved significantly (in terms of both transfer index and aggregate predictions) simply by updating its constants using local data. This improvement can be attributed largely to the property of discrete choice models (especially multinomial logit) that updating constants can do the trick in getting the aggregate predictions right rather than to the improvement in the model's capture of behavior in the application context. In other words, there is no guarantee that a transferred model with updated constants can provide credible policy responses in the application context. However, empirical evidence is required to support/contrast this hypothesis.

2.4.2 Transfer Scaling

Updating the constants of a model helps in capturing the differences in the *average* influence of the unobserved factors between the base and application contexts. But it does not recognize the possible differences in the magnitude of *variation* in the influence of unobserved factors. The transfer scaling method overcomes this shortcoming. 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 (θ). To understand this, consider the utility specification in the application context (U_j) as:

$$U_j = C_i + \theta\beta_i^{/} X_i + \varepsilon_i \quad (2.1)$$

The scale factor (θ) in the above equation represents the ratio between the magnitudes of the variation in unobserved factors influencing the choice in the two contexts i and j (i.e., $\theta = \sigma_i / \sigma_j$). Since the parameter estimates in compensatory discrete choice models are confounded by the scale of the unobserved factors, updating the scale helps in reconciling the differences in the variation of the unobserved factors between the two contexts. The closer the value of θ is to 1, the smaller are the differences in the scales of the unobserved factors between the two contexts. Of course, the constants can also be updated (along with the scale) to capture the differences in the average influence of unobserved factors between the two contexts. In essence, it is assumed that the transfer bias is simply due to the differences in the average effects of unobserved factors (i.e., alternative specific constants) and the magnitude of variation in the unobserved factors (i.e., scales) and therefore, can be eliminated by simply updating the constants and the scale of the estimation context model using a sample of data from the application context. There is a potential pitfall of this approach, as discussed below and elsewhere (Ben-Akiva and Bolduc, 1987).

To update the base context parameters (β_i) according to equation (2.1), the approach uses estimated parameters ($\hat{\beta}_i$) in place of the true parameters (β_i) from the base context. Thus, any estimation errors (say, sampling errors) in the base context $(\beta_i - \hat{\beta}_i)$ are carried over to the application context, as below:

$$\begin{aligned} \beta_j &= \theta\beta_i = \theta(\hat{\beta}_i + \beta_i - \hat{\beta}_i) \\ &= \theta(\hat{\beta}_i) + \theta(\beta_i - \hat{\beta}_i) \end{aligned} \tag{2.2}$$

To the extent that the estimation bias in the base context $(\beta_i - \hat{\beta}_i)$ is non-negligible, the updated parameters will be biased by $\theta(\beta_i - \hat{\beta}_i)$.

While there is empirical evidence that much of the transfer bias can indeed be eliminated by adjusting model constants and scales (Algers et al., 1994; Badoe and Miller

1995), this approach doesn't really recognize the possibility of true behavioral differences between the two contexts. Controlling for the effects of unobserved factors does not help in eliminating the transfer bias due to the true differences in the true parameters; it only eliminates the confounding effects due to unobserved factors.

Transfer scaling is sometimes performed to estimate separate scaling factors for different groups of variables in the base context model. This approach is called partial transfer (see Gunn et al. (1985)). For example, the level of service variables in a mode choice variable can be associated with one scaling factor and the socio-demographic variables can be associated with another scaling factor. If a separate scale parameter is estimated for each variable, it is equivalent to complete re-estimation. Unless it is necessary to re-estimate the coefficients of all variables, a *cleaner* approach is to retain the same scaling factor for all the variables (which accounts for the differences in the variation in the influence of unobserved factors across the two contexts) while allowing for differences in the influence of groups of explanatory variables. This approach allows in recognizing behavioral differences between the two contexts.

While some studies (Algers et al., 1994; Badoe and Miller 1995) found improved performance (in terms of improved aggregate-level predictions and log-likelihood measures), other studies (Koppelman et al., 1985) suggested considerable but less improvement when compared to updating the model constants. Besides, it is not clear if the improvement in the model in terms of aggregate predictions and log-likelihood based measures translates into improvement in the model's sensitivity to changes in explanatory variables.

2.4.3 Bayesian Updating

Proposed by Atherton and Ben-Akiva (1979), this approach involves a Bayesian updating of the base context parameter estimates using estimates obtained from a small sample in the application context. The prior distribution (distribution of the base context parameters) is combined with the sample distribution (distribution of the parameters estimated from a small sample in the application context) to obtain the posterior (i.e., updated) distribution of the parameters.

Updated parameter estimates, $\hat{\beta}_{updated} = (\sum_i^{-1} + \sum_j^{-1})^{-1}(\sum_i^{-1}\hat{\beta}_i + \sum_j^{-1}\hat{\beta}_j)$ (2.3)

Updated covariance matrix, $\sum_{updated} = (\sum_i^{-1} + \sum_j^{-1})^{-1}$ (2.4)

The updated parameter estimates $\hat{\beta}_{updated}$ are a weighted average of the base context parameter estimates $(\hat{\beta}_i)$ and the parameter estimates $\hat{\beta}_j$ from the application context, the weights being the inverse of their respective variances. The use of the covariance matrices helps in accounting for the sampling error in the base context and the application context. The estimates with lower variance (or greater certainty) contribute more to the updated parameters than those with greater variance.

Though this approach provides an advantage of combining prior information with a small sample from the application context, the quality of the posterior/updated parameter distribution depends on the distributional assumption (normal distribution in most of the cases) used in the updating process. Another criticism of this approach is that it assumes transfer bias (Δ) as zero, i.e. there are no differences between the true parameters in the estimation and application contexts. If the size of the sample used to estimate the application context parameters is too small, then the Bayesian updating places a greater emphasis on the estimation context parameters assuming no transfer bias from the estimation context to the application context. But in practice, significant transfer biases can potentially exist for at least some of the parameters in the model, especially for transfers between significantly different contexts. As argued by Karasmaa (2007), unless we know if the transfer bias is small (which is difficult to know in real transfer situations), it can be risky to use Bayesian updating (also see Badoe and Miller, 1995 who warn against using the Bayesian approach).

2.4.4 Combined Transfer Estimator

This approach, proposed by Ben-Akiva and Bolduc (1987), is an extension of the Bayesian updating method to take into account the transfer bias between the estimation and application contexts. The combined transfer estimator follows a mean squared error (MSE) criterion to combine both transfer bias and the variance of the estimates in the base and application contexts results. To do so, the estimator is expressed as a linear combination of the unbiased parameter estimates from the estimation and application contexts, as shown below:

$$\hat{\beta}_{updated} = \left[(\Sigma_i + \Delta\Delta')^{-1} + \Sigma_j^{-1} \right]^{-1} \left[(\Sigma_i + \Delta\Delta')^{-1} \hat{\beta}_i + \Sigma_j^{-1} \hat{\beta}_j \right]^{3} \qquad (2.5)$$

$$\Sigma_{updated} = \begin{bmatrix} \Sigma_i^2 & 0 \\ 0 & \Sigma_j^2 \end{bmatrix}^{-1} \qquad (2.6)$$

Note that if transfer bias $\Delta = 0$, equation (2.5) reduces to the Bayesian updating equation

[3] Since the transfer bias Δ used in this equation is unknown, its estimate ($\hat{\Delta} = \hat{\beta}_i - \hat{\beta}_j$) is used.

(2.6). On the other hand, if the transfer bias (Δ) is large, the term $(\sum_1 + \Delta\Delta')^{-1}$ in equation (2.5) becomes negligible and therefore, $\hat{\beta}_{updated} = \hat{\beta}_j$ the parameter estimates from the application context. That is, for large transfer bias, the combined transfer estimator results in estimates equivalent to the parameter estimates from the application context. Specifically, the benefit of combining the two estimators is lost when the transfer bias becomes large enough to result in a mean square error greater than the variance of the parameter estimates in the application context.

Several studies that have used this approach suggest its superior performance compared to Bayesian updating (Badoe and Miller, 1995; Santoso and Tsunokova, 2010). As suggested by Karasmaa (2007), and for the reasons discussed above, this approach works the best when the transfer bias is small between the estimation and application contexts. Since the transfer bias is typically estimated as a difference between the estimated parameters in the estimation and application contexts, in situations with small sample sizes in the application context, the estimated transfer bias is likely to be large leading to an increased emphasis on the application context (with small data).

2.4.5 Joint Context Estimation

This approach (proposed by Bradley and Daly, 1997; Ben-Akiva and Morikawa, 1990) combines data (not parameter estimates) from the base and application contexts to estimate a joint, base-application context model. Depending on the data availability in two contexts, common parameters can be estimated for a subset of variables while allowing context-specific parameters for other variables. Let U_t and X_t denote the utility components and the vector of all explanatory variables in the joint context model respectively (t = i and j).

$$U_i = (\alpha_i^{/})r_i + (\gamma^{/})s_i + \varepsilon_i \quad (2.7)$$

$$U_j = (\alpha_j^{/})r_j + (\gamma^{/})s_j + \varepsilon_j \quad (2.8)$$

$$\begin{aligned} X_i &= \begin{bmatrix} r_i & 0 & s_i \end{bmatrix}^{/} \\ X_j &= \begin{bmatrix} 0 & r_j & s_j \end{bmatrix}^{/} \end{aligned} \quad (2.9)$$

where, γ is the vector of common parameters and α_i and α_j are the context-specific parameter vectors. To recognize the differences in the variance of the influence of unobserved factors in the two contexts, the scale of the distributions of ε_i and ε_j are allowed to be different. During estimation, a ratio (θ) of the two scale parameters can be estimated, where $\theta^2 = \mathrm{var}(\varepsilon_i)/\mathrm{var}(\varepsilon_j)$.[4] To do so, the application context utility can be scaled by θ as:

$$\theta U_j = (\theta\alpha_j^{/})r_j + (\theta\gamma^{/})s_j + \varepsilon_j = (\theta\beta_j^{/})X_j + \varepsilon_j \quad (2.10)$$

This approach has similarities with the transfer scaling approach in that it allows the scale of the unobserved factors to be different. But since this approach uses data (not parameter estimates) from the two contexts, errors in the estimation process (e.g., sampling errors) of the base context parameters do not shift automatically to the updated parameter estimation. Of course, in situations where data is not available (but only parameter estimates are available) from the base context, the approach cannot be used.

[4] Two different scales – one for each dataset – cannot be estimated due to identification issues. Only the ratio of the scales can be estimated only in situations when at least one of the variable coefficients is the same between the two contexts. One cannot even estimate the ratio of the scales when all parameters are different between the two contexts. Thus, the underlying hypothesis behind joint context estimation is that the travel behavior (reflected in variable coefficients) is similar between the two contexts for at least one explanatory variable in the model. If all the parameters are different between the two contexts, one cannot estimate a joint model with a scale ratio (there is no need to do so because the models are not transferable anyway). See Bradley and Daly (1997), Ben-Akiva and Morikawa (1990), and Louviere et al., (1981) for the basics of choice model estimation using data from multiple contexts.

But if the data is available, the analyst can explore different specifications allowing different coefficients for a sub-set of variables and estimating common coefficients for other variables (for whom data from any one single context is too small to estimate context-specific parameters). This helps in getting improved (and efficient) parameter estimates for variables whose data availability in either of the contexts is small, which is not an uncommon occurrence in practice. Specifically, in situations where the variation in important socio-demographic, land-use, and level-of-service variables is insufficient in either contexts, pooling data can potentially help in achieving sufficient variation for parameter estimability. Further, when sufficient data is available from the two contexts, the approach allows the analyst to test the possibility of contextual differences in the parameter estimates while controlling for the differences in error scales and not getting bogged down with sampling error issues.

In summary, the above discussed methods to transfer models differ from each other in assumptions, and also in the ways they are applied. The updating constants approach assumes no transfer bias in parameters other than constants. The transfer scaling approach does not consider the sampling error in the estimation context; it attempts to accounts for only the transfer bias by using a small sample data from the application context. On the other hand, Bayesian approach considers sampling error in both contexts, but assumes that transfer bias is zero. Thus, unless we know that the transfer bias is small (which is difficult to know in real transfer situations), it can be risky to use Bayesian updating (Karasmaa, 2007); careful attention is required in selecting updating methods. The combined transfer estimator extends the Bayesian approach by taking into account the transfer bias as well as sampling error. The joint context estimation method also considers both the transfer bias and the sampling error of the model parameters.[5] While several empirical studies assessed the relative performance of different model updating methods (see Tables 2.1(a) & 2.1(b)), to our knowledge, Karasmaa (2007) is the only study that compared all the four methods discussed above in the context of spatial transferability. The timing of most other comparisons (Atherton and Ben-Akiva, 2010; Galbraith and Hensher, 1982) was before the joint context estimation was proposed, thus eliminating joint context estimation as a potential alternative method in the comparison. Karasmaa (2007) concludes that joint context estimation as the best transfer method if data is available from both estimation and application contexts. Badoe and Miller (1998) also suggest the joint context estimation approach, albeit in the context of developing temporally transferable models (by pooling data from different temporal contexts). More recently, an ongoing project on developing activity-based models for the Jacksonville and Tampa regions in Florida employs joint context estimation of the model parameters by combining data from both the regions. In situations where data is not available from the estimation context, one has to choose from other methods. Nevertheless, more empirical evidence is needed to make conclusive statements on which model updating method works best under which conditions.

2.4.6 Improvements to Model Specification

While the model updating methods discussed above can potentially help in improving model transferability, first and foremost, it is paramount to consider improvements in model specification as a way to enhance model transferability. Without

[5] While Bayesian updating and combined transfer estimation requires the parameter estimates and corresponding covariance matrices from both contexts, updating constants and transfer scaling requires only the parameter estimates from the base context and a sample of data from the application context. Joint context estimation requires model estimation data from both contexts.

adequate model specification, it would be difficult to transfer models to other spatial contexts. As Koppleman and Wilmot (1985) suggest, a certain minimum adequate specification is necessary for achieving reasonable transferability, even with the model updating methods discussed above. In the context of mode choice models, for example, models with only LOS variables have been found to fall short of this minimum adequate specification criterion (Koppelman and Wilmot 1985).[6] Thus, to the extent possible, model specifications should accommodate different sources of heterogeneity in behaviors – demographic heterogeneity in preference to different alternatives, demographic heterogeneity in response to alternative attributes (e.g., differences in sensitivity to travel times and travel costs), and other sources of heterogeneity such as non-linearity in response to level of service attributes and variations due to unobserved factors (that can be captured using methods such as mixed logit). Incorporating these different sources of heterogeneity is better possible with disaggregate-level (individual/household-level) models as opposed to aggregate-level models.

In addition to the heterogeneity due to demographic and level-of-service characteristics, as argued by Louviere (1981), a large portion of the variation in observed travel behavior is due to the activity-travel environment attributes, including spatial land-use and urban form attributes, network structure, and cultural characteristics that show

[6] The natural next question is: what should be the criteria to choose which model specification is better (for the purpose of transferring to a region).In choosing between different model specifications to transfer from, model goodness of fit should not be used as the sole criterion. Evidence exists that models with greater fit to the base context (e.g., as measured by greater rho-square value) do not necessarily transfer better if the specifications were not theoretically sound. For instance, Galbraith and Hensher (1982) found that models with mode-specific LOS coefficients exhibited significantly greater fit to the base context data but poorer transferability (when compared to models with generic LOS coefficients). Koppelman and Wilmot (1982) found that, if identically specified models were available to transfer from different regions, goodness of fit to the base context was not necessarily the most appropriate measure to select the base context from which to transfer. These findings suggest that statistical fit as well as theoretical and intuitive considerations should have bearing on the model specification to choose for the purpose of transferring to a region.

little variation within a single context. To address this issue, the joint context estimation method discussed in the previous section offers the ability to pool data from multiple contexts to explore the possibility of enhancing model transferability. Since the approach involves pooling data from different contexts, it offers opportunities to include context-level spatial land-use, network structure and cultural variables that do not vary within a context but vary across contexts and have an influence on the choice outcome being modeled. Without pooling data from multiple contexts, it is not possible to include variables that do not exhibit sufficient variation within a single context. Most empirical use of this approach involves pooling of data from only two contexts (base and application contexts), but it is possible to pool data from more than two contexts to better capture context-level variables in the model specification and enhance the potential for model transferability. To the extent that such variables have an influence on travel behavior and vary across the different contexts, it becomes important to include such variables in the model specification for enhanced model transferability. Besides, the method can potentially help improve model specification (hence improve transferability) not only through the enhancement of the utility specification using context-level variables but also through the specification of the scale parameters (of the utility functions) themselves as a function of context-level variables. Capturing the heterogeneity in the influence of unobserved factors (i.e., the scale of the error terms) through contextual variables can also help improve model transferability.

To be sure, the possibility of enhancing model transferability by pooling data from multiple contexts has been discussed several times in the literature, although only a few empirical studies have explored this approach in the context of spatial transferability.

For instance, Karasmaa (2007) and Ou and Yu (1983) allude to the possibility of "universal" models that are more transferable. More recently, Hood (2012) gainfully explored this option in the context of linear regression models of transit ridership, specifically by using a multi-level modeling approach. Multi-level models help in controlling for local unobserved heterogeneity (from different spatial contexts), which can potentially lead to the estimation of relationships that are more global (i.e., transferable) in nature. This approach of pooling data is seeing increasing use in the context of developing temporally transferable models. For instance, Badoe and Miller (1998) and Habib et al. (2012) pool data from different years. However, further exploration of the above discussed ideas using joint context estimation with data from multiple regions is a potentially fruitful avenue for developing spatially transferable models.

2.5 Transferability of Activity-Based Models (and Model Systems)

As can be observed from column 2 of Table 2.1(a), most work to date has been devoted to the transferability of linear regression-based travel generation models and logit-based mode-choice models. Only a few studies in the table (23-30) are in the context of tour-based/activity-based models. As several planning agencies are moving toward (or considering the move to) the activity-based approach to modeling travel, and at the same time, building and maintaining activity-based models takes significantly more amount of data and resources, the issue of model transferability is more critical for the activity-based models. Further, there is hope that the greater theoretical basis and the behavioral realism with which the travel patterns are represented and modeled in activity-based models makes them more transferable (than trip-based models) to other contexts.

But the available evidence on the transferability of tour-based/activity-based models is not sufficient to provide any conclusive statements on the transferability of these models.

Empirical literature in Table 2.1 (studies 24-27) suggests that in addition to specific individual model components, activity-based model systems (or parts of the model systems) have also been transferred from one region to another. It is worth noting here that though several attempts have been undertaken to transfer entire activity-based model system across geographical contexts, there is no framework yet for assessing the transferability of activity-based model system.

2.6 Notable Gaps in the Literature

Below are some of the notable gaps in the literature that are addressed in this dissertation research:

1. Several activity-based model systems (or parts of the model systems) have been transferred across regions. But there is no framework yet for assessing the transferability of activity-based model systems. The next chapter of this dissertation attempts to provide a framework that can guide analysts assessing the transferability of activity-based model systems as opposed to specific model components.

2. Existing empirical evidence on model transferability is predominantly geared toward trip-based mode choice and travel generation model components, with only a handful of empirical studies on the transferability of tour-based /activity-based model components. This dissertation research investigates the transferability of two model components used in activity-based model systems: activity participation and time-use models, and tour-based time-of-day choice models.

3. The model structures used in most previous transferability assessments are limited to linear regression and multinomial logit (MNL). Little or no evidence exists on the transferability of advanced model structures such as nested logit (NL) and multiple discrete continuous extreme value (MDCEV). This dissertation research uses the MDCEV structure in the transferability assessment of activity participation and time-use models.

4. There are only a few studies in literature that assess transferability based on the policy response measures. Since the main objective of developing a travel demand model is to use for forecasting and policy analysis, it is essential for the transferred model to be able to provide appropriate predictions of the responses to changes in explanatory variables (i.e., demographic characteristics and policy variables). This research uses policy response measures in the transferability assessment of activity participation and time-use models.

5. Most studies in literature ignore sampling variance in the parameter estimates and use only point estimates in the transferability assessment metrics. Instead of relying only on the point estimates, it is important to consider sampling variance in the parameter estimates while assessing transferability. The sampling variance issue is taken into account in this dissertation research by using bootstrap method.

6. Different updating techniques were used in the literature. Despite using these techniques, the available evidence on model transferability is still mixed and inconclusive, with much of the empirical research suggesting the difficulty of transferring models. This warrants the need for exploring alternate ways of enhancing model transferability e.g., pooling data from different geographical contexts, or improving the

model structure. This dissertation research investigates the performance of these two alternate ways of enhancing model transferability.

2.7 Summary

This chapter provides a synthesis of the extant literature on spatial transferability of travel forecasting models. Specifically, different theoretical and practical issues related to model transferability, methods used in the literature to transfer models, and metrics used to assess the effectiveness of these transfer methods are discussed in this chapter. The discussion is based on available empirical evidence on spatial transferability of travel forecasting models. The available evidence is mixed and inconclusive, makes it difficult to draw solid conclusions on the conditions under which models are transferable (or not).

Based on the discussion, this chapter identifies several important gaps in the literature. Among them, some of the notable ones are addressed in the following chapters of this dissertation. Specifically, a framework for assessing the transferability of an entire activity-based model system is presented in the next chapter. Chapter 4 investigates the transferability of an important component of activity-based model system: activity participation and time-use model. The effects of sampling variance and data pooling (from different geographic regions) on the transferability results are also examined in this chapter. Chapter 5 investigates the influence of a model structure on its transferability across areas. Specifically, first a new model structure named as the Multiple Discrete Continuous Heteroscedastic Extreme Value (MDCHEV) Model is formulated, and then it is used to assess the influence of a model structure on its transferability across areas. Transferability of another important component of activity-based model system, time-of-day choice model, is assessed in Chapter 6.

CHAPTER 3

A FRAMEWORK FOR ASSESSING THE TRANSFERABILITY OF ACTIVITY-BASED MODEL SYSTEMS

3.1 Introduction

As discussed in Chapter 1, assessing the transferability of the individual model components of an activity-based model system is not necessarily the same as assessing the transferability of an entire activity-based model system. The transferability of an activity-based model *system* comprises much more than the transferability of the individual model *component*. This warrants the need for a framework can guide the researchers and practitioners in assessing the transferability of activity-based model systems. This chapter attempts to provide a guiding framework for assessing the transferability of activity-based model *systems*.

3.2 Empirical Evidence on the Transferability of Activity-based Travel Model Systems

Several activity-based model systems (or parts of the model systems) were transferred from one region to another. Within the U.S., for example, the CT-RAMP activity-based model developed for the MORPC region (PB Consult, 2007) was transferred to Lake Tahoe, the Daysim model system developed for Sacramento (Bradley and Bowman, 2008) was transferred to four regions in California (Fresno, Northern San Joaquin Valley, Sacramento and San Diego) and two regions in Florida (Jacksonville and

Tampa) (Bowman et al., 2013), the CEMDAP model system developed for Dallas Fort-worth (DFW) region (Bhat et al., 2004; Pinjari et al., 2006) was transferred to the South California region (Goulias et al., 2012).[7] Outside the U.S., the TASHA model system developed for Toronto was transferred to London (Le vine et al., 2010) and the Albatross model system was transferred across different regions in Netherlands. Given the increasing attempts to transfer activity-based model systems or parts of model systems across geographical contexts, it would be useful to have a high-level framework for assessing the transferability of model systems.

3.3 Transferability Framework for Activity-based Model Systems

We propose the following hierarchy, with two broad levels, as a guiding framework for assessing the transferability of activity-based model systems:

1. Transferability of the Design Features of the Model System
   a. The traveler markets to be modeled
   b. Structure of the overall model system
      i. Presence or absence of specific model components,
      ii. Sequence of different model components,
      iii. Linkages among model components (top-down and bottom-up linkages)
   c. Spatial and temporal resolution
2. Transferability of Individual model components
   a. Hierarchy of model components

[7] Most of these transfers, however, were only initial steps toward developing a model system more suitable for the planning needs of the application context and with the local data. For example, the activity-based model developed in the South California region is quite different from the CEMDAP system initially transferred from DFW.

i. Population synthesizer,

ii. Long-term choice components,

iii. Activity and travel generation,

iv. Tour scheduling models (time of day, destination, and mode),

v. Trip-level models

b. Transferability hierarchy for an individual model component (as discussed in section 2.2.1 of Chapter 2)

i. Underlying theory of travel behavior,

ii. Mathematical model structure,

iii. Empirical specification,

iv. Model parameter estimates

3.3.1 Transferability of the Design Features of the Model System

Several activity-based model systems are being used and developed both within the US and elsewhere. While the underlying concepts of these model systems are similar, the overall modeling framework and the design features vary substantially. While some of the differences are due to lack of consensus on how to model individuals' activity-travel patterns (there is still scope for innovation in this area), several differences can be attributed to the variety in the makeup of the traveler markets, the activity-travel environments, planning and policy needs for which the models are used, and practical issues such as the availability of resources to build, maintain, and use the models.

3.3.1.1 Traveler Markets

Almost all ABMs focus on the travel by residents of the study area, relegating other traveler markets (e.g., tourists) to simpler "auxiliary" modules. Within the residents, the traveler markers generally modeled are workers, non-workers, students, and children. However, some regions (e.g., Florida) may need to separately model the travel patterns of seasonal residents, in addition to permanent residents. Some regions may need to pay explicit attention to tourist travel. Clearly, the modeling frameworks used for typical residents cannot be used to model seasonal residents and tourists.

3.3.1.2 Structure of the Model System

With the populations of the metropolitan regions ranging from about 50,000 to several millions, metropolitan planning priorities and needs can vary considerably across these regions (not to mention the range of available data, resources and constraints across these regions). Therefore, a single ABM modeling framework may not necessarily be the most appropriate framework for all regions. It is likely that large urban regions may need a sophisticated modeling framework with a variety of model components to address a wide range of policy questions while a simpler framework might suffice for smaller regions. For example, regions with high occupancy vehicle/toll (HOV/HOT) lanes may need to model individuals' choice of travel by HOV/HOT lanes, whereas other regions need not do so. Therefore, transferability of an entire activity-based modeling framework depends on what choices ought to be modeled (hence the presence or absence of specific model components) and the sequence in which choices are modeled. For example, a region interested in understanding the implications of tax incentives on alternative fueled vehicles might need to model households' vehicle type choice while other regions might simply model the number of cars owned by a household without regard to the vehicle type mix. In another example, the sequence in which destination and mode choices are modeled might be different between large urban regions and smaller regions (Newman and Bernardin, 2010).

3.3.1.3 Spatial and Temporal Resolution

Other design features such as spatial resolution at which destinations are modeled (e.g., parcels vs. zones) and the temporal resolution at which the level of service inputs are considered also influence the transferability of ABM systems. While it sounds easy to impose a uniformly finer spatial and temporal resolution across different regions (for the sake of model transferability), the costs and effort associated with a fine spatial and temporal resolution could be avoided if the corresponding benefits (e.g., better representation of transit access, and walk/bike trips) are not necessary (or not a priority) for a region.

Due to the reasons discussed above, a *transferred* ABM framework may have to be "tweaked" to include additional model components, different design considerations, and/or reduce the model components. The extent and nature of the tweaks determine whether the elements lower in the hierarchy (individual model components, parameter estimates, etc.) can be transferred. For example, if the spatial representation is different between the two regions (e.g., parcels vs. zones), it is likely that several model components need to be re-estimated. It may be difficult to directly transfer the parameter estimates of several variables in a parcel-level model (e.g., spatial descriptors, accessibility variables) to a more aggregate, zonal-level model or vice versa.

3.3.2 Transferability of Individual Model Components

Once the transferability of the overall modeling framework and its design features are determined, the natural next step is to determine whether the individual model components of the framework (to the extent that the framework is transferable) can be transferred. In the context of the model components of a typical activity-based model, it is useful to identify the hierarchy in which the different model components are usually put together.

1. Population synthesizer (to generate disaggregate demographic inputs required for ABMs)
2. Long-term choice model components (e.g., car ownership, work/school locations)
3. Activity and tour generation model components
4. Tour scheduling model components (tour-level timing, destination, & mode choices)
5. Trip-level scheduling model components (trip-level timing, destination, & mode choices).

The first and foremost component of an ABM is a population synthesizer which generates disaggregate demographic characteristics needed as inputs for all other subsequent models. It is rarely considered that the differences in the way the population is synthesized can influence the transferability of ABMs. Even if the rest of the ABM, including its parameters, is fully transferable, differences in the distributions of the explanatory variables (that are generated using different population synthesizers) can result in different distributions of the predicted travel patterns. Fortunately though, the procedures used in population synthesizers can usually be transferred between two regions; unless the differences in the socio-demographic composition of the two populations are large enough to warrant the consideration of: (1) different control variables in the population synthesizer or (2) different travel markets altogether. While the former issue does not necessarily pose a significant transferability problem (the same population synthesizer can be used, albeit with different or additional control variables), the latter issue might warrant the consideration of modifications or additions to the population synthesizer. For example, a population synthesizer designed for generating the disaggregate population of permanent residents cannot be used *as it is* to generate the disaggregate characteristics of either seasonal residents or tourists.

Long-term choices such as household car ownership, individuals' work location, and work type (part-time/full-time) are typically not generated during the population generation stage. That is, such variables are not used as control variables in the population synthesis procedure. They are generated post population synthesis either using a series of econometric models or by directly drawing the variables from the disaggregate inputs (e.g., the public use micro samples) used to synthesize the population. Not much attention has been given to the transferability of these model components (except a few studies, Yamamoto et al. (2012) on auto ownership, Vovsha et al. (2012) on work location choice). Since considerable effort goes into building these models and since outputs from these models enter as inputs into almost all model components lower in the hierarchy, understanding the conditions under which these models become transferable will be very useful.

The next three modules, activity and tour generation, tour scheduling, and trip-level model components form the core of an ABM. Within each module, there can be several model components. Since it is difficult to model all the choices in a unified modeling framework, a sequence is usually assumed on the order in which choices are made. The model components higher in the hierarchy automatically influence the choices lower in the hierarchy (top-down integrity). Different techniques, such as log-sum variables, are employed to integrate the model components for enabling the influence of lower-level choice on higher-level choices (bottom-up integrity). Due to the tight integration of the different model components, any differences in the modeling framework (i.e., the presence/absence and the sequence of model components) can potentially influence the transferability of an individual model component *as it is*. This is because some of the explanatory variables in a particular model component may depend on the position of the model component in the overall modeling sequence. Thus, adjustments may be needed to account for such differences before transferring an individual model component.

The hierarchy of transferability discussed in Section 2.2.1 (underlying theory, model structure, specification, and parameter estimates) is applicable to each individual model component. It is worth noting here that there is a dearth of empirical evidence on the transferability of different model components of an activity-based system. While much of the literature has focused on the transferability of trip-based model components, there is significant scope for research on the transferability of activity and travel generation components (see Nowrouzian and Srinivasan, 2012 for recent studies), tour-based time-of-day choice, destination choice, and mode choice components, and trip-based models conditional on tour-level choices. Further, most efforts have been in the context of the transferability of mode choice models, with a few efforts in the context of trip-based travel generation models and even fewer in the context of activity-based time-use and tour generation and time-of-day models. Based on the evidence reviewed in

Table 2.1, it appears that trip-based travel generation models were found to be more transferable than mode choice models. This is potentially because mode choices (as well as destination choices) are more likely to be closely tied to the local spatial and network features and unobserved modal characteristics (such as comfort and reliability) that are different across the different contexts. Besides, differences in the availability of modes may make it difficult to transfer mode choice models. For example, it may be difficult to transfer a mode choice model from a region without a light-rail mode to a region with significant presence of light rail. In other words, the models that focus on spatial organization may be difficult to transfer from one region to another. Compared to these models, as discussed by Bowman et al. (2013), the models that focus on social organization (e.g., activity-based time use and travel generation) may be easier to transfer across areas (see Bowman et al., 2013 for details). For instance, Gangrade et al. (2000) reported considerable similarities in the aggregate activity participation and time-use patterns in California and Florida suggesting that activity-based time-use and travel generation models could potentially be transferred across different contexts. But such hypotheses need to be empirically tested in a variety of contexts before arriving at any conclusions. Further, if mode and destination models are not transferable between two contexts, then what are the implications of using the log-sum variable built from the mode and destination choice model as an explanatory variable in the tour generation and time-of-day choice models?

3.4 Assessment of the Transferability of Activity-based Travel Model Systems

As discussed in section 3.2, several attempts have been undertaken in literature to transfer entire model systems across areas. However, there is need for a more thorough investigation (i.e., more controlled experiments) of the transferability of such large-scale activity-based model systems. Anecdotally (and as reviewed in Table 2.1), some of the transfers seem to have worked reasonably well, in terms of predicting the aggregate-level activity-travel patterns (e.g., mode shares) after updating the constants of the model components with local data. However, interpretation of these results must be cognizant of the property of discrete-choice models (which are typically used to build activity-based models) that models with updated constants are bound to predict the aggregate shares right. Thus, as discussed in the previous chapter, prediction of aggregate patterns does not necessarily imply an appropriate prediction of policy sensitivity. Nevertheless, the available evidence is not sufficient to make any conclusive inferences yet. Further, a more thorough documentation of the findings from such transfers is essential.

A relatively air-tight way to assess the transferability of activity-based travel model systems is to perform a variety of "real-life" policy assessments and compare the predicted results of a transferred model system to the results from a locally built model system, or to the observed changes in activity-travel patterns. Further, comparison of results (of transferred and local models) from forecasting exercises such as future-year forecasts or past-year forecasts will be helpful. Of course, to begin with, one has to assess and understand the transferability of each and every individual component transferred. However, comparing the policy predictions of an entire model system to that of a local model system can provide additional insights into the transferability of integrated model systems.

Further, when comparing the different model sensitivities, the bootstrapping procedure discussed in Chapter 3 (to incorporate sampling variance) should be incorporated into the transferability assessment of activity-based travel forecasting model systems. Since the tour-based/activity-based travel models use micro-simulation as the mechanism for prediction, the incorporation of the influence of variance due to the uncertainty in the parameter estimates (i.e., sampling variance) on activity-travel predictions should be rather straightforward. Most activity-based travel forecasting systems in use today (or in development) attempt to account for the simulation variance. But little to no attention is given to the issue of estimation variance. Depending on the sample sizes used to estimate the parameters, estimation variance can potentially be much more important than simulation variance. Neglecting estimation variance can potentially bias the results of transferability assessments toward "less" transferable.

To reduce the issues related to sampling variance, one can use "estimation-based" approach (recently used by Bowman et al., 2013) in the transferability assessment. This approach of assessing transferability is slightly different from the application-based approach in a way that this investigates the transferability of model coefficients on specific variables while the latter approach assesses transferability of the model as a whole. If the data samples are available in both the contexts and the sample sizes are reasonable, "estimation-based" approach (joint context estimation) can be used to examine which coefficients are more transferable and which are not (i.e., coefficients on level-of-service variables vs. coefficients on socio-demographic variables). This approach is simple, easy and also less influenced by sampling variance issues.

3.5 Summary

This chapter presents a two-level framework for assessing the transferability of an activity-based model system. Of these two levels, the first level is associated with the transferability of the design features of model system while the second level is associated with the transferability of individual model components. The discussion in this chapter suggests that an activity-based model system cannot be naively transferred from one region to another. Depending on the planning needs and priorities of the application region, a transferred ABM framework may have to be "tweaked" to include additional model components, different design considerations, and/or reduce the model components. Because of the different design feature requirements and tight integration among different model components of an activity-based model system, it may also be difficult to transfer an individual model component as it is. That means adjustments may be required before transferring even an individual model component to a region. To assess the effectiveness of different transfers, for both activity based model system and individual model components, policy response measures and sampling variance should be considered with special attention. Further, in addition to assessing the transferability of a model as whole, one should use joint context estimation (i.e., estimation-based approach) to assess the transferability of model coefficients on specific variables.

CHAPTER 4

AN EMPIRICAL ASSESSMENT OF THE SPATIAL TRANSFERABILITY OF PERSON-LEVEL DAILY ACTIVITY GENERATION AND TIME-USE MODELS

4.1 Introduction and Motivation

Chapter 2 presented a detailed review of the literature on spatial transferability of travel forecasting models. The review suggests that most work to date has been devoted to the transferability of linear regression-based travel generation models and logit-based mode-choice models. Few studies focus on travel choices other than trip generation or mode-choice and on econometric model structures other than linear regression, ordered response, or multinomial logit. Transferability assessments in the context of tour-based/activity-based model systems are much fewer (although there has been a recently increasing literature on this topic). Only a handful of studies (e.g., Arentze et al., 2002, Le vine et al., 2010; PB Consult, 2007) document the transferability assessment of activity-based model systems to varying degrees, while some recent efforts are underway (e.g., the SHRP-2 C10 studies) and a few studies focus on the transferability of specific components of ABMs (e.g., Nowrouzian and Srinivasan, 2012).

Among the different model components of an ABM system, the transferability of activity/travel generation components is of particular interest. Since activity/travel generation is modeled at either person-level or household-level, the amount of data typically available for such models can, sometimes, be smaller compared to the data available for tour-level and trip-level models. At the same time, activity/travel generation model components might be more transferable than those for other travel choices (e.g., mode choice, destination choice). This is perhaps due to a comparatively lower dependency of individuals' daily activity and travel generation on the spatial structures and transport system characteristics of their regions. Further, empirical studies (e.g., Gangrade et al., 2000) suggest notable similarities in activity participation and time-use patterns across a variety of geographical contexts within the United States. However, there is a dearth of empirical evidence on the transferability of activity/travel generation model components used in ABMs.

