A TOUR-BASED NATIONAL MODEL SYSTEM TO FORECAST LONG-DISTANCE PASSENGER TRAVEL IN THE UNITED STATES

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Word Count: 5,698 Figure Count: 3@250each = 750 Table Count: 1@250 each = 250
Total Count: 6,698

Paper Submitted: August 1, 2014

Key Words: Long-Distance Travel, Synthetic Population, Scheduling, Time Use and Activity Participation, Joint Mode and Destination Choice, Business and Leisure Travel, Tour Frequency

ABSTRACT

Intercity travel is rising in importance in the U.S. with many states and the federal government faced with improving mobility and reducing impacts for these travelers. The Federal Highway Administration (FHWA) has invested in several studies to better understand intercity travel; this study is an extension of that interest, focused on exploratory research to develop a long distance passenger travel demand model framework. The modeling framework is a tour-based micro-simulation model of annual long distance passenger travel for all households in the U.S. The models schedule travel across a full year to capture business travel (conferences, meetings and combined business/leisure) and leisure travel (visiting friends and family, personal business and shopping, relaxation, sight-seeing, outdoor recreation, and entertainment). The models are multimodal (auto, rail, bus, and air) based on national networks for each mode to provide opportunities for evaluation of intercity transportation investments or testing national policies for economic, environmental and pricing. Advanced modeling methods were tested for the scheduling, time use, activity participation and joint mode and destination models, including multiple discrete-continuous extreme value (MDCEV) for the scheduling models and cross nested logit choice for the joint mode and destination models. The modeling framework will be demonstrated, with application software that can simulate long distance travel for all U.S. households, but this work is ongoing. The focus of this paper is on the exploration of long distance travel model forms.

1. INTRODUCTION

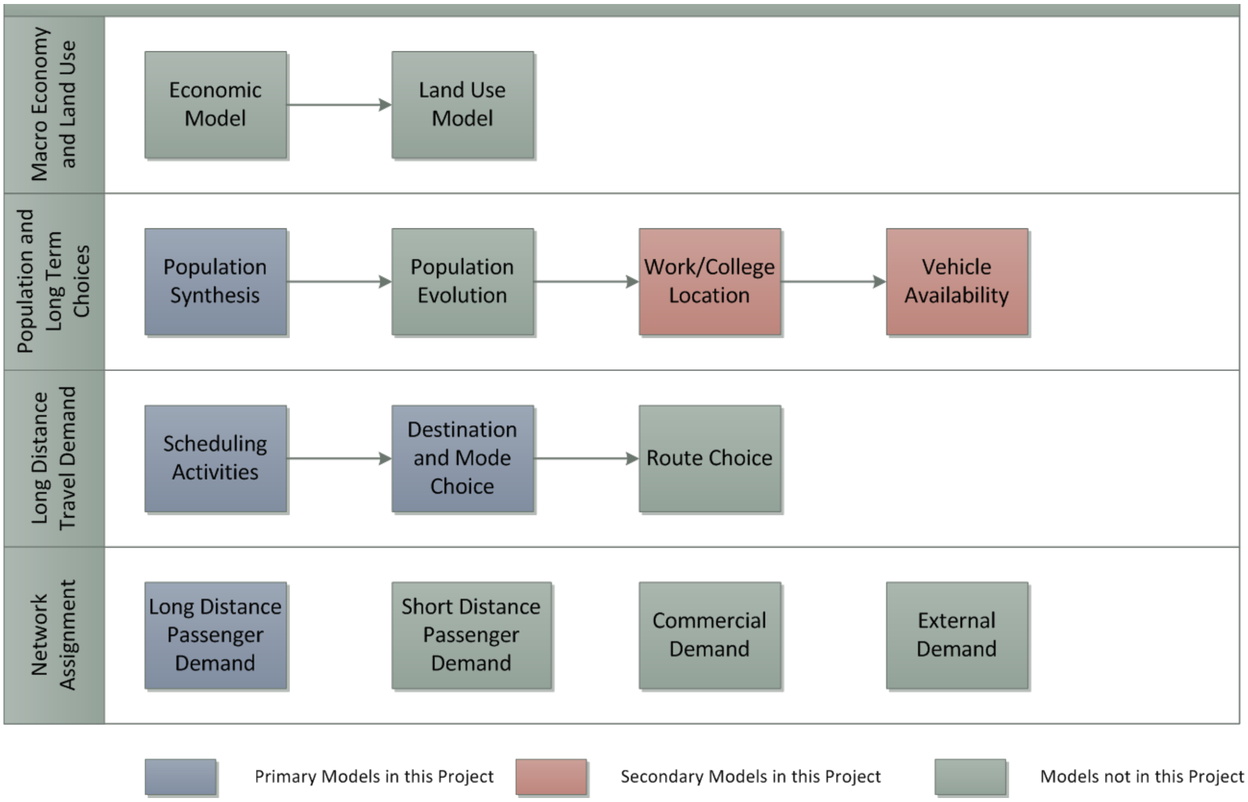
Methods for modeling long-distance passenger movements are in their infancy in the United States. Federal and state entities have recently become interested in modeling long-distance passenger movements as part of highway infrastructure planning; similarly, agencies studying high-speed rail, or those involved in airport planning, have also expressed interest due to their dependence on long-distance travel markets. This stronger interest at the federal and state level has created an intersection of policy needs for long-distance passenger modeling. In practice, some states and regions have expressed interest in long-distance passenger modeling for statewide models (e.g., California, Ohio and Arizona) and for high-speed rail ridership studies (e.g., Florida, California and the Northeast Corridor). However, these models rely on traditional travel demand forecasting methods rather than on a robust understanding of the underlying behavior and how and why it is different than other passenger travel. This research contributes to the development of a national passenger framework.