Among the different approaches to model activity/travel generation, time-use based approaches are of particular interest. This is because a fundamental tenet of the activity-based approach is to view individuals' activity-travel patterns as a result of their time-use decisions. With a given amount of time (e.g., 24 hours in a day), individuals decide how to allocate the time to different activities subject to their socio-demographic, spatio-temporal, and other constraints and opportunities. Motivated by the theoretical strength of the time-use based approaches, significant methodological developments have occurred in the recent past on modeling individuals' activity participation and time-use patterns. Notable among those is the development of the multiple discrete-continuous extreme value (MDCEV) model (Bhat, 2008), which has now been used in a large number of activity participation and time-use studies (e.g., Habib and Miller, 2008). The MDCEV structure is now at the heart of a household-level activity generation model component of an activity-based model system being developed in the South California region (Bhat et al., 2012).

Most of the empirical researches reviewed in Chapter 2 suggest the difficulty of transferring models and thus, warrants the need for exploring ways of enhancing model transferability. One such possible way is to estimate the model using data pooled from different geographic regions. Pooling data from different regions, on the one hand, increases the sample size for model estimation, and on the other hand brings variation in the data which can make a model more transferable. The benefit of using such pooled data set in model estimation has been discussed in some earlier studies as well (e.g. Richards and Ben-Akiva, 1975; Galbraith and Hensher, 1982). Despite recognizing such potential advantage of using data with a high degree of variability, it has not been discussed with special attention in the literature; neither the impact of data variability on model transfer nor how to bring this variability in the data have been investigated.

4.2 Contribution and Organization of the Chapter

In view of the above discussion, this chapter aims to provide an empirical assessment of the spatial transferability of person-level daily out-of-home activity generation and time-use models. The geographical contexts of interest in this research are different regions in the State of Florida. Since Florida is considering different options (e.g., develop new models vs. transfer models) to develop ABMs in the state, the results from this chapter will be of potential use. In addition, this chapter investigates model transferability between two different states – California (CA) and Florida (FL). This provides an opportunity to compare the extent of transferability between different states (inter-state transferability) to that across different regions of a state (intra-state transferability). The demographic segment of focus in the chapter is unemployed adults (age >18).

The econometric model structure used to model activity participation and time-use is the MDCEV model. Since this is the first empirical assessment of the transferability of an MDCEV-based model, some effort was devoted to understanding the prediction properties of the MDCEV model. This helped shed new light on the prediction properties of the MDCEV model that will have implications to model transferability.

As discussed in chapter 2, the simplest approach to transfer a model is called the naïve transfer, where the specification and parameter estimates of a model developed in one context (*estimation context*) are directly used in another context (*application context*) without any modifications. Most empirical evidence suggests the difficulty of transferring models *as it is*. Thus, a variety of different approaches have been used in the literature to update a transferred model using available information from the application context. These include, updating constants, transfer scaling, Bayesian updating, combined transfer estimation, and joint context estimation. In the empirical assessment of this chapter, we mainly focus on naïve transfer and updating constants.

Different metrics have been used in the literature to assess model transferability (see chapter 2 for details). These can be broadly categorized as: (1) Statistical tests of equivalence of parameters, (2) Aggregate-level predictive accuracy metrics, and (3) Policy prediction performance. The empirical assessment in this chapter uses at least one metric from each category. Further, recently introduced metrics are used to assess the predictive accuracy and transferability of the MDCEV model.

This chapter also investigates the performance of an alternate way of enhancing model transferability. This involves pooling data from different geographical contexts for model estimation and then transferring the model across areas. Recently, this approach of transferring models is getting quite a bit of attention in the field. For example, Bowman et al. (2013) and Hood (2012) used pooled data set in their transferability analysis. Among them, Hood (2012) suggests pooling data from at least three geographical contexts (including the region the model is transferred to i.e., the application context) for the better performance of the transferred model. The approach investigated in this chapter, on the other hand, pools data from different contexts except the application context. The reasons behind not including the application context data are: (1) to assess the performance of data pooling technique more precisely by avoiding the bias in the transferability results (toward indicating better performance) that may occur due to the presence of application context data in the model estimation data, (2) to investigate the performance of data pooling technique in a more practical situation where no data is available in the application context. Besides, while Hood (2012) examines the performance of the technique by pooling data from three different states, we investigate the same using data from different regions (but not limited to only three regions) within a state. This investigation, on the one hand, will explore the performance of data pooling technique in intra-state model transfer, and on the other hand, it will shed light on whether or not data from at least three geographical regions are always required to be pooled.

The next section provides an overview of the data used in the chapter. Section 4.4 briefly discusses the MDCEV model structure and its prediction properties. Section 4.5

summarizes the empirical model estimation results. Section 4.6 presents and discusses the transferability assessment results. Section 4.7 discusses the results of data pooling technique assessment. Section 4.8 provides a summary of the chapter.

4.3 Data

4.3.1 Data Source

The primary data source used for the analysis is the 2009 National Household Travel Survey (NHTS) for the states of California and Florida. The survey collected detailed information on all out-of-home travel undertaken by the respondents. The information includes trip purpose, mode of travel, and travel start and end time, and dwell time (time spent) at the trip destination. For intra-state transferability assessment, in addition to the NHTS data, several secondary data sources were used to derive activity-travel environment measures of the neighborhoods in which the sampled households are located[8]. The secondary sources are: (1) 2009 property appraiser data for all 67 counties in Florida, (2) 2007 infoUSA business directory, (3) 2010 NAVTEQ data, and (4) GIS layers of: (a) all parcels in Florida from the property appraiser data, (b) employment from the 2007 infoUSA business directory, and (c) intersections from the NAVTEQ data.

4.3.2 Sample Formation

Several steps were undertaken to prepare the data for the current analysis:

1. Only the adult non-workers (aged 18 years or over) who were surveyed on a weekday that was not a holiday were selected. It is useful to note that the employed adults who didn't go to work on the survey day were not included in the non-working groups

[8] Since the exact locations (i.e., latitude and longitude) of households in California data were not available to us, we couldn't bring activity-travel environment measures from other secondary sources to the NHTS data for California. Thus, the activity-travel environment measures available only in the NHTS data were used in inter-state transferability assessment.

because the activity participation and time-use patterns of such workers are likely to be different from that of the non-workers.

2. All out-of-home activities in the NHTS data were aggregated into eight broad activity categories: (a) Shopping (Shop), (b) Other maintenance (buying goods/services and attend meeting), (c) Social/Recreational (visiting friends/relatives, go out/hang out, visit historical sites, museums and parks), (d) Active recreation (working out in gym, exercise, and playing sports), (e) Medical, (f) Eat out (such as meal, coffee, and ice cream) (g) Pick up/drop, and (h) Other activities.

3. The amount of time spent in each of these activity categories was calculated by using the "dwell time" variable in the NHTS data. The time spent in in-home activities was computed as total time in a day (24 hours) minus the time allocated to the above mentioned out-home activities, sleep, and travel activities. Though sleep activity is a part of in-home activities, time spent in this activity was not included in the time spent in in-home activities for the model estimation purpose. In general, it is difficult to estimate utility functions of a model with non-linear utility structure (e.g., MDCEV) when one alternative consistently takes a very large amount of time compared to other alternatives in the model. Therefore, the average amount of time allocated to sleep activities (8.7 hours, 2010 American Time Use Survey) was removed from the total time (24 hours in a day) while calculating the time spent in in-home activities.

4. To develop the activity-travel environment measures from secondary data sources, various GIS layers (from property appraiser, infoUSA and NAVTEQ data) were overlaid onto circular buffers centered on the NHTS household locations. The buffer sizes used for this purpose are: ¼ mile, ½ mile and 1 mile. The activity-travel

environment measures obtained from these sources were then merged with the NHTS data.

5. Next records with missing or inconsistent data were removed from the final data set.

4.3.3 Geographical Regions Considered for Transferability Assessment

For intra-state transferability assessment, the state of Florida was divided into seven geographical regions based on existing travel demand modeling regions in the state. These are: (1) Southeast Florida (SEF), (2) Central Florida (CF), (3) Tampa Bay (TB), (4) Northeast Florida (NEF), (5) Urban areas in district 1 (D1U), (6) Urban areas in district 3 (D3U), and (7) Rural Florida. Figure 4.1 shows these seven geographic regions in the Florida map. Two of the seven regions (D3U and NEF) were not included in the initial transferability analysis because of small sample sizes. Of the remaining 5 regions, SEF, CF, and TB include some of the major urban regions in Florida (Miami, Orlando, and Tampa), while D1U comprises counties that are less urbanized compared to the major urban regions and Rural Florida includes all rural counties in Florida with low population and employment densities. Models were transferred only from three regions (SEF, CF, and TB) to all other 5 regions (SEF, CF, TB, DIU, and R). Lower sample sizes of DIU and Rural regions played a role in the decision to not transfer from these regions. At the same time, the state of Florida is considering options for transferring models to, D1U and Rural locations, while the major urban regions are moving ahead with the development of their own activity-based models. For inter-state transferability assessment, the entire data in the state of Florida was used to construct the Florida (FL)

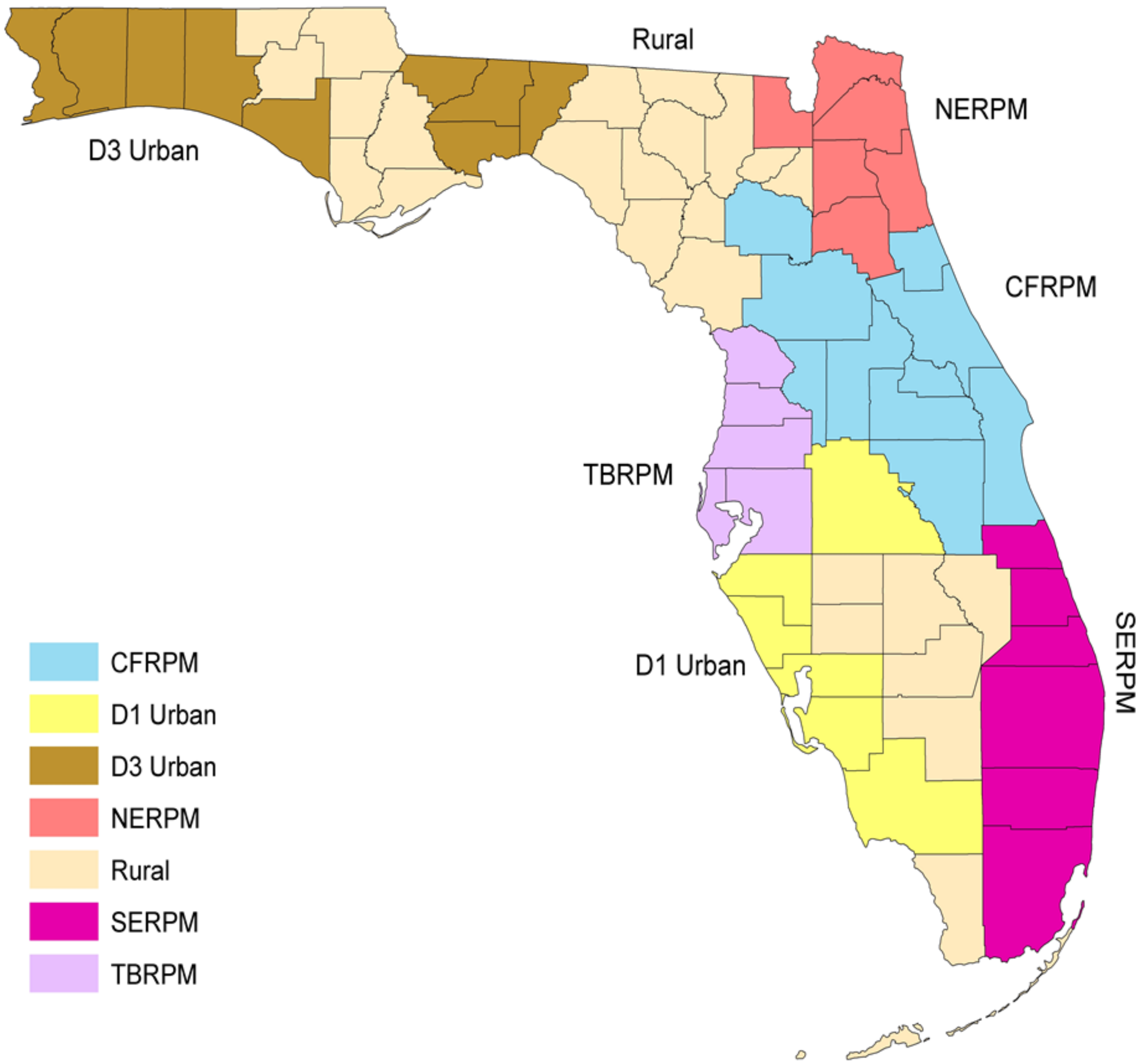


Figure 4.1: Study Areas in Florida

model and likewise for the California (CA) model. For the data pooling technique assessment, all of the 7 geographical regions in Florida were considered. Specifically, the major urban regions (i.e., SEF, CF, TB and NE) were kept separate, and all other regions were pooled together and named as "other region" in this assessment.

4.3.4 Sample Description

Tables 4.1- 4.3 present descriptive information about the data used in the analysis. Of these, Table 4.1 presents the descriptive statistics of the socio-demographic characteristics with the first row presenting the sample sizes for different geographies considered in the chapter while Table 4.2 and Table 4.3 present the descriptive statistics of activity participation and time allocation to different activities respectively. It can be observed from Table 4.1 that the aggregate-level differences in the demographic characteristics are greater across the two states (CA and FL) than those across different regions within Florida. For example, the proportion of unemployed elderly (age > 65) in Florida (65%) is considerably higher than that in California (53.0%). Greater proportions of whites, less educated individuals, and lower income levels are also observed in Florida than in California. The different regions within Florida are more similar in the demographic makeup, except a few exceptions (noted in bold font) such as greater proportion of non-whites in the Southeast (Miami) region, greater proportion of elderly in D1U region, and greater proportions of lower education and income levels in rural Florida.

In the context of activity participation rates (percentage of individuals participating in each activity) and average daily time allocation (Table 4.2 and Table 4.3),

Table 4.1 Descriptive Statistics of Socio-demographics in the Datasets

	California(CA)	Florida(FL)	SEF	CF	TB	D1U	R
Sample Size	10, 821	8,396	2,088	1,458	1,334	995	757
Male	40.0%	41.8%	41.4%	42.2%	42.6%	42.9%	43.9%
Age: 18 - 29 years	7.8%	3.1%	3.4%	2.5%	2.5%	3.1%	3.2%
Age: 30 - 64 years	39.2%	31.9%	29.0%	33.3%	32.8%	26.5%	34.1%
Age: ≥65 years	**53.0%**	**65.0%**	67.7%	64.1%	64.6%	**70.4%**	62.7%
Race: White	**78.6%**	**89.8%**	**84.1%**	92.0%	93.0%	94.9%	91.0%
Race: Black	3.7%	5.6%	7.9%	3.9%	3.7%	2.3%	5.0%
Race: Other	17.7%	4.6%	8.0%	4.1%	3.4%	2.8%	4.0%
Driver	85.5%	87.1%	82.7%	90.1%	86.5%	90.4%	87.6%
Edu.: H.school/low	**35.6%**	**44.0%**	39.8%	42.2%	45.2%	43.2%	**57.2%**
Edu.:Some College	31.7%	27.5%	26.7%	29.1%	27.6%	27.9%	25.6%
Edu.:Bach./higher	32.7%	28.4%	33.5%	28.7%	27.2%	28.8%	17.2%
Income: <25 K	23.4%	29.3%	29.9%	29.0%	31.7%	**23.2%**	**37.6%**
Income: 25-75K	46.1%	49.4%	46.3%	51.1%	49.9%	52.9%	51.0%
Income: > 75 K	**30.5%**	**21.4%**	23.7%	20.0%	18.4%	23.9%	11.4%
Avg. HH Size	2.5	2.2	2.1	2.1	2.0	2.1	2.1
Avg. No. of Drivers	1.8	1.8	1.7	1.7	1.6	1.7	1.7

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

Table 4.2 Descriptive Statistics of Activity Participation (% who participated) in the Datasets

	California (CA)	Florida (FL)	SEF	CF	TB	D1U	R
Activity Types	% Part.	% Part.	% Part.	% Part.	% Part.	% Part.	% Part.
In-home activities	100.0	100.0	100.0	100.0	100.0	100.0	100.0
OH-Shopping	**42.9**	**48.4**	51.0	49.9	48.5	51.0	48.1
OH-Other Main.	**24.2**	**29.6**	30.6	30.4	31.6	30.7	30.`1
OH-Soc./Rec.	**23.1**	**29.2**	30.5	30.0	27.1	31.3	28.9
OH-Active Rec.	**14.1**	**20.2**	20.6	21.9	21.2	24.6	14.7
OH-Medical	**12.7**	**22.5**	24.8	24.3	23.4	24.8	19.8
OH-Eat out	**19.4**	**24.9**	24.3	27.2	24.4	28.0	23.8
OH-Pick/Drop	**13.3**	**15.2**	17.0	16.2	15.5	16.0	12.8
OH-Other activities	**7.8**	**6.1**	5.7	5.7	7.0	5.0	7.5
Avg. No. OH activities	**1.6**	**2.0**	2.0	2.1	2.0	2.1	1.9

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

Table 4.3 Descriptive Statistics of Time Allocation (average duration among those who participated) in the Datasets

	California (CA)	Florida (FL)	SEF	CF	TB	D1U	R
Activity Types	Duration	Duration	Duration	Duration	Duration	Duration	Duration
In-home activities	743.4	740.3	**729.2**	741.1	744.2	**729.7**	748.4
OH-Shopping	59.7	55.1	56.0	56.5	51.5	54.6	50.3
OH-Other Main.	56.7	50.3	**56.54**	44.4	45.2	47.0	46.6
OH-Soc./Rec.	**157.3**	**126.9**	129.1	**117.5**	131.4	**119.8**	130.3
OH-Active Rec.	**83.9**	**52.9**	49.9	52.9	52.0	**61.9**	**29.3**
OH-Medical	**80.9**	**60.4**	**67.4**	50.7	57.5	58.6	**65.9**
OH-Eat out	**61.6**	**48.5**	47.6	48.7	45.5	50.3	48.2
OH-Pick/Drop	17.9	15.9	16.8	13.6	16.3	12.5	16.5
OH-Other activities	34.7	22.2	**28.3**	14.8	18.1	20.5	16.2

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

one can observe considerable differences between the non-workers in California and Florida. Specifically, individuals in Florida exhibit higher participation rates in different activities but lower time allocations (than those in CA). This is probably because those in Florida participate in greater number of OH activities per day than those in California (as shown in the last row of Table 4.2). Within different regions of Florida, the differences in the aggregate activity participation rates and time allocations are not as much different (as those across the two states). Of course, a few exceptions (noted in bold font) are notable - the activity participation and time allocation to active recreation is significantly lower in rural Florida.

In summary, unemployed adults in California appear to be significantly different from those in Florida in terms of socio-demographic characteristics, activity participation and time-use patterns. The differences across different regions within Florida appear to be smaller, although rural locations display some notable differences than other locations. Though the descriptive statistics cannot shed full light on the transferability of a time-use model from region to another, the noted differences may, in part, have a bearing.

4.4 The MDCEV Model

4.4.1 Model Structure

Numerous consumer choices are characterized by "multiple discreteness" where consumers can potentially choose multiple alternatives from a set of discrete alternatives available to them. Along with such discrete-choice decisions of which alternative(s) to choose, consumers typically make continuous-quantity decisions on how much of each chosen alternative to consume. To model such multiple discrete-continuous (MDC) choices, a variety of approaches have been used in the literature. Among these, a particularly attractive approach is based on the classical microeconomic consumer theory of constrained utility maximization. Specifically, consumers are assumed to optimize a quasi-concave, increasing, continuously differentiable, direct utility function $U(\mathbf{x})$ over a set of non-negative consumption quantities $\mathbf{x} = (x_1, ..., x_k, ..., x_K)$ subject to a linear budget constraint, as:

$$Max\ U(\mathbf{x}) \text{ such that } \mathbf{x}.\mathbf{p} = y \text{ and } x_k \geq 0\, \forall k = 1, 2, ..., K \qquad (4.1)$$

In the above Equation, $U(\mathbf{x})$ is a quasi-concave, increasing and continuously differentiable utility function with respect to the consumption quantity vector $\mathbf{x}$, $\mathbf{p}$ is the vector of unit prices for all goods, and y is a budget for total expenditure. An increasingly popular approach for deriving the demand functions from the utility maximization problem in Equation (4.1), due to Hanemann (1978) and Wales and Woodland (1983), is based on the application of familiar Karush-Kuhn-Tucker (KKT) conditions of optimality with respect to the consumption quantities.

Over the past decade, the above-discussed KKT approach has received significant attention for the analysis of MDC choices in a variety of scientific fields including environmental economics, marketing research and transportation. In the transportation field, the multiple discrete-continuous extreme value (MDCEV) model formulated by Bhat (2005) and enlightened further by Bhat (2008) lead to an increased use of the KKT approach for analyzing a variety of choices, including daily time-use (Bhat 2005; Habib and Miller, 2008; Pinjari et al., 2009; You et al., 2013), household vehicle ownership and usage (Ahn et al., 2008; Bhat et al., 2009; Jaggi et al., 2011), long-distance leisure destination choices (Van Nostrand et al., 2013), energy consumption choices (Pinjari and

Bhat, 2011; Yu et al., 2011; Frontuto, 2011) and builders' land-development choices (Farooq et al., 2013).

The MDCEV model estimated in this chapter is based on the following utility form (Bhat, 2008):

$$U(\mathbf{t}) = \psi_1 \ln(t_1) + \sum_{k=2}^{K} \gamma_k \psi_k \ln\left((t_k / \gamma_k) + 1\right) \tag{4.2}$$

In the above function, $U(\mathbf{t})$ is the total utility derived by an individual from his/her daily time-use. It is the sum of sub-utilities derived from allocating time (t_k) to each of the activity types *k* (*k =1,2,…,K*). ψ_k , labelled the baseline utility for alternative *k*, is the marginal utility of time allocation to activity *k* at the point of zero time allocation. Between two alternative activities, the activity with greater baseline marginal utility is more likely to be participated (or chosen). γ_k accommodates corner solutions (i.e., possibility of not choosing an alternative) and differential satiation (diminishing marginal utility with increasing consumption) effects for different activity types. The 1st alternative, designated as in-home activity, doesn't have a γ_k parameter since all individuals in the data participate in the in-home activity. This alternative is called the *outside good*, while all other activities (out-of-home activities) that have a likelihood of not being chosen are called *inside goods*.

The influence of observed and unobserved individual characteristics and activity-travel environment (ATE) measures are accommodated as $\psi_1 = \exp(\varepsilon_1)$; $\psi_k = \exp(\beta' z_k + \varepsilon_k)$; and $\gamma_k = \exp(\theta' w_k)$; where, z_k and w_k are observed socio-demographic and ATE measures influencing the choice of and time allocation to activity *k*, β and θ are corresponding parameter vectors, and ε_k (*k=1,2,…,K*) is the random error term in the sub-utility of activity type *k*. The model is derived based on the assumptions that: (1) individuals choose their daily time-use patterns to maximize the total utility subject to a time budget constraint $T = \sum_{t=1 \text{ to } K} t_k$ (*T* is a known amount of time budget available to the individual), and (2) the random error terms ε_k ($k=1,2,\ldots,K$) follow the independent and identically distributed (iid) standard Gumbel distribution with unit scale parameter.

4.4.2 Prediction Properties of the MDCEV Model

Table 4.4 presents the prediction results of the models estimated for the 5 regions in Florida. For each region, the prediction was performed on its own estimation sample. All the predictions in this chapter were performed using the MDCEV forecasting algorithm proposed by Pinjari and Bhat (2011), using 100 sets of random draws to cover the error term distributions for each individual in the data.

The first set of rows present the predicted (and observed) aggregate shares of individuals participating in each activity type (i.e., the discrete choice component) and the average daily time allocation (or duration) to each activity. The predicted aggregate shares for each activity were computed as the proportion of the instances the activity was predicted with a positive time allocation across all 100 sets of random draws for all individuals. The predicted average duration for an activity was computed as the average of the predicted duration (or time allocation) across all random draws for all individuals. It can be observed that the MDCEV models for all 5 regions perform well in predicting the aggregate shares of participation in each type of activity (i.e., the discrete choice of each alternative). In fact, we noticed that a constants only model resulted in the predicted discrete choice shares same as the observed shares. These results suggest the existence of a fundamental property of the MDCEV model similar to that of the multinomial logit (MNL) model that a constants only model, when applied to the estimation data, would yield the same discrete choice shares as observed in the data. This property has implications to the transferability of models with MDCEV structure. Specifically, an MDCEV model transferred from elsewhere can simply be adjusted by updating the constants using data from the application context to help improve its prediction of the aggregate discrete choice share.

In the context of aggregate time allocation (or duration) to each activity type (i.e., the continuous choice component), the model is under-predicting the aggregate duration of in-home activities (outside good) and over-predicting the aggregate duration of all out-of-home activities (inside goods) except the active recreation activity. The second set of rows show the predicted and observed shares of a few combinations of chosen out-of-home activities (e.g., shopping and social/recreational). The model seems to consistently under-predict the choice of combinations of activities. Further, note from the last column that the model is under-predicting the average number of out-of-home activities chosen as well.

The third set of rows in Table 4.4 is based on disaggregate-level metrics proposed for the MDCEV model by Jaggi et al. (2011). The first measure is an average of the hit ratio across all individuals for all sets of error draws, where hit ratio is the number of chosen alternatives correctly predicted divided by the observed number of alternatives chosen. The hit ratio for the different models in Florida range from 63.4% to 66.7%. The second measure is an average of *relative residual* (Jaggi et al., 2011) across all individuals in the data. Relative residual is:

Table 4.4 Predicted and Observed Activity Participation (% participation) and Duration[1]

Predicted and Observed Activity Participation & Duration in individual activities

		In-home	Shopping	Other Maintenance	Social/ Recreational	Active Recreation	Medical	Eat Out	Pick Up/ Drop Off	Other Activities
SEF	% Part.	100.0 (100.0)	49.2 (51.0)	29.9 (30.6)	29.0 (30.5)	19.1 (20.6)	23.1 (24.8)	22.8 (24.3)	16.0 (17.0)	5.3 (5.7)
	Avg. Dur	688.0 (729.2)	45.4 (28.5)	24.9 (17.1)	48.9 (39.4)	6.7 (10.3)	20.3 (16.7)	17.3 (11.6)	3.7 (2.9)	2.1 (1.6)
CF	% Part.	100.0 (100.0)	49.3 (49.9)	30.9 (30.4)	29.1 (30.0)	20.4 (21.9)	23.0 (24.3)	26.2 (27.2)	15.5 (16.2)	5.3 (5.7)
	Avg. Dur	697.0 (741.1)	45.6 (28.2)	22.1(13.5)	43.9 (35.2)	6.8 (11.6)	17.1 (12.3)	20.6 (13.2)	3.5 (2.2)	1.5 (0.8)
TB	% Part.	100.0 (100.0)	47.9 (48.5)	31.9 (31.6)	26.3 (27.1)	19.6 (21.2)	22.4 (23.4)	23.6 (24.4)	14.4 (15.5)	6.6 (7.0)
	Avg. Dur	701.4 (744.2)	42.4 (25.0)	22.6 (14.3)	44.2 (35.6)	6.8 (11.0)	17.3 (13.4)	18.1 (11.1)	3.6 (2.5)	2.1 (1.3)
D1U	% Part.	100.0 (100.0)	48.3 (51.0)	30.5 (30.7)	30.1 (31.3)	22.7 (24.6)	22.9 (24.8)	26.6 (28.0)	15.1 (16.0)	4.6 (5.0)
	Avg. Dur	688.4 (729.7)	44.3 (27.8)	22.5 (14.4)	46.9 (37.4)	10.1 (15.2)	17.9 (14.5)	21.5 (14.1)	3.0 (2.0)	1.6 (1.0)
R	% Part.	100.0 (100.0)	47.9 (48.1)	30.7 (30.1)	29.0 (28.9)	14.1 (14.7)	19.1 (19.8)	23.0 (23.8)	12.1 (12.8)	7.2 (7.5)
	Avg. Dur	706.0 (748.4)	40.4 (24.2)	20.0 (14.0)	48.0 (37.7)	2.7 (4.3)	15.3 (13.1)	18.6 (11.5)	2.9 (2.1)	2.5 (1.2)

Predicted and Observed Participation in Selected Activity Combinations

		Shopping & Other Maintenance	Shopping & Social/Recreational	Shopping & Medical	Shopping & Eat out	Avg. no. of out-of-home activities predicted (observed)
SEF	% Part.	2.9 (5.2)	2.9 (3.4)	2.0 (2.6)	1.8 (2.2)	1.9 (2.0)
CF	% Part.	2.8 (4.0)	2.6 (3.4)	1.9 (2.3)	2.2 (2.4)	2.0 (2.1)
TB	% Part.	3.2 (4.9)	2.4 (3.1)	1.9 (2.9)	2.0 (2.1)	1.9 (2.0)
D1U	% Part.	2.7 (4.3)	2.7 (4.4)	1.7 (2.5)	2.1 (2.0)	2.0 (2.1)
R	% Part.	3.5 (4.2)	3.2 (3.0)	1.8 (2.5)	2.2 (2.1)	1.8 (1.9)

Disaggregate Prediction Measures

Hit Ratio	SEF (65.2%)	CF (65.3%)	TB (64.3%)	D1U (63.4%)	R (66.7%)
Relative Residuals	SEF (0.19)	CF (0.18)	TB (0.18)	D1U (0.19)	R (0.18)

[1] Observed shares and durations are in the parentheses
Average durations are only among those who were predicted (or observed) with positive time allocations to different activities
SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

$$R_{rel} = \frac{1}{T}\left(\sum_{k=1}^{K} \frac{|t_k - \hat{t}_k|}{2}\right) \tag{4.3}$$

where, t_k is the observed duration of participation in activity type k, and $\hat{t}_k$ is the corresponding predicted duration (averaged over all error draws for the individual), K is the total no. of alternatives, and T is the total time budget available to the individual. This formula aggregates the errors in predicted time allocation for all alternatives into a composite measure. The relative errors for the 5 different models in Florida range from 18% to 19%. That is, on average, about 18%-19% of the time budget is wrongly allocated.

In summary, the MDCEV model provides reasonable predictions of activity participation and time-use when applied to the estimation data. Specifically, the aggregate-level activity participation rates in individual activities are predicted very accurately, while the participation in specific combinations of alternatives and the average durations of time allocation to out-of-home activities are under-estimated.

4.5 Empirical Model Estimates

Appendix A presents the MDCEV time-use model estimation results for the geographies considered in the analysis. For presentation ease, model estimation results from these seven tables are summarized in Table 4.5. In this table, the parameter estimates and t-statistics are not reported. Only short acronyms of the regions in which the variables are present in the models for different geographies are indicated. The acronyms are: CA-California, FL-Florida, S-Southeast Florida, C-Central Florida, T-Tampa Bay, D-D1U region, and R-Rural Florida. An acronym with an underline indicates that the sign of the corresponding parameter is negative in the model estimated for that geography. For example, females are less likely than males (because of the negative coefficient, as depicted by underlined acronyms) to participate in active recreation in CA, FL, SEF and D1U regions.

Overall, the parameter estimates have intuitive interpretations and identical signs in all the models. The same factors are often found to influence the time-use choices across all geographies. The alternative specific constants are not reported either for baseline utility parameters or for satiation parameters. But it is worth noting that the baseline utility constants for the out-of-home activities in the CA model are larger in magnitude (with –ve signs) than those in the Florida models, reflecting that the out-of-home activity participation rates in California are lower than that in Florida. Further, the constants in the satiation parameters of the California model are larger (with +ve sign) than those in the Florida models, since the average time allocation to out-of-home activities by Californians (if they participate in the activity) is greater than that by Floridians. The differences in the model constants as well as other parameter estimates within the different regions of Florida were not as high as compared to those across the two states. To the extent that the scale of unobserved factors influencing choices across the different regions are similar, the differences in the model coefficients suggest that models may be better transferable within a state than across states that are as different as California and Florida.

4.6 Transferability Assessment

To assess inter-state transferability, the model estimated for California was transferred to Florida and vice-versa. For intra-state transferability assessment, the model estimated for each of the three major urban regions (SEF, CF, and TB) was transferred

Table 4.5 Empirical Model Results

Explanatory Variables	Shop	Maintenance	Soc/Rec	Active Rec	Medical	Eat Out	Pickup /Drop	Other
Baseline Utility Parameters								
Female (Male is base)	CA,FL,S, C,T, D, R	-	-	CA , FL, S, D	-	-	CA, FL, T, D, R	-
Age <30 years (30-54 is base)	-	-	CA, FL, S	CA	-	-	-	-
Age 55-64 years (30-54 is base)	-	-	-	-	CA, FL, C, T	C, D	CA, FL, S, C, R	-
Age 65-74 years (30-54 is base)	-	-	-	-	CA, FL, S, C, T,R	C, D	CA, FL, S, C,D, R	-
Age >= 75 years (30-54 is base)	-	-	CA, FL,T	CA, FL,T	CA, FL,S,C,T, D,R	C, D	CA,FL,S,C,T,D,R	-
White (Non-white is base)	-	-	-	-	-	CA, FL, S, C, T, R	-	-
Driver (Non-driver is base)	CA,D, R	CA, S, D, R	CA,T	T, R	-	C,T	CA, FL, R	-
College (H. Sch./low is base)	-	CA, FL, S,T, R	-	CA, FL, D	-	-	-	-
Bachelor/Higher (H. Sch/low is base)	-	CA,FL,S, C,T, R	-	CA, FL, S, C,T,D, R	-	-	-	-
Born in US (others is base)	-	-	FL* S	D	-	CA, FL, S, C	-	-
Children 0-5 years	FL, C,T, R	CA,FL, S, C,D	-	CA	-	-	CA,FL,S,C,T,D, R	-
Children 6-15 years	-	CA	-	-	-	-	CA,FL,S,C,T,D, R	-
No. of Workers	CA, FL, S, C	-	-	-	-	-	CA, FL, C, T, D	-
Income <25 k	-	-	-	R	-	R	-	-
Income 25- 50 K	CA	CA, FL, C	CA, FL, C	CA, FL, C	-	CA, FL, S, C, D	-	-
Income 51-75 K	CA	CA, FL, C	CA, FL, C	CA, FL, S, C,T, D	-	CA, FL, S, C, T,D	-	-
Income >75 K	CA	CA, FL, C	CA, FL, C	CA, FL, S, C,T, D	-	CA, FL, S, C, T,D	-	-
Urban (Rural is base)	CA, FL	-	CA, FL	CA, FL	CA, FL	CA	FL	-
# Rec. Sites (1 mile buffer)	-	-	S, C, T, D	-	-	-	-	-
# Employments (1mile buffer)	-	-	T, D	-	-	-	-	-

Table 4.5 (Contd.)

Explanatory Variables	Shop	Maintenance	Soc/Rec	Active Rec	Medical	Eat Out	Pickup /Drop	Other
Baseline Utility Parameters								
# Cul-de-sacs (0.25 mile buffer)	-	-	-	S	-	-	-	-
# Intersections (0.25 mile buffer)	-	-	-	C, T, R	-	-	-	-
Monday (Tue.-Thurs.is base)	-	-	CA, FL, D	-	-	CA, FL, S, C, D,R	-	-
Friday (Tue.-Thurs.is base)	-	-	CA, FL, C, T	-	-	CA , FL,C, T	-	-
Satiation Function Parameters								
Female (Male is base)	CA, FL, S	CA, FL, T, R	-	FL, S	-	-	-	-
18 - 29 years (≥ 55 years is base)	-	-	CA	CA	-	-	-	-
30 - 54 years (≥ 55 years is base)	-	-	FL, S	CA, D	-	-	-	-
S. College (H. Sch./low is base)	-	-	-	CA, FL, S, C, D	-	-	-	-
Bac./Higher (H. Sch./low - base)	-	-	-	CA, FL, S, C, D	-	-	-	-
Monday (Tue.-Thurs. - base)	-	-	-	-	-	FL	-	-
Friday (Tue.-Thurs. - base)	-	-	FL, S	-	-	FL, S, T	-	-

[a] CA – California, FL – Florida, S – Southeast Florida, C – Central Florida, T – Tampa Bay, D – Urban area in Florida District1, R – Rural Florida

to the other four regions in Florida (including D1urban and rural regions). Thus, 14 different transfers were performed (2 inter-state transfers and 12 intra-state transfers) for each of the two transfer methods - naïve transfer and updating constants (28 transfers in all).

4.6.1 Transferability Test Statistic (TTS)

Transferability test statistic (TTS) is used to test the hypothesis that the transferred model is statistically equivalent to a model estimated in the application context (Atherton & Ben-Akiva, 1976).

$$TTS = -2[L_j(\beta_i) - L_j(\beta_j)] \tag{4.4}$$

where, $L_j(\beta_i)$ = log-likelihood of the transferred model applied to the application context data, and $L_j(\beta_j)$ = log-likelihood of the locally estimated model using data from the application context.