The goal of this research is to develop a framework for a long-distance passenger travel demand model that can be used to build a national model for the United States, one based on exploring new ways to simulate behavior of long-distance passenger movements. This framework includes model specifications based on statistical analysis of available data, recommendations for data collection that will facilitate the development of the national model, and a framework application demonstration. In addition, this national model will be estimated, calibrated, and validated on current long-distance travel data in the United States. Ultimately, success will be marked by transition of the research into use for planning applications across the country. These applications include:

- Testing national policies (e.g., modal investments, pricing, economics, environmental, livability, safety, and airport/rail planning);
- Measuring system performance;
- Evaluating the impacts of private sector decisions;
- Providing input to statewide and regional planning; and
- Assessing regional differences.

The long-distance passenger travel demand forecasting model fits within a larger integrated national modeling system (Figure 1). This system was developed to include economic and land-use models, as well as assignment models; however, the focus of this research was to develop the long-distance passenger models. These models simulate long-distance travel for each household in the United States (117 million households and 309 million people based on the 2010 U.S. Census) using an annual scheduling of long-distance tours (round trips). Household and person characteristics are synthesized for the United States by Census Tract. The annual scheduling and joint mode and destination models are the centerpiece of the long-distance passenger models; these use advanced methods not previously applied in urban passenger demand travel models (e.g., activity-based models).

Figure 1. Integrated National Modeling System



2. LITERATURE REVIEW

Long-distance passenger travel models are typically developed to evaluate infrastructure investments (i.e., for a corridor study) or to evaluate transportation policies or multimodal investment programs (i.e., for a national or statewide plan). To provide a comprehensive review of the long-distance passenger travel models, we reviewed 34 long-distance passenger travel models in the United States, Europe, South America, and Australia. A summary of our findings is provided below:

- Many models were found to evaluate long-distance rail travel or high-speed rail *(1) (2) (3) (4) (5) (6)*
- Several models were found to primarily evaluate long-distance air travel *(7) (8) (9)*.
- One model was found to primarily evaluate ferry options to islands off the coast of the United Kingdom *(10)*
- Several European national-scale long-distance models *(11) (12) (13) (14) (15) (16) (17)* were found to be used to evaluate national transportation policies and investments.
- Several statewide models were found to include long-distance travel as a component *(18) (19) (20) (21) (22) (23)*.
- The remainder were international models *(24) (25) (26) (27) (28) (29)* focused in Europe.