The TTS values for all transfers are reported in Table 4.6. As can be observed from this table, for no single transfer is the TTS value lower than the critical chi square value even at 90% confidence level. These results echo the well-established finding that statistically rigorous tests usually reject model transferability (e.g., Gunn et al., 1985). However, rejection by a statistical test does not necessarily mean the poor prediction or forecasting ability of a model. Since the end-objective of a model is for use in prediction and policy analysis, several other measures are used for transferability assessment, as discussed next.

4.6.2 Log-likelihood-based Measure: Transfer Index (TI)

Transfer index (TI), first used by Koppelman and Wilmot (1982), measures the degree to which the log-likelihood of a transferred model exceeds that of a reference model (e.g., a constants only model) relative to a model estimated in the application context.

$$TI_j(\beta_i) = \frac{L_j(\beta_i) - L_j(\beta_{reference,j})}{L_j(\beta_j) - L_j(\beta_{reference,j})} \tag{4.5}$$

where, $L_j(\beta_i)$ and $L_j(\beta_j)$ are the same as defined earlier and $L_j(\beta_{reference,j})$ is the log-likelihood of a reference model in the application context. The closer the value of TI is to 1, the closer is the transferred models' performance to a locally estimated model (in terms of the information captured). The upper bound of this index is 1 unless the transferred model performs better than the locally estimated model.

From Table 4.7, one can observe that the TI values for inter-state naïve transfers are rather poor with negative values (-0.67 and -1.67), suggesting that the transferred models perform worse than locally estimated constants only models. For intra-state naïve transfers within Florida, the TI values range from -0.11 to 0.59 with greater values for transfers between major urban regions (SEF, CF, and TB) and lower values for transfers from these three urban regions to D1U and rural region. The highest TI values can be noted for the models transferred between the SEF and CF regions. Of course, the TI values for transfers from one region to another are not the same as those for transfers in the other direction, suggesting that transferability is asymmetric.

After updating the model constants with the application context data, the TI values improved in all cases. Most previous studies (e.g., Koppelman et al., 1985) found this result in the context of the MNL model. These results suggest that the MDCEV model structure also lends itself to improved TI values (hence improved performance) after updating constants using data from the application context. This is probably due to

Table 4.6 Transferability Test Statistic (TTS)

Inter-state Transfer				
Transferred To / Transferred From	California		Florida	
	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
California	-	-	3768.1	288.8
Florida	4324.1	370.1	-	-

Intra-state Transfer										
Transferred To / Transferred From	SEF		CF		TB		D1U		R	
	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
SEF	-	-	123.9	84.6	130.5	72.6	129.5	99.5	107.6	41.5
CF	232.2	172.9	-	-	95.8	64.6	134.1	121.2	82.7	38.4
TB	403.4	334.9	189.5	157.2	-	-	170.7	134.7	136.1	85.2

Table 4.7 Transferability Assessment Results: Transfer Index (TI)

Inter-state Transfer				
Transferred To / Transferred From	California		Florida	
	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
California	**1.00**	**1.00**	-1.67	0.80
Florida	-0.67	0.86	**1.00**	**1.00**

Intra-state Transfer										
Transferred To / Transferred From	SEF		CF		TB		D1U		R	
	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constan ts
SEF	**1.00**	**1.00**	0.53	0.68	0.26	0.59	0.20	0.38	0.12	0.66
CF	0.59	0.70	**1.00**	**1.00**	0.46	0.64	0.17	0.25	0.15	0.76
TB	0.29	0.41	0.28	0.41	**1.00**	**1.00**	-0.06	0.17	-0.11	0.30

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

the property discussed in Section 4.4. There was a significant improvement in the TI value for the inter-state transfers and considerable improvement for intra-state transfers. Even among intra-state transfers, the percentage improvement in TI value after updating constants is greater for those transfers with low initial TI value. In fact, the models with rather poor TI values (-ve values) for naïve transfer were the ones with the most improved TI values after updating constants.

4.6.3 Aggregate-level Predictive Accuracy

To assess the aggregate-level predictions of a transferred model, two metrics were used: (1) Root mean square error (RMSE) and (2) Relative aggregate transfer error (RATE). RMSE measures the aggregate-level predictive ability of a model against aggregate observed patterns in the data. Two types of RMSE values were computed for the MDCEV models estimated in this chapter: (1) RMSE for discrete choice component (activity participation), and (2) RMSE for continuous component (time allocation).

$$RMSE = \left(\frac{\sum_k P_k \times REM_k^2}{\sum_k P_k} \right)^{1/2} \tag{4.6}$$

where, P_k and O_k are the aggregate predicted and observed shares (or durations averaged over all individuals), respectively for alternative k , and $REM_k = \frac{P_k - O_k}{O_k}$ is the percentage error in the prediction of alternative *k*. The RMSE aggregates the REM measure across all alternatives into a composite error measure. RATE is a relative measure; it measures the aggregate predictive ability of the transferred model relative to that of a locally estimated model.

$$RATE = \frac{RMSE_j(\beta_i)}{RMSE_j(\beta_j)}. \tag{4.7}$$

Table 4.8 reports the RMSE and RATE values for all the transfers conducted in the analysis. The values inside are RATEs. As expected, the aggregate errors of the locally estimated models (in bold) are lower than those of transferred models. For naïve transfers, the RATEs for inter-state transfers are higher than those for intra-state transfers, suggesting that model transfers across the states can result in poorer aggregate predictions than transfers within the state. This is consistent with the findings in the context of TI. Among intra-state naïve transfers, the RATEs are higher for the rural locations (ranging from 1.48 to 4.00) than those for urban-urban transfers (ranging from 1.00 to 2.33), suggesting greater transferability from urban regions to urban regions than to a rural region. The lowest aggregate relative errors can be observed for these transfers: SEF→CF, CF→TB, and CF→SEF.

After updating the constants of the transferred models, there is significant improvement in the RMSE values. In most cases, regardless of how poor the naïve transfer performance was, the aggregate prediction errors from transferred models drop to the level of the errors from the corresponding locally estimated model (bringing down the RATE value close to or equal to 1). These results suggest that, similar to previous findings in the context of MNL model (Koppelman et al., 1985), updating the constants of a transferred MDCEV model can help in improving its aggregate prediction performance to that of a locally estimated model. Recall that similar results were found in the context of transfer index as well; with significant improvements in the TI values after updating the constants of poorly performing naïve transfers. But intuition suggests that if

Table 4.8 Transferability Assessment Results: Root Mean Square Error (RMSE) & Relative Aggregate Transfer Error (RATE)

Inter-state Transfer

	Transferred To → / Transferred From ↓	California		Florida	
		Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
Discrete Component	California	**0.07 (1.00)**	**0.07 (1.00)**	0.23(5.75)	0.04 (1.00)
Discrete Component	Florida	0.25 (3.35)	0.07 (1.00)	**0.04 (1.00)**	**0.04 (1.00)**
Continuous Component	California	**0.17 (1.00)**	**0.17 (1.00)**	0.33 (1.57)	0.21 (1.00)
Continuous Component	Florida	0.24 (1.41)	0.17 (1.00)	**0.21 (1.00)**	**0.21 (1.00)**

Intra-state Transfer

	Transferred To → / Transferred From ↓	SEF		CF		TB		D1U		R	
		Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
Discrete Component	SEF	**0.03(1.00)**	**0.03(1.00)**	0.04(1.00)	0.04(1.00)	0.07(2.33)	0.03(1.00)	0.06(1.50)	0.04(1.00)	0.08(4.00)	0.03 (1.50)
Discrete Component	CF	0.04(1.33)	0.04(1.33)	**0.04(1.00)**	**0.04(1.00)**	0.04(1.33)	0.04(1.33)	0.04(1.00)	0.04(1.00)	0.06(3.00)	0.02(1.00)
Discrete Component	TB	0.05(1.67)	0.03(1.00)	0.06(1.50)	0.04(1.00)	**0.03(1.00)**	**0.03(1.00)**	0.08(2.00)	0.04(1.00)	0.06(3.00)	0.02(1.00)
Continuous Component	SEF	**0.11(1.00)**	**0.11(1.00)**	0.31(1.94)	0.16(1.00)	0.31(1.80)	0.18(1.05)	0.28(2.13)	0.15(1.15)	0.22(2.00)	0.10 (0.90)
Continuous Component	CF	0.16(1.41)	0.14(1.20)	**0.16(1.00)**	**0.16(1.00)**	0.18(1.05)	0.17(1.00)	0.15(1.15)	0.15(1.15)	0.18(1.66)	0.16(1.48)
Continuous Component	TB	0.17(1.48)	0.15(1.31)	0.16(1.00)	0.14(0.87)	**0.17(1.00)**	**0.17(1.00)**	0.13(1.00)	0.15(1.15)	0.16(1.48)	0.15(1.39)

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida
The values outside the parentheses indicate absolute RMSE while the values within the parentheses indicate relative RMSE with respect to a locally estimated model (RATE)

the naïvely transferred model performs rather poorly, simply updating the model constants doesn't do the *magic* of getting things right. As discussed in Section 4.4, it is the property of the MDCEV model structure that updating its constants helps improve the aggregate-level predictions, rather than an improvement in the way the model captures behavior in the application context. To examine this, the next subsection presents transferability assessment based on the ability of the transferred models to forecast changes in activity time-use patterns in response to changes in explanatory variables.

4.6.4 Policy Response Measures

To assess model transferability based on how the models respond to changes in explanatory variables, we used a policy scenario where the age of individuals older than 29 years was increased by 10 years (to reflect aging of the population). Next, each estimated model was applied to its estimation sample and all the application context datasets (to which the model was transferred) for both base and policy scenarios. The changes in the time-use patterns (due to the policy) were computed at two levels – disaggregate and aggregate.

At the disaggregate-level, first, for each set of error term draws for each individual, the overall change in activity participation and time-use patterns was measured as below.

$$T_c = \frac{1}{T}\left(\sum_{k=1}^{K}\frac{|\hat{t}_k^p - \hat{t}_k^b|}{2}\right) \tag{4.8}$$

where, $\hat{t}_k^p$ is the predicted duration for alternative k in the policy case, and $\hat{t}_k^b$ = predicted duration for alternative k in the base case. This measure is similar to the relative error measure proposed by Jaggi et al. (2011) in that it is a composite measure of changes in time allocation for all alternatives. Next, the above metric was averaged over all sets of error term draws for all individuals. We label this metric as disaggregate-level policy response.

The aggregate-level policy assessment metric is defined as the total absolute change in predicted shares for all choice alternatives: $\sum_{k=1}^{K}\left|\hat{p}_k^p - \hat{p}_k^b\right|$, where $\hat{p}_k^p$ and $\hat{p}_k^b$ are the predicted aggregate shares for alternative k in the policy and base case scenarios, respectively. This metric focuses on the discrete (activity participation) component of choice.

Table 4.9 presents the above-discussed metrics, with the values outside the parentheses indicating the predicted policy response by the transferred model, and the values inside the parentheses indicating the ratio of the same metric with respect to that of a locally estimated model. The closer (farther) the values in the parenthesis are to 1 (from 1), the closer (farther) is the transferred model's policy response prediction to the corresponding locally estimated model, and therefore, better (poorer) transferability. These results suggest that for both inter-state and intra-state transfers, updating constants does not help much in improving the performance of the transferred model (i.e., in predicting the policy changes closely to that from a locally estimated model). In some cases, it rather seems to deteriorate the performance of the transferred model. These results are quite in contrast to the findings from the log-likelihood based (TI) and aggregate prediction-based (RMSE and RATE) metrics. While updating constants has been found to provide significant improvement in the TI values and aggregate-level prediction (as in many studies), the results here suggest that such improvements do not necessarily translate to improvement in the policy responses of the transferred model.

To gain better perspective from these findings, the above discussed policy measures were computed for 50 sets of bootstrapped values drawn from the sampling distributions implied by the parameter estimates and their covariance matrix (only for intra-state transfers). Table 4.10 presents the policy response measures for all transferred and locally estimated models in the form of average policy response values (averaged over all bootstrapped parameter estimates). Similar to the previous table, the values outside the parentheses indicate the predicted policy response by the transferred model while the values inside the parentheses indicate the ratio of the same metric with respect to that of a locally estimated model. One notable difference between the results from point and bootstrapped estimates that warrants attention here is that the values inside the parenthesis in Table 4.10 are much closer to 1 than those in Table 4.9, suggesting better transferability (in terms of policy response prediction) in almost all the cases. This indicates that neglecting sampling variance can potentially bias the results of transferability assessments toward "less" transferable. But interestingly, the overall findings from the bootstrapped parameter estimates are almost same as that obtained from the point estimates discussed in the previous paragraph.

It is useful to note here that, to update the constants of transferred models, we used all the data available in the application context to update the model constants while retaining the other parameters from the estimation context. In reality, only a small sample (if any) is typically available from the application context. Updating the model constants with such small data samples may not lead to as significant improvements in the aggregate predictions as observed here. But the takeaway point is that the updated models

Table 4.9 Transferability Assessment Results: Disaggregate and Aggregate Policy Response Measures (point estimates)

Inter-state Transfer

Policy Response		Transferred From \ Transferred To	California: Naïve Transfer	California: Updated Constants	Florida: Naïve Transfer	Florida: Updated Constants
Policy Response	Disaggregate	California	**4.88(1.00)**	**4.88(1.00)**	4.86(1.64)	5.54(1.87)
		Florida	2.46(0.50)	2.57(0.53)	**2.96(1.00)**	**2.96(1.00)**
	Aggregate	California	**4.72(1.00)**	**4.72(1.00)**	4.68(1.31)	6.74(1.88)
		Florida	3.70(0.78)	2.68(0.57)	**3.58(1.00)**	**3.58(1.00)**

Intra-state Transfer

Policy Response		Transferred From \ Transferred To	SEF: Naïve Transfer	SEF: Updated Constants	CF: Naïve Transfer	CF: Updated Constants	TB: Naïve Transfer	TB: Updated Constants	D1U: Naïve Transfer	D1U: Updated Constants	R: Naïve Transfer	R: Updated Constants
Policy Response	Disaggregate	SEF	**2.25(1.00)**	**2.25(1.00)**	2.57(1.58)	2.20(1.36)	2.50(0.51)	2.20(0.45)	2.21(0.55)	1.90(0.47)	2.71(2.22)	2.14(1.74)
		CF	1.42(0.63)	1.48(0.66)	**1.62(1.00)**	**1.62(1.00)**	1.50(0.31)	1.33(0.27)	1.37(0.34)	1.37(0.34)	1.65(1.35)	1.51(1.23)
		TB	4.90(2.18)	5.18(2.30)	5.36(3.31)	5.36(3.31)	**4.88(1.00)**	**4.88(1.00)**	5.52(1.36)	5.75(1.42)	5.32(4.35)	5.31(4.34)
	Aggregate	SEF	**3.15(1.00)**	**3.15(1.00)**	3.42(1.36)	3.24(1.31)	3.33(0.65)	3.15(0.61)	3.24(2.49)	3.06(2.35)	3.69(2.54)	2.88(1.96)
		CF	2.43(0.77)	2.52(0.79)	**2.52(1.00)**	**2.52(1.00)**	2.43(0.47)	1.35(0.26)	2.07(1.60)	2.07(1.60)	2.70(1.84)	2.25(1.52)
		TB	5.31(1.69)	5.49(1.74)	5.94(2.38)	6.12(2.46)	**5.13(1.00)**	**5.13(1.00)**	6.12(4.78)	6.3(4.92)	5.67(3.88)	5.31(3.63)

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

Table 4.10 Transferability Assessment Results: Disaggregate and Aggregate Policy Response Measures (using bootstrap)

		Intra-state Transfer										
		Transferred To / Transferred From	SEF		CF		TB		D1U		R	
			Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants	Naïve Transfer	Updated Constants
Policy Response	Disaggregate	SEF	**2.76(1.00)**	**2.76(1.00)**	3.19(0.94)	2.73(0.80)	3.07(0.56)	2.70 (0.49)	2.82 (0.63)	2.43 (0.54)	3.38 (1.56)	2.65 (1.23)
		CF	2.92(1.06)	3.22(1.17)	**3.40(1.00)**	**3.40(1.00)**	3.16(0.58)	3.22 (0.59)	3.09 (0.69)	3.26 (0.73)	3.53 (1.63)	3.36 (1.56)
		TB	5.42(1.96)	5.64(2.04)	6.01(1.77)	5.83(1.71)	**5.46(1.00)**	**5.46 (1.00)**	6.16 (1.38)	6.21 (1.39)	6.00 (2.78)	5.73 (2.65)
	Aggregate	SEF	**3.18(1.00)**	**3.18(1.00)**	3.77(1.24)	3.49(1.14)	3.46(0.64)	3.21(0.59)	3.37 (1.29)	3.22 (1.23)	3.89 (1.74)	3.05 (1.37)
		CF	2.66(0.84)	2.75(0.86)	**3.05(1.00)**	**3.05(1.00)**	2.69(0.50)	2.71 (0.50)	2.84 (1.09)	2.80 (1.07)	3.02 (1.35)	2.65 (1.19)
		TB	5.56(1.75)	5.63(1.77)	6.25(2.05)	6.31(2.07)	**5.41(1.00)**	**5.41 (1.00)**	6.43 (2.46)	6.58 (2.52)	6.00 (2.69)	5.50 (2.47)

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

have not shown any improvement in policy sensitivity even after using all the data available in the application context.

4.6.5 Overall Assessment

Table 4.11 presents a summary of the results (for transfers within Florida) from all the transferability assessment metrics used in this chapter except TTS (the TTS anyway rejects the hypothesis of transferability in all cases). To gain a better perspective from the results, we define four levels of transferability based on the error in the performance of a transferred model in the application context (for details, see the notes below Table 4.11). Specifically, the transferability of a model is categorized as level 1 if the error is less than 25%, level 2 for errors in the 25%-50% range, level 3 for errors in the 50%-100% range, and level 4 for errors greater than 100%. For each model transferred, the *level* of transferability (1, 2, 3, or 4) is denoted as the superscript for the region where the model was transferred from. Also, following Nowrouzian and Srinivasan (2012), for each application context, the various transferred models are arranged in the descending order of transferability defined by the above scheme of categorization in to 4 different *levels*. For example, based on transfer index for naïve transfers, the transferability to rural region of the SEF model is similar to that of the CF model (similarity denoted by "~") but better than (">") that of the TB model. Of course, the levels are defined based on arbitrarily defined thresholds, but the analyst has to determine the *acceptable error thresholds* to draw broad conclusions on transferability.

The RATEs suggest that, regardless of the level of transferability of a naively transferred model, any transferred model can be improved (to transferability level 1) by simply updating its constants. However, as discussed earlier and can be observed from

Table 4.11 Overall Transferability Assessment Results

<table>
<tr><th rowspan="2"></th><th rowspan="2">Transferred To</th><th colspan="4">Transferred From</th></tr>
<tr><th colspan="2">Naïve Transfer</th><th colspan="2">Updated Constants</th></tr>
<tr><td rowspan="5">Transfer Index</td><td>SEF</td><td colspan="2">$CF^{2} > TB^{3}$</td><td colspan="2">$CF^{2} > TB^{3}$</td></tr>
<tr><td>CF</td><td colspan="2">$SEF^{2} > TB^{3}$</td><td colspan="2">$SEF^{2} > TB^{3}$</td></tr>
<tr><td>TB</td><td colspan="2">$SEF^{3} \sim CF^{3}$</td><td colspan="2">$SEF^{2} \sim CF^{2}$</td></tr>
<tr><td>D1U</td><td colspan="2">$SEF^{3} \sim CF^{3} > TB^{4}$</td><td colspan="2">$SEF^{3} \sim CF^{3} \sim TB^{3}$</td></tr>
<tr><td>R</td><td colspan="2">$SEF^{3} \sim CF^{3} > TB^{4}$</td><td colspan="2">$CF^{1} > SEF^{2} > TB^{3}$</td></tr>
<tr><td rowspan="5">RATE: Discrete Component</td><td>SEF</td><td colspan="2">$CF^{2} > TB^{3}$</td><td colspan="2">$CF^{2} > TB^{1}$</td></tr>
<tr><td>CF</td><td colspan="2">$SEF^{1} \gg TB^{3}$</td><td colspan="2">$SEF^{1} \sim TB^{1}$</td></tr>
<tr><td>TB</td><td colspan="2">$CF^{1} \gg SEF^{4}$</td><td colspan="2">$CF^{1} \sim SEF^{1}$</td></tr>
<tr><td>D1U</td><td colspan="2">$CF^{1} > SEF^{2} > TB^{3}$</td><td colspan="2">$CF^{1} \sim SEF^{1} \sim TB^{1}$</td></tr>
<tr><td>R</td><td colspan="2">$SEF^{4} \sim CF^{4} \sim TB^{4}$</td><td colspan="2">$SEF^{1} \sim CF^{1} \sim TB^{1}$</td></tr>
<tr><td rowspan="5">RATE: Continuous Component</td><td>SEF</td><td colspan="2">$CF^{2} \sim TB^{2}$</td><td colspan="2">$CF^{1} > TB^{2}$</td></tr>
<tr><td>CF</td><td colspan="2">$TB^{1} \gg SEF^{3}$</td><td colspan="2">$TB^{1} \sim SEF^{1}$</td></tr>
<tr><td>TB</td><td colspan="2">$CF^{1} \gg SEF^{3}$</td><td colspan="2">$CF^{1} \sim SEF^{1}$</td></tr>
<tr><td>D1U</td><td colspan="2">$TB^{1} \sim CF^{1} \gg SEF^{4}$</td><td colspan="2">$TB^{1} \sim CF^{1} \sim SEF^{1}$</td></tr>
<tr><td>R</td><td colspan="2">$TB^{2} > CF^{3} \sim SEF^{3}$</td><td colspan="2">$SEF^{1} > TB^{2} \sim CF^{2}$</td></tr>
<tr><td rowspan="6">Policy Response: Disaggregate Measure</td><td></td><td>Using Point Estimates</td><td>Using Bootstrap</td><td>Using Point Estimates</td><td>Using Bootstrap</td></tr>
<tr><td>SEF</td><td>$CF^{2} \gg TB^{4}$</td><td>$CF^{2} \gg TB^{4}$</td><td>$CF^{2} \gg TB^{4}$</td><td>$CF^{1} \gg TB^{4}$</td></tr>
<tr><td>CF</td><td>$SEF^{3} > TB^{4}$</td><td>$SEF^{2} \gg TB^{4}$</td><td>$SEF^{2} \gg TB^{4}$</td><td>$SEF^{1} \gg TB^{3}$</td></tr>
<tr><td>TB</td><td>$SEF^{2} > CF^{3}$</td><td>$SEF^{3} \sim CF^{3}$</td><td>$SEF^{3} \sim CF^{3}$</td><td>$CF^{2} > SEF^{3}$</td></tr>
<tr><td>D1U</td><td>$SEF^{2} \sim TB^{2} > CF^{3}$</td><td>$TB^{2} > SEF^{3} \sim CF^{3}$</td><td>$TB^{2} > SEF^{3} \sim CF^{3}$</td><td>$SEF^{2} \sim CF^{2} \sim TB^{2}$</td></tr>
<tr><td>R</td><td>$CF^{2} \gg SEF^{4} \sim TB^{4}$</td><td>$CF^{1} \gg SEF^{3} > TB^{4}$</td><td>$CF^{1} \gg SEF^{3} > TB^{4}$</td><td>$SEF^{2} > CF^{3} > TB^{4}$</td></tr>
<tr><td rowspan="5">Policy Response: Aggregate Measure</td><td>SEF</td><td>$CF^{1} \gg TB^{3}$</td><td>$CF^{1} \gg TB^{3}$</td><td>$CF^{1} \gg TB^{3}$</td><td>$CF^{1} \gg TB^{3}$</td></tr>
<tr><td>CF</td><td>$SEF^{2} \gg TB^{4}$</td><td>$SEF^{2} \gg TB^{4}$</td><td>$SEF^{2} \gg TB^{4}$</td><td>$SEF^{1} \gg TB^{4}$</td></tr>
<tr><td>TB</td><td>$SEF^{2} > CF^{3}$</td><td>$SEF^{2} > CF^{3}$</td><td>$SEF^{2} > CF^{3}$</td><td>$SEF^{2} \sim CF^{2}$</td></tr>
<tr><td>D1U</td><td>$CF^{3} > SEF^{4} \sim TB^{4}$</td><td>$CF^{3} > SEF^{4} \sim TB^{4}$</td><td>$CF^{3} > SEF^{4} \sim TB^{4}$</td><td>$CF^{1} \sim SEF^{1} \gg TB^{4}$</td></tr>
<tr><td>R</td><td>$CF^{3} > SEF^{4} \sim TB^{4}$</td><td>$CF^{3} \sim SEF^{3} > TB^{4}$</td><td>`$CF^{3} \sim SEF^{3} > TB^{4}$</td><td>$CF^{1} \gg SEF^{3} > TB^{4}$</td></tr>
</table>

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida
* Superscripts
  Level 1: less than 25% error - Transfer Index (0.75 –1.00), RATE (1.00 –1.25), Policy Response Ratio (0.75 –1.00 ~1.00 –1.25)
  Level 2: 25% - 50% error - Transfer Index (0.50 – 0.74), RATE (1.26 –1.50), Policy Response Ratio (0.50 – 0.74 ~ 1.26 –1.50)
  Level 3: 50% - 100% error - Transfer Index (0.00 – 0.49), RATE (1.51 –2.00), Policy Response Ratio (0.00 – 0.49 ~ 1.51 –2.00)
  Level 4: >100% error - Transfer Index (< 0.00), RATE (>2 .00), Policy Response Ratio (>2.00)
* Signs
  "~" - Transferability of one model is *similar* to that of the other model
  ">"-Transferability of one model is *better* than that of the other model
  ">>"-Transferability of one model is *far better* than that of the other model

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District1, and R: Rural Florida

the last two sets of rows, this improvement doesn't translate to improvement in the level of transferability in terms of the ability to provide appropriate policy predictions. Recall that the TI values also improved after updating constants, but the improvement for intra-state transfers was not sufficient enough to enable jumps in the *level* of transferability unless the naïve transfer had a rather low TI value. The takeaway point here is that updating model constants can help with predicting the observed aggregate activity participation and time-use patterns closely, but not necessarily in predicting appropriate policy responses. Since updating model constants is a widely used practice to transfer models, it is important for modelers and model-users to be cognizant of this issue.

For any application context, the order of transferability of different transferred models does not change (or it doesn't get reversed) after updating constants. However, the order seems to vary by the metric used to assess transferability – specifically between the aggregate prediction metrics (RATE) and the disaggregate metrics such as TI and policy responses.

There is greater correlation between the inferences from TI and policy response-based assessment (based on both point and bootstrapped estimates), whereas inferences from the aggregate prediction-based metrics tally less with those from other metrics. For instance, both TI and policy assessments imply almost similar order of transferability of different models (for any application context). Similarly, although TI values improved after updating constants, neither TI nor policy assessments suggested significant improvement in transferability after updating model constants (except that TI showed significant improvement if the naïve transfer has a poor TI value). These findings suggest that greater TI value of a naively transferred model is likely to imply better policy response of that model, but better neither aggregate prediction of observed patterns nor improvements in the TI after updating constants necessarily imply better policy prediction. Thus, future policy response assessments should place greater emphasis on log-likelihood based metrics (before updating constants) and even greater emphasis on policy response measures.

The transferability from urban region models to D1U and Rural regions seems to be much lower than transferability among the three major urban region models (SEF, CF, TB). Further, the SEF and CF models are more transferable to other regions in Florida than the TB model. Nevertheless, in most cases, the level of transferability is at most 2 (suggesting 25-50% errors in the transferred model compared to the local model) even after updating model constants (when the aggregate prediction-based metrics are ignored). Thus, future research should investigate if other model updating methods used in the literature can enhance transferability. Further, improving the empirical specification with additional urban form measures and transport system performance measures (e.g., accessibility) will likely have a considerable positive influence on model transferability.

4.7 Data Pooling Technique Assessment

Table 4.12 presents the data pooling technique assessment results. As can be observed from this table, only two metrics were used in this assessment: (a) transfer index, and (b) policy response measure. The first column of Table 4.12 presents the combination of the regions the data pooled from for model estimation, while the other columns present the transferability results (of those pooled models) obtained from the assessment metrics mentioned to the left of the first column.

It is important to note that while pooling the data, data from all the regions were not pooled at a time; it was done sequentially. For a given metric and a transfer to a particular region, we started with data of the model that provided the best performance (in the application region) in the previous transferability assessments, and then added data from other regions sequentially. As one can imagine, for a total of four regions, there will be three combinations in this sequential procedure. The transferability results of the models developed based on all of these combined regions data are provided in the table. Among these, the combinations that performed the best in application context are indicated in bold.

To understand the procedure better, let us consider an example. In the previous transferability analysis, the CF model was found to perform better than the TB model (in terms of transfer index values) when both of them were naively transferred to SEF (0.59 vs. 0.29). Hence, for transfer index metric and for the transfer to SEF region, data from different regions were pooled with the CF data one by one (e.g., first from the TB region, and then from the NE region), and then models were estimated using those pooled datasets. Next, transferability of the pooled model was assessed by using transfer index metric. The TI values suggest the better performance of the first naively transferred pooled model (i.e., estimated on pooled CF and TB data) than the CF model (0.66 vs.0.59). The performance appears to improve further after pooling data from the NE region. But after that, pooling data from other regions does not appear to improve the performance of the naively transferred model (i.e., the TI value remains the same). Similarly the policy response measure was used to assess the performance of the data pooling technique.

Table 4.12 Data Pooling Technique Assessment Results

	Transferred to / Transferred from	SEF Naïve Transfer	SEF Updated Constants	CF Naïve Transfer	CF Updated Constants	TB Naïve Transfer	TB Updated Constants
Transfer Index	CF	0.59[2]	0.70[2]	-	-	-	-
	CF+TB	0.66[2]	0.76[1]	-	-	-	-
	CF +TB +NE	***0.70[2]***	***0.81[1]***	-	-	-	-
	CF+TB+NE+OTHER	0.70[2]	0.80[1]	-	-	-	-
	SEF	-	-	0.53[2]	0.68[2]	-	-
	SEF+TB	-	-	0.70[2]	0.78[1]	-	-
	SEF+TB+OTHER	-	-	**0.75[1]**	**0.81[1]**	-	-
	SEF+TB+OTHER+NE	-	-	0.74[2]	0.81[1]	-	-
	CF	-	-	-	-	0.46[3]	0.64[2]
	CF+SEF	-	-	-	-	0.56[2]	0.75[1]
	CF+SEF+NE	-	-	-	-	0.61[2]	0.77[1]
	CF+SEF+NE+OTHER	-	-	-	-	**0.67[2]**	**0.81[1]**
Policy Sensitivity: Disaggregate Measure	CF	1.42 (0.63[2])	1.48 (0.66[2])	-	-	-	-
	CF+TB	3.04(1.35[2])	3.30 (1.47[2])	-	-	-	-
	CF+TB+NE	**2.54 (1.13[1])**	**2.82 (1.25[1])**	-	-	-	-
	CF+TB+NE+OTHER	3.06 (1.36[2])	3.40 (1.51[3])	-	-	-	-
	SEF	-	-	***2.57 (1.58[3])***	***2.20 (1.36[2])***	-	-
	SEF+NE	-	-	3.20 (1.97[3])	3.08 (1.90[3])	-	-
	SEF+NE+OTHER	-	-	3.22 (1.99[3])	3.13(1.93[3])	-	-
	SEF+NE+OTHER+TB	-	-	3.47 (2.14[4])	3.39 (2.09[4])	-	-
	SEF	-	-	-	-	2.50(0.51[2])	2.20 (0.45[3])
	SEF+CF	-	-	-	-	***2.93 (0.60[2])***	***2.81 (0.57[2])***
	SEF+CF+NE	-	-	-	-	2.42 (0.50[2])	2.42(0.50[2])
	SEF+CF+NE+OTHER	-	-	-	-	2.60 (0.53[2])	2.60 (0.53[2])
Policy Sensitivity: Aggregate Measure	CF	0.27(0.76[1])	0.28(0.79[1])	-	-	-	-
	CF+TB	0.42(1.20[1])	0.45 (1.29[2])	-	-	-	-
	CF+TB+NE	***0.40 (1.15[1])***	***0.43 (1.23[1])***	-	-	-	-
	CF+TB+NE+OTHER	0.23 (0.66[2])	0.25(0.70[2])	-	-	-	-
	SEF	-	-	***0.38 (1.36[2])***	***0.36 (1.31[2])***	-	-
	SEF+OTHER	-	-	0.41(1.50[2])	0.43 (1.54[3])	-	-
	SEF+OTHER+NE	-	-	0.42 (1.51[3])	0.43 (1.53[3])	-	-
	SEF+OTHER+NE+TB	-	-	0.47(1.70[3])	0.49 (1.78[3])	-	-
	SEF	-	-	-	-	0.37 (0.65[2])	0.35 (0.61[2])
	SEF+CF	-	-	-	-	***0.40 (0.69[2])***	***0.39(0.67[2])***
	SEF+CF+NE	-	-	-	-	0.38 (0.66[2])	0.37 (0.64[2])
	SEF+CF+NE+OTHER	-	-	-	-	0.36 (0.62[2])	0.35(0.61[2])

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District 1, and R: Rural Florida

* Superscripts

Level 1: less than 25% error - Transfer Index (0.75 –1.00), Policy Response Ratio (0.75 –1.00 ~1.00 –1.25)

Level 2: 25% - 50% error - Transfer Index (0.50 – 0.74), Policy Response Ratio (0.50 – 0.74 ~ 1.26 –1.50)

Level 3: 50% - 100% error - Transfer Index (0.00 – 0.49), Policy Response Ratio (0.00 – 0.49 ~ 1.51 –2.00)

Level 4: >100% error - Transfer Index (< 0.00), Policy Response Ratio (>2.00)

Several important observations may be made from the table. First, the results indicate that pooling data from different regions helps in improving the performance of a naively transferred model, but up to a certain extent. After that, pooling data does not appear to improve the performance of the transferred model; in some cases, it rather seems to deteriorate the performance of the transferred model. Second, to obtain the best performance, the number of the regions required to pool the data from appears to vary with the transferability assessment metric and the application region. However, in most cases, pooling data from just one or two regions appears to be sufficient i.e., don't need to pool data from all the regions possible. Third, as expected, the performance of the data pooling technique seems to depend on the data characteristics more than the sample size of the data pooled from other regions. For instance, although the NE region has a small sample size (688) compared to other regions such as TB (1334) and others (2430), it appears to play an important role in the transferability of a model. Fourth, the data pooling technique suggest the following combinations of the regions (to pool the data from) for transferring the activity participation and time-use model to three major urban regions in Florida: (a) CF +TB +NE → SEF, (b) SEF → CF, and (c) SEF +CF → TB. These combinations suggest that the data from other *urban areas* need to be pooled to improve the transferability of a model to another urban region. It is important to note that the scale differences across the areas were not considered in this data pooling technique assessment. Allowing for scale differences across different regions can potentially shed further light on the performance of the data pooling technique.

4.8 Summary

This chapter presents an empirical assessment of the spatial transferability of person-level activity generation and time-use models among different regions in Florida (intra-state transferability) and between Florida and California (inter-state transferability). The empirical models are for unemployed adults based on the multiple discrete-continuous extreme (MDCEV) structure. An examination of the prediction properties of the MDCEV model is provided first, followed by an assessment of transferability for two approaches to transferring models – (1) Naïve transfer, and (2) Updating model constants. Transferability is evaluated using different measures such as log-likelihood based measures, aggregate predictive ability, and model sensitivity to changes in demographic characteristics. In addition, the performance of new approach of enhancing model transferability is investigated in this chapter.

The results shed new light on the prediction properties of the MDCEV model that has implications to transferability. The most important of these is that, similar to the multinomial logit model, the MDCEV model estimated with only constants, when applied to the estimation data, provides accurate aggregate shares of the choice of discrete alternatives. This property has implications to model transferability. Specifically, updating the constants of a transferred MDCEV model using data from the application context can help improve its aggregate-level discrete choice predictions.

The MDCEV model appears to perform very well in predicting the aggregate-level activity participation rates in individual activities. But the model appears to under-predict the aggregate activity durations for the outside good (in-home activity) and over-predict the aggregate durations for most of the inside goods (out-of-home activities).

The transferability assessment revealed several findings. First, the ability to predict aggregate observed patterns is not an adequate measure of transferability. Greater emphasis should be placed on disaggregate-level prediction metrics and more importantly policy prediction ability. Similar findings were reported in Karasmaa (2007) and Nowrouzian and Srinivasan (2012). Second, updating the constants of a transferred MDCEV model can significantly improve its ability to predict aggregate shares in the context to which it is transferred. But this does not necessarily translate into an improvement in the transferred model's ability to provide appropriate sensitivities to changes in demographic characteristics and other variables. While these results do not argue against updating the model constants, it is important that the transferred model must exhibit a minimum level of performance without any updates. Only then does it make sense to update its constants. Thus, empirical research should be more focused on the development of more transferable models by better capturing the behavior than directly utilizing updating methods that simply rely on the mechanics (or properties) of the model to match aggregate predictions. Third, the extent of transferability between different regions within a state is greater than that across different states. Thus, whenever possible, attempts should be made to transfer models within a state. Within the state of Florida, the transferability between urban regions is greater than that from urban to rural region. Specifically, there appears to be greater transferability of time-use models between the Southeast Florida and the Central Florida regions.

The results also suggest that pooling data helps in improving the spatial transferability of a model but up to a certain extent. After that, pooling data does not appear to result significant improvement in model transferability. Besides, data from all the regions do not appear to result in similar improvements. For instance, data pooled from major urban regions (as compared to that from other regions) was found to result in greater improvement in the transferability of a model to another major urban region.

CHAPTER 5

ENHANCING SPATIAL TRANSFERABILITY BY IMPROVING MODEL STRUCTURE: FORMULATION AND APPLICATION OF THE MULTIPLE DISCRETE-CONTINUOUS HETEROSCEDASTIC EXTREME VALUE (MDCHEV) MODEL

5.1 Introduction and Motivation

The previous chapters uses the Karush-Kuhn-Tucker (KKT) based Multiple Discrete Continuous Extreme Value (MDCEV) model to investigate the spatial transferability of person-level daily activity participation and time-use models. The investigation of the prediction properties of the MDCEV model in that chapter suggest that the MDCEV model performs well in predicting the aggregate-level discrete choices observed in the estimation data (i.e., the market shares for each choice alternative) but not the aggregate activity durations. Specifically, the model is found to under-predict the aggregate activity durations for the outside good (in-home activity) and over-predict the aggregate durations for most of the inside goods (out-of-home activities). It is possible that this problem in prediction is due to the fat right tail of the extreme value distributions assumed in the MDCEV model, and can be rectified to a considerable extent by using alternative distributions in the model structure. In addition to improving the prediction ability of the model, this improvement to the structure can also enhance its transferability across areas.

5.2 Contribution and Organization of the Chapter

In view of the above discussion, this chapter aims to formulate a KKT-based MDC model that allows heteroscedastically distributed random components across different choice alternatives available to a decision-maker. More specifically, the Multiple Discrete-Continuous Heteroscedastic Extreme Value (MDCHEV) structure that employs heteroscedastic extreme value (HEV) distributed random utility components in KKT-based MDC models is proposed in this chapter. The HEV distribution was originally used by Bhat (1995) for modeling single discrete choice situations (also see Hensher, 1999, who used the HEV specification as a search mechanism for appropriate nesting structures in nested logit models).

To be sure, the concept of incorporating heteroscedastically distributed random utility components is not new in KKT-based MDC modeling. Bhat and Sen (2006) and Spissu et al. (2009) do so using a mixed-MDCEV mechanism where heteroscedastically distributed normal error components are mixed over an IID extreme value kernel. However, the likelihood function of the mixed-MDCEV formulation is a multidimensional integral of as many dimensions as the number of heteroscedastic choice alternatives. Evaluation of this integral requires computationally intensive simulation techniques as the choice alternatives increase beyond a modest number. The other alternative is to use the MDCP structure (Kim et al., 2002; Farooq et al., 2013; and Bhat et al., 2012) whose MVN distribution automatically allows heteroscedasticity across choice alternatives. However, the estimation of MDCP models has not been straight forward because of the difficulty of evaluating the resulting multidimensional integrals in the likelihood function (although see Bhat et al., 2012 for a new method to address this problem). One advantage of the proposed MDCHEV approach over the other two approaches (i.e., mixed-MDCEV and MDCP) is that the resulting likelihood function is a uni-dimensional integral that can be easily (and accurately) evaluated using quadrature methods; a reason why Bhat (1995) used it in his paper.

Regardless of the method used, the primary reason behind accommodating heteroscedastically distributed random utility components is to recognize the differences in the variation of unobserved influences on the preferences for different choice alternatives. As often cited in the literature, doing so helps in improving the model fit to the data as well as accommodates the influence of heteroscedastic random variance on the elasticity effects of alternative attributes. For instance, the self-price elasticity estimate of a choice alternative is dampened by the variance in its random utility component. However, what has been unknown (and unexplored) so far is the potential influence of heteroscedasticity on the distributions of the consumptions implied by a KKT demand system such as the MDCEV model. This chapter demonstrates empirically that neglecting heteroscedasticity in KKT models leads to not only inferior model fit, but also poor predictions of the consumption patterns, especially the continuous quantity decisions, both in the estimation and validation samples. Specifically, the distributions of the predicted continuous quantity decisions for certain choice alternatives can potentially have longer right tails than the observed distributions; implying overestimation of the continuous quantity predictions for those choice alternatives. This chapter discusses how this problem is related to the fat right tail of the IID extreme value distributions assumed in the MDCEV model. It is also demonstrated empirically that allowing for heteroscedasticity (through the MDCHEV model) helps in addressing this problem to a considerable extent. This is because the MDCHEV model results in smaller variances (hence tighter distributions) of the random utility components for the choice alternatives for which the MDCEV model over-predicts the continuous quantity choices. Such tightly distributed random utility components, as will be demonstrated later in this chapter, reduce the probability of unreasonably large continuous quantity predictions.

For the empirical demonstration, both the MDCEV and MDCHEV models are estimated on a daily time-use dataset derived from the National Household Travel Survey (NHTS) data in Florida. In addition to comparing the goodness of statistical fit and goodness of predictions on the estimation data, the transferability of these two models among different regions in Florida are compared. It has long been discussed in the model transferability literature (see chapter 2 for a detailed review) that empirical models that transfer better to other geographical and/or temporal contexts reflect a better underlying theory, econometric structure, and empirical specification. However, there is little empirical evidence in the field on whether (and what) improvements in econometric structure contribute to improvements in model transferability. Thus, in addition to proposing a methodological extension to modeling MDC choices (i.e., the MDCHEV model), this chapter investigates whether the proposed methodological extension helps in enhancing the spatial transferability of time-use models.

The remainder of this chapter is organized as follows. The next section presents the structure of the MDCHEV model and outlines the estimation procedure. Section 5.4 briefly overviews the empirical data and geographical contexts considered for the empirical analysis. Section 5.5 presents the empirical results and Section 5.6 summarizes the chapter.

5.3 The MDCHEV Model

This section formulates the MDCHEV model for analyzing individuals' time-use (i.e., activity participation and time allocation) and outlines the procedure used to estimate the model parameters.

5.3.1 Model Formulation

Consider the following random utility function proposed by Bhat (2008) for modeling multiple discrete-continuous choice situations:

$$U(\mathbf{t}) = \psi_1 \ln t_1 + \sum_{k=2}^{K} \left\{ \psi_k \gamma_k \ln\left(\left(t_k / \gamma_k\right) + 1\right) \right\} \tag{5.1}$$

In the above function, $U(\mathbf{t})$ is the total utility derived by an individual from his/her daily time-use. It is the sum of sub-utilities derived from allocating time (t_k) to each of the activity types k ($k = 1, 2, ..., K$). Individuals are assumed to make their activity participation and time-use decisions such that they maximize $U(\mathbf{t})$ subject to a linear budget constraint $\sum_k t_k = T$, where T is the total available time budget. Note that the subscript for the individual is suppressed for simplicity in notation.

Within the utility function in Equation (5.1), ψ_k, called the baseline marginal utility for alternative k, is the marginal utility of time allocation to activity k at the point of zero time allocation. ψ_k governs the discrete choice decisions in that an activity type with greater baseline marginal utility is more likely to be chosen than other activities. γ_k accommodates corner solutions (i.e., the possibility of not choosing an alternative). Both

ψ_k and γ_k accommodate differential satiation effects (diminishing marginal utility with increasing consumption) for different activity types. Thus, both these parameters influence the time allocation decisions. Specifically, a greater value of either ψ_k or γ_k implies a larger allocation of time to the corresponding activity. Note that the 1^{st} alternative, designated as in-home activity, does not have a γ_k parameter since all individuals in the data allocate some time to the in-home activity (i.e., there is no need of corner solutions for this activity). From now on, this alternative will be called the *outside good*, while all other activities (out-of-home activities) are called *inside goods*.[9]

The influence of observed and unobserved individual characteristics and activity-travel environment (ATE) measures are accommodated into the utility function as $\psi_1 = \exp(\varepsilon_1)$; $\psi_k = \exp(\beta' z_k + \varepsilon_k)$; and $\gamma_k = \exp(\theta' w_k)$; where, z_k and w_k are observed socio-demographic and ATE measures influencing the choice of and time allocation to activity k, β and θ are corresponding parameter vectors, and ε_k ($k=1,2,\ldots,K$) is the random error term capturing unobserved and unmeasured influences on the utility contribution of time allocation in activity type k. Note that ψ_1 does not include any observed explanatory variables as the coefficients of all explanatory variables for this alternative are normalized to zero for identification purposes. This is because the budget

[9] The outside good is a composite good that represents all goods other than the *K-1 inside* goods of interest to the analyst. The presence of the outside good helps in ensuring that the budget constraint is binding. Besides, the outside good helps in endogenously determining the total resource allocation for (or total consumption of) inside goods. It is not uncommon to treat the outside good as a numeraire with unit price, assuming that the prices and characteristics of the goods grouped into the outside category do not influence the choice and resource allocation among the inside goods (see Deaton and Muelbauer 1980). While the current empirical context is such that the outside good is an essential good (where all individuals consume some amount of it), it is not always necessary for the outside good to be specified as an essential good.

constraint implies that the time investments of only *K-1* of the *K* alternatives are the decision variables in the utility maximization problem (Bhat, 2008).

To obtain the optimal time allocations ($t_1^*, t_2^*, ..., t_K^*$), one can form the Lagrangian and derive the following Karush-Kuhn-Tucker (KKT) conditions of optimality (Bhat 2008):

$$V_k + \varepsilon_k = V_1 + \varepsilon_1 \text{ if } t_k^* > 0, (k = 2, 3, ..., K)$$

$$V_k + \varepsilon_k < V_1 + \varepsilon_1 \text{ if } t_k^* = 0, (k = 2, 3, ..., K) \tag{5.2}$$

where, $V_1 = \ln\left(t_1^*\right)$, and $V_k = \beta' z_k + \ln\left(\left(t_k^* / \gamma_k\right) + 1\right), (k = 2, 3......, K).$

The above stochastic KKT conditions form the basis for the derivation of likelihood expressions. In the general case, if the joint probability density function of the ε_k terms is $g(\varepsilon_1, \varepsilon_2, ..., \varepsilon_k)$, and if M alternatives are chosen out of the available K alternatives, and if the consumptions of these M alternatives are $(t_1^*, t_2^*, t_3^*, ..., t_M^*)$, as given in Bhat (2008), the joint probability expression for this consumption patterns is as follows:

$$P(t_1^*, t_2^*, t_3^*, ..., t_M^* 0, 0, 0..., 0) = |J| \int_{\varepsilon_1=-\infty}^{+\infty} \int_{\varepsilon_{M+1}=-\infty}^{V_1 - V_{M+1} + \varepsilon_1} \int_{\varepsilon_{M+2}=-\infty}^{V_1 - V_{M+2} + \varepsilon_1} \cdots \int_{\varepsilon_{k-1}=-\infty}^{V_1 - V_{k-1} + \varepsilon_1} \int_{\varepsilon_k=-\infty}^{V_1 - V_k + \varepsilon_1}$$
$$g(\varepsilon_1, V_1 - V_2 + \varepsilon_1, V_1 - V_3 + \varepsilon_1, ..., V_1 - V_M + \varepsilon_1, \varepsilon_{M+1}, \varepsilon_{M+2}, ..., \varepsilon_{K-1}, \varepsilon_K)$$
$$d\varepsilon_k d\varepsilon_{k-1} ... d\varepsilon_{M+2} d\varepsilon_{M+1} d\varepsilon_1 \tag{5.3}$$

where $|J|$ is the determinant of a Jacobian whose elements are given by (see Bhat, 2005)

$$J_{ih} = \frac{\partial\left[V_1 - V_{i+1} + \varepsilon_1\right]}{\partial t_{h+1}^*} = \frac{\partial\left[V_1 - V_{i+1}\right]}{\partial t_{h+1}^*}; i, h = 1, 2, ..., M-1. \tag{5.4}$$

For the MDCHEV model, it is assumed that the random components in the baseline marginal utilities of different choice alternatives are independent but heteroscedastically extreme value (HEV) distributed. Specifically, the random error term ε_k of each alternative k $(k=1,2,3,....,K)$ is assumed to have a type-1 extreme value distribution with a location parameter equal to zero and a scale parameter equal to σ_k. With the HEV distribution, the probability expression in Equation (5.3) becomes:

$$P(t_1^*,t_2^*,...,t_M^*,0,...,0)=|J|\int_{\varepsilon_1=-\infty}^{\varepsilon_1=+\infty}\left\{\left(\prod_{j=2}^{M}\frac{1}{\sigma_j}g\left[\frac{V_1-V_j+\varepsilon_1}{\sigma_j}\right]\right)\right\}\times\left\{\prod_{s=M+1}^{K}G\left[\frac{V_1-V_s+\varepsilon_1}{\sigma_s}\right]\right\}\frac{1}{\sigma_1}g\left[\frac{\varepsilon_1}{\sigma_1}\right]d\varepsilon_1 \quad (5.5)$$

where g(.) and G(.) are the probability density function and cumulative distribution function, respectively, of the standard type I extreme value distribution. If the scale parameters σ_k across all alternatives are assumed to be equal, then the above expression simplifies to the closed-from MDCEV model derived by Bhat (2005).

5.3.2 Model Estimation

The parameters of the MDCHEV model can be estimated using the familiar maximum likelihood procedure. However, there is no analytical form for the integral appearing in the probability expression of Equation (5.5), which enters the likelihood function. In this chapter, the Laguerre Gaussian Quadrature (Press et al., 1986) is employed to compute the integral. To employ this technique, first the probability expression in Equation (5.3) is expressed in a particular form. To do so, following (Bhat, 1995), define $w=\frac{\varepsilon_1}{\sigma_1}$ and $u=e^{-w}$. Then, $g(w)dw=-e^{-u}du$ and $\varepsilon_1=-\sigma_1\ln u$.

Substituting these in Equation (5.5), the probability expression can be re-written as follows:

$$P(t_1^*,t_2^*,t_3^*,...,t_M^*0,0,...,0)=|J|\int_{u=0}^{\infty}f(u)e^{-u}du \quad (5.6)$$

where $f(u)=\left\{\left(\prod_{j=2}^{M}\frac{1}{\sigma_j}g\left[\frac{V_1-V_j-\sigma_1\ln u}{\sigma_j}\right]\right)\right\}\times\left\{\prod_{s=M+1}^{K}G\left[\frac{V_1-V_s-\sigma_1\ln u}{\sigma_s}\right]\right\}$

According to the Laguerre Gaussian Quadrature technique, the integral in Equation (5.6) can be computed as follows:

$$P(t_1^*,t_2^*,t_3^*,...,t_M^*,0,0,0...,0)=|J|\sum_i w_i f(u_i) \tag{5.7}$$

where, i is the support point at which the function $f(u_i)$ is evaluated and w_i is the weight associated with support point i. We used 15 support points to evaluate the integral. Since the integral being evaluated is uni-dimensional, the quadrature method is computationally efficient and accurate. The likelihood function was coded in the maximum likelihood estimation module of the GAUSS matrix programming language.

Note that, since there is no variation in the prices of unit consumption of the different activity alternatives in the current empirical context, one cannot estimate the scale parameters for all K alternatives. For identification purposes, at least one of the scale parameters must be fixed to an arbitrary value (Bhat, 2008). In the current context, it is convenient to fix the scale parameter of the essential outside good (in-home activity) to 1. Therefore, the interpretation of all other scale parameters would be in reference to that of the outside good. Specifically, a σ_k value less (greater) than 1 implies that the unobserved variation in utility derived from time investment in activity type k is smaller (larger) than that in the in-home activity.

5.4 Data

This chapter uses the same activity participation and time-use data used in chapter 4. While chapter 4 uses this dataset to assess the spatial transferability of a time-use model with an MDCEV structure, this chapter uses the dataset to assess the extent to which the MDCHEV helps resolve the prediction-related issues associated with the MDCEV model. Another important reason of using the same data set is to compare the spatial transferability of these two model structures (i.e., MDCEV vs. MDCHEV) among different regions in Florida. Since a detailed discussion on data cleaning and sample formation procedures is provided in chapter 4, these are not repeated here; only a brief discussion is provided in this section.

As mentioned in chapter 4, the activity participation and time use data were prepared for unemployed adults (age >18 years) in Florida using their weekday information from the 2009 National Household Travel Survey (NHTS). The eight out-of-home activity categories considered are: (1) Shopping, (2) Other maintenance (buying goods/services and attend meeting), (3) Social/Recreational (visiting friends/relatives, go out/hang out, visit historical sites, museums and parks), (4) Active recreation (working out in gym, exercise, and playing sports), (5) Medical, (6) Eat out (such as meal, coffee, and ice cream) (7) Pickup/drop-off, and (8) Other activities. For each individual, the daily time-allocation to each of these activity categories was derived by aggregating the dwell time of each trip made for that activity purpose. The time spent in in-home (IH) activities was computed as total time in a day (24 hours) minus the time allocated to the above out-of-home activities, sleep, and travel. Based on the information from the 2010 American Time Use Survey (ATUS) for Florida, an average amount of 8.7 hours was assumed for sleep. For each individual in the data, the time spent in in-home activities and in all out-of-home activities together forms the available time budget (T) for subsequent analysis. The empirical analysis in this chapter focuses only on three geographical regions in Florida: (1) Southeast Florida (SEF), (2) Central Florida (CF), and (3) Tampa Bay (TB).

For the sample characteristics, the reader is referred to chapter 4. Without presenting the descriptive statistics of the sample once again in this section, the patterns of relevance is quickly summarized here.

The activity participation and time allocation patterns observed in the data were found to be reasonable for the most part. For example, time allocation to social/recreational activities was observed to be larger than that to other activities while that to pickup/drop-off activities was smaller. However, it is worth noting one anomaly that was observed in the context of daily time allocation to active recreational activities. According to the data, a large proportion (more than 30%) of those who participated in active recreation appear to have done so for only 2 minutes or less in a day. Given the activities considered in this category (e.g., working out in gym, or playing sports), there is a high chance that such unreasonably small activity durations for a large proportion of the sample is a result of measurement error; presumably due to misreporting by the respondents or errors in coding of the data. It is important to note that the possibility of activities of very short duration such as walking around the house is also considered here; such a trip would begin and end at the same location. But the NHTS collected information on only those trips that were made to a different address. Also, the auto travel mode was used to arrive at many of these activities suggesting that these activities are not likely to be short strolls. Such measurement errors can potentially have bearing on the estimated variance of the random error term for the active recreation activity.

5.5 Empirical Results

This section is divided into three sub-sections. Section 5.5.1 presents and compares the estimation results of the MDCEV and MDCHEV models. Section 5.5.2 compares the prediction performance of the two models on the estimation sample. Section 5.5.3 examines the influence of incorporating heteroscedasticity on the transferability of these two model structures among different geographical regions in Florida. Similar to chapter 4, all prediction exercises in this chapter are performed using the forecasting algorithm proposed by Pinjari and Bhat (2011), using 100 sets of random draws to cover the random error term distributions for each individual in the data.

5.5.1 Model Estimation Results

To assess the accuracy of the Laguerre Gaussian Quadrature technique, first the MDCEV model was estimated (for all 3 regions) using the MDCHEV likelihood expression in Equation (5.7) but fixing all scale parameters to 1. The resulting parameter estimates, standard errors, and log-likelihood values were all very close to those from the MDCEV model estimated using Bhat's closed-form likelihood expression. This demonstrates the accuracy of the Laguerre Gaussian Quadrature technique used for estimating the MDCHEV model. Next, the activity generation and time-use models were estimated for each of the three geographic regions by using the MDCHEV structure (using the quadrature-based likelihood expression in Equation 5.7), and compared with that of the results obtained from the MDCEV structure (using Bhat's closed-from probability expression) in chapter 4. These results are presented in Table 5.1.

5.5.1.1 Scale Parameters

The scale parameter estimates are reported first in the table. As discussed earlier, the MDCEV model restricts all the scale parameters for all activities as equal to 1. On the other hand, the MDCHEV model allows the scale parameters to be different across

Table 5.1 Model Estimation Results

	South East Florida (SEF)		Central Florida (CF)		Tampa Bay (TB)	
	MDCEV	MDCHEV	MDCEV	MDCHEV	MDCEV	MDCHEV
	Coef. (t-stat)	Coef.(t-stat)	Coef. (t-stat)	Coef. (t-stat)	Coef.(tstat)	Coef.(t-stat)
Scale Parameters (t-stats against 1)						
Shopping	1.00(fixed)	0.73(11.1)	1.00(fixed)	0.68(12.1)	1.00(fixed)	0.68(11.1)
Other Maintenance	1.00(fixed)	0.52(22.1)	1.00(fixed)	0.42(27.9)	1.00(fixed)	0.47(25.8)
Social/Rec.	1.00(fixed)	0.60(16.9)	1.00(fixed)	0.58(16.2)	1.00(fixed)	0.55(17.3)
Active Recreation	1.00(fixed)	1.14(1.8)	1.00(fixed)	1.18(1.9)	1.00(fixed)	1.40(3.5)
Medical	1.00(fixed)	0.73(11.1)	1.00(fixed)	0.68(12.1)	1.00(fixed)	0.68(11.1)
Eat out	1.00(fixed)	0.60(16.9)	1.00(fixed)	0.58(16.2)	1.00(fixed)	0.55(17.3)
Pick-Up/Drop-Off	1.00(fixed)	0.52(22.1)	1.00(fixed)	0.42(27.9)	1.00(fixed)	0.47(25.8)
Other Activities	1.00(fixed)	1.00(fixed)	1.00(fixed)	1.00(fixed)	1.00(fixed)	1.00(fixed)
Baseline Utility Parameters						
Constants						
Shopping	-7.45(-74.8)	-7.26(-90.1)	-7.55(-53.3)	-7.30(-65.6)	-6.69(-89.8)	-6.7(-122.2)
Other Maintenance	-8.90(-49.1)	-7.98(-71.4)	-8.54(-53.1)	-7.74(-68.5)	-7.41(-83.9)	-7.0(-131.9)
Social/Rec.	-8.48(-77.2)	-7.94(-92.9)	-8.68(-53.1)	-7.98(-64.7)	-8.18(-34.5)	-7.52(-53.7)
Active Recreation.	-8.99(-67.1)	-8.98(-48.4)	-9.33(-44.3)	-9.33(-33.6)	-8.69(-30.1)	-9.63(-19.9)
Medical	-8.75(-75.6)	-8.25(-85.2)	-8.78(-45.5)	-8.13(-55.3)	-7.99(-45.3)	-7.62(-60.9)
Eat out	-9.48(-51.5)	-8.56(-65.6)	-9.65(-29.2)	-8.50(-39.6)	-8.07(-31.3)	-7.50(-49.9)
Pick-Up/Drop-Off	-8.46(-56.7)	-7.91(-77.5)	-9.85(-18.3)	-8.26(-33.5)	-8.99(-26.5)	-7.94(-39.8)
Other Activities	-10.20(-84.6)	-9.97(-87.9)	-10.3(-61.8)	-9.52(-31.7)	-9.04(-84.5)	-9.04(-84.8)
Gender (Male Base)						
Female - Shopping	0.06(0.79)	0.02(0.4)	0.13(1.6)	0.10(1.7)	0.16(1.8)	0.11(1.8)
Female -Active Rec.	-0.20(-1.97)	-0.26(-2.2)	-	-	-	-
Female - Pick / Drop	-	-	-	-	0.27(1.7)	0.13(1.5)
Age (30- 54 yrs base)						
18-29 yrs- Soc./Rec.	0.75(3.57)	0.50(3.8)	-	-	-	-
55-64 yrs - Medical	-	-	0.15(0.8)	0.07(0.54)	0.39(1.8)	0.28(1.9)
55-64 yrs - Eat out	-	-	0.39(2.0)	0.20(1.8)	-	-
55-64 yrs Pick/Drop	-0.48(-2.64)	-0.24(-2.3)	-0.38(-1.7)	-0.23(-2.2)	-	-
65-74 yrs.- Medical	0.28(2.33)	0.21(2.5)	0.16(0.9)	0.08(0.7)	0.30(1.5)	0.21(1.5)
65-74 yrs - Eat out	-	-	0.43(2.4)	0.21(1.9)	-	-
65-74 yrs Pick/Drop	-0.62(-3.78)	-0.29(-3.1)	-0.43(-1.9)	-0.26(-2.6)	-	-
≥75 yrs -Soc./ Rec.	-	-	-	-	-0.31(-2.5)	-0.18(-2.5)
≥75 yrs –Act. Rec.	-	-	-	-	-0.16(-1.2)	-0.21(-1.1)
≥ 75 yrs - Medical	0.24(2.11)	0.20(2.4)	0.20(1.1)	0.11(0.9)	0.36(1.8)	0.26(1.9)
≥ 75 yrs - Eat out	-	-	0.39(2.2)	0.19(1.8)	-	-
≥ 75 yrs -Pick/Drop	-1.00(-5.9)	-0.49(-5.1)	-0.65(-2.8)	-0.34(-3.3)	-0.59(-3.2)	-0.33(-3.1)
White race - Eat out	0.27(1.7)	0.17(1.8)	0.44(1.7)	0.24(1.6)	0.28(1.1)	0.15(1.0)
Driver(Non-driver)						
Driver – Other Main	0.44(2.4)	0.14(1.4)	-	-	-	-
Driver -Soc./ Rec.	-	-	-	-	0.68(2.9)	0.32(2.4)
Driver - Active Rec.	-	-	-	-	0.60(2.3)	0.90(2.4)
Driver - Pick/Drop	-	-	1.06(2.1)	0.37(1.7)	0.72(2.3)	0.33(1.8)

Table 5.1 (Contd.)

	South East Florida (SEF)		Central Florida (CF)		Tampa Bay (TB)	
	MDCEV Coef. (t-stat)	MDCHEV Coef.(t-stat)	MDCEV Coef.(t-stat)	MDCHEV Par. (t-stat)	MDCEV Coef. (t-stat)	MDCHEV Coef. (t-stat)
Education (H. Sch/low base)						
College-Oth Maint.	0.35(3.1)	0.17(2.76)	-	-	0.33(2.64)	0.15(2.3)
Bac./High-Oth Maint.	0.50(4.7)	0.27(4.52)	0.22(1.9)	0.07(1.3)	0.32(2.52)	0.13(1.9)
Bac./High-Active Rec.	0.20(1.8)	0.24(1.91)	0.39(2.9)	0.49(3.1)	0.21(1.51)	0.31(1.6)
Born in US						
Social/Recreational	0.17(1.7)	0.10(1.74)	-	-	-	-
Eat out	0.49(4.1)	0.30(4.19)	0.14(0.6)	0.08(0.7)	-	-
Number of Children						
0-5 years - Shopping	-	-	-0.50(-2.5)	-0.33(-2.4)	-0.14(-0.85)	-0.12(-1.0)
0-5 years - Oth Maint.	-0.29(-1.6)	-0.17(-1.64)	-0.26(-1.3)	-0.10(-1.1)	-	-
0-5 years - Pick/Drop	0.26(1.8)	0.16(1.44)	0.58(3.9)	0.30(3.8)	0.23(1.30)	0.11(1.0)
6-18 years - Pick/Drop	0.48(5.0)	0.28(4.88)	0.46(2.9)	0.20(2.6)	0.58(3.95)	0.34(3.8)
Income (<25K is base)						
25 -55 K - Oth Maint.	-	-	0.34(2.4)	0.15(2.2)	-	-
25 -55 K – Soc./Rec.	-	-	0.29(2.1)	0.16(1.8)	-	-
25 -55 K - Active Rec.	-	-	0.39(2.3)	0.44(2.2)	-	-
25 -55 K - Eat out	0.29(2.0)	0.17(1.94)	0.31(2.1)	0.16(1.8)	-	-
55 - 75k - Oth Maint.	-	-	0.28(1.6)	0.12(1.4)	-	-
55 - 75k - Soc./Rec.	-	-	0.27(1.6)	0.13(1.3)	-	-
55 - 75k - Active Rec.	0.28(2.0)	0.33(2.10)	0.43(2.1)	0.49(2.1)	0.19(1.02)	0.20(0.7)
55 - 75k - Eat out	0.30(1.8)	0.17(1.75)	0.33(1.9)	0.17(1.6)	0.31(1.87)	0.20(2.0)
>75 K - Oth Maint.	-	-	0.37(2.2)	0.15(1.8)	-	-
>75 K - Soc./Rec.	-	-	0.38(2.4)	0.18(1.9)	-	-
>75 K - Active Rec.	0.55(4.5)	0.63(4.41)	0.51(2.6)	0.54(2.4)	0.67(4.36)	0.88(4.0)
>75 K - Eat out	0.82(5.9)	0.46(5.42)	0.47(2.8)	0.23(2.2)	0.51(3.63)	0.29(3.5)
No. of Workers						
Shopping	-0.14(-2.2)	-0.09(-2.12)	-0.10(-1.2)	-0.06 (-1.0)	-	-
Pick-up/ Drop-off	-	-	0.14(1.2)	0.09(1.5)	0.38(3.24)	0.21(3.0)
# Recreation sites in a mile from HH. Social/Recreational	0.005(3.5)	0.003(3.81)	0.07(2.0)	0.04(1.9)	0.004(2.42)	0.002(2.1)
# Intersections in 0.25 miles from HH. Active Recreation	-	-	0.006(1.2)	0.005(1.0)	0.01(1.59)	0.01(1.7)
No. of Cul-de-sacs in 0.25 miles from HH. Active Recreation	0.009(0.9)	0.01(1.08)	-	-	-	-
Day of the Week						
Monday - Eat out	-0.28(-2.0)	-0.16(-1.87)	-0.16(-1.1)	-0.11(-1.2)	-	-
Friday - Soc./Rec.	-	-	0.22(1.8)	0.11(1.5)	0.19(1.38)	0.13(1.6)
Friday - Eat out	-	-	0.30(2.2)	0.16(2.0)	0.18(1.23)	0.12(1.4)
Satiation Parameters						
Constants						
Shopping	2.82(33.9)	3.25(38.3)	3.04(46.9)	3.55(48.7)	3.01(44.7)	3.51(45.4)
Other Maintenance	3.17(46.6)	3.96(54.8)	2.94(37.0)	3.89(50.0)	2.72(21.7)	3.66(29.6)
Social/ Recreational	4.31(49.4)	4.99(52.2)	4.19(49.0)	4.90(50.8)	4.44(46.9)	5.21(49.1)
Active Recreation	1.64(8.5)	1.46(6.6)	1.57(9.0)	1.37(6.5)	2.04(16.8)	1.48 (8.1)
Medical	3.38(42.4)	3.86(43.6)	3.11(32.6)	3.70(36.0)	3.19(31.7)	3.76(34.1)
Eat out	3.02(34.7)	3.71(40.2)	3.15(36.1)	3.86(41.1)	3.05(28.6)	3.80(34.8)

Table 5.1 (Contd.)

	South East Florida (SEF)		Central Florida (CF)		Tampa Bay (TB)	
	MDCEV Coef. (t-stat)	MDCHEV Par. (t-stat)	MDCEV Coef. (t-stat)	MDCHEV Par. (t-stat)	MDCEV Coef. (t-stat)	MDCHEV Coef.(t-stat)
Satiation Parameters (continued)						
Constants						
Pick-up/Drop-off	1.44(15.9)	2.32(23.5)	1.41(12.9)	2.49(22.5)	1.59(13.5)	2.37(19.4)
Other Activities	2.41(16.4)	2.41(16.4)	1.97(11.7)	2.20(10.0)	2.09(12.8)	2.09(12.8)
Gender (Male is Base)						
Female -Shopping	0.34(3.1)	0.34(3.5)	-	-	0.34(2.1)	0.26(2.0)
Female - Active Rec.	-0.25(-1.3)	-0.22(-1.1)	-	-	-	-
Age (<35 and >45 base) 35-45 years-Soc./Rec.	-0.32(-1.8)	-0.37(-2.2)	-	-	-	-
Education (< Col. base)						
S. College-Active Rec.	0.36(1.5)	0.34(1.3)	0.31(1.1)	0.27(0.9)	-	-
Bac.to Hi.-Active Rec.	0.94(4.28)	0.86(3.8)	0.76(2.9)	0.65(2.4)	-	-
Day of the Week						
Friday - Soc./Rec.	0.31(1.8)	0.34(2.1)	-	-	-	-
Friday - Eat out	0.26(1.4)	0.27(1.6)	-	-	0.39(1.6)	0.40(1.9)
Log-likelihood at constants	-29681.3	-29454.6	-20518.7	-20297.6	-18390.8	-18234.3
Log-likelihood at convergence	-29397.2	-29204.4	-20386.6	-20180.0	-18302.1	-18148.3

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District 1, and R: Rural Florida

different activities while normalizing the scale of in-home activity to 1. In the current empirical context, the MDCHEV estimates of scale for all out-of-home activities except active recreation and "other" activities are significantly smaller than 1, while that for active recreation is greater than 1 and that for "other" activity is not different from (therefore fixed to) 1. Similar patterns can be observed from the parameter estimates for all three geographical regions. Plausible reasons for these patterns in the scale parameter estimates are discussed next. As discussed in many references on choice modelling (e.g., Ben-Akiva and Lerman, 1985; Koppelman and Bhat, 2006), the random error terms ε_k represent a sum of errors (made by the analyst) in characterizing the consumers' utility functions. Commonly cited sources of errors include omitted alternative attributes and decision-maker characteristics, measurement errors in the explanatory variables included in the utility functions, and errors in the functional form of the utility function. In the current context, we attribute the specific patterns observed in the scale parameter estimates to the following three major sources of unobserved variation. First, recall from Section 5.4 that each activity category (i.e., choice alternatives) used in the model specification is an aggregation of many finely categorized activity types. The influence of explanatory variables included in the utility function of an aggregate activity category can potentially vary by each disaggregate activity type in that category. Such variation resulting from aggregation of choice alternatives is unobservable and manifests in the form of additional variance of random error terms (Daly, 1982). Among the nine activity categories considered in the current empirical context, the in-home activity is an aggregation of a wider variety of finer activities when compared to out-of-home activities. Recall that the in-home activity category combines all activities other than out-of-home activities into a *composite outside good*. This is one reason why the stochastic component of in-home activity has greater variance compared to most out-of-home activity categories. Second, note from Table 5.1 that the utility specifications for all activities except the in-home and "other" activity categories include explanatory variables. While the in-home activity category was treated as a reference alternative in the specification for identification purposes, no explanatory variable turned out to be significant in the utility function for the "other" activity category; presumably due to the arbitrary nature of the "other" activity category. Besides, similar to the in-home activity category, the "other" activity category combines all out-of-home activities other than those of interest into a single composite category. Thus, the final empirical specification of the deterministic utility components views in-home and "other" activities as similar (except the alternative-specific constant for "other" activity). This is perhaps a reason why the scale parameter for the "other" activity is not different from the in-home activity. Third, in the context of discrete-continuous choice modelling, measurement errors in the continuous dependent variables can potentially be significant. This is unlike traditional discrete choice models, where there might not be significant errors in dependent variables (because it is easier to elicit information on the discrete choice decisions made by the consumers than to measure the continuous quantity decisions). In the current empirical application, recall from Section 5.4 that time allocation to the active recreational activity might be associated with substantial measurement errors leading to greater unobservable variation. This may be a reason why the estimated scale parameter for the active recreational activity is greater than 1.

In summary, The MDCHEV model estimates reveal the presence of substantial heteroscedasticity in the random utility components of choice alternatives and point to different sources of unobservable variation.

5.5.1.2 Baseline Utility and Satiation Parameters

All the parameter estimates in baseline utility and satiation functions have intuitive interpretations and identical signs in both the MDCEV and MDCHEV models for all three regions. The substantive interpretations are not a focus of this chapter. Therefore only the influence of incorporating heteroscedasticity on parameter estimates is discussed. Specifically, for all out-of-home activities, except active recreation, the magnitude of baseline utility parameter estimates in the MDCHEV model is slightly smaller than that in the MDCEV model. For active recreation, however, the baseline utility parameter estimates from the MDCHEV model are of greater magnitude than those from MDCEV. This pattern can be attributed to the differences in scale parameters between the MDCEV and MDCHEV models. Specifically, the baseline parameter estimates in the MDCEV model are confounded with the unknown scale parameters (which are simply assumed to be equal to 1). But the MDCHEV model helps in disentangling the baseline parameter estimates from the scale difference between the out-of-home and in-home activities. As a result, all activities with smaller (greater) scale parameters in the MDCHEV than in MDCEV model have smaller (larger) magnitudes for baseline parameter estimates from the former model.

In the context of satiation functions, the parameter estimates of MDCHEV model are greater (in magnitude) for all out-of-home activities that have a tighter distribution of the random utility component (i.e., smaller scale parameter) than that in the MDCEV model. For active recreation activity, the satiation function parameter estimates of the MDCHEV model are smaller in magnitude than those from the MDCEV model.

Since the true parameter values are unknown, it is difficult to assert which model provides better/less-biased parameter estimates. However, note from the log-likelihood measures for all three geographical regions (last two rows of the table) that the MDCHEV model yields a significantly better fit to the estimation data than the MDCEV model. For example, the likelihood ratio test statistic between the two models for the South East Florida region is 385.12, which is larger than the chi-squared statistic with four degrees of freedom at any reasonable level of significance. This suggests that ignoring heteroscedasticity (i.e., estimating an MDCEV model) can potentially lead to biased parameter estimates in both baseline marginal utility and satiation functions and inferior model-fit.