Some of the studies reviewed have not yet been published (Eurotunnel, Union Railways and value of time studies in Sweden, Australia, Norway and New Zealand) or were published in another language and not included as reference here (e.g., Invermo in German, Northern Chile in Spanish Norwegian National Model in Norwegian).

Definition of a Long-Distance Tour

In the case of models applicable to a specific project, the definition of the trips that are included is obviously those that would or might use the project. The more general models typically have a rigorous specification of trip length, often 100 km (62 miles) or 50 miles, with some instances of thresholds greater than 50 miles. The international models often use the 100 km threshold, while examples in the United States often use the 50 miles threshold, highlighting the somewhat arbitrary nature of this threshold setting. In some cases, the models consider any travel between urban areas without a specific distance threshold. This research assumes a long-distance tour includes an outbound trip and a return trip to a destination more than 50 miles from home, with or without stops along the way.

Model Structure and Form

The majority of long-distance trip models in the United States rely on modifications to the traditional four-step planning process. While there are many assumptions inherent in this process, the four-step planning process makes it: 1) easier to implement long-distance models across a state; and 2) easier to compare long-distance modeling results to those from local urban models. This capability is important given that many long-distance travel models in the United States serve as a supplement (and are estimated simultaneously) to daily travel models. However, more long-distance models have moved toward the tour-based modeling approach. Tour-based modeling is more insightful and offers more detailed results and opportunities for analysis; however, it requires extensive surveys of travelers.

The international models were found to include the following major components:

- The majority of the models described have at their core a logit choice sub-model describing mode choice (and often other choices, including sub-mode, major routes, and timing choices).
- Some of the models, chiefly those that are not specific to corridors, represent destination choice. This is often more sensitive to network effects than mode choice (i.e., it should be placed lower in a nested logit hierarchy).
- Several models have an elastic trip generation component, in which change in accessibility is represented as changing the total number of trips made.
- The majority of models included overall growth in trips based on population and employment growth, with (possibly) income, car ownership, and purchasing power taken into account.

The Matisse model (26), which uses an assignment concept, and Dargay's model (14), which is based on elasticities, are exceptions to the general trend of these models. Estimation generally uses maximum likelihood, although in many cases this is not a full-information procedure as sequential estimations are made. Some models use trips (origin-destination) as the basic unit, while others use return tours or production-attraction relationships.

Segmentation

Among models in the United States, the most common long-distance trip purposes are business, leisure, and personal business. However, a significant number of models do not define trip purpose. Few states consider segments of long-distance travel beyond the main trip purpose. It was found that all of the international models are segmented by travel purpose, separating business and leisure trips (although commuting is occasionally grouped with business). Further purpose segmentations often concern the identification of commute and education, holiday, and social ("visit friends or relatives") trips. Length of stay is associated with the purpose segmentations, perhaps isolating day trips, perhaps distinguishing short stays from long stays with a split at 3–5 days. Further trips are sometimes split and modeled separately for medium and long trips, with a split at 150–300 miles. A key further segmentation, which for data reasons is not included in many models, is by income group. Other segmentations used in some models concern residence location (e.g., country), party size, age, sex, employment, and car ownership (sometimes considered to be car availability). Specific segmentations that are not widely used are by area type in the UK National Travel Model and the detailed segmentation used in the French Matisse (26) model and the German Invermo model.

3. MODEL ESTIMATION DATA

There were five household survey datasets that met minimum requirements for use in estimating long-distance travel models:

- 1995 American Travel Survey (ATS)
- 2001 National Household Travel Survey (NHTS)
    - Add-on for New York state
    - Add-on for Wisconsin state
- 2003 Ohio Statewide Household Travel Survey—Phase III
- 2010 Colorado Front Range Travel Survey
- 2012 California Household Travel Survey (CHTS)

The first dataset, the 1995 ATS, was used only for scheduling models, since it was the only dataset that contained one full year of long-distance travel data for each person. The remaining household surveys for New York, Wisconsin, Ohio, Colorado, and California were considered for use in estimating the destination, mode, and frequency models. We estimated models in this paper using the CHTS, since the associated travel-time and cost data were available for these. Further work on the research involves using household data from all five states to better represent behavior across the United States, combined with national data on multimodal travel times and costs.