5.5.2 In-sample Prediction Performance

Table 5.2 presents the predicted aggregate shares of individuals participating in each activity type (i.e., the discrete choice component) for both MDCEV and MDCHEV models for all three geographical regions. The predicted aggregate shares for each activity were computed as the proportion of instances the activity was predicted with a positive time allocation across all 100 sets of random draws for all individuals. For each prediction result presented, the corresponding observed values in the estimation sample are presented in the parentheses. As can be observed from the table, both the MDCEV and MDCHEV models perform well in predicting the aggregate shares of participation in each activity type.

Table 5.2: Predicted and Observed Activity Participation (% participation) Rates

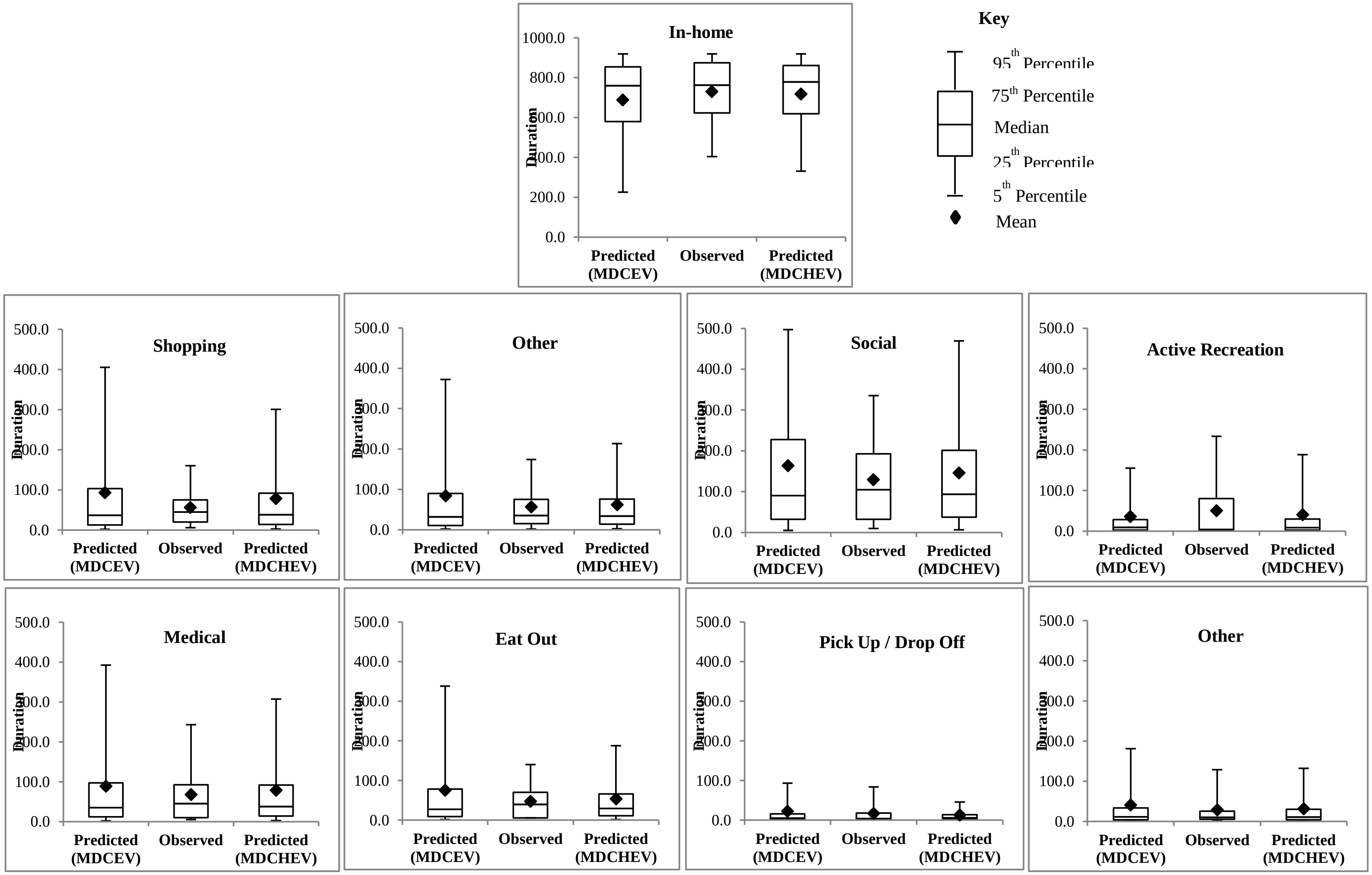
		In-home	Shop.	Other Maint.	Soc./Rec.	Active Rec.	Medical	Eat Out	Pick / Drop	Other
SEF	% Part. (MDCEV)	100.0 (100.0)	49.2 (51.0)	29.9 (30.6)	29.0 (30.5)	19.1 (20.6)	23.1 (24.8)	22.8 (24.3)	16.0 (17.0)	5.3 (5.7)
	% Part. (MDCHEV)	100.0 (100.0)	47.6 (51.0)	29.3 (30.6)	29.0 (30.5)	19.8 (20.6)	22.9 (24.8)	22.2 (24.3)	16.0 (17.0)	5.5 (5.7)
CF	% Part. (MDCEV)	100.0 (100.0)	49.3 (49.9)	30.9 (30.4)	29.1 (30.0)	20.4 (21.9)	23.0 (24.3)	26.2 (27.2)	15.5 (16.2)	5.3 (5.7)
	% Part. (MDCHEV)	100.0 (100.0)	47.1 (49.9)	30.3 (30.4)	28.5 (30.0)	21.0 (21.9)	22.8 (24.3)	25.3 (27.2)	15.3 (16.2)	5.5 (5.7)
TB	% Part (MDCEV)	100.0 (100.0)	47.9 (48.5)	31.9 (31.6)	26.3 (27.1)	19.6 (21.2)	22.4 (23.4)	23.6 (24.4)	14.4 (15.5)	6.6 (7.0)
	% Part (MDCHEV)	100.0 (100.0)	45.9 (48.5)	31.1 (31.6)	25.8 (27.1)	20.3 (21.2)	21.9 (23.4)	22.9 (24.4)	14.3 (15.5)	6.8 (7.0)

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District 1, and R: Rural Florida

To evaluate the model predictions of time allocations to each activity (i.e., the continuous choice component), the distributions of the predicted time allocations (for only those predicted with positive time allocation) were compared with the distributions of observed time allocations. (again, for only those observed with positive time allocation). The distributions are presented in the form of box-plots in Figure 5.1 (for

South East Florida region only). There are total of 9 sub-figures in Figure 5.1, one for each activity type. In each sub-figure, the distributions of predicted activity durations from both MDCEV and MDCHEV models are presented as box-plots along with the distributions of observed activity durations. Interesting observations can be made from these box-plots. First, in the context of in-home activities, the predicted distributions from both the MDCEV and MDCHEV models show larger left tails than the observed distribution. However, the discrepancy between predicted and observed distributions is much greater for the MDCEV model than for the MDCHEV model. This suggests a greater chance of under-prediction of in-home activity durations by the MDCEV model. Second, for all out-of-home activities other than active recreation, the distributions of activity durations predicted with the MDCEV model show a significant chance of over-prediction. For active-recreation, the MDCEV model shows under-prediction of activity durations when compared to the observed data. Third, the MDCHEV model rectifies all these issues to a considerable extent. As can be observed, the predicted distributions of the MDCHEV model are much closer to the observed distributions than those of the MDCEV model for almost all activities.

The differences in the distributional assumptions between the MDCEV and MDCHEV models explain the above differences in performance between the two models. The MDCEV model assumes unit scale parameter for all activity categories. For all activities for which the “true” scale parameter is smaller than the assumed value, the MDCEV model shows significant over-prediction of activity durations. These include all out-of-home activities other than active recreation. This is due to the the asymmetry and the *fat right tail* of the standard Gumbel distribution used in its structure. For instance,



* The range of the duration in vertical axis is different for in-home activities

* The statistics are only for those predicted (or, orbserved) with positive time allocations to different activities

Figure 5.1: Observed and Predicted Distributions of Activity Durations (for the Southeast Florida Region)

the probability of drawing any less than -2 from a standard Gumbel distribution is very low (0.06%), while that of drawing greater than 2 is high (12.65%). Since the Gumbel terms enter the model in an exponentiated multiplicative fashion (i.e., $\psi_k = \exp(\beta' z_k) \times \exp(\varepsilon_k)$), there is a non-negligible chance that the ψ_k values become quite large and therefore lead to unrealistically large time allocations for several out-of-home activities (e.g., 700 minutes for out-of-home eating activity!). Whenever an out-of-home activity hogs up a large amount of available time budget, it leaves a very small amount of time for the in-home activity (hence the under-prediction of time allocation for the in-home activity). Therefore, employing a larger value (than what it is) for the scale parameter of an activity implies a fatter right tail for the random utility component, which in turn implies a fatter right tail (than what it should be) for the distribution of the predicted consumptions/durations. Similarly, a smaller value of the scale parameter assumed in the MDCEV model for active recreation (than what is revealed in the MDCHEV model) leads to under-estimation of the time allocated to active recreational activities.[10]

The MDCHEV model overcomes the above-discussed problems by allowing the scale parameters to be different from each other. Recall that the MDCHEV scale parameter estimates are smaller than 1 for all out-of-home activities except active recreation and "other" categories. This implies tighter distributions of the ψ_k values and therefore a smaller chance of over-prediction of time allocation for those activities. For active recreation, the estimated scale parameter in the MDCHEV model is greater than 1.

[10] The under-estimation is with respect to the observed values, assuming that the observed values are free of errors.

This implies a more spread-out distribution of the corresponding ψ_k value than that in the MDCEV model, and hence a smaller chance of under-estimation.

In summary, the in-sample prediction exercises suggest that both the MDCEV and MDCHEV models perform similarly in predicting the aggregate discrete-choice shares for each activity type. However, the MDCHEV model performs far better than the MDCEV model in predicting the time allocation to different activities. Note, however, that the MDCHEV-predicted durations are still not very close to the observed durations. In this context, exploring the influence of alternative distributional assumptions to extreme value distributions – including right-truncated extreme value distributions, multivariate normal distributions, and multivariate skew-normal distributions – on the prediction properties of MDC models is a useful avenue for further research.

5.5.3 Transferability Assessments

This subsection examines the influence of incorporating heteroscedasticity on the transferability of MDCEV and MDCHEV models among different geographical regions in Florida. Specifically, both the models estimated for each of the three geographical regions (SEF, CF, and TB) were transferred to the other two regions. Thus, 12 transfers were performed in total – 6 for the MDCEV model and 6 for the MDCHEV model. Subsequently, three different types of transferability metrics were used to assess model transferability: (1) log-likelihood based measures, (2) measures of aggregate-level predictive ability, and (3) model sensitivity to changes in explanatory variables. The results obtained from these metrics are discussed next.

Note that, in all transferability assessments, the geographical context from which a model is transferred is called the *estimation context* and the geography to which a model is transferred is called the *application context*. For the application context, a model estimated using data from the same geography is called the *locally estimated model* and a model transferred from a different geography is called the *transferred model*.

5.5.3.1 Log-likelihood Based Measures of Transferability

Table 5.3 presents the log-likelihood values of the transferred and locally estimated MDCEV and MDCHEV models for each of the 12 model transfers conducted in this chapter. One can observe that, for model transfers between any two regions (i.e., in any row of the table), the predictive log-likelihood of the transferred MDCHEV model (column 5) is better than that of the transferred MDCEV model (column 3), suggesting that an MDCHEV model transfers better than an MDCEV model. What is more interesting is that the log-likelihood of all transferred MDCHEV models (column 5) are better than that of the corresponding locally estimated MDCEV models (column 4). This highlights the importance of incorporating heteroscedasticity in improving the spatial transferability of MDC models.

Table 5.3 Transferability Assessment Results: Log-likelihood of Transferred and Locally Estimated Models

Transferred Form	Transferred To	Log-likelihood Values			
		Transferred MDCEV	Local MDCEV	Transferred MDCHEV	Local MDCHEV
SEF	CF	-20448.60	-20386.63	-20257.74	-20180.03
	TB	-18367.31	-18302.08	-18223.37	-18148.27
CF	SEF	-29513.25	-29397.16	-29348.51	-29204.44
	TB	-18349.97	-18302.08	-18217.24	-18148.27
TB	SEF	-29598.86	-29397.16	-29393.82	-29204.44
	CF	-20481.40	-20386.63	-20274.07	-20180.03

* SEF: Southeast Florida, CF: Central Florida, TB: Tampa Bay, DIU: Urban area in Florida District 1, and R: Rural Florida

To quantify how much better the transferability of an MDCHEV model is over that of an MDCEV model, Transferability Index (TI) value (as suggested in Koppelman and Wilmot, 1982) was computed. TI measures the degree to which the log-likelihood of a transferred model exceeds that of a reference model relative to a locally estimated model in the application context (Koppelman and Wilmot, 1982).

$$TI_j(\beta_i) = \frac{L_j(\beta_i) - L_j(\beta_{reference,j})}{L_j(\beta_j) - L_j(\beta_{reference,j})} \tag{5.8}$$

where, $L_j(\beta_i)$ = log-likelihood of the transferred model applied to the application context data, $L_j(\beta_j)$ = log-likelihood of the locally estimated model, and $L_j(\beta_{reference,j})$ is the log-likelihood of a locally estimated reference model (e.g., a constants only model). In this chapter, the constants only specification of the MDCEV structure is taken as the reference model. The closer the value of TI is to 1, the closer is the transferred model's performance to a locally estimated model (in terms of the information captured in the application context relative to the reference model). The TI values for all transfers conducted in the chapter are presented in Table 5.4. The diagonal elements in the table that have a TI value of 1 (in bold) are not of interest, because they are not for model transfers from one region to another. It can be observed from the non-diagonal elements that incorporating heteroscedasticity lead to a considerable improvement in the TI value. For example, for models transferred from South East Florida and Central Florida, allowing for heteroscedasticity resulted in an improvement of the TI value from 0.53 to

Table 5.4 Transferability Assessment Results: Transfer Index (TI)

Transferred To / Transferred From	SEF		CF		TB	
	MDCEV	MDCHEV	MDCEV	MDCHEV	MDCEV	MDCHEV
SEF	**1.00**	**1.00**	0.53	0.77	0.26	0.69
CF	0.59	0.70	**1.00**	**1.00**	0.46	0.72
TB	0.29	0.60	0.28	0.72	**1.00**	**1.00**

0.77 (or 53% to 77%). Similar improvements in TI values can be observed for all other transfer as well.

5.5.3.2 Aggregate-level Predictive Accuracy

To assess the aggregate-level predictive accuracy of the transferred models, two types of root mean square error (RMSE) metrics were used in this chapter: (1) RMSE for the discrete (activity participation) choice component, and (2) RMSE for the continuous (time allocation) component.

$$RMSE = \left(\frac{\sum_k P_k \times REM_k^2}{\sum_k P_k} \right)^{1/2} \tag{5.9}$$

where, P_k and O_k are the aggregate predicted and observed shares for activity type k, respectively (or durations averaged over all individuals who participated in activity type k), and $REM_k = \{(P_k - O_k)/O_k\}$ is the percentage error in the prediction of alternative k.

Table 5.5 reports the RMSEs for all transfers conducted in the chapter. As expected, in any row of the table, the aggregate errors of the locally estimated models (in bold) are lower than those of transferred models of the same model structure. For any

Table 5.5 Transferability Assessment Results: Root Mean Square Error (RMSE)

	Transferred To → / Transferred From ↓	SEF		CF		TB	
		MDCEV	MDCHEV	MDCEV	MDCHEV	MDCEV	MDCHEV
Discrete Component	SEF	**0.03**	**0.05**	0.04	0.04	0.07	0.06
	CF	0.04	0.08	**0.04**	**0.04**	0.04	0.06
	TB	0.05	0.08	0.06	0.09	**0.03**	**0.04**
Continuous Component[1]	SEF	**0.11**	**0.07**	0.31	0.16	0.31	0.16
	CF	0.16	0.07	**0.16**	**0.07**	0.18	0.10
	TB	0.17	0.08	0.16	0.10	**0.17**	**0.08**

transfer, the RMSEs for the discrete components of the two model structures (MDCEV and MDCHEV) are very similar. However, considerable differences can be observed in the RMSEs for the continuous components of the two model structures. Specifically, the RMSEs for the continuous component of the MDCHEV models (both transferred and locally estimated models) are considerably smaller than the corresponding values for the MDCEV models. A closer examination suggests that the RMSEs for the continuous component of even transferred MDCHEV models are smaller than those of locally estimated MDCEV models, suggesting that the transferred MDCHEV models are providing better prediction performance than locally estimated MDCEV models. Recall that predictive log-likelihood values of the transferred MDCHEV models were better than the log-likelihood values of locally estimated MDCEV models. These results reiterate the benefit of incorporating heteroscedasticity in improving the spatial transferability of MDC models.

5.4.3.3 Response to Changes in Explanatory Variables

To compare the transferability of MDCEV and MDCHEV models based on their responses to changes in explanatory variables, we simulated the influence of a scenario where the age of individuals older than 29 years was increased by 10 years (to reflect aging of the population). Each estimated model was applied to its own estimation sample as well as the other two geographical context datasets for both base and policy scenarios. To measure the resulting changes in the time-use patterns, a *policy response* measure was computed. To do so, first, for each set of error term draws for each individual, the overall change in activity participation and time-use patterns was measured as below (see Jaggi et al., 2011):

$$T_c = \frac{1}{T}\left(\sum_{k=1}^{K} \frac{|\hat{t}_k^p - \hat{t}_k^b|}{2} \right) \tag{5.10}$$

where, $\hat{t}_k^p$ is the predicted duration for alternative k in the policy case, and $\hat{t}_k^b$ = predicted duration for alternative k in the base case. Next, the above metric was averaged over all sets of error term draws for all individuals.

The *policy response* measure was computed for 50 sets of bootstrapped values drawn from the sampling distributions implied by the parameter estimates and their covariance matrix. Table 5.6 presents the policy response measures for all transferred and locally estimated models in the form of average policy response values (averaged over all bootstrapped estimates). The corresponding standard errors are provided in the parentheses next to each average policy response measure. Since the true policy response is unknown, the policy response obtained from the model with the best data fit (i.e., the locally estimated MDCHEV model) in each region is taken as the reference for that region. The corresponding cells in the table are shaded in gray. The transferability performance of transferred MDCEV and MDCHEV models are assessed by comparing their policy response measures to that from the corresponding reference model (i.e., the policy response measure from the locally estimated MDCHEV model).

Table 5.6 Transferability Assessment Results: Policy Response Measures

Transferred To / Transferred From	SEF		CF		TB	
	MDCEV	MDCHEV	MDCEV	MDCHEV	MDCEV	MDCHEV
SEF	2.76 (0.71)	**2.30 (0.57)**	3.19 (0.84)	2.68 (0.68)	2.39 (0.80)	2.59 (0.65)
CF	2.92 (0.72)	1.96 (0.49)	3.40 (0.85)	**2.30 (0.59)**	2.17 (0.78)	2.13 (0.54)
TB	5.42 (1.43)	4.31 (1.10)	6.01 (1.61)	4.80 (1.24)	5.46 (1.44)	**4.33 (1.11)**

It can be observed that, for each of the three regions, the policy response measures of transferred MDCHEV models are better than (i.e., closer to the policy response implied by the locally estimated MDCHEV model) those of the transferred MDCEV models. Further, except for transfers to and from the Tampa bay region, the policy response of a transferred MDCHEV model appears to be better even than that of a locally estimated MDCEV model. These results suggest that improvement in model structure (i.e., incorporation of heteroscedasticity) has not only resulted in a better data-fit but also a better ability to predict responses to changes in explanatory variables.

In summary, all the transferability assessments conducted in this chapter suggest that the proposed methodological extension (of incorporating heteroscedasticity) helps in enhancing the spatial transferability of time-use models. That is, empirical models based on the MDCHEV structure are more transferable than those based on the MDCEV structure.

5.6 Summary

This chapter presents a Multiple Discrete Continuous Heteroscedastic Extreme Value (MDCHEV) model that allows heteroscedastically (i.e., independent but non-identically) distributed type-1 extreme value random utility components in multiple discrete continuous (MDC) models. Heteroscedasticity is accommodated by allowing the scale parameters of the random utility components to be different across the different choice alternatives. Therefore, the MDCHEV model collapses to the MDCEV model when all the scale parameters are constrained to be equal. The likelihood of the MDCHEV model is a uni-dimensional integral that can be easily evaluated using familiar quadrature techniques.

In addition to formulating the MDCHEV model, this chapter investigates the influence of improved model structure (i.e., incorporation of heteroscedasticity in the MDC model) on the transferability of daily activity participation and time use model among different geographical regions in Florida. To do so, the MDCHEV and the MDCEV models are compared in terms of their empirical parameter estimates, in-sample prediction performance, and transferability to different geographical regions. The National Household Travel Survey (NHTS) data for three major urban regions in Florida – South East Florida, Central Florida, and Tampa Bay – was used for the empirical analysis. For spatial transferability assessments, the models estimated for each of the three regions were transferred to the other two regions.

The parameter estimates of the MDCHEV model reveal the presence of substantial differences in the scale parameters (i.e., heteroscedasticity) of the random utility components across different activity type choice alternatives. Plausible reasons for heteroscedasticity include aggregation of choice alternatives into broader activity categories and measurement errors in the continuous dependent variables. These findings suggest that data collection efforts and model specifications for discrete-continuous choice models need to be cognizant of potential aggregation and measurement errors.

Neglecting heteroscedasticity (when present) in MDC models can have several ramifications. As revealed from the empirical application in this chapter, ignoring heteroscedasticity can potentially lead to biased parameter estimation and inferior statistical fit to the estimation sample. Furthermore, the predicted distributions of the continuous quantity decisions (time allocations, in the current empirical context) can be distorted when compared to the distributions observed in the estimation sample.

Specifically, the MDCEV-predicted distributions of continuous quantities exhibit thicker right tails (i.e., greater chance of over-prediction) for some alternatives and thinner right tails (i.e., greater chance of under-prediction) for other alternatives when compared to the distributions observed in the estimation sample. In the current empirical context, the time allocations for many out-of-home activities were over-estimated and those for in-home and active recreation activities were under-estimated. The MDCHEV model overcomes these issues to a considerable extent by allowing the scale parameters to be different from each other. This results in tighter (wider) distributions of random utility components for the alternatives for which the MDCEV over-predicts (under-predicts) the time allocations and therefore reduces the chances of over-prediction (under-prediction).

Spatial transferability assessments using a variety of different assessment metrics suggest better predictive ability for MDCHEV models transferred from other regions than MDCEV models transferred from those same regions. In most cases, the transferred MDCHEV models appear to perform not only better than transferred MDCEV models but also better than locally estimated MDCEV models. These results not only reiterate the importance of incorporating heteroscedasticty in MDC choice models, but also suggest that the proposed enhancement to the model structure lead to an enhanced spatial transferability of time-use models. A caveat is in order here regarding the transferability results. All the transferability results in this chapter are based on relative transferability assessments. Specifically, the transferability of a model is assessed by comparing the performance of a transferred model with that of a locally estimated model assuming that the locally estimated model is perfect in the context it is estimated for. Finally, additional empirical assessments are warranted to corroborate the conclusions from this chapter.

CHAPTER 6

AN EMPIRICAL ASSESSMENT OF THE SPATIAL TRANSFERABILITY OF TOUR-BASED TIME-OF-DAY CHOICE MODELS

6.1 Introduction and Motivation

As discussed in the previous chapters, spatial transferability of the tour-based/activity-based models has become extremely relevant, due to the potential it offers for cost and time-savings. However, the available empirical evidence on the transferability of tour-based models is limited at best, with only a handful of recent studies (e.g., Nowrouzian and Srinivasan, 2012) documenting transferability of tour-based model components. Within the limited available literature on this topic, we are not aware of any documented transferability assessments of tour-based time-of-day (TOD) choice models that are used to forecast the timing of travel of residents (and the resulting temporal variations in travel patterns) in a study area.

A sound time-of-day choice model is paramount to an activity-based model system (ABM). This is because evaluations of travel demand management strategies (such as time-of-day based congestion pricing) rely on accurate predictions of the temporal variation of travel volumes in the study region. Besides, accurate estimation of vehicular emissions and resulting air quality impacts depends on the accuracy of the predicted temporal variations in travel, which in turn depends on the quality of underlying time-of-day (TOD) choice models. Considering the importance of the TOD model, several studies in literature (e.g., Abou Zeid et al., 2006; Komma and Srinivasan, 2008; Popuri et al., 2008; Lemp, 2010) developed this model component of activity-based model systems. But none of them assessed the spatial transferability of this model component. Thus, as Abou Zeid et al. (2006) mentioned, transferability assessment of time-of-day (TOD) choice models is a potentially fruitful avenue for research.

6.2 Contribution and Organization of the Chapter

In view of the above discussion, this chapter aims to provide an empirical assessment of the spatial transferability of tour-based time-of-day choice models. The specific time-of-day choice model of interest in this chapter is the work tour start- and end-time choice model for employed adults over the age of 18.

The geographical regions considered in this chapter are the nine counties in the San Francisco Bay Area of California – Alameda, Contra Costa, Marin, Napa, Santa Clara, San Francisco, San Mateo, Solano and Sonoma. For transferability assessments, we focus on the following four counties: Alameda (AL), San Francisco (SF), Santa Clara (SC), and San Mateo (SM). Specifically, we test the transferability from each of these four counties to the other. In addition, for each county, we assess if a model built using data pooled from all other eight counties is better transferable than a model from only one of the counties.

The model structure used in this chapter is the multinomial logit (MNL) model. To model the time-of-day choices at a fine temporal resolution, individuals work tour start-and end-times were categorized in terms of discrete, half hour timing intervals in a day (see next section for a detailed discussion on this categorization procedure). Each feasible combination of work tour start-time interval and end-time interval was treated as a discrete choice alternative in the MNL model. To get time-varying transportation system characteristics (i.e., travel time) for each of these alternatives, an auxiliary regression model was developed.

So far in the dissertation, the primary approach used to assess transferability was the “application-based” approach, in which the base context model was “applied” in the application context to assess its transferability. In this chapter, in addition to using the “application-based” approach, another approach called the “estimation-based” approach (recently used by Bowman et al. 2013) is used to investigate model transferability. The basic idea behind the estimation approach is to estimate a joint model by combining data from both the base context and the application context (this approach is called joint context estimation) and assess if the parameter estimates are different between the two contexts for each parameter in the model. To do so, one can estimate “difference” parameters that capture the differences in the parameters between the base and estimation contexts. Simple t-tests or log-likelihood ratio tests on these “difference” parameters shed light on whether the parameter estimates are different between the two contexts. A particular advantage of this approach is that one can test if each (and every) parameter in a model is transferable or not (as opposed to the entire model) and understand which parameters are more transferable and which parameters are not. Once statistically different parameters are identified, further tests can be conducted to see if these differences are practically important. On the other hand, the “application-based” approaches generally test the transferability of models as a whole, and do not allow an examination of which parameters are transferable and which are not (unless the sensitivity of each parameter is compared through elasticity values, marginal effects, etc.).

Two important caveats related to the "estimation-based" approach are in order here. First, the relative scale between the two contexts needs to be estimated, lest the scale differences between the two contexts can confound the results. In this chapter, we assumed that there are no scale differences between the different counties in the San Francisco Bay area for the time-of-day choice model. This assumption can potentially be contested. Second, issues due to small sample sizes can confound transferability assessments. Some of the counties have smaller data samples for which the transferability assessments ought to be made with extreme caution. Of course, this caution applies equally to the application-based approach as well.

The remainder of this chapter is organized as follows. The next section provides an overview of the data used in the analysis. Section 6.4 discusses the model structures and transferability assessment approaches used in this chapter. Section 6.5 summarizes the regression and TOD model estimation results. Section 6.6 discusses the transferability assessment results. Section 6.7 provides a summary of the chapter.

6.3 Data

6.3.1 Data Source

The primary data source used for the analysis is the 2000 San Francisco Bay Area Household Travel Survey (BATS) designed and administered by MORPACE International Inc. for the Bay Area Metropolitan Transportation Commission. This survey collected detailed information on the daily activity and travel episodes for 34,680 individuals in the San Francisco Area for a two-day period. In addition to the data from this travel survey, data on zonal-level land use (e.g., area types) and transportation level-of-service measures (e.g., travel time and travel cost) were obtained from the Metropolitan Transportation Commission (MTC).

6.3.2 Sample Formation

Two sets of data were formed for the analysis: (1) for travel duration regression model, and (2) for time-of-day (TOD) choice model. The next subsections describe the procedures of the final sample formation using the above mentioned primary and secondary sources of data.

6.3.2.1 Sample Formation for Travel Duration Regression Model

This subsection describes the procedure used to form the sample for travel duration regression model. The following steps were undertaken in this procedure:

1. First, only the weekday auto trips were selected from the data set. Then for each trip, travel duration was calculated from trip start- and end-times.

2. Next, a trip was removed from the data set if the reported travel duration was greater than 2 hours or the trip distance was greater than 50 miles (these conditions were developed based on the empirical considerations for the BATS data, see Komma and Srinivasan, 2008 for details).

3. For the remaining trips, the necessary inter-zonal level of service (such as free flow travel time, peak and off-peak travel time, and travel cost) and land-use variables were appended based on trip origin and destination zone information.

4. The 24 hr day was categorized into 48 half hour timing intervals (3:00 -3:30 AM, 3:30 - 4:00 AM, and so on). Next, travel duration of the trips occurring between the same origin-destination zones and at the same time period were averaged across trips.

5. Finally, the ratio of the average travel duration and free flow time was used as dependent variable in the regression model.

6.3.2.2 Sample Formation for Time-of-Day Choice Model

This subsection describes the procedure used to prepare the sample for the tour-based time-of-day choice models. In activity-based model systems, a tour is usually defined as a journey that starts and ends at the same location and consists of more than one trip. In this research, we focus only on the home-based work tour, meaning the tour that starts and ends at home and the primary purpose is work. The following steps were undertaken to prepare the home-based work tour data set.

1. Only the employed adults (aged 18 years or over) surveyed on a weekday with at least one out-of-home work activity on any of the survey days were selected.

2. Next, a home-based work tour data set was created from the activity information available for each individual in the data set.

3. Finally, records with missing information were removed. For example, the tours for which the zone information (i.e., either home or work zone) is missing were removed from the data set. This is because several land-use and transportation level-of-service variables were added in the data set based on zone information. The resulting sample comprises 19,785 records. Each of these records represents a tour that starts and ends at home. Note that this number includes the work tours undertaken in both days of the survey period. To avoid correlations across tours made by a single individual, only one tour per person was selected for the final model estimation, resulting in a sample of 10,063 tours.

4. To create the alternatives for the TOD model, first the entire day was divided into 48 half-hour time slots. Next, based on the observed tour start- and end-times in the data set and common perceptions, some of the consecutive half-hour time intervals were aggregated into larger time intervals. As a result, a total of 25 different time-slots were used for the tour start time choice (i.e., the 48 half-hour intervals in a day were aggregated into 25 intervals) and 21 time-slots were used for the tour end time periods (i.e., the 48 half-hour intervals in a day were aggregated into 21 intervals). Since the model will be developed for predicting the joint choice of tour start-and end-times, the tour start time slots were combined with those of tour end time slots, resulting in a total 386 alternatives, each representing a combination of tour start and tour end time slots. As a result, the MNL model has a total of 386 start and end time combination alternatives.

6.3.3 Geographical Regions Considered for Transferability Assessment

As mentioned earlier, the geographical regions considered in this chapter are the nine counties in the San Francisco Bay Area of California – Alameda, Contra Costa, Marin, Napa, Santa Clara, San Francisco, San Mateo, Solano and Sonoma. For transferability assessments, we focus on the following four counties: Alameda (AL), San Francisco (SF), Santa Clara (SC), and San Mateo (SM). Specifically, we test the transferability from each of these four counties to the other using the application-based approach (specifically, by computing the transfer index value). In addition, for each county, we assess if a model built using data pooled from all other eight counties is better transferable than a model from only one of the counties. This is done using the joint context estimation-based approach where a model was estimated by combining data from all 9 counties, but with county-specific "difference" variables. As explained before, this helps in comparing the parameter estimates for each (and every) variable in the model and shed light on which are transferable to each county from the rest the Bay area. In addition to examining the "difference" variables, from the jointly-estimated models for each of the four Counties, the county-specific model and the model for the rest of the Bay area were extracted. The latter models are labeled the base-c models[11]. Subsequently, the base-c model was transferred to the data from each County to compute the transfer index value.

6.3.4 Sample Description

Table 6.1 presents the descriptive information about the data with the first row presenting information on the sample sizes for different geographies considered in the analysis. It can be observed from the table that the employed adults in Santa Clara are different from those in other counties – at least in some socio-demographic characteristics. For example, there appear to be greater proportions of full time workers, flexibility in work schedules, and higher income levels in Santa Clara than in other three counties. Greater proportions of females and Caucasian individuals are observed in San Mateo (than in other counties). In the contexts of land use characteristics and household structures, San Francisco County appears to be different than the other counties in the Bay Area. Specifically, greater proportions of single person households, employed adults living in urban areas are observed in San Francisco County. It is important to note that the sample size for San Francisco County is small (538), which can make it difficult to interpret the model transferability results with high confidence. Though the descriptive

[11] From now on and throughout the chapter, the model for nine counties (as a whole) will be indicated by the term "base" model and the model for eight counties (i.e., the pooled model without a specific county) will be indicated by the term "base-c" model, where c denotes Al (Alameda), SC (Santa Clara), SF (San Francisco), or SM (San Mateo). For example, "base-AL" indicates the model that includes all counties in the Bay Area except Alameda.

statistics cannot shed full light on the transferability of a time-of-day choice model, the noted differences may, in part, have a bearing.

Figure 6.1 presents the tour start-and end-time profiles (i.e., the percentage of the work tours starting and ending during 24 discrete time-choice periods) of the employed adults in the Bay Area. As can be observed from the figure, the morning and evening peaks occur in the periods 7:30 - 8:00 AM and 5:30 - 6:00 PM respectively.

6.4 Methodology

In this section, we discuss the approaches used for: (1) The ordinary least squares (OLS) regression model developed for estimating the time-varying travel time variables needed as explanatory variables for the time of day choice model, and (2) The multinomial logit (MNL) model used in the time-of-day choice modeling, and the transferability assessment approaches used in this chapter.