4. NATIONAL SYNTHETIC POPULATION GENERATION

The generation of a nationwide synthetic population is essential for modeling long-distance travel demand at the level of the individual traveler. In this study, a nationwide synthetic population has been generated using the procedures embedded in the PopGen software package *(30)*, controlling for both household- and person-level attributes in the synthetic population generation process. One major challenge was to synthesize a population for the entire nation in an efficient process. For this reason, the parameters and levels of spatial disaggregation adopted in the synthetic population generation process were established in a such a way that a careful balance is struck between the desire for a synthetic population generated based on controls at a fine geographical resolution and the desire for rapid computational time.

The methodological procedure generates a synthetic population using a variety of control variables at both the household and person levels (i.e., household income, size and type, householder age, presence of children, number of workers, person age, gender, race, and employment status). Three steps guide synthesis of the population:

1. First, the joint distribution of the attributes of interest is determined for each geography. The marginal control totals from the census files are used to expand this joint distribution matrix so that the marginal control totals are matched. This procedure, known as iterative proportional fitting (IPF), is applied to both the household level and person-level attribute joint distributions. As a result of the first step, the total number of households or persons that need to be generated for each cell of the joint distribution matrix is determined.
2. In the second step, every household in the sample is given a weight such that the weighted total of households (persons) matches the total number of households (persons) as calculated through the IPF procedure. This step is referred to as the Iterative Proportional Updating (IPU) algorithm, wherein the weights associated with households are iteratively updated such that the weighted frequencies of households and persons match the expanded joint distribution totals at both the household and person levels.
3. In the third step, households are drawn through a Monte Carlo simulation process using the weights computed in the second step. This completes the synthetic population generation procedure.

In the procedure adopted for this study, the output of the synthetic population generation process is a sample of households with a frequency or weight variable that indicates the number of times the (sample) household is replicated in the synthetic population. In other words, the synthetic population is not expanded to comprise an exhaustive dataset of more than 300 million records. Instead, a sparse representation of the synthetic population data files is used to achieve efficiency in data handling and storage. In addition, this format is consistent with the notion of computing "expected" travel demand using the weight variable, as opposed to simulating long-distance travel for every agent in the population, which would be vastly more computationally burdensome. Ideally, the synthetic population generation process should be performed at the level of the block group. The block group is a detailed level of geography for which the census data provides a rich set of marginal control totals. As a compromise between the geographic detail offered by the block group level synthesis, and the computational ease afforded by the county level, we performed a tract-level synthesis of the national population. The tract-level synthesis involves generating a population for just over 65,000 census tracts in the country; the deployment of a modest parallel computer architecture provides reasonable computational time for such a synthesis effort.

5. SCHEDULING, TIME USE, AND ACTIVITY PARTICIPATION

Scheduling, time use, and activity participation for long-distance travel is quite different from travel models built for short-distance travel. This is because scheduling occurs over the course of one year—rather than one day or shorter—and choices are made at the household, rather than person, level. This is true for both leisure and business travel; even though business travel is primarily conducted by an individual, it affects the household.

Business Travel Scheduling

Business travel scheduling involves a linear decision-making process. For each tour, a traveler is likely to make, he/she must decide on a main activity purpose, a geographic scale destination, a season of the year in which to complete the tour, and the duration of the tour. These business tours are more likely to be scheduled based on demand for such travel (from, for example, a workplace); as such, coordination among different types of business tours is not required. Business travel is segmented by the purpose (i.e., regular business, joint business/leisure, and conferences or meetings), geography (i.e., in-state, neighboring state, within the U.S., and international), and season (quarters).

Business travel was modeled sequentially according to the three tour characteristics (i.e., purpose, geography, and season) in stages:

1. Estimate the total number of annual business, business/leisure, and conference/meeting trips using a negative binomial regression to predict number of tours by purpose.
2. Distribute these business tours using a linear regression count model by geography and/or season.
3. Estimate duration of each tour (measured as nights away from home) using a Cox Hazard duration model.

Householder characteristics (i.e., age, race, employment status, and ethnicity), economic characteristics (i.e., household size, income, and vehicles owned), and residence characteristics (i.e., tenure, housing type, location (9 regions), and family structure) are explanatory variables in one or more of the business scheduling models. Parameters affecting selected business scheduling models are presented for the third quarter in Table 1.

The 1995 ATS was used to estimate the business scheduling models because it has data on all long-distance travel (over 100 miles) for a full year and includes information on time use. There were 48,527 households for this analysis, making 122,833 long-distance business tours (2.5 tours per household per year). Eighty-two percent of business travel activity is purely business; 40% of all business travel activity is in-state, and the first two quarters of the year are the most heavily traveled (29% and 28% respectively). These data have only coarse spatial resolution, so accessibility was not considered. Commute travel was not included in this dataset.

1 **Table 1. Parameters Affecting Selected Business and Leisure Scheduling Models**

	July–September Tour-Frequency Models									Duration Models	
	Business	Business/ Leisure	Conference/ Meeting	Visit	Relaxation	Sightsee	Outdoor Recreation	Entertainment	Personal Business or Shopping	Business Nights Away	Leisure Time Budget Model
Personal Characteristics											
Respondent Age (4 groups)	+/-	+/-	+	+	+/-	+	+/-	-	+	+	+
Ethnicity other than Caucasian (3 groups)	-	-	+		+/-	-	+/-		+/-	-	-
Respondent Working Position (full and part-time)	+			+	+	+/-	+/-	+/-	-	+/-	+
Respondent Education (4 groups)	+	+	+								
Household Characteristics											
Household Size	+	+		+	+			+			+
Household Income (4-7 groups)	+/-	+/-	+/-	-	+	+	+		-	-	+
Number of Personal Vehicles				-		-	+	+		+	
Presence of Children (2 groups by age)	-		+							+	
Household Structure (16 groups)	+	+	+	-	+/-	+/-	+/-	+	-	+	+/-
Residence Characteristics											
Tenure (own, rent)		-	+		+	+	+	+	+	-	
Housing Type (house, apartment)					+			+			+
Household in Metro Area	+	+/-	+								
Household Location (9 Regions)				-	+/-	+/-	-	-	+/-		+/-
Travel Characteristics											
Travel Party (Household Members, Adults)										+/-	
Travel Distance										-	
Weekend Travel										-	
Geography (In-State, Neighbor State, In US)										+	
Seasons/Quarters										-	
Main Purpose										-	

Leisure Travel Scheduling

Leisure travel accounts for 75% of all long-distance travel in the 1995 ATS and 70% of all long-distance travel in the 2001 NHTS. These tours have multiple purposes: visit friends and relatives (42%), personal business or shopping (20%), relaxation (14%), outdoor recreation (10%), entertainment (8%), and sightseeing (6%); the majority of these leisure tours are multipurpose (86%). Householder characteristics (i.e., age, race, employment status and ethnicity), economic characteristics (i.e., household size, income, and vehicles owned), and residence characteristics (i.e., tenure, housing type, location (9 regions) and family structure) are explanatory variables in one or more of the leisure scheduling models.

Leisure travel scheduling was modeled using three different approaches, each based on a different choice set of alternatives:

1. Determine the number of non-business tours using a negative binomial regression method for each purpose, season, and accompaniment combination.
2. Determine whether a household participates in non-business tours over the course of one year, and the total time budget if the household decides to participate using linear regression. Allocate the total annual time budget to different combinations of purposes and seasons using a Multiple Discrete-Continuous Extreme Value (MDCEV) method. For each purpose-season combination, determine the number of tours by accompaniment type using a truncated Poisson regression method.
3. Follow the same three-step process identified in the second option, except that the second step allocates the total annual time budget to different combinations of purposes and seasons *and* accompaniment types. Then, for each purpose-season-accompaniment type combination, determine the number of tours.