6.4.1 Travel Duration Regression Model

As discussed earlier, the main reason for estimating OLS regression models in this chapter is to predict travel durations at the categorized discrete timing intervals in a day for any origin-destination pair. Such regression models were developed in several studies in the literature (see, e. g., Abou -Zeid et al. 2006, Komma and Srinivasan 2008, Popuri et al. 2008). Among these, Komma and Srinivasan (2008) used the ratio of reported travel times to free flow times as dependent variable and several zonal land-use characteristics (e.g., area types), trip distance and travel time as independent variables in the regression model. A similar approach is used here to model the inter-zonal travel

Table 6.1 Sample Characteristics

	Alameda	Santa Clara	San Francisco	San Mateo	All Counties
Sample Size	1940	3001	538	1209	10063
Gender					
Male	53.6(%)	56.2(%)	56.9(%)	50.04(%)	53.18(%)
Female	46.4(%)	43.8(%)	43.1(%)	49.96(%)	46.82(%)
Age					
19-25 (young adult)	7.1(%)	6.1(%)	4.5(%)	6.0(%)	5.9(%)
26-65 (middle-aged)	90.0(%)	91.7(%)	93.7(%)	91.0(%)	91.5(%)
65+ (elderly)	2.9(%)	2.1(%)	1.9(%)	2.9(%)	2.5(%)
Ethnicity					
Caucasian	73.4(%)	72.8(%)	72.3(%)	77.9(%)	77.5(%)
African American	4.6(%)	1.6(%)	2.8(%)	1.5(%)	2.4(%)
Asian/Pacific Islander	11.9(%)	15.8(%)	13.8(%)	10.3(%)	10.3(%)
Other	10.1(%)	9.8(%)	11.1(%)	10.3(%)	9.8(%)
Occupation					
Govt. Employee	18.2(%)	10.1(%)	17.3(%)	14.0(%)	15.2(%)
Others	81.8(%)	89.9(%)	82.7(%)	86.0(%)	84.8(%)
Employment Status					
Full-Time	87.8(%)	90.0(%)	93.7(%)	89.3(%)	88.9(%)
Part-Time	12.2(%)	10.0(%)	6.3(%)	10.7(%)	11.1(%)
Flexibility					
Yes	63.8(%)	74.4(%)	70.4(%)	68.7(%)	66.4(%)
No	36.2(%)	25.6(%)	29.6(%)	31.3(%)	33.6(%)
Household Size					
1	16.0(%)	15.1(%)	28.6(%)	17.0(%)	15.8(%)
2	36.9(%)	40.9(%)	43.7(%)	40.7(%)	40.2(%)
3+	47.1(%)	44.0(%)	27.7(%)	42.3(%)	44.0(%)
Number of Children					
0	63.4(%)	64.3(%)	78.6(%)	66.8(%)	64.3(%)
1	16.4(%)	15.7(%)	8.7(%)	14.1(%)	15.2(%)
2	15.5(%)	15.1(%)	10.6(%)	15.1(%)	15.5(%)
3+	4.7(%)	4.9(%)	2.1(%)	4.0(%)	5.0(%)
Household Income					
Low(<=25K)	2.7(%)	1.5(%)	2.8(%)	2.2(%)	2.6(%)
Medium(25K-75K)	40.1(%)	28(%)	39.6(%)	32.8(%)	36.7(%)
High(>75K)	57.3(%)	70.4(%)	57.6(%)	65.1(%)	60.6(%)
Number of Vehicles					
1	81.1(%)	83.1(%)	81.8(%)	84.2(%)	82.9(%)
2	13.9(%)	12.5(%)	13.0(%)	12.3(%)	12.4(%)
3+	5.0(%)	4.3(%)	5.2(%)	3.4(%)	4.6(%)
Area Types					
Home zone					
CBD	0.3(%)	0.2(%)	14.7(%)	0.0(%)	0.9(%)
Urban	22.2(%)	18.1(%)	85.3(%)	24.7(%)	18.8(%)
Suburban	74.4(%)	79.7(%)	0.0(%)	71.2(%)	75.2(%)
Rural	3.1(%)	2.0(%)	0.0(%)	4.1(%)	5.0(%)
Work zone					
CBD	10.6(%)	5.5(%)	35.9(%)	9.4(%)	8.8(%)
Urban	39.8(%)	54.4(%)	44.1(%)	52.4(%)	40.0(%)
Suburban	47.3(%)	38.4(%)	18.2(%)	35.7(%)	47.9(%)
Rural	2.3(%)	1.7(%)	1.9(%)	2.4(%)	3.3(%)
Commute Travel					
Free Flow Time(minutes)	18.0(10.5)	16.1(9.0)	19.2(12.2)	19.4(11.3)	18.6(11.5)
Distance(miles)	12.9(10.3)	10.9(8.8)	11.9(11.9)	13.5(10.3)	12.7(11.0)
Tour Duration (hours)	9.8(2.8)	9.8(2.6)	9.8(2.9)	9.9(2.60)	9.7(2.8)

*The values mentioned in the parentheses are standard deviations of the corresponding variables

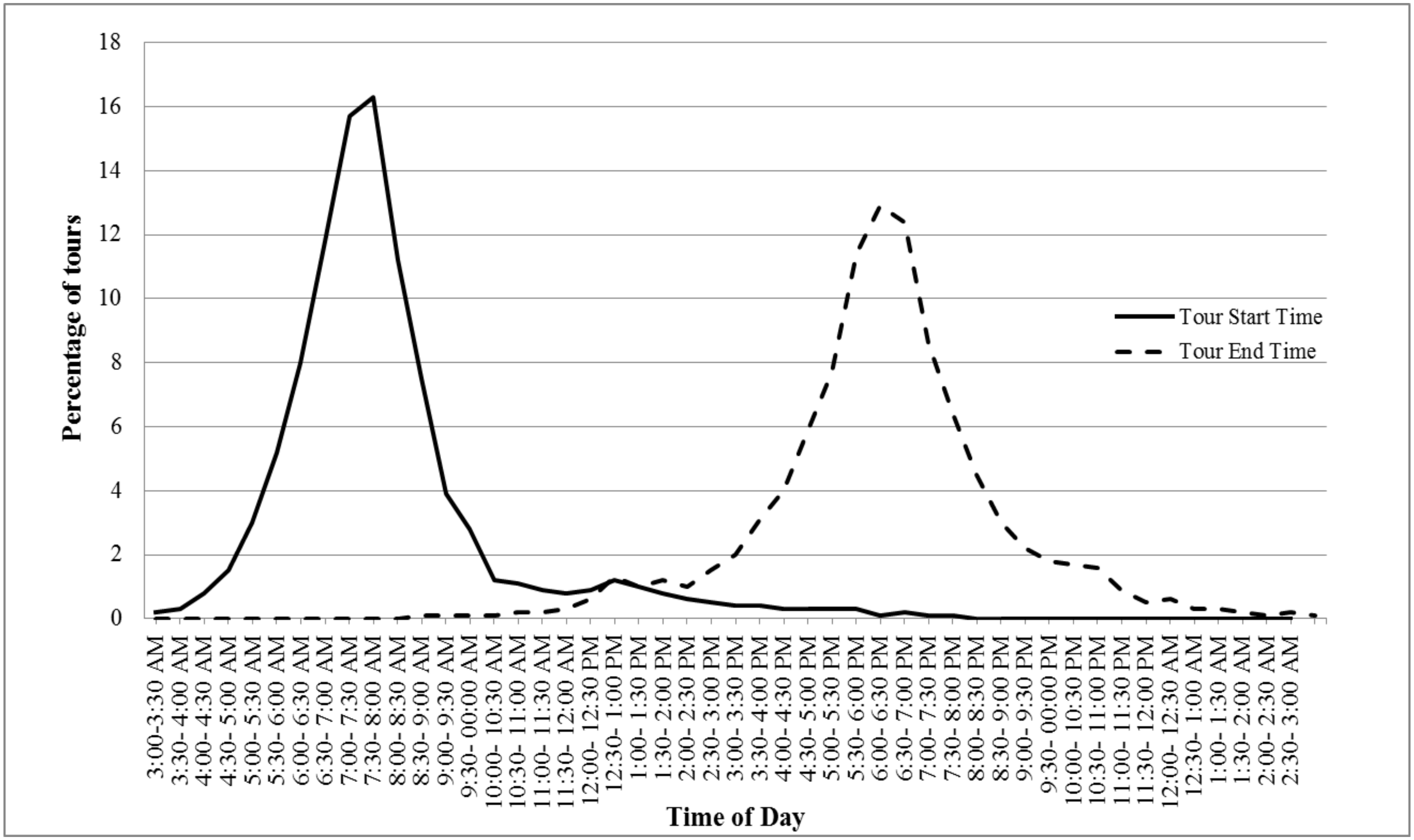


Figure 6.1 Distribution of Work Tour Start- and End-times in 9 Counties of San Francisco Bay Area (BATS 2000 Data)

duration. The model is formulated as follows:

$$\frac{[\text{Travel Duration}]_{ijt}}{[\text{Free Flow Time}]_{ij}} = \text{intercept} + \sum_k \beta_k x_k + \alpha_n \exp[\sin^n(\frac{\pi t}{12})] + \gamma_n \exp[\cos^n(\frac{\pi t}{12})] \quad (6.1)$$

In the above equation, $[\text{Travel Duration}]_{ijt}$ is the reported travel duration between zone i and zone j at time t, and $[\text{Free Flow Time}]_{ij}$ is the free flow travel time between zone i and zone j. The time "t" is usually measured as hours elapsed from an arbitrary time, such as midnight or starting time of the survey day. In this research, we measured "t" from 3:00AM, the starting time of the survey day. In this equation, x_k represents the variables used in the model. The coefficients α_n and γ_n on the cyclic functions represent the effects of the time-of-day choice on travel duration. The number of α_n and γ_n coefficients to be estimated is determined based on the statistical fit and the intuitive considerations. In our case, we used n = 3 i.e. we estimated 3 parameters for each of them (i.e., $\alpha_1, \alpha_2, \alpha_3$ and $\gamma_1, \gamma_2, \gamma_3$). The reason behind using cyclic functions for specifying the effect of time-of-day is to ensure that the function value (and hence the predicted travel time) at a time period "t" is the same the function value at a time period "t+24" (i.e., the same time period next day).

6.4.2 Time-of-Day Choice MNL Model

Following Ben-Akiva and Abou-Zeid (2012), the utility function of the MNL model used in this chapter consists of three functions as below:

$$U(s,e) = U^s(t_s) + U^e(t_e) + U^{dur}(t_e - t_s) \quad (6.2)$$

In the above equation, $U(s,e)$ is the joint utility of starting the tour in time slot s and ending in time slot e, $U^s(t_s)$ is start-time function, $U^e(t_e)$ is end-time function, and

$U^{dur}(t_e - t_s)$ is duration function. These functions are defined as below:

start time function, $U^s(t_s) = \sum_r x_r f^s(t_s) + \beta_{thw}(\text{Travel Time})_{hw} + \beta_{chw}(\text{Travel Cost})_{hw} + 1.\ln(\text{\# half-hour periods in slot s})$

end time function, $U^e(t_e) = \sum_r x_r f^e(t_e) + \beta_{twh}(\text{Travel Time})_{wh} + \beta_{cwh}(\text{Travel Cost})_{wh} + 1.\ln(\text{\# half-hour periods in slot e})$

duration function, $U^{dur}(t_e - t_s) = \beta_1^{dur}(t_e - t_s) + \beta_2^{dur}(t_e - t_s)^2 + \beta_3^{dur}(t_e - t_s)^3 \ldots\ldots\ldots\beta_d^{dur}(t_e - t_s)^D$ (6.3)

In the above equations, r is the number of demographic explanatory variables x_r used in the model, including constants and other demographic variables, and

$$f^s(t_s) = \beta_1^s \sin\left(\frac{2\pi t_s}{24}\right) + \beta_2^s \sin\left(\frac{2.2\pi t_s}{24}\right) + \beta_3^s \sin\left(\frac{3.2\pi t_s}{24}\right) \ldots\ldots\ldots + \beta_n^s \sin\left(\frac{n.2\pi t_s}{24}\right) \quad (6.4)$$

$$f^e(t_e) = \beta_1^e \sin\left(\frac{2\pi t_e}{24}\right) + \beta_2^e \sin\left(\frac{2.2\pi t_e}{24}\right) + \beta_3^s \sin\left(\frac{3.2\pi t_e}{24}\right) \ldots\ldots\ldots + \beta_n^e \sin\left(\frac{n.2\pi t_e}{24}\right) \quad (6.5)$$

The values of n and d are determined based on the statistical tests and the reasonableness of resulting utility profiles. Note that the coefficients on the number of half-hour periods in slots s and e were fixed to 1 to take into account for the unequal period lengths in these slots (see Ben-Akiva and Abou-Zeid, 2012 for details).

As discussed earlier, the demographic variable specifications are specified as cyclic functions to recognize that a person's preference for a specific time-of-day remains the same the next day as well. It is important to note here the individual coefficients in the above cyclic functions cannot be interpreted. For interpreting the effect of a variable (say female with kids), all the corresponding coefficients in the cyclic function should be used to plot the utility profiles as a function of time of day. For example, the tour start time-of-day preference of females with kids can be interpreted by using all the coefficients of the female with kid variable in the start time cyclic function (i.e., $\beta_1^s, \beta_2^s, ..., \beta_n^s$) to plot the utility profile as a function of start time. Similarly, the tour end time-of-day preference of females with kids can be interpreted by using all the coefficients of the female with kid variable in the end time cyclic function (i.e., $\beta_1^e, \beta_2^e, ..., \beta_n^e$) to plot the utility profile as a function of end time.

6.4.3 Transferability Assessment

As mentioned earlier, to assess the transferability of the TOD models, two approaches (estimation-based and application-based) are used in this chapter. Since the estimation-based approach is used for the first time in this dissertation research, it is briefly discussed in this subsection.

According to this approach, first a model was estimated using data from all 9 counties in the San Francisco Bay area (i.e., base model). Next, for a selected county, the dummy variable for that county was interacted with each of the variables in the base model. Groups of such interaction variables were included one by one in the model specification. For example, to test if females with kids in Santa Clara County had different time-of-day preferences from those in all other counties, the dummy variable for Santa Clara was interacted with all the variables in the cyclic functions for the female with kids demographic segment. All these interactions were introduced at a time over the base model. The resulting model would recognize any potential differences in the time of day preferences of females with kids between Santa Clara and other Counties. The decision of whether or not the preferences of females with kids were actually different between Santa Clara and other Counties was made based on a log-likelihood ratio test (for the entire set of Santa Clara specific variables just added) along with a visual examination of the statistical significance of the coefficients of the interaction variables. If the interaction variables (or "difference" variables) are statistically different from zero, that indicates that statistically significant differences in the time-of-day preferences between females with Kids in Santa Clara and those in other Counties (hence the corresponding coefficients in the base model are NOT transferable). In addition to such statistical tests, the utility profiles were plotted as a function of time-of-day for females with kids in Santa Clara and for those in all other 8 counties to visually examine if the profiles appeared different (see Figure 6.2 for examples of such utility profiles). This approach was repeated for all demographic variables and level of service variables in the model specification until a final specification is arrived at. The final specification contains the specification for the base-SC model (that is the model for all 8 counties except Santa Clara) as well as the "difference" variables that were deemed to be statistically different from the base specification (the "difference" variables that were deemed insignificant were dropped from the model). Using this same approach, joint context specifications were developed for each of the four counties -- Alameda, Santa Clara, San Francisco, and San Mateo.

6.5 Empirical Model Results

This section discusses the travel duration regression model and time-of-day choice model results.

6.5.1 Travel Duration Regression Model Results

Using equation 6.1, regression models were developed for: (1) home to work journey, and (2) work to home journey. The model estimates are reported in Table 6.2.

As can be observed from the table, almost all the parameters in the model have expected signs, and are significant at the 95% confidence interval. For example, the negative coefficient on the distance variable indicates that the times required to travel a fixed distance in longer trips are lower than that in shorter trips. That is, travel speeds are higher for longer distance trips than the speeds for shorter-distance trips. The area type variables (i.e., CBD, urban and suburban) were introduced with the rural area type as the base category. As expected, the coefficients on all of these area type variables are positive, indicating that the travel times required for the journeys between any origin-

Table 6.2 Travel Duration Ratio Regression Model Results

	Home to Work Journey	**Work to Home Journey**
Variables	**Coeff. (t-stat)**	**Coeff. (t-stat)**
Intercept	2.44(30.84)	1.42(20.10)
Distance	-0.02(-51.70)	-0.02(-51.76)
Area types		
CDB origin	0.44(23.71)	0.43(23.51)
Urban origin	0.27(19.04)	0.26(18.86)
Suburban origin	0.23(16.96)	0.23(16.95)
CDB destination	0.28(14.21)	0.28(14.56)
Urban destination	0.22(15.81)	0.23(16.05)
Suburban destination	0.22(16.65)	0.22(16.64)
Cyclic Functions		
Exp (sin (π t/12))	-0.25(-22.12)	0.28(22.27)
Exp(sin^2 (π t/12))	-0.31(-14.54)	0.03(1.62)
Exp(sin^3 (π t/12))	0.32(22.28)	-0.40(-22.24)
Exp (cos (π t/12))	0.18(12.10)	0.14(10.71)
Exp(cos^2 (π t/12))	-0.30(-13.46)	-0.01(-0.40)
Exp(cos^3 (π t/12))	-0.27(-9.76)	-0.02(-8.53)
Adjusted R^2	0.059	0.061
Total observations	69,623	69,623

destination pair of these area types are higher than that a journey between two rural areas. This is mainly because of the congestion effects associated with these area types. The next set of variables comprises the cyclic functions with respect to time, which capture the temporal nature of the congestion effects in the bay area. The reason for using cyclic functions is that the congestion effect at a time interval “t” can be ensured to be the same at “t+24” (i.e., next day).

6.5.2 Time-of-Day Choice Model Results

The base model results (that includes data from all 9 counties) are presented in Table 6.3. As discussed before, the interpretation of the parameter estimates of this model is not as straightforward as in other typical MNL models. Table 6.3 shows that there are 2k parameter estimates for each variable, making it difficult to interpret the influence of a variable on the time-of-day choices. Hence, instead of trying to interpret these parameter estimates separately, it is better to interpret their effects as a whole. One possible way to do so is to examine their time-varying utility profiles. Figure 6.2 shows such utility profiles for some of the variables used in the model. Note that the utility values presented in the figures are relative utilities, normalized with respect to the utility values at 8:00 AM (tour-start time profiles) and 5:00 PM (tour-end time profiles) respectively.

Overall the profiles have intuitive interpretations. For example, the tour start-time profiles (Figure 6.2 (a)) show that the full time workers are likely to start their work tours earlier than the part time workers (because the utility curve for full-time workers is toward the left compared to the base curve). This is mainly because of the difference in their work schedules. As expected, the female workers with kids in households show a higher propensity to start their work tours later in the day as compared to their counterparts (i.e., males or females without kids in households). This may be because of their responsibilities to take care of the kids at home, or drop them off at schools. Further,

Table 6.3 Multinomial Logit (MNL) Model Results (base model)

Variables	Coeff. (t-stat)
Start Time Function	
Sin(2πTs/24)	3.58(1.66)
Sin(4πTs/24)	2.66(3.70)
Sin(6πTs/24)	-0.32(-0.82)
Sin(8πTs/24)	-0.88(-7.38)
Cos(2πTs/24)	-2.19(-0.82)
Cos(4πTs/24)	0.71(0.63)
Cos(6πTs/24)	1.05(2.78)
Cos(8πTs/24)	0.20(1.77)
End Time Function	
Sin(2πTe/24)	-0.89(-0.28)
Sin(4πTe/24)	-0.12(-0.12)
Sin(6πTe/24)	0.02(0.08)
Sin(8πTe/24)	0.12(1.42)
Cos(2πTe/24)	-0.90(-0.67)
Cos(4πTe/24)	0.23(0.24)
Cos(6πTe/24)	-0.31(-0.70)
Cos(8πTe/24)	-0.45(-3.66)
Duration Function	
Duration	6.41(0.78)
$Duration^2$	-6.48(-1.81)
$Duration^3$	-1.44(-0.57)
Level-of-Service	
Home to Work travel time	-0.17(-10.05)
Work to Home travel time	-0.03(-1.76)
Travel Cost	-0.15(-3.05)
Size of intervals	
Ln(# of half hour in tour start time period)	1.00(fixed)
Ln(# of half hour in tour end time period)	1.00(fixed)
Female with Kids	
Start Time	
Sin(2πTs/24)*Female with kids	0.39(1.64)
Sin(4πTs/24)*Female with kids	0.74(5.38)
Cos(2πTs/24)*Female with kids	-1.04(-5.80)
Cos(4πTs/24)*Female with kids	-0.15(-1.48)
End Time	
Sin(2πTe/24)*Female with kids	-0.07(-0.39)
Sin(4πTe/24)*Female with kids	-0.08(-0.70)

Table 6.3 (Contd.)

Variables	Coeff. (t-stat)
Cos(2πTe/24)*Female with kids	-0.43(-2.32)
Cos(4πTe/24)*Female with kids	0.21(2.75)
Full-Time Workers	
Start Time	
Sin(2πTs/24)*Full-time workers	0.16(0.12)
Sin(4πTs/24)*Full-time workers	0.31(0.72)
Sin(6πTs/24)*Full-time workers	0.45(2.38)
Cos(2πTs/24)*Full-time workers	0.58(0.34)
Cos(4πTs/24)*Full-time workers	-0.18(-0.28)
Cos(6πTs/24)*Full-time workers	-0.17(-0.93)
End Time	
Sin(2πTe/24)*Full-time workers	-0.77(-0.39)
Sin(4πTe/24)*Full-time workers	-0.14(-0.25)
Sin(6πTe/24)*Full-time workers	-0.19(-1.32)
Cos(2πTe/24)*Full-time workers	-0.15(-0.15)
Cos(4πTe/24)*Full-time workers	0.19(0.31)
Cos(6πTe/24)*Full-time workers	0.42(1.88)
Flexibility	
Start Time	
Sin(2πTs/24)*Flexibility	0.76(0.73)
Sin(4πTs/24)*Flexibility	0.68(0.75)
Sin(6πTs/24)*Flexibility	0.35(1.47)
Sin(8πTs/24)*Flexibility	0.15(0.95)
Cos(2πTs/24)*Flexibility	-1.10(-1.45)
Cos(4πTs/24)*Flexibility	-0.27(-0.74)
Cos(6πTs/24)*Flexibility	0.53(1.04)
Cos(8πTs/24)*Flexibility	0.33(2.13)
End Time	
Sin(2πTe/24)*Flexibility	0.68(2.28)
Sin(4πTe/24)*Flexibility	0.56(1.37)
Sin(6πTe/24)*Flexibility	0.46(1.39)
Sin(8πTe/24)*Flexibility	0.04(0.30)
Cos(2πTe/24)*Flexibility	0.20(0.38)
Cos(4πTe/24)*Flexibility	-0.11(-0.34)
Cos(6πTe/24)*Flexibility	0.07(0.44)
Cos(8πTe/24)*Flexibility	0.003(0.03)

Table 6.3 (Contd.)

Variables	Coeff. (t-stat)
High Income (> 75k)	
Start Time	
Sin(2πTs/24)*High income	0.31(1.91)
Sin(4πTs/24)*High income	0.09(0.99)
Cos(2πTs/24)*High income	-0.06(0.56)
Cos(4πTs/24)*High income	0.02(0.27)
End Time	
Sin(2πTe/24)*High income	-0.08(-0.60)
Sin(4πTe/24)*High income	0.04(0.46)
Cos(2πTe/24)*High income	-0.14(-1.10)
Cos(4πTe/24)*High income	-0.35(-6.33)
Government Employees	
Start Time	
Sin(2πTs/24)*Govt. employees	-2.49(-1.76)
Sin(4πTs/24)*Govt. employees	-2.36(-1.95)
Sin(6πTs/24)*Govt. employees	-0.65(-1.98)
Sin(8πTs/24)*Govt. employees	0.01(0.05)
Cos(2πTs/24)*Govt. employees	2.00(1.98)
Cos(4πTs/24)*Govt. employees	-0.49(-0.98)
Cos(6πTs/24)*Govt. employees	-1.31(-1.86)
Cos(8πTs/24)*Govt. employees	-0.82(-3.78)
End Time	
Sin(2πTe/24)*Govt. employees	0.01(0.05)
Sin(4πTe/24)*Govt. employees	-0.11(-0.92)
Cos(2πTe/24)*Govt. employees	-0.22(-1.21)
Cos(4πTe/24)*Govt. employees	0.29(3.68)
Interaction Variables	
Full-time workers*Duration	-10.77(-1.98)
Full-time workers*Duration^2	27.96(7.06)
Full-time workers*Duration^3	-16.91(-6.15)
Home to Work travel time*Flexibility	0.05(1.77)
Observations	10,063
Log-likelihood at constants	-52,607
Log-likelihood at convergence	-50,806

flexibility appears to affect the tour start-times of the employed adults. As can be observed from the figure, the full time workers with flexible schedules are likely to start their tours later in the day as compared to the full time workers without flexible schedules. Similarly the tour end-time profiles of the employed adults (Figure.6.2 (b)) show the influences of employment status (full time vs. part time), presence of kids at home, and flexibility in the work schedule on their work tour end-time choices. For instance, the full time workers show a higher propensity to end their work tours after 5:00 PM as compared to their counterparts (i.e., part time workers). The female workers with kids in households are found to end their work tours earlier (especially just before 5 PM) than their counterparts (i.e., male, or female without kids in households). This may be again because of their responsibilities to pick up the kids from schools/day cares, or take care of the kids at home.

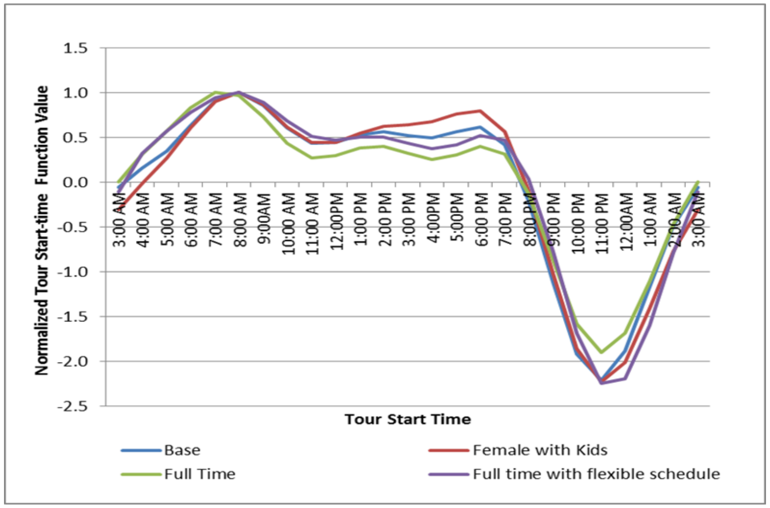
In addition to the profiles of different socio-demographic variables, the utility profiles obtained from the parameters on the tour duration function are also examined in this chapter. Figure 6.2 (c) shows that the maximum utility of the full time and part time workers occurs at durations of 11 hours and 7 hours respectively, which are very close to the average values (10 and 7.27 hours respectively) in their observed duration profiles.

6.6 Transferability Assessment Results

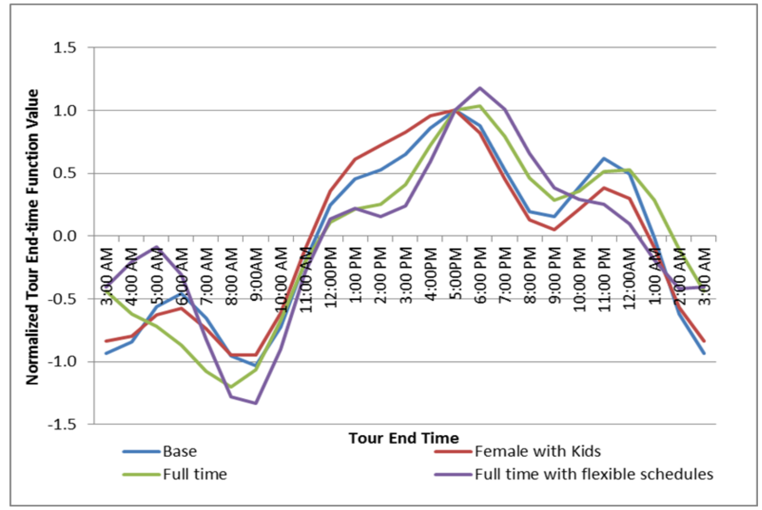
In this section, the transferability assessment results obtained from the two-approaches (estimation-based and application-based) used in this chapter are discussed.

6.6.1 Results from Estimation-based Approach

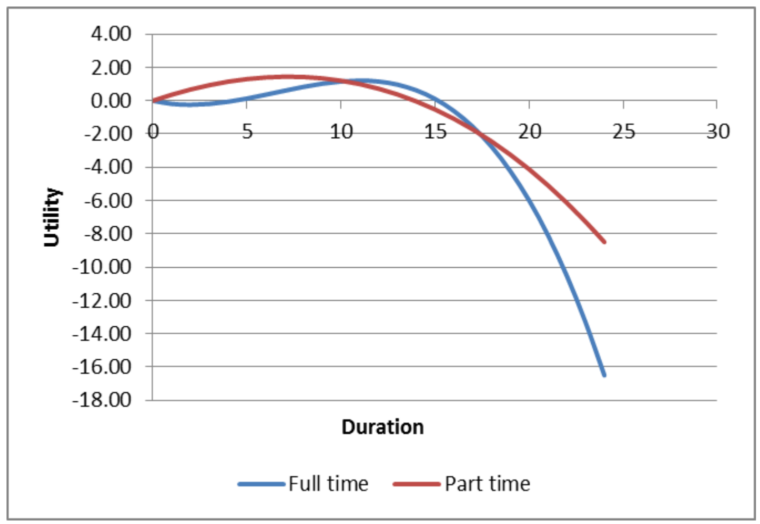
As discussed earlier, county-specific "difference" variables were added to the base specification discussed in the previous section to explore any potential differences in the parameter estimates for the county and the remaining eight counties. Four such models were developed, one for each of the four counties – Alameda, Santa Clara, San Francisco, and San Mateo. The model specifications are presented in Appendix B. Based on the statistical tests and intuitive considerations, the coefficients that were found to be different in a specific county (as compared to those in the base-c model) are presented at the end of the table (after the row labeled "interactions with counties"), while the common coefficients are presented in the beginning of the table. Several important observations may be made from the model results. First, the constants in the TOD models of 3 counties (Santa Clara, San Francisco, and San Mateo) are not significantly different from those in the base-c models, indicating the potential transferability of the TOD model constants between a pooled and a specific county model. Second, among the level-of-service variables, while the travel time co-efficient for the home to work journey appears to be statistically different (i.e., not transferable) between counties and the base-c model, the travel time co-efficient for the work to home journey and the travel cost co-efficient appears to be transferable. One possible reason of not observing significant differences in the travel cost coefficients of different counties is the less variation of travel cost variable across the alternatives considered in the model. The travel cost information was available only for two broad time period categories: peak and off-peak. Third, in the context of other variables, (e.g., socio-demographic variables), almost 95% of the coefficients (or more) in a county TOD model are not significantly different from the corresponding base-c model. This provides an evidence of the potential transferability of these coefficients between a pooled and a specific county model in the Bay Area. Overall, it appears that less than 5% of the coefficients (especially the level-of-service variables)



(a) Tour Start-time Functions



(b) Tour End-time Functions



(c) Tour Duration Functions

Figure 6.2 Profiles of (a) Tour Start-time Functions, (b) Tour End-time Functions, and (c) Tour Duration Functions

need to be estimated for the 4 counties considered in this transferability assessment. The remaining coefficients can be transferred from the corresponding base-c models (if available) in the Bay Area, providing strong empirical evidence of the transferability of TOD model coefficients from a pooled model.

In addition to comparing the coefficients of a county model with those of the corresponding "base-c" model, time-varying utility profiles of the variables that were found to have significantly different coefficients in these two models were also compared. These are presented in Figures 6.3 and 6.4. As can be observed from Figure 6.3 (a), the tour start-and end-time profiles of the full time employed adults in Santa Clara are different than those of the employed adults in other eight counties (as a whole). Such differences in the time-of-day choice profiles are observed for household income variable as well (see Figure 6.3 (b)). These differences can be partially attributed to the differences observed in socio-demographic characteristics (especially in full time employee and household income variables) between Santa Clara and other counties in the Bay Area. Figure 6.4 shows the variations in the tour start-and end-time profiles of the female with kids in households in San Mateo and other eight counties (as a whole) in the Bay Area. The differences in the utility profiles indicate that the corresponding coefficients can not be transferred from a pooled model to a specific county; these need to be estimated separately for that county. Another important observation from all of these profiles is that for a specific variable, the difference in the tour end-time profiles is greater than the corresponding difference in the tour-start time profiles. This indicates that the coefficients related to home to work journeys may be more transferable than that related to work to home journeys.

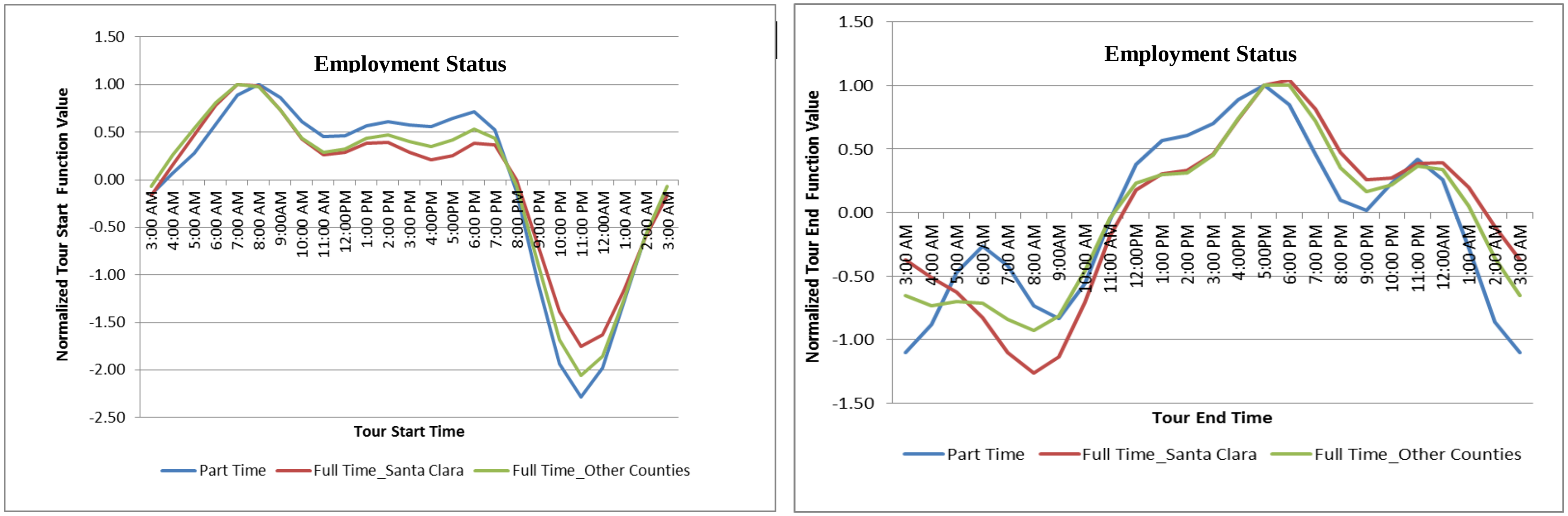


Figure 6.3 (a)

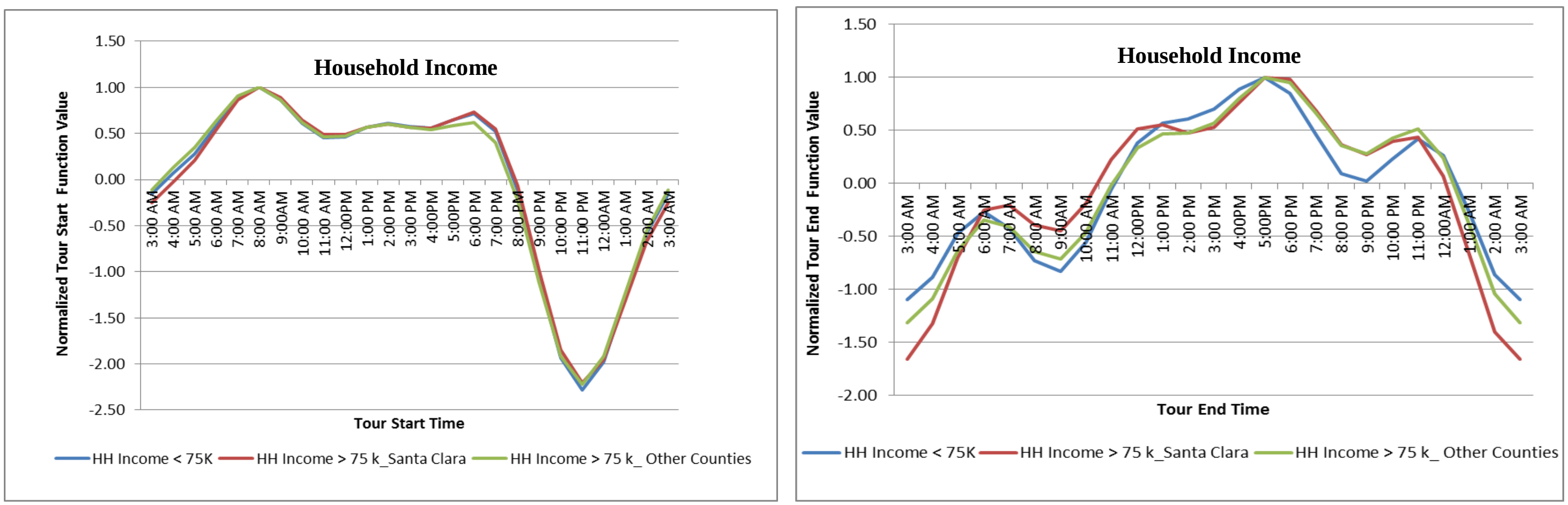


Figure 6.3 (b)

Figure 6.3 Differences in the Profiles of (a) Employment Status and (b) Household Income Variables between Santa Clara and Other Counties

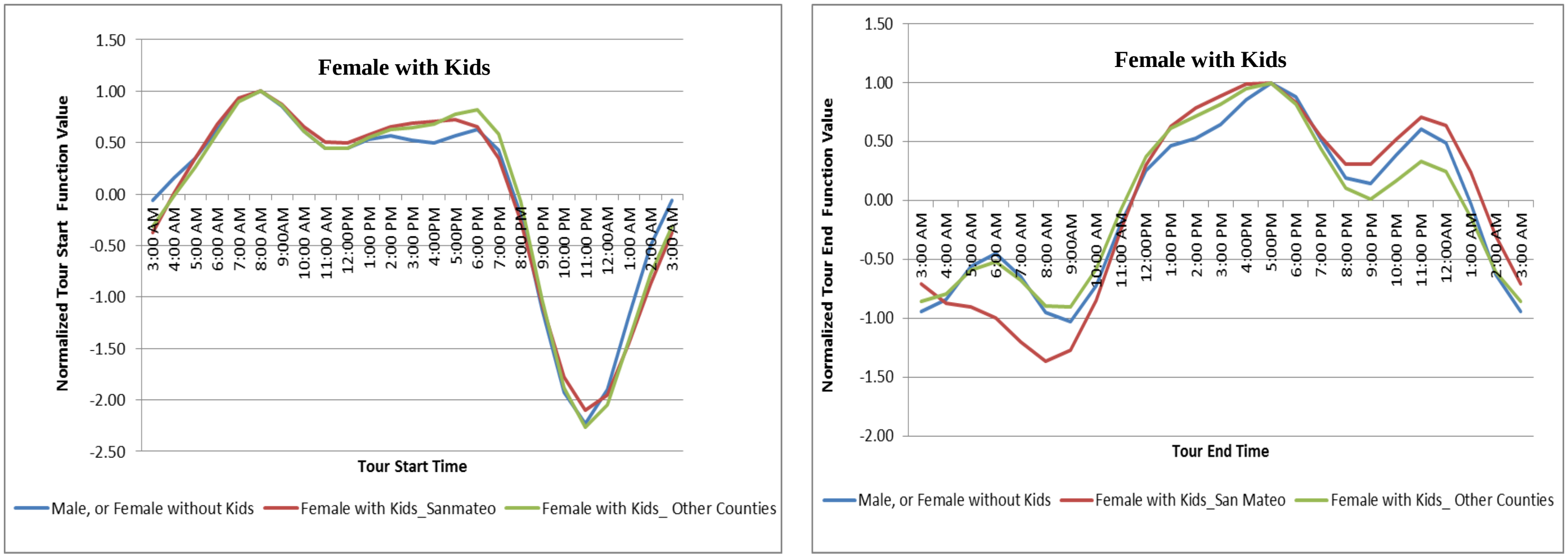


Figure 6.4 Differences in the Profiles of "Female with Kids" Variable between San Mateo and Other Counties

6.6.2 Results from Application-based Approach

The following table shows the TI values for all transfers with the first four rows presenting the TI values for inter-county transfers and the last row presenting the TI values for base-c model transfers. As indicated earlier, the base-c models are basically pooled models developed using data from eight counties. Also, the models were transferred using the naïve transfer approach i.e., the models were not updated using any information from the county they were transferred to. As can be observed from the table, the models transferred from and to San Francisco provide lower TI values compared to the corresponding models of all other counties. Because of the small sample size of the

Table 6.4 Transferability Assessment Results: Transfer Index (TI)

Transferred From \ Transferred To	Alameda	Santa Clara	San Francisco	San Mateo
Alameda	**1.00**	0.66	0.42	0.56
Santa Clara	0.68	**1.00**	0.44	0.74
San Francisco	0.23	0.42	**1.00**	0.40
San Mateo	0.37	0.56	0.39	**1.00**
Base – c	0.85	0.82	0.62	0.79

San Francisco County (only 538), it is not clear whether these lower TI values are due to the differences in the travel behavior between San Francisco and other counties in the bay area or if these are simply artifacts of small sample size. Among all the counties, the TI values appear to be higher for the models transferred from and to Santa Clara. One important observation from the table is that for a transfer to a particular county, the TI value improves significantly after pooling data from all other eight counties, indicating the potential benefits of pooling data in model transfer. It appears that it is better to transfer a model based on pooled data from several counties than to transfer a model of a single county.