The second and third approaches can represent satiation effects in the number and duration of long-distance tours, time budgets, and dependencies across the types of tours.

Parameters affecting selected leisure scheduling models are presented for the third quarter in Table 1. These are similar to the business scheduling models, but household structures are more detailed (e.g., in family, female or male head of household, single, with and without children) and education and households located in metropolitan areas were not included.

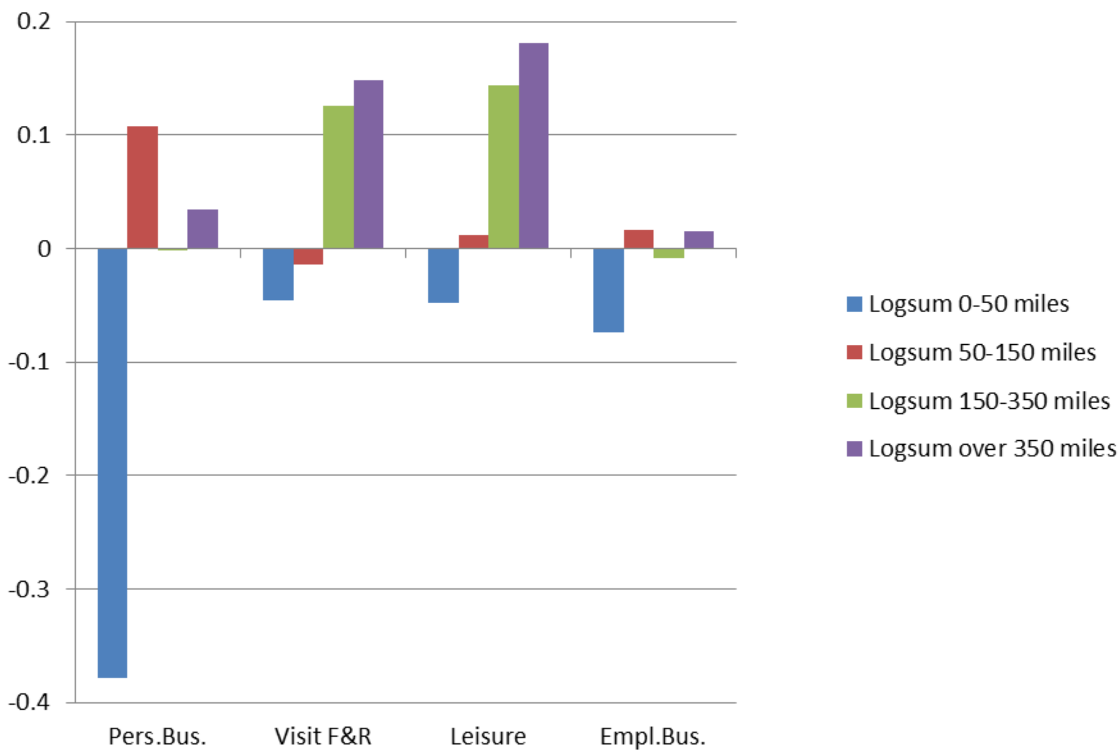
The 1995 ATS was also used to estimate the leisure scheduling models for the same reasons. After cleaning, there were 44,520 households for this analysis, making 378,385 long-distance leisure tours (8.5 tours per household per year). These data have only coarse spatial resolution, so accessibility was not considered. Commute travel was not included in this dataset.

Tour Frequency

Tour-frequency models were estimated to address three limitations of the business and leisure scheduling models: 1) spatial detail is limited to states; 2) temporal detail is limited to seasons; and 3) the ATS data are 20 years old (1995). These models were estimated using the 2012 California Statewide Travel Survey, which contained 42,431 households and 40,899 long-distance tours over eight weeks; however, a high percentage of households do not make any long-distance tours (56%)

and a high percentage make only one trip on a tour (43%), indicating that they did not record all their trips. Mode/destination logsums were included to represent accessibility to destinations close by (within 50 miles) and to destinations farther away (more than 50 miles) and are significant for all tour purposes, but primarily for personal business and shopping travel (see Figure 2). Accessibility has a minimal impact on business travel.

Figure 2. Mode/Destination Logsum Coefficients by Purpose and Distance Band



Another important evaluation from the tour-frequency models was an evaluation of the impact of non-response bias related to longer retrospective periods. In the California survey, the retrospective period was eight weeks and each successive week resulted in smaller number of tours—regardless of purpose—indicating a non-response bias for longer retrospective periods.

6. JOINT DESTINATION AND MODE CHOICE

There are 5,191 destination zones and four main modes (i.e., auto, bus, rail, air) in the long-distance modeling framework. In a joint model, this results in 20,764 alternatives, which can be complex to estimate. To prepare to estimate the joint models, we estimated separate destination and mode-choice models. These models included time and cost parameters for each mode, location attributes, and destination-size attributes.

We tested multinomial, nested, and cross-nested logit model structures for joint destination and mode-choice models. To reduce the complexity of the tests, we reduced the 5,191 destination zones to 58, resulting in 232 alternatives. Both the mode above destination (M>D) and the destination above mode (D>M) nested logit models were tested.

There was evidence of non-linearity in both time and cost sensitivities, and there appeared to be strong confounding between these effects and the overall preference for choosing destinations closer to home. For the air mode constant, shift parameters for trips over 500, 600, 700, and 800 miles were used to ensure negative travel-time coefficients for these longer trips. For those respondents who make journeys closer to home, the attributes of the journey—in terms of time and cost—appeared to matter much more (Daly et al., 2009) than for respondents making journeys farther afield, where the role of unmeasured attributes was increased relative to the characteristics of the journey. This effect was found to be consistent across the alternatives, being a function of the chosen distance, rather than the characteristics of each individual alternative.

The elasticity values for the four key models are calculated by adding 10% to the car time or cost, as would occur in the case of an overall increase in fuel cost or congestion. For brevity, only the cost elasticities are shown in Figure 3.The model predicts the changes in mode and destination-choice probability that would occur for the estimation sample of tours. Elasticity values are then calculated using the following equations:

$$Tour\ Elasticity = \log\left(\frac{ForecastTours}{BaseTours}\right) / \log(1.1)$$

$$Tour\ Length\ Elasticity = \log\left(\frac{ForecastTourLength}{BaseTourLength}\right) /\log(1.1)$$

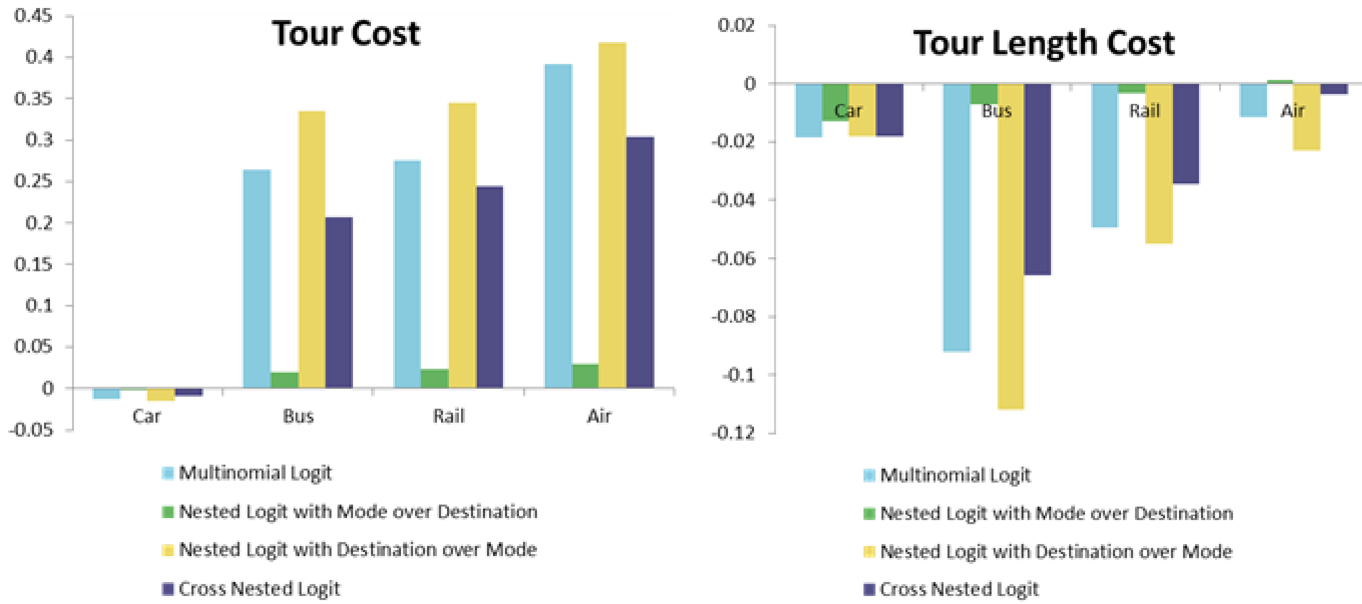
The changes in time and cost are unrealistic, and the estimation sample may not be representative, but the intention of these tests is only to indicate the degree of responsiveness of the model.