6.7 Summary

This chapter presents an empirical assessment of the spatial transferability of tour-based time-of-day choice models among different counties in the San Francisco Bay Area of California. The empirical models are based on the work tour start- and end-time choices of the employed adults in the Bay Area. The model structure used to model the time-of-day choices is the Multinomial Logit (MNL) Structure, for which an OLS regression model was developed to obtain time varying travel time variables for the home-work and work-home journeys.

In this chapter, the performance of data pooling technique is assessed by using two approaches: (1) estimation-based approach and (2) application-based approach. Results from both the approaches suggest the potential benefits of pooling data in TOD model transfer. Specifically, results from the estimation-based approach suggest that a majority of the alternative-specific constants and the coefficients on socio-demographic variables in a pooled model can be transferred to a county; but the level of service variable coefficients need to be estimated separately for the county. Further, the results from the "application-based" approach (based on the transfer index values) suggest that the transferability of a model can be improved significantly by pooling data from different geographic contexts. These results support the findings in Chapter 4 that pooling data can potentially improve the spatial transferability of a model.

In addition to assessing the performance of data pooling technique, this chapter investigates the inter-county transferability of TOD models. In this assessment, only application-based approach was used. Results from this assessment suggest different levels of transferability of the TOD models developed for four counties in the Bay Area. For example, while the models transferred from and to Santa Clara appear to show higher transferability across the counties, the models transferred from and to San Francisco show lower transferability compared to the corresponding models of other counties. It is important to note these results are based on only transfer index values; policy responses of the transferred TOD models were not considered in this transferability assessment. Considering the importance of the policy response measures, it should be included in the future TOD model transferability assessment. Another important caveat is in order here regarding the transferability results. All of these results are based on the assumption that the scale of the random utility components is similar across different models. Allowing for scale differences across different counties can potentially shed further light on model transferability.

CHAPTER 7

CONCLUSION

7.1 Introduction

This dissertation research seeks to contribute to the area of travel demand modeling by investigating the spatial transferability of activity-based models. Specifically, we attempt to develop a framework for assessing the transferability of activity-based model systems, and assess the transferability of two important model components used in activity-based model systems: (1) activity participation and time-use models, and (2) tour-based time-of-day choice models. In addition, the performance of two alternate ways (data pooling and improving the model structure) of enhancing model transferability is assessed in this dissertation.

The rest of this chapter is organized as follows. The next section summarizes the main findings of this dissertation research. Section 7.3 highlights the contributions of this research, and Section 7.4 suggests the directions for future research.

7.2 Summary

This dissertation research started with an extensive review of literature on the spatial transferability of travel forecasting models. The review identified several gaps in literature. Some of these gaps, especially the notable ones, are addressed in this research. Results from these research efforts are summarized below.

The research first attempted to develop a conceptual framework that can guide the analysts assessing the transferability of activity-based model (ABM) systems. At the higher level of this framework are the various design features of the model system, including the traveler markets to be modeled, the temporal and spatial resolution at which travel is modeled, and the structure of the model system (i.e., the presence or absence of specific model components and sequence of the model components). At the lower level of this framework comes the transferability of the specific model components of the ABM system, including long-term choice models, activity and tour generation models, tour-level models (for mode, time-of-day, and destination choices), and trip level models.

Next, the research investigated the spatial transferability of an important component of activity-based model systems being tested in different metropolitan regions in the U.S. - a person-level daily activity generation and time-use model. Data from 2009 National Household Travel Survey (NHTS) was used for this investigation. The model structure used for this is the Multiple Discrete Continuous Extreme Value (MDCEV) model. Since this is the first application of the MDCEV structure in spatial transferability assessment, some efforts were given to investigate the prediction properties of this model structure before assessing its transferability. Results from this investigation suggest that the MDCEV model performs well in predicting the aggregate-level activity participation rates in individual activities but not the aggregate activity durations. Specifically, the model is found to under-predict the aggregate activity durations for the outside good (in-home activity) and over-predict the aggregate durations for most of the inside goods (out-of-home activities). Another important property of the MDCEV model explored in this research is related to its constants-only specification. It was found that similar to the

Multinomial Logit (MNL) model, constants-only specification of an MDCEV model can reproduce the observed shares in the estimation data. This property has implications to the transferability of models with MDCEV structure in that an MDCEV model transferred from elsewhere can simply be adjusted by updating the constants.

In the transferability assessment of the person-level daily activity generation and time-use model, both the inter-state and intra-state transferability were considered. For inter-state transferability assessment, the model was transferred between Florida and California where as for the intra-state transferability assessment the model was transferred among different regions in Florida. Results from the inter-state and intra-state transferability assessments suggest that the model component (i.e., the activity participation and time-use model) is more transferable among different regions within a state than that between two states. This is mainly because of the greater similarity in socio-demographic characteristics, activity participation and time-use patterns of individuals in different regions within a state than that of the individuals in two different states. Thus, whenever possible, attempts should be made to transfer models within a state. Further, within the state of Florida, the transferability between urban regions is found to be greater than that from urban to rural region. Specifically, there appears to be greater transferability of this model component between the Southeast Florida and the Central Florida regions than the Tampa Bay region.

To transfer the model across geographical contexts, two methods were used in this analysis: (a) naïve transfer, and (b) updating constants. The effectiveness of these transfers was assessed by using different metrics. Among these, a statistically rigorous test rejected the hypothesis of transferability in all the cases. Since rejection by a statistical test doesn't necessarily mean the poor transferability of a model, other metrics such as log-likelihood based measures, aggregate level prediction ability and policy response measures were used in this transferability assessment. Results from log-likelihood based measures and aggregate predictions suggest that the performance of a transferred MDCEV model can be improved significantly by updating the constants. But this improvement doesn't translate to improvement in the policy responses of the transferred model, indicating the transferability results obtained from the the log-likelihood based measures and aggregate predictions are not always same as the results obtained from policy prediction measures. Since the main objective of developing a forecasting model is to use for forecasting and policy analysis, it is important for the model to be able to provide appropriate predictions of the responses to changes in explanatory variables (i.e., demographic characteristics and policy variables). Hence, the log-likelihood based measures and aggregate predictions are necessary but not sufficient metrics for model transferability assessment.

To investigate the influence of sampling variance in parameter estimates on the model transferability assessment results, the policy response measures were computed for 50 sets of bootstrapped values drawn from the sampling distributions implied by the parameter estimates and their covariance matrix. Next, the transferability results obtained from the bootstrapped parameter estimates were compared with that from the point estimates. This comparison shows that neglecting sampling variance can potentially bias the results of transferability assessments toward "less" transferable (assuming that sufficient data is used to estimate the transferred and local models).

Using the same data set and model structure, this research also investigated if pooling data from multiple regions helps in developing models that are more transferable than those developed using data from a single region. Results from this investigation suggest that pooling data from different regions helps in enhancing model transferability, but up to a certain extent. After that, pooling data does not appear to result in significant improvement of model transferability. Further, data from all the regions do not appear to result in similar improvements. For instance, data pooled from major urban regions (as compared to that from other regions) was found to result in greater improvement in the transferability of a model to another major urban region.

As discussed earlier, the MDCEV model structure used in the aforementioned transferability analysis has some limitations in predicting the aggregate durations which might have influence on its transferability across areas. It is possible that improvements to the MDCEV structure may enhance its prediction ability, and thus improve transferability across areas. To test this hypothesis, the independent and identically distributed (IID) assumption of the random utility components in MDCEV model was relaxed by incorporating heteroscedastically distributed random utility components in the structure. Specifically, it was assumed that the random utility components are independent but non-identically distributed across the choice alternatives. Using this assumption, a new econometric model named the Multiple Discrete Continuous Heteroscedastic Extreme Value (MDCHEV) Model was formulated. Next, the prediction properties and transferability of this MDCHEV model were investigated using the same geographical and empirical contexts used for MDCEV model in the aforementioned analysis. Results obtained for these two model structures were then compared to investigate the benefits of incorporating heteroscedasticity in the multiple discrete continuous (MDC) choice model. It was found that the incorporation of heteroscedasticity among random utility components not only improves the prediction ability of the MDC choice model but also enhance its transferability across areas. Specifically, spatial transferability assessments using a variety of different transferability metrics suggest that the MDCHEV model clearly outperforms the MDCEV model. More interestingly, in most cases, the transferred MDCHEV models appear to perform not only better than transferred MDCEV models but also better than locally estimated MDCEV models. These results indicate that improvements to a travel forecasting model structure may help in enhancing its transferability across areas.

Next, the research investigated the spatial transferability of tour-based time-of-day choice models among four counties in the San Francisco Bay Area of California. Data from the 2000 San Francisco Bay Area Household Travel Survey (BATS) was used in this investigation. The model structure used for this is the Multinomial Logit (MNL) structure, for which an OLS regression model was developed to obtain time varying travel time variables for the home-work and work-home journeys. In the transferability assessment, first the performance of data pooling technique was investigated (using "estimation-based" and "application-based" approaches), and then inter-county transferability of the models was assessed.

Results from the data pooling technique assessment suggest that a majority of the alternative-specific constants and the coefficients on socio-demographic variables in a pooled model can be transferred to a county; but the level of service variable coefficients may need to be estimated separately for the county. Further, it was found that the transferability of a model can be improved significantly by pooling data from different geographic contexts. The inter-county transferability assessment results suggest different levels of transferability of the TOD models developed for four counties in the Bay Area. Among the four counties, models transferred from and to Santa Clara appear to show higher transferability while the models transferred from and to San Francisco show lower transferability compared to the corresponding models of other counties. The comparison of the transferability results from a pooled and a single county model suggest that it is better to transfer a model based on pooled data from several counties than to transfer a model of a single county.

7.3 Contributions

The overarching goal of this dissertation research is to contribute to the field of travel demand modeling by investigating the spatial transferability of activity-based models. The specific major contributions of this research are summarized below:

First, the extensive literature review conducted in this research identifies several important gaps in spatial transferability literature, and provides possible directions for future research. A brief summary of these directions is provided in the next subsection.

Second, the framework laid out in this research provides guidance for assessing the transferability of activity-based model systems. The framework can help agencies and analysts assessing the transferability of activity-based model systems.

Third, to our knowledge, this is the first attempt to assessing the spatial transferability of two important model components used in activity-based model systems: (1) activity participation and time-use models, and (2) tour-based time-of-day choice models. The results obtained from these assessments will be of potential use for the geographical contexts like Florida which are considering different options (e.g., develop new models vs. transfer models) to develop ABMs in the state.

Fourth, the research demonstrates the importance of incorporating policy prediction measures and sampling variance in the transferability assessment. Though important, to our knowledge, there are only a few studies in literature that considers these two with special attention.

Fifth, this dissertation research formulates a new econometric model named the Multiple Discrete Continuous Heteroscedastic Extreme Value (MDCHEV) model. The important features of this model structure are: (a) it allows heteroscedastically (i.e. independent but non-identically) distributed type-1 extreme value random components in multiple discrete continuous (MDC) models, and (b) the resulting likelihood is uni-dimensional integral that can be easily evaluated using quadrature method. The incorporation of heteroscedasticity in the MDC models allows the scale parameters of the random utility components to be different across different choice alternatives. In other words, the differences in the unobserved influences on the preferences for different choice alternatives (a common phenomena in many choice making processes) are recognized by accommodating heteroscedasticity in this model structure.

Sixth, this research investigates the performance of two alternate ways of enhancing model transferability- (a) pooling data, and (b) improving the model structure. While investigating the performance of the data pooling technique, in addition to using the "application-based" approach, another approach called the "estimation-based" (recently used by Bowman et al. 2013) is used.

Seventh, to our knowledge, this is the first research that addresses notable gaps in spatial transferability literature by using latest model structures such as the MDCEV (Multiple Discrete Continuous Heteroscedastic Extreme Value) and MDCHEV (Multiple Discrete Continuous Heteroscedastic Extreme Value). These shed new light on the transferability of multiple discrete continuous (MDC) choice models.

In addition to these, several other small-scale contributions are made that are discussed in the previous chapters of this dissertation.

7.4 Directions for Future Research

The previous sections summarize the overall findings of this dissertation research and highlight the contributions to the field of travel demand modeling. In this section, we discuss the limitations and the possible directions for future research.

7.4.1 Limitations

Empirical specification of the daily activity generation and time-use models estimated in this research could be improved significantly by including additional urban form measures and transport system performance measures (e.g. accessibility) in the model. Because of lack of appropriate data, it was not possible to include these variables in the model. Improving the empirical specification with these variables may enhance the spatial transferability of this model component. Further, the scale of the random utility components was assumed to be similar across different models. Allowing for scale differences across different regions can potentially shed further light on model transferability.

The data used for activity participation and time-use models shows that a large proportion (more than 30%) of those who participated in active recreation appear to have done so for only 2 minutes or less in a day. Given the activities considered in this category (exercising, working out in gym, or playing sports), there is a high chance that such unreasonably small activity durations for a large proportion of the sample is a result of measurement error; presumably due to misreporting by the respondents of errors in coding of the data. Though such measurement error can potentially have bearing on transferability, it was not possible to address this issue in this research.

All the transferability results in this dissertation research are based on relative transferability assessments. Specifically, the transferability of a model is assessed by comparing the performance of a transferred model with that of a locally estimated model assuming that the locally estimated model is perfect in the context it is estimated for.

In the transferability assessment of the tour-based time-of-day choice models, the scale of the random utility components was assumed to be similar across different counties which can potentially be contested. Besides, in the "application-based" approach of transferability assessment, only transfer index metric was used; policy responses of the transferred TOD models were not considered. Further, the samples sizes for some of the counties were very small which may have an influence on the transferability results.

7.4.2 Future Research Directions

Some directions in which the research can be extended are presented below.

As discussed in Chapter 2, it is useful to view transferability of an empirical model at different levels of a hierarchy, beginning with the underlying theory of travel behavior, the model structure, the empirical specification, and then the parameters of the empirical model. A model ought to be transferable at all these different levels of hierarchy for it to be perfectly transferable. There is consensus that theoretically perfect transferability is difficult to achieve. Therefore, it is more constructive to assess if models can be transferred up to certain practical criteria. But these practical criteria are not well defined yet in the profession, and thus warrant attention in the future research. Further, little empirical evidence exists on the transferability of a model at the first three levels of the above mentioned hierarchy. There is a scope for future research on which travel behavior theories (e.g., expected utility maximization vs. other theories) and which model structures are more transferable under what contexts.

In addition, though the literature recognizes that the yardsticks used to measure transferability ought to allow for errors (since perfect transferability is difficult to achieve), no guidance exists on the level of acceptable error thresholds. Thus, it will be useful to accumulate empirical evidence toward arriving at robust error thresholds for transferability assessments. In this context, it will be helpful to establish relationships among the different metrics used to assess model transferability in the literature.

The outcome of a model transferability assessment exercise can be influenced by a variety of confounding factors, including measurement errors in the variables used in model specification, and differences in the data collection procedures between different geographical contexts. Not controlling for these influences can potentially bias the assessment results toward less transferable. Thus, an important avenue for future research is to investigate the extent of the influence of these factors on model transferability results.

The review in Chapter 2 suggests that there is no evidence on which model components of ABM systems are more transferable than the others. This dissertation research investigates the spatial transferability of two model components used in ABM systems: (1) person-level daily activity generation and time use models, and (2) tour-based time-of-day choice models. A fruitful avenue for future research is thus to assess the spatial transferability of other model components used in ABM systems (e.g., location choice and mode choice models), and compare their transferability across areas.

This dissertation research raises a more general issue of the importance of distributional assumptions in MDC Models. In this context, exploration of the influence of alternative distributional assumptions – such as multivariate heteroscedastic extreme value and multivariate normal and skew normal distributions – on the prediction performance of MDC models is a potentially fruitful avenue for further research. Equally important is the need for investigating the suitability of different distributional assumptions for different empirical contexts involving MDC choices.

Finally, given the revival of interest in the issue of spatial transferability of models and the recent moves of several planning agencies to tour-based/activity based model systems, we look forward to seeing more empirical studies (and documentation of the findings from these studies) focusing on when and how best to transfer activity-based models. Equally important is the need to investigate the temporal stability of travel forecasting models.

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APPENDICES

Appendix A: Additional Tables

Table A1 MDCEV Model Results for California

	Shopping	Other Maintenance	Social/ Recreational	Active Recreation	Medical	Meal	Pick up /Drop Off	Other activities
Baseline Utility Parameters								
Constants	-8.03 (-91.62)	-9.09 (-94.00)	-8.95 (-78.73)	-9.78 (-72.32)	-9.43 (-78.98)	-9.36 (-76.91)	-9.57 (-69.94)	-9.60 (-154.61)
Gender (Male is base)								
Female	0.18 (4.87)	-	-	-0.20 (-3.74)	-	-	0.32 (5.02)	-
Age (30 – 54 years is base)								
<30 years	-	-	0.52 (6.68)	0.12 (1.06)	-	-	-	-
55-64 years	-	-	-	-	0.14 (1.61)	-	-0.54 (-6.30)	-
65-74 years	-	-	-	-	0.05 (0.68)	-	-0.75 (-8.59)	-
>= 75 years	-	-	-0.18 (-3.51)	-0.30 (-4.44)	0.26 (3.48)	-	-1.27 (-12.17)	-
Race (Black and others are base)								
White	-	-	-	-	-	0.04 (0.66)	-	-
Driver (Non-Driver is base)								
Driver	0.25 (3.38)	0.53 (5.24)	0.24 (2.57)	-	-	0.55 (4.50)	-	-
Education(H. school/ lower is base)								
Some college	-	0.18 (3.24)	-	0.20 (2.60)	-	-	-	-
Bachelor to higher	-	0.25 (4.51)	-	0.60 (8.12)	-	-	-	-
Born in US (others are base)	-	-	-	-	-	0.49 (6.59)	-	-
Total No. of Children								
Children aged 0-5years	-	-0.33 (-5.41)	-	-0.11 (-1.63)	-	-	0.36 (7.88)	-
Children aged 6-15 years	-	-0.10 (-2.35)	-	-	-	-	0.61 (17.80)	-

Appendix A (Contd.)

Table A1 (Contd.)

	Shopping	**Other Maintenance**	**Social/ Recreational**	**Active Recreation**	**Medical**	**Meal**	**Pick up /Drop Off**	**Other activities**
Total Number of Workers	-0.09 (-3.52)	-	-	-	-	-	0.14 (3.35)	-
Income (< 25 K is base)								
25 – 50K	0.11 (2.29)	0.19 (2.93)	0.23 (3.49)	0.35 (3.89)	-	0.20 (2.79)	-	-
51-75K	0.12 (2.13)	0.21 (2.85)	0.25 (3.54)	0.26 (2.60)	-	0.32 (4.11)	-	-
>75K	0.16 (3.17)	0.25 (3.71)	0.22 (3.47)	0.61 (6.86)	-	0.42 (6.02)	-	-
Land –Use Variables (Rural is Base)								
Urban	0.12 (2.03)	-	0.14 (1.99)	0.37 (3.74)	0.24 (2.47)	0.10 (1.31)	-	-
Survey Day (Tue. –Thur. is base)								
Monday	-	-	-0.18 (-3.14)	-	-	-0.22 (-3.55)	-	-
Friday	-	-	0.11 (2.11)	-	-	0.07 (1.12)	-	-
Satiation Parameters								
Constants	3.15 (79.64)	2.88 (54.48)	4.76 (123.54)	3.48 (33.09)	4.09 (91.23)	3.69 (102.50)	2.47 (54.02)	2.53 (44.63)
Gender (Male is base)								
Female	0.25 (4.83)	0.22 (3.15)	-	-	-	-	-	-
Age (≥ 55 years is base)								
18-29 years	-	-	0.56 (3.98)	0.65 (3.12)	-	-	-	-
30-54 years	-	-	-	0.17 (1.58)	-	-	-	-

Appendix A (Contd.)

Table A1 (Contd.)

	Shopping	Other Maintenance	Social/ Recreational	Active Recreation	Medical	Meal	Pick up /Drop Off	Other activities
Education(H. school/ lower is base)								
Some college	-	-	-	0.23 (1.75)	-	-	-	-
Bachelor to higher	-	-	-	0.27 (2.28)	-	-	-	-
Number of Cases	10821							
Log likelihood value at constants	-129773.01							
Log likelihood value at convergence	-128476.50							

Appendix A (Contd.)

Table A2 MDCEV Model Results for Florida

	Shopping	**Other Maintenance**	**Social/ Recreational**	**Active Recreation**	**Medical**	**Meal**	**Pick up /Drop Off**	**Other activities**
Baseline Utility Parameters								
Constants	-7.55 (-116.92)	-8.42 (-132.70)	-8.54 (-88.46)	-9.17 (-93.66)	-8.90 (-96.70)	-9.32 (-80.09)	-9.53 (-54.07)	-10.06 (-160.44)
Gender (Male is base)								
Female	0.07 (1.78)	-	-	-0.07 (-1.42)	-	-	0.13 (2.15)	-
Age (30 – 54 years is base)								
<30 years	-	-	0.55 (4.69)	-	-	-	-	-
55-64 years	-	-	-	-	0.11 (1.30)	-	-0.25 (-2.68)	-
65-74 years	-	-	-	-	0.14 (1.81)	-	-0.39 (-4.27)	-
>= 75 years	-	-	-0.12 (-2.47)	-0.08 (-1.48)	0.23 (3.04)	-	-0.66 (-6.86)	-
Race (Black and others are base)								
White	-	-	-	-	-	0.37 (3.97)	-	-
Driver (Non-Driver is base)								
Driver	-	-	-	-	-	0.47 (3.25)	-	-
Education(H. school/ lower is base)								
Some college	-	0.20 (3.77)	-	0.08 (1.22)	-	-	-	-
Bachelor to higher	-	0.26 (4.71)	-	0.37 (5.67)	-	-	-	-
Born in US (others are base)	-	-	0.08 (1.19)	-	-	0.27 (3.53)	-	-
Total No. of Children								
Children aged 0-5years	-0.12 (-1.93)	-0.19 (-2.30)	-	-	-	-	0.38 (5.53)	-
Children aged 6-15 years	-	-	-	-	-	-	0.48 (9.80)	-

Appendix A (Contd.)

Table A2 (Contd.)

	Shopping	Other Maintenance	Social/ Recreational	Active Recreation	Medical	Meal	Pick up /Drop Off	Other activities
Total Number of Workers	-0.05 (-1.60)	-	-	-	-	-	0.14 (2.95)	-
Income (< 25 K is base)								
25 – 50K	-	0.14 (2.44)	0.12 (2.10)	0.12 (1.62)	-	0.32 (4.96)	-	-
51-75K	-	0.18 (2.48)	0.17 (2.46)	0.30 (3.53)	-	0.40 (5.19)	-	-
>75K	-	0.19 (2.81)	0.15 (2.35)	0.51 (6.46)	-	0.58 (8.49)	-	-
Land –Use Variables (Rural is Base)								
Urban	0.07 (1.62)	-	0.17 (3.01)	0.19 (2.91)	0.17 (2.85)	-	0.25 (3.38)	-
Survey Day (Tue. –Thur. is base)								
Monday	-	-	-0.17 (-2.93)	-	-	-0.24 (-3.76)	-	-
Friday	-	-	0.08 (1.49)	-	-	0.07 (1.09)	-	-
Satiation Parameters								
Constants	2.90 (69.50)	2.95 (57.95)	4.34 (100.17)	1.76 (17.84)	3.27 (79.36)	3.16 (65.22)	1.50 (31.63)	2.23 (32.20)
Gender (Male is base)								
Female	0.26 (4.83)	0.14 (2.05)	-	-0.17 (-1.72)	-	-	-	-
Age (18-29 years & ≥ 55 years base)								
30-54 years	-	-	0.24 (-2.37)	-	-	-	-	-

Appendix A (Contd.)

Table A2 (Contd.)

	Shopping	**Other Maintenance**	**Social/ Recreational**	**Active Recreation**	**Medical**	**Meal**	**Pick up /Drop Off**	**Other activities**
Education(H. school/ lower is base)								
Some college	-	-	-	0.37 (3.03)	-	-	-	-
Bachelor to higher	-	-	-	0.69 (6.10)	-	-	-	-
Survey Day (Tue.-Thur. is base)								
Monday	-	-	-	-	-	-0.14 (-1.36)	-	-
Friday	-	-	0.12 (1.40)	-	-	0.20 (2.10)	-	-
Number of Cases	8396							
Log likelihood value at constants	-115046.19							
Log likelihood value at convergence	-114340.93							

Appendix A (Contd.)

Table A3 MDCEV Model Results for Southeast Florida Region

	Shopping	**Other Maintenance**	**Social/ Recreational**	**Active Recreation**	**Medical**	**Meal**	**Pick up /Drop Off**	**Other activities**
Baseline Utility Parameters								
Constants	-7.45 (-74.79)	-8.89 (-49.01)	-8.48 (-77.19)	-8.99 (-67.10)	-8.75 (-75.57)	-9.48 (-51.48)	-8.46 (-56.68)	-10.20 (-84.54)
Gender (Male is base)								
Female	0.09 (1.15)	-	-	-0.20 (-1.97)	-	-	-	-
Age (30 – 54 years is base)								
<30 years	-	-	0.75 (3.57)	-	-	-	-	-
55-64 years	-	-	-	-	-	-	-0.48 (-2.64)	-
65-74 years	-	-	-	-	0.28 (2.33)	-	-0.62 (-3.78)	-
>= 75 years	-	-	-	-	0.24 (2.11)	-	-1.00 (5.99)	-
Race (Black and others are base)								
White	-	-	-	-	-	0.27 (1.73)	-	-
Driver (Non-Driver is base)								
Driver	-	0.44 (2.36)	-	-	-	-	-	-
Education(H. school/ lower is base)								
Some college	-	0.35 (3.10)	-	-	-	-	-	-
Bachelor to higher	-	0.50 (4.76)	-	0.20 (5.67)	-	-	-	-
Born in US (others are base)	-	-	0.17 (1.77)	-	-	0.49 (4.18)	-	-
Total No. of Children								
Children aged 0-5years	-	-0.29 (-1.68)	-	-	-	-	0.26 (1.81)	-
Children aged 6-15 years	-	-	-	-	-	-	0.48 (5.09)	-

Appendix A (Contd.)

Table A3 (Contd.)

	Shopping	**Other Maintenance**	**Social/ Recreational**	**Active Recreation**	**Medical**	**Meal**	**Pick up /Drop Off**	**Other activities**
Total Number of Workers	-0.14 (-2.26)	-	-	-	-	-	-	-
Income (< 25 K is base)								
25 – 50K	-	-	-	-	-	0.29 (2.08)	-	-
51-75K	-	-	-	0.29 (2.03)	-	0.30 (1.86)	-	-
>75K	-	-	-	0.55 (4.59)	-	0.82 (5.98)	-	-
Land –Use Variables (Rural is Base)								
No. of Recreation Sites (within 1 mile buffer)	-	-	0.005 (3.55)	-	-	-	-	-
No. of Cul-de-sacs (within 0.25 mile buffer)	-	-	-	0.01 (0.96)	-	-	-	-
Survey Day (Tue. –Thur. is base)								
Monday	-	-	-0.17 (-2.93)	-	-	-0.24 (-3.76)	-	-
Satiation Parameters								
Constants	2.82 (34.00)	3.17 (46.65)	4.31 (49.46)	1.64 (8.56)	3.38 (42.48)	3.02 (34.73)	1.44 (15.93)	2.41 (16.38)
Gender (Male is base)								
Female	0.34 (3.13)	-	-	-0.25 (-1.30)	-	-	-	-
Age (18-29 years & ≥ 55 years base)								
30-54 years	-	-	-0.32 (-1.77)	-	-	-	-	-

Appendix A (Contd.)

Table A3 (Contd.)

	Shopping	Other Maintenance	Social/ Recreational	Active Recreation	Medical	Meal	Pick up /Drop Off	Other activities
Education(H. school/ lower is base)								
Some college	-	-	-	0.36 (1.49)	-	-	-	-
Bachelor to higher	-	-	-	0.94 (4.28)	-	-	-	-
Survey Day (Tue.-Thur. is base)								
Friday	-	-	0.31 (1.83)	-	-	0.26 (1.41)	-	-
Number of Cases	2088							
Log likelihood value at constants	-29681.30							
Log likelihood value at convergence	-29397.20							

Appendix A (Contd.)

Table A4 MDCEV Model Results for Central Florida Region

	Shopping	Other Maintenance	Social/ Recreational	Active Recreation	Medical	Meal	Pick up /Drop Off	Other activities
Baseline Utility Parameters								
Constants	-7.55 (-53.30)	-8.54 (-53.07)	-8.68 (-53.06)	-9.33 (-44.29)	-8.78 (-45.52)	-9.65 (-29.19)	-9.85 (-18.27)	-10.26 (-61.80)
Gender (Male is base)								
Female	0.13 (1.56)	-	-	-	-	-	-	-
Age (< 55 years is base)								
55-64years	-	-	-	-	0.15 (0.77)	0.39 (2.01	-0.38 (-1.65)	-
65-74 years	-	-	-	-	0.16 (0.93)	0.43 (2.44)	-0.43 (-1.96)	-
>= 75 years	-	-	-	-	0.28 (2.33)	0.39 (2.16)	-0.65 (-2.82)	-
Race (Black and others are base)								
White	-	-	-	-	-	0.44 (1.72)	-	-
Driver (Non-Driver is base)								
Driver	-	-	-	-	-	1.06 (2.07)	-	-
Education (Some col./ lower is base)								
Bachelor to higher	-	0.22 (1.94)	-	0.39 (2.96)	-	-	-	-
Born in US (others are base)	-	-	-	-	-	0.14 (0.67)	-	-
Total No. of Children								
Children aged 0-5years	-0.50 (-2.55)	-0.26 (-1.38)	-	-	-	-	0.58 (3.90)	-
Children aged 6-15 years	-	-	-	-	-	-	0.46 (2.95)	-

Appendix A (Contd.)

Table A4 (Contd.)

	Shopping	Other Maintenance	Social/ Recreational	Active Recreation	Medical	Meal	Pick up /Drop Off	Other activities
Total Number of Workers	-0.10 (-1.20)	-	-	-	-	-	0.14 (1.21)	-
Income (< 25 K is base)								
25 – 50K	-	0.34 (2.43)	0.29 (2.12)	0.39 (2.34)	-	0.29 (2.08)	-	-
51-75K	-	0.28 (1.62)	0.27 (1.61)	0.43 (1.61)	-	0.30 (1.86)	-	-
>75K	-	0.37 (2.26)	0.38 (2.48)	0.38 (2.48)	-	0.82 (5.98)	-	-
Land –Use Variables (Rural is Base)								
No. of Recreation Sites (within 1 mile buffer)	-	-	0.07 (2.02)	-	-	-	-	-
No. of Cul-de-sacs (within 0.25 mile buffer)	-	-	-	0.006 (1.25)	-	-	-	-
Survey Day (Tue. –Thur. is base)								
Monday	-	-	-	-	-	-0.16 (-1.10)	-	-
Friday	-	-	0.22 (1.80)	-	-	0.29 (2.29)	-	-
Satiation Parameters								
Constants	3.04 (47.0)	2.94 (37.04)	4.19 (49.04)	1.57 (9.02)	3.11 (32.69)	3.15 (36.18)	1.41 (12.98)	1.97 (11.90)
Education(H. school/ lower is base)								
Some college	-	-	-	0.31 (1.10)	-	-	-	-
Bachelor to higher	-	-	-	0.76 (2.93)	-	-	-	-

Appendix A (Contd.)

Table A4 (Contd.)

	Shopping	Other Maintenance	Social/ Recreational	Active Recreation	Medical	Meal	Pick up /Drop Off	Other activities
Number of Cases	1458							
Log likelihood value at constants	-20518.7							
Log likelihood value at convergence	-20386.6							

Appendix A (Contd.)

Table A5 MDCEV Model Results for Tampa Bay Region

	Shopping	**Other Maintenance**	**Social/ Recreational**	**Active Recreation**	**Medical**	**Meal**	**Pick up /Drop Off**	**Other activities**
Baseline Utility Parameters								
Constants	-6.69 (-89.77)	-7.41 (-83.86)	-8.18 (-34.51)	-8.69 (-30.04)	-7.99 (-45.27)	-8.07 (-31.25)	-9.00 (-26.47)	-9.04 (-84.49)
Gender (Male is base)								
Female	0.16 (1.82)	-	-	-	-	-	-	-
Age (< 55 years is base)								
55-64years	-	-	-	-	0.39 (1.80)	-	-	-
65-74 years	-	-	-	-	0.30 (1.47)	-	-	-
>= 75 years	-	-	-0.31 (-2.52)	-0.16 (-1.21)	0.36 (2.04)	-	-0.59 (-3.21)	-
Race (Black and others are base)								
White	-	-	-	-	-	0.28 (1.08)	-	-
Driver (Non-Driver is base)								
Driver	-	-	0.68 (2.97)	0.60 (2.29)	-	0.72 (2.26)	-	-
Education (Some col./ lower is base)								
Some college	-	0.33 (2.64)	-	-	-	-	-	-
Bachelor to higher	-	0.32 (2.52)	-	0.21 (1.51)	-	-	-	-
Total No. of Children								
Children aged 0-5years	-0.14 (-0.85)	-	-	-	-	-	0.23 (1.30)	-
Children aged 6-15 years	-	-	-	-	-	-	0.58 (3.95)	-
Total Number of Workers	-	-	-	-	-	-	0.38 (3.24)	-

Appendix A (Contd.)

Table A5 (Contd.)

	Shopping	Other Maintenance	Social/ Recreational	Active Recreation	Medical	Meal	Pick up /Drop Off	Other activities
Income (< 25 K is base)								
51-75K	-	-	-	0.19 (1.02)	-	0.31 (1.87)	-	-
>75K	-	-	-	0.67 (4.36)	-	0.51 (3.63)	-	-
Land –Use Variables (Rural is Base)								
No. of Recreation Sites (within 1 mile buffer)	-	-	0.004 (2.42)	-	-	-	-	-
No. of Employments (within 1 mile buffer)	-	-	0.002 (1.39)	-	-	-	-	-
Total Number of Intersections (within 0.25 mile buffer)	-	-	-	0.006 (1.59)	-	-	-	-
Survey Day (Mon. –Thur. is base)								
Friday	-	-	0.19 (1.33)	-	-	0.18 (1.23)	-	-
Satiation Parameters								
Constants	3.01 (44.73)	2.71 (21.76)	4.44 (46.92)	2.04 (16.81)	3.19 (31.79)	3.05 (28.65)	1.59 (13.58)	2.09 (12.84)
Gender (Male is base)								
Female	-	0.34 (2.12)	-	-	-	-	-	-
Survey Day (Mon. –Thur. is base)								
Friday	-	-	-0.32 (-1.77)	-	-	-	-	-
Number of Cases	1334							
Log likelihood value at constants	-18390.8							
Log likelihood value at convergence	-18302.0							

Appendix A (Contd.)

Table A6 MDCEV Model Results for D1Urban Region

	Shopping	Maintenance	Social/ Recreational	Active Recreation	Medical	Meal	Pick up /Drop Off	Other activities
Baseline Utility Parameters								
Constants	-6.99 (-33.88)	-7.62 (-29.53)	-7.36 (-80.03)	-7.61 (-28.02)	-7.69 (-84.54)	-8.51 (-30.69)	-8.21 (-40.91)	-9.39 (-64.71)
Gender (Male is base)								
Female	0.14 (1.35)	-	-	-0.19 (-1.40)	-	-	0.15 (0.89)	-
Age (< 55 years is base)								
55-64years	-	-	-	-	-	0.70 (2.45)	-	-
65-74 years	-	-	-	-	-	0.89 (3.35)	-0.17 (-0.79)	-
>= 75 years	-	-	-	-	0.14 (1.02)	0.69 (2.60)	-0.13 (-0.63)	-
Driver (Non-Driver is base)								
Driver	0.39 (1.92)	0.41 (1.55)	-	-	-	-	-	-
Education (Some col./ lower is base)								
Some college	-	0.37 (2.10)	-	-	-	-	-	-
Bachelor to higher	-	0.54 (3.01)	-	-	-	-	-	-
Born in US (others are base)	-	-	-0.39 (-1.52)	-	-	-	-	-
Total No. of Children								
Children aged 0-5years	-	-0.43 (-1.35)	-	-	-	-	0.26 (1.17)	-
Children aged 6-15 years	-	-	-	-	-	-	0.81 (4.61)	-
Total Number of Workers	-	-	-	-	-	-	0.38 (3.24)	-

Appendix A (Contd.)

Table A6 (Contd.)

	Shopping	Other Maintenance	Social/ Recreational	Active Recreation	Medical	Meal	Pick up /Drop Off	Other activities
Income (< 25 K is base)								
25K-50K	-	-	-	-	-	0.40 (2.16)	-	-
51-75K	-	-	-	0.41 (2.20)	-	0.57 (2.60)	-	-
>75K	-	-	-	0.40 (2.35)	-	0.61 (3.07)	-	-
Land –Use Variables (Rural is Base)								
No. of Recreation Sites (within 1 mile buffer)	-	-	0.004 (2.42)	-	-	-	-	-
No. of Employments (within 1 mile buffer)	-	-	0.002 (1.39)	-	-	-	-	-
Survey Day (Mon. –Thur. is base)								
Monday	-	-	-0.50 (-2.94)	-	-	-0.19 (1.08)	-	-
Satiation Parameters								
Constants	3.06 (39.6)	3.02 (31.60)	4.29 (40.46)	1.15 (5.97)	3.20 (27.99)	3.20 (30.68)	1.28 (9.74)	2.27 (10.40)
Age (18-29 years, >= 55 years base)								
30-54 years	-	-	-	-0.46 (-1.39)		-	-	-
Education(H. school/ lower is base)								
Some college	-	-	-	1.37 (4.29)	-	-	-	-
Bachelor to higher	-	-	-	1.68 (5.73)		-	-	-

Appendix A (Contd.)

Table A6 (Contd.)

	Shopping	**Other Maintenance**	**Social/ Recreational**	**Active Recreation**	**Medical**	**Meal**	**Pick up /Drop Off**	**Other activities**
Number of Cases	995							
Log likelihood value at constants	-14506.10							
Log likelihood value at convergence	-14425.41							

Appendix A (Contd.)

Table A7 MDCEV Model Results for Rural Region

	Shopping	**Other Maintenance**	**Social/ Recreational**	**Active Recreation**	**Medical**	**Meal**	**Pick up /Drop Off**	**Other activities**
Baseline Utility Parameters								
Constants	-7.20 (-30.73)	-8.32 (-26.86)	-7.42 (-93.09)	-9.83 (-17.91)	-8.03 (-52.51)	-7.90 (-22.28)	-9.42 (-14.27)	-8.97 (-65.07)
Gender (Male is base)								
Female	0.04 (0.57)	-	-	-	-	-	0.26 (1.14)	-
Age (<55 years is base)								
55-64 years	-	-	-	-	-	-	-0.61 (-1.72)	-
65-74 years	-	-	-	-	0.23 (1.12)	-	-0.41 (-1.33)	-
>= 75 years	-	-	-	-	0.20 (0.93)	-	-0.59 (-1.76)	-
Race (Black and others are base)								
White	-	-	-	-	-	0.58 (1.64)	-	-
Driver (Non-Driver is base)								
Driver	0.65 (2.86)	1.00 (3.21)	-	1.38 (2.62)	-	-	-1.35 (2.25)	-
Education(H. school/ lower is base)								
Some college	-	0.30 (1.79)	-	-	-	-	-	-
Bachelor to higher	-	0.30 (1.60)	-	0.64 (2.91)	-	-	-	-
Total No. of Children								
Children aged 0-5years	-	-0.20 (-1.06)	-	-	-	-	0.71 (3.43)	-
Children aged 6-15 years	-	-	-	-	-	-	0.19 (1.30)	-

Appendix A (Contd.)

Table A7 (Contd.)

	Shopping	**Other Maintenance**	**Social/ Recreational**	**Active Recreation**	**Medical**	**Meal**	**Pick up /Drop Off**	**Other activities**
Income (> 25 K is base) < 25k	-	-	-	-0.32 (-1.44)	-	-0.52 (-2.94)	-	-
Land –Use Variables (Rural is Base) No. of Intersections (within 0.25 mile buffer)	-	-	-	0.02 (3.14)	-	-	-	-
Survey Day (Tue. –Thur. is base) Monday	-	-	-	-	-	-0.87 (-3.31)	-	-
Satiation Parameters								
Constants	2.92 (32.07)	2.63 (15.90)	4.39 (36.37)	1.29 (8.07)	3.27 (22.30)	3.22 (25.23)	1.44 (8.53)	2.20 (10.7)
Gender (Male is base) Female	-	0.32 (1.46)	-	-	-	-	-	-
Number of Cases	757							
Log likelihood value at constants	-9719.88							
Log likelihood value at convergence	-9658.71							

Appendix A (Contd.)

Table A8 MNL Model Results for Four Counties (using application-based approach)

Variables	Alameda	Santa Clara	San Francisco	San Mateo
	Coef. (t-stat)	Coef. (t-stat)	Coef. (t-stat)	Coef. (t-stat)
Start Time Function				
Sin(2πTs/24)	-1.95(-0.38)	10.16(2.51)	-15.30(-0.70)	15.04(0.92)
Sin(4πTs/24)	7.40(3.60)	3.51(2.36)	9.57(1.86)	13.46(3.30)
Sin(6πTs/24)	1.94(1.90)	-1.17(-1.55)	4.61(1.33)	2.15(1.25)
Sin(8πTs/24)	-0.89(-2.78)	-1.48(-6.20)	-0.08(-0.11)	-1.30(-2.65)
Cos(2πTs/24)	-17.65(-2.51)	2.66(0.53)	-34.80(-1.27)	-16.44(-1.02)
Cos(4πTs/24)	-3.51(-1.26)	4.22(1.99)	-11.64(-1.05)	1.04(0.16)
Cos(6πTs/24)	2.17(2.18)	2.50(3.23)	0.92(0.40)	4.56(2.35)
Cos(8πTs/24)	0.78(2.73)	0.20(0.90)	1.40(2.15)	0.92(2.29)
End Time Function				
Sin(2πTe/24)	13.94(1.80)	-7.79(-1.31)	31.48(1.07)	-2.58(-0.15)
Sin(4πTe/24)	3.57(1.62)	-2.46(-1.31)	7.69(1.19)	-3.62(-0.98)
Sin(6πTe/24)	0.06(0.08)	-0.71(-1.21)	1.24(0.62)	-1.59(-1.06)
Sin(8πTe/24)	-0.26(-1.15)	0.02(0.09)	0.44(0.76)	-0.37(-1.05)
Cos(2πTe/24)	-8.59(-2.23)	1.77(0.71)	-18.01(-0.94)	-6.43(-0.43)
Cos(4πTe/24)	-5.39(-2.17)	2.16(1.24)	-9.76(-0.92)	-1.02(-0.15)
Cos(6πTe/24)	-3.02(-2.69)	0.77(0.90)	-3.78(-1.03)	-0.14(-0.07)
Cos(8πTe/24)	-0.94(-3.12)	-0.07(-0.29)	-1.24(-1.7)	-0.60(-1.47)
Duration Function				
Duration	47.76(2.31)	-9.06(-0.59)	93.65(1.09)	20.12(0.36)
Duration^2	-13.71(-1.86)	-10.80(-1.63)	-5.32(-0.28)	-12.40(-0.84)
Duration^3	4.00(0.77)	1.33(0.30)	-0.03(-0.01)	-1.59(-0.16)
Level-of-Service				
Home to Work travel time	-0.18(-4.32)	-0.27(-6.28)	0.01(0.03)	-0.18(-2.73)
Work to Home travel time	0.03(0.68)	-0.07(-1.48)	0.11(1.45)	-0.02(-0.22)
Travel Cost	-0.13(-1.08)	-0.16(-1.06)	-0.13(-1.33)	-0.24(-1.79)
Size of intervals				
Ln(# of half hour in tour start time)	1.00(fixed)	1.00(fixed)	1.00(fixed)	1.00(fixed)
Ln(# of half hour in tour end time)	1.00(fixed)	1.00(fixed)	1.00(fixed)	1.00(fixed)
Female with Kids				
Start Time				
Sin(2πTs/24)*Female with kids	-0.34(-0.72)	1.65(2.76)	3.17(1.46)	2.52(1.94)
Sin(4πTs/24)*Female with kids	0.52(1.90)	1.22(3.99)	2.49(2.05)	2.12(3.32)
Cos(2πTs/24)*Female with kids	-0.76(-2.19)	-1.56(-3.75)	-3.29(-2.00)	-2.59(-2.89)
Cos(4πTs/24)*Female with kids	-0.37(-1.70)	0.37(1.57)	0.25(0.34)	0.13(0.29)

Appendix A (Contd.)

Table A8 (Contd.)

Variables	Alameda	Santa Clara	San Francisco	San Mateo
	Coef. (t-stat)	Coef. (t-stat)	Coef. (t-stat)	Coef. (t-stat)
End Time				
Sin(2πTe/24)*Female with kids	0.18(0.43)	-0.02(-0.05)	0.89(0.97)	-0.90(-1.21)
Sin(4πTe/24)*Female with kids	0.05(0.19)	0.09(0.38)	0.46(0.70)	-0.66(-1.57)
Cos(2πTe/24)*Female with kids	-0.61(-1.43)	-0.05(-0.12)	0.39(0.43)	-1.10(-1.68)
Cos(4πTe/24)*Female with kids	0.09(0.46)	0.36(2.41)	-0.16(-0.42)	0.28(1.05)
Full-Time Workers				
Start Time				
Sin(2πTs/24)*Full-time workers	-4.65(-1.24)	1.72(0.7)	-1.78(-0.12)	-15.18(-1.00)
Sin(4πTs/24)*Full-time workers	0.71(0.62)	-0.02(-0.02)	-3.65(-0.97)	-2.97(-1.13)
Sin(6πTs/24)*Full-time workers	0.74(1.47)	0.35(0.98)	0.03(0.02)	0.07(0.07)
Cos(2πTs/24)*Full-time workers	-5.11(-1.01)	2.77(0.87)	7.04(0.38)	-5.61(-0.43)
Cos(4πTs/24)*Full-time workers	-2.19(-1.20)	0.17(0.14)	0.24(0.04)	-4.13(-0.73)
Cos(6πTs/24)*Full-time workers	-0.46(-1.08)	-0.33(-0.89)	-1.50(-1.09)	-1.38(-1.19)
End Time				
Sin(2πTe/24)*Full-time workers	5.67(1.04)	-4.01(-1.08)	-3.77(-0.19)	17.27(1.17)
Sin(4πTe/24)*Full-time workers	1.02(0.81)	-1.03(-0.96)	-0.55(-0.16)	5.51(2.37)
Sin(6πTe/24)*Full-time workers	-0.07(-0.2)	-0.26(-0.93)	0.18(0.17)	0.43(0.48)
Cos(2πTe/24)*Full-time workers	-3.8(-1.15)	0.97(0.55)	2.60(0.19)	-6.37(-0.46)
Cos(4πTe/24)*Full-time workers	-1.48(-0.8)	1.00(0.88)	1.85(0.26)	-5.60(-0.96)
Cos(6πTe/24)*Full-time workers	0.06(0.1)	0.75(1.73)	0.69(0.37)	-1.92(-1.54)
Flexibility				
Start Time				
Sin(2πTs/24)*Flexibility	-2.11(-0.74)	-2.74(-1.41)	8.78(1.40)	-0.34(-0.11)
Sin(4πTs/24)*Flexibility	-0.97(-0.43)	-2.74(-1.61)	6.23(1.28)	-0.28(-0.10)
Sin(6πTs/24)*Flexibility	1.01(1.94)	-0.31(-0.65)	0.37(0.34)	-0.08(-0.10)
Sin(8πTs/24)*Flexibility	0.62(1.53)	0.65(2.21)	-1.02(-1.20)	0.34(0.70)
Cos(2πTs/24)*Flexibility	0.14(0.07)	1.85(1.28)	-5.98(-1.46)	-0.50(-0.21)
Cos(4πTs/24)*Flexibility	-1.83(-1.61)	-0.97(-1.46)	2.78(1.16)	-0.23(-0.19)
Cos(6πTs/24)*Flexibility	-0.71(-0.54)	-1.13(-1.17)	4.24(1.50)	0.05(0.03)
Cos(8πTs/24)*Flexibility	0.51(1.46)	-0.17(-0.56)	0.38(0.54)	0.04(0.07)
End Time				
Sin(2πTe/24)*Flexibility	2.25(2.27)	0.86(1.60)	-4.56(-0.90)	4.05(1.97)
Sin(4πTe/24)*Flexibility	2.85(2.19)	0.98(1.32)	-5.82(-1.02)	5.10(2.01)
Sin(6πTe/24)*Flexibility	2.54(2.69)	0.84(1.39)	-3.99(-1.30)	3.47(2.20)
Sin(8πTe/24)*Flexibility	0.98(2.86)	0.18(0.70)	-1.18(-1.58)	0.83(1.77)
Cos(2πTe/24)*Flexibility	3.09(1.93)	0.81(0.85)	-7.75(-1.23)	5.67(1.94)

Appendix A (Contd.)

Table A8 (Contd.)

Variables	Alameda	Santa Clara	San Francisco	San Mateo
	Coef. (t-stat)	Coef. (t-stat)	Coef. (t-stat)	Coef. (t-stat)
Cos(4πTe/24)*Flexibility	1.58(1.85)	0.35(0.57)	-3.53(-1.87)	2.13(1.83)
Cos(6πTe/24)*Flexibility	0.44(1.11)	0.27(0.92)	0.05(0.04)	-0.19(-0.32)
Cos(8πTe/24)*Flexibility	-0.34(-1.49)	-0.08(-0.52)	0.94(1.12)	-0.54(-1.38)
High Income (>75K)				
Start Time				
Sin(2πTs/24)*High income	0.23(0.62)	-0.21(-0.56)	1.33(1.67)	0.66(1.08)
Sin(4πTs/24)*High income	0.34(1.79)	0.07(0.38)	0.62(1.46)	-0.14(-0.46)
Cos(2πTs/24)*High income	-0.36(-1.53)	-0.33(-1.32)	-0.27(-0.49)	0.17(0.41)
Cos(4πTs/24)*High income	0.14(0.78)	-0.29(-1.74)	0.24(0.66)	0.30(1.14)
End Time				
Sin(2πTe/24)*High income	-0.23(-0.78)	0.01(0.03)	-0.19(-0.30)	0.11(0.27)
Sin(4πTe/24)*High income	-0.04(-0.17)	-0.03(-0.15)	0.21(0.51)	0.18(0.71)
Cos(2πTe/24)*High income	-0.63(-2.13)	-0.37(-1.42)	-0.33(-0.55)	0.25(0.66)
Cos(4πTe/24)*High income	-0.46(-3.62)	-0.54(-4.85)	-0.49(-2.06)	-0.07(-0.40)
Government Employees				
Start Time				
Sin(2πTs/24)*Govt. employees	3.78(0.60)	-1.23(-0.34)	3.78(0.42)	-14.33(-2.79)
Sin(4πTs/24)*Govt. employees	1.56(0.37)	-1.03(-0.34)	2.37(0.36)	-10.55(-2.53)
Sin(6πTs/24)*Govt. employees	-0.87(-0.92)	-0.40(-0.49)	-0.39(-0.26)	0.25(0.22)
Sin(8πTs/24)*Govt. employees	-0.69(-0.87)	0.01(0.02)	-0.19(-0.15)	1.60(2.01)
Cos(2πTs/24)*Govt. employees	-1.41(-0.41)	0.58(0.23)	-1.41(-0.26)	8.84(2.56)
Cos(4πTs/24)*Govt. employees	2.04(0.69)	-0.34(-0.26)	1.80(0.46)	-6.15(-3.05)
Cos(6πTs/24)*Govt. employees	1.03(0.40)	-0.80(-0.46)	1.25(0.31)	-6.04(-2.40)
Cos(8πTs/24)*Govt. employees	-0.42(-0.89)	-0.80(-1.56)	-0.45(-0.50)	-1.21(-1.73)
End Time				
Sin(2πTe/24)*Govt. employees	-0.05(-0.11)	-0.94(-1.68)	0.76(0.93)	-1.55(-1.62)
Sin(4πTe/24)*Govt. employees	0.07(0.23)	-0.83(-2.47)	0.22(0.40)	-0.66(-1.36)
Cos(2πTe/24)*Govt. employees	-0.43(-1.00)	-1.58(-2.70)	0.81(1.18)	-0.80(-1.18)
Cos(4πTe/24)*Govt. employees	0.23(1.28)	0.29(1.41)	0.64(2.22)	0.86(2.87)
Interaction Variables				
Full-time workers*duration	6.39(0.41)	-19.80(-1.94)	-19.53(-0.32)	22.45(0.44)
Full-time workers*duration^2	35.81(4.31)	33.25(4.44)	27.07(1.34)	37.81(2.42)
Full-time workers*duration^3	-23.00(-4.01)	-21.22(-4.21)	-17.02(-1.22)	-19.42(-1.86)
Home to Work traveltime*Flex.	0.03(0.40)	0.24(3.10)	-0.01(-0.02)	0.18(1.61)
Observations	1940	3001	538	1209
Log-likelihood at constants	-10245.3	-15414.9	-2800.4	-6232.3
Log-likelihood at convergence	-9843.4	-14809.2	-2682.61	-5958.9

Appendix A (Contd.)

Table A9 MNL Model Results for Four Counties (using estimation-based approach)

	Alameda	Santa Clara	San Francisco	San Mateo
Variables	**Coef. (t-stat)**	**Coef. (t-stat)**	**Coef. (t-stat)**	**Coef. (t-stat)**
Start Time Function				
Sin(2πTs/24)	-3.08(-1.42)	3.38(1.57)	3.58(1.67)	3.61(1.68)
Sin(4πTs/24)	2.29(3.08)	2.66(3.70)	2.66(3.70)	2.69(3.74)
Sin(6πTs/24)	-0.33(-0.84)	-0.29(-0.75)	-0.32(-0.82)	-0.31(-0.79)
Sin(8πTs/24)	-0.81(-6.50)	-0.88(-7.32)	-0.88(-7.38)	-0.88(-7.37)
Cos(2πTs/24)	-1.99(-0.75)	-2.42(-0.91)	-2.18(-0.82)	-2.22(-0.83)
Cos(4πTs/24)	0.45(0.40)	0.60(0.53)	0.71(0.63)	0.71(0.63)
Cos(6πTs/24)	0.80(2.02)	1.03(2.73)	1.05(2.78)	1.06(2.82)
Cos(8πTs/24)	0.15(1.25)	0.20(1.79)	0.20(1.77)	0.20(1.81)
End Time Function				
Sin(2πTe/24)	-0.79(-0.25)	-0.59(-0.20)	-0.89(-0.28)	-0.88(-0.28)
Sin(4πTe/24)	-0.10(-0.09)	-0.02(-0.02)	-0.12(-0.13)	-0.12(-0.12)
Sin(6πTe/24)	0.03(0.09)	0.06(0.19)	0.02(0.08)	0.026(0.09)
Sin(8πTe/24)	0.12(1.42)	0.12(1.45)	0.12(1.42)	0.12(1.43)
Cos(2πTe/24)	-0.94(-0.69)	-1.02(-0.75)	-0.90(-0.66)	-0.91(-0.67)
Cos(4πTe/24)	0.20(0.21)	0.16(0.17)	0.23(0.24)	0.22(0.24)
Cos(6πTe/24)	-0.33(-0.74)	-0.35(-0.79)	-0.31(-0.70)	-0.31(-0.70)
Cos(8πTe/24)	-0.45(-3.69)	-0.46(-3.78)	-0.45(-3.66)	-0.45(-3.67)
Tour Duration Function				
Duration	6.65(0.811)	7.20(0.89)	6.40(0.78)	6.44(0.79)
Duration2	-6.49(-1.81)	-6.45(-1.80)	-6.47(-1.81)	-6.47(-1.81)
Duration3	-1.42(-0.56)	-1.47(-0.57)	-1.44(-0.57)	-1.45(-0.57)
Level-of-Service				
Home to Work travel time	-0.17(-10.17)	-0.15(-8.36)	-0.17(-10.21)	-0.17(-10.35)
Work to Home travel time	-0.04(-2.04)	-0.03(-1.64)	-0.03(-1.75)	-0.03(-1.77)
Travel Cost	-0.15(-3.07)	-0.15(-3.17)	-0.14(-2.96)	-0.14(-2.97)
Size of intervals				
Ln(# of half hour in tour start time)	1.00(fixed)	1.00(fixed)	1.00(fixed)	1.00(fixed)
Ln(# of half hour in tour end time)	1.00(fixed)	1.00(fixed)	1.00(fixed)	1.00(fixed)
Female with Kids				
Start Time				
Sin(2πTs/24)*Female with kids	0.39(1.66)	0.39(1.65)	0.40(1.67)	0.25(1.05)
Sin(4πTs/24)*Female with kids	0.74(5.41)	0.74(5.39)	0.74(5.44)	0.65(4.69)
Cos(2πTs/24)*Female with kids	-1.05(-5.83)	-1.04(-5.82)	-1.05(-5.85)	-0.97(-5.31)
Cos(4πTs/24)*Female with kids	-0.15(-1.48)	-0.16(-1.55)	-0.15(-1.5)	-0.16(-1.57)

Appendix A (Contd.)

Table A9 (Contd.)

	Alameda	Santa Clara	San Francisco	San Mateo
Variables	**Coef. (t-stat)**	**Coef. (t-stat)**	**Coef. (t-stat)**	**Coef. (tstat)**
End Time				
Sin(2πTe/24)*Female with kids	-0.07(-0.39)	-0.07(-0.39)	-0.07(-0.39)	0.02(0.08)
Sin(4πTe/24)*Female with kids	-0.08(-0.70)	-0.08(-0.70)	-0.08(-0.69)	-0.04(-0.29)
Cos(2πTe/24)*Female with kids	-0.43(-2.32)	-0.43(-2.33)	-0.43(-2.32)	-0.41(-2.15)
Cos(4πTe/24)*Female with kids	0.21(2.74)	0.21(2.72)	0.21(2.75)	0.19(2.36)
Full-Time Workers				
Start Time				
Sin(2πTs/24)*Full-time workers	0.14(0.10)	0.18(0.13)	0.15(0.11)	0.14(0.10)
Sin(4πTs/24)*Full-time workers	0.32(0.74)	0.39(0.86)	0.31(0.70)	0.30(0.69)
Sin(6πTs/24)*Full-time workers	0.45(2.38)	0.43(2.28)	0.45(2.38)	0.45(2.38)
Cos(2πTs/24)*Full-time workers	0.54(0.32)	0.49(0.29)	0.59(0.35)	0.58(0.34)
Cos(4πTs/24)*Full-time workers	-0.19(-0.28)	-0.10(-0.14)	-0.18(-0.28)	-0.19(-0.29)
Cos(6πTs/24)*Full-time workers	-0.17(-0.91)	-0.11(-0.58)	-0.17(-0.93)	-0.18(-0.97)
End Time				
Sin(2πTe/24)*Full-time workers	-0.73(-0.37)	-0.63(-0.32)	-0.78(-0.39)	-0.76(-0.39)
Sin(4πTe/24)*Full-time workers	-0.13(-0.23)	-0.13(-0.24)	-0.14(-0.25)	-0.13(-0.24)
Sin(6πTe/24)*Full-time workers	-0.18(-1.32)	-0.23(-1.59)	-0.18(-1.32)	-0.18(-1.31)
Cos(2πTe/24)*Full-time workers	-0.17(-0.17)	-0.20(-0.20)	-0.15(-0.15)	-0.15(-0.16)
Cos(4πTe/24)*Full-time workers	0.18(0.29)	0.08(0.14)	0.19(0.31)	0.19(0.31)
Cos(6πTe/24)*Full-time workers	0.42(1.86)	0.37(1.63)	0.42(1.88)	0.42(1.87)
Flexibility				
Start Time				
Sin(2πTs/24)*Flexibility	0.81(0.77)	0.82(0.78)	0.79(0.75)	0.77(0.74)
Sin(4πTs/24)*Flexibility	0.71(0.79)	0.72(0.81)	0.70(0.78)	0.69(0.77)
Sin(6πTs/24)*Flexibility	0.35(1.48)	0.35(1.46)	0.35(1.47)	0.35(1.47)
Sin(8πTs/24)*Flexibility	0.14(0.90)	0.14(0.92)	0.15(0.94)	0.15(0.94)
Cos(2πTs/24)*Flexibility	-1.12(-1.48)	-1.13(-1.48)	-1.13(-1.48)	-1.12(-1.47)
Cos(4πTs/24)*Flexibility	-0.25(-0.68)	-0.22(-0.60)	-0.27(-0.74)	-0.28(-0.74)
Cos(6πTs/24)*Flexibility	0.56(1.09)	0.56(1.10)	0.54(1.05)	0.53(1.04)
Cos(8πTs/24)*Flexibility	0.34(2.17)	0.33(2.15)	0.33(2.14)	0.33(2.13)
End Time				
Sin(2πTe/24)*Flexibility	0.68(2.28)	0.70(2.34)	0.68(2.28)	0.68(2.29)
Sin(4πTe/24)*Flexibility	0.56(1.37)	0.56(1.37)	0.56(1.37)	0.56(1.37)
Sin(6πTe/24)*Flexibility	0.46(1.40)	0.45(1.37)	0.46(1.39)	0.46(1.39)
Sin(8πTe/24)*Flexibility	0.041(0.31)	0.04(0.32)	0.04(0.30)	0.04(0.30)
Cos(2πTe/24)*Flexibility	0.21(0.39)	0.21(0.39)	0.20(0.38)	0.20(0.39)

Appendix A (Contd.)

Table A9 (Contd.)

	Alameda	**Santa Clara**	**San Francisco**	**San Mateo**
Variables	**Coef. (t-stat)**	**Coef. (t-stat)**	**Coef. (t-stat)**	**Coef. (t-stat)**
Cos(4πTe/24)*Flexibility	-0.11(-0.33)	-0.12(-0.38)	-0.11(-0.34)	-0.11(-0.34)
Cos(6πTe/24)*Flexibility	0.07(0.44)	0.05(0.35)	0.07(0.44)	0.07(0.44)
Cos(8πTe/24)*Flexibility	0.002(0.02)	0.0005(0.06)	0.003(0.03)	0.002(0.03)
High Income (>75K)				
Start Time				
Sin(2πTs/24)*High income	0.31(1.89)	0.45(2.36)	0.31(1.91)	0.31(1.88)
Sin(4πTs/24)*High income	0.086(1.01)	0.14(1.48)	0.09(1.02)	0.08(0.91)
Cos(2πTs/24)*High income	-0.06(-0.57)	-0.04(-0.30)	-0.06(-0.58)	-0.05(-0.49)
Cos(4πTs/24)*High income	0.02(0.30)	0.14(1.58)	0.02(0.26)	0.02(0.29)
End Time				
Sin(2πTe/24)*High income	-0.08(-0.60)	-0.13(-0.91)	-0.08(-0.60)	-0.08(-0.60)
Sin(4πTe/24)*High income	0.04(0.44)	0.03(0.34)	0.04(0.46)	0.04(0.45)
Cos(2πTe/24)*High income	-0.14(-1.11)	-0.11(-0.74)	-0.14(-1.10)	-0.14(-1.10)
Cos(4πTe/24)*High income	-0.35(-6.34)	-0.28(-4.43)	-0.35(-6.32)	-0.35(-6.32)
Government Employees				
Start Time				
Sin(2πTs/24)*Govt. employees	-2.60(-1.85)	-2.57(-1.82)	-2.49(-1.76)	-2.49(-1.76)
Sin(4πTs/24)*Govt. employees	-2.45(-2.03)	-2.43(-2.00)	-2.35(-1.94)	-2.36(-1.95)
Sin(6πTs/24)*Govt. employees	-0.65(-1.99)	-0.65(-1.98)	-0.64(-1.97)	-0.65(-1.98)
Sin(8πTs/24)*Govt. employees	0.03(0.13)	0.02(0.07)	0.01(0.05)	0.012(0.06)
Cos(2πTs/24)*Govt. employees	2.07(2.06)	2.04(2.03)	1.20(1.98)	1.20(1.98)
Cos(4πTs/24)*Govt. employees	-0.54(-1.08)	-0.54(-1.09)	-0.49(-0.98)	-0.49(-0.98)
Cos(6πTs/24)*Govt. employees	-1.36(-1.94)	-1.34(-1.90)	-1.31(-1.85)	-1.31(-1.86)
Cos(8πTs/24)*Govt. employees	-0.83(-3.83)	-0.82(-3.80)	-0.82(-3.78)	-0.82(-3.78)
End Time				
Sin(2πTe/24)*Govt. employees	0.011(0.06)	0.0001(0.07)	0.01(0.05)	0.01(0.05)
Sin(4πTe/24)*Govt. employees	-0.11(-0.90)	-0.11(-0.92)	-0.11(-0.92)	-0.11(-0.91)
Cos(2πTe/24)*Govt. employees	-0.22(-1.20)	-0.23(-1.26)	-0.22(-1.21)	-0.22(-1.21)
Cos(4πTe/24)*Govt. employees	0.29(3.69)	0.27(3.49)	0.28(3.68)	0.29(3.68)
Interaction Variables				
Full-time workers*duration	-10.66(-1.96)	-10.63(-1.95)	-10.77(-1.98)	-10.72(-1.97)
Full-time workers*duration2	27.98(7.07)	27.75(7.01)	27.95(7.06)	27.95(7.06)
Full-time workers*duration3	-16.92(-6.16)	-16.74(-6.09)	-16.90(-6.14)	-16.89(-6.14)
Home to Work travel time*Flex.	0.06(1.85)	0.06(1.94)	0.05(1.58)	0.05(1.62)

Appendix A (Contd.)

Table A9 (Contd.)

	Alameda	Santa Clara	San Francisco	San Mateo
Variables	**Coef. (t-stat)**	**Coef. (t-stat)**	**Coef. (t-stat)**	**Coef. (t-stat)**
Interactions with Counties				
Starting Time Function				
Sin(2πTs/24)	2.61(1.94)	-	-	-
Sin(4πTs/24)	2.14(1.99)	-	-	-
Sin(6πTs/24)	0.14(0.52)	-	-	-
Sin(8πTs/24)	-0.36(-1.83)	-	-	-
Cos(2πTs/24)	-1.62(-1.82)	-	-	-
Cos(4πTs/24)	1.18(2.25)	-	-	-
Cos(6πTs/24)	1.34(2.10)	-	-	-
Cos(8πTs/24)	0.27(1.55)	-	-	-
Level-of-Service				
Home to Work travel time	-	-0.08(-2.22)	0.09(2.54)	0.07(2.68)
Work to Home travel time	0.04(1.59)	-	-	-
Full-Time Workers				
Start Time				
Sin(2πTs/24)*Full-time workers	-	-0.13(-0.26)	-	-
Sin(4πTs/24)*Full-time workers	-	-0.24(-0.64)	-	-
Sin(6πTs/24)*Full-time workers	-	0.11(1.10)	-	-
Cos(2πTs/24)*Full-time workers	-	0.22(0.59)	-	-
Cos(4πTs/24)*Full-time workers	-	-0.43(-1.80)	-	-
Cos(6πTs/24)*Full-time workers	-	-0.24(-1.45)	-	-
End Time				
Sin(2πTe/24)*Full-time workers	-	-0.46(-1.36)	-	-
Sin(4πTe/24)*Full-time workers	-	-0.06(-0.18)	-	-
Sin(6πTe/24)*Full-time workers	-	0.12(1.01)	-	-
Cos(2πTe/24)*Full-time workers	-	0.04(0.12)	-	-
Cos(4πTe/24)*Full-time workers	-	0.33(2.02)	-	-
Cos(6πTe/24)*Full-time workers	-	0.18(2.16)	-	-
High Income (>75K)				
Start Time				
Sin(2πTs/24)*High income	-	-0.39(-1.16)	-	-
Sin(4πTs/24)*High income	-	-0.10(-0.52)	-	-
Cos(2πTs/24)*High income	-	-0.20(-0.83)	-	-
Cos(4πTs/24)*High income	-	-0.33(-2.14)	-	-

Appendix A (Contd.)

Table A9 (Contd.)

	Alameda	Santa Clara	San Francisco	San Mateo
Variables	**Coef. (t-stat)**	**Coef. (t-stat)**	**Coef. (t-stat)**	**Coef. (t-stat)**
End Time				
Sin(2πTe/24)*High income	-	0.27(1.10)	-	-
Sin(4πTe/24)*High income	-	0.04(0.23)	-	-
Cos(2πTe/24)*High income	-	-0.06(-0.25)	-	-
Cos(4πTe/24)*High income	-	-0.22(-1.91)	-	-
Female with Kids				
Start Time				
Sin(2πTs/24)*Female with kids	-	-	-	2.29(2.02)
Sin(4πTs/24)*Female with kids	-	-	-	1.31(2.22)
Cos(2πTs/24)*Female with kids	-	-	-	-1.43(-1.77)
Cos(4πTs/24)*Female with kids	-	-	-	0.30(0.75)
End Time				
Sin(2πTe/24)*Female with kids	-	-	-	-0.94(-1.41)
Sin(4πTe/24)*Female with kids	-	-	-	-0.47(-1.23)
Cos(2πTe/24)*Female with kids	-	-	-	-0.22(-0.36)
Cos(4πTe/24)*Female with kids	-	-	-	0.25(1.05)
Observations	1,940	3,001	538	1,209
Log-likelihood at constants	-10,245.33	-15,414.87	-2,800.38	-6,232.34
Log-likelihood at convergence	-9,884.57	-14,840.26	-2,723.84	-6,002.82

Appendix B: Permissions

Permission to incorporate the TRB papers into dissertation.

From: Awan, Javy [mailto:JAWAN@nas.edu]
Sent: Monday, July 01, 2013 5:31 PM
To: Burke, Merilyn
Cc: Kisiner, Andrea; Barber, Phyllis
Subject: RE: FW: A General Questions from the Contact Us portion of the website

To: Merilyn Burke
Sujan Sikder has permission to incorporate the TRB papers into his dissertation. If possible, please ask him to note that

- **Spatial Transferability of Travel Forecasting Models: A Review and Synthesis** was presented at the 4th Transportation Research Board Conference on Innovations in Travel Modeling, April 2012, and

- **Spatial Transferability of Person-Level Daily Activity Generation and Time-Use Models: An Empirical Assessment** was presented at the Transportation Research Board 93rd Annual Meeting, Washington, D.C., January 2013, and was accepted for publication in the 2013 series of the *Transportation Research Record: Journal of the Transportation Research Board* (in progress). The volume, page numbers, and publication release schedule should be available by early September.

Thanks!
--Javy Awan
Director of Publications
Transportation Research Board of the National Academies
500 Fifth Street, NW
Washington, DC 20001

ABOUT THE AUTHOR

Sujan Sikder was born to his parents, Samiran Sikder and Swapna Sikder, in Chittagong, Bangladesh. He got the degree of Bachelor of Science (B.Sc.) in Civil Engineering from Bangladesh University of Engineering and Technology (BUET) in 2006. Following graduation, he worked as a Lecturer at a University in Bangladesh for almost 2 years. After that, he joined University of South Florida (USF) for his graduate study in Civil Engineering with specialization in Transportation Systems, and in August 2010, he received the degree of Master of Science in Civil Engineering. Mr. Sikder began his doctoral study in Transportation Systems at USF in August 2010.

During his four and a half years graduate study at USF, he worked on several research projects funded by the Florida Department of Transportation (FDOT) and published several research papers. He was a recipient of the Dwight David Eisenhower Graduate Fellowship in 2011. He was also one of the three student scholars selected by the National Center on Senior Transportation (NCST) in 2011. His primary research interests include Transportation Planning, Travel Demand Modeling, Activity-Based Models, Econometric Modeling, and Travel Data Collection.