These car elasticities show—in all cases—that a cost or time increase will reduce the number of tours and reduce the tour length. The second nested logit model (D > M) shows car elasticities akin to the multinomial logit model, as is to be expected since the models are similar. However, the first nested logit model (M > D), which gives a better fit to the data as shown by the log likelihood, gives higher destination-choice (tour-length) elasticities and greatly reduced mode-choice elasticities, as is to be expected from the model structure. The cross nested logit model, which gives the best fit to the data, has elasticities that are not very different from the multinomial logit model.

The cross-elasticity tour elasticities are positive—as they should be—and have values that are considerably larger than the individual mode elasticities. This is because the market shares for these modes is less than for car—a transfer from car that represents a small fraction of the car market gives a large proportional increase for the other modes.

The cross-elasticity tour-length elasticities are mostly negative; an increase in car cost (or time) reduces the car tour length and the tour length for other modes. For air, these elasticities are small and both positive and negative values are seen. In general, one would not expect a change in car characteristics to impact the tour length for other modes. However, we found that bus and rail are more competitive with car over short distances, so a reduction in car demand transfers more of the shorter trips to bus and rail.

Figure 3. Elasticities for Advanced Destination and Mode Choice Models



Our research has demonstrated the advantages of joint models over standard models, with gains in model fit and different elasticity results coming out of the cross nested logit model, which allows for correlation along both dimensions of choice. Similar results were also obtained from a model that uses a latent class structure with separate classes for the two nested logit specifications, but the fit was lower than for cross nested logit and the estimation cost was higher.

7. CONCLUSIONS AND NEXT STEPS

The focus of the model estimation work in this research was on testing new model forms and enhancing possible options for developing model components needed for a long-distance passenger travel demand modeling framework. There are estimated models for all primary model components and recommendations for including secondary model components in the demonstration of the framework. Limitations on available data for estimating these models are noted and create inconsistencies in combining the individual model components into a modeling system. The data limitations and inconsistencies are not an issue for the demonstration research and were addressed specifically in a discussion of recommendations for data collection (complete but not included in this paper) and the modeling framework (currently underway) in this research. The development of the modeling framework will include a demonstration of the integrated modeling system to produce long-distance passenger trip tables and recommendations for improvements to this modeling system when data focused on long-distance travel across the United States are collected.

FHWA has extended this exploratory research to include calibration and validation of the long-distance passenger travel demand modeling framework. This will include adding a trip assignment model, calibrating individual model components, and validating trip tables and volumes by mode.

The model components will be re-estimated based on a combined dataset of California, Colorado, Wisconsin, Ohio, and New York to provide a more representative sample of long-distance travel across the United States. Sensitivity tests will be used to ensure reasonable response from the models to policies. These tests will also be used to evaluate the influence of the data limitations noted earlier on the modeling outputs. This work will also include improvement of the performance of the application software to facilitate wider use by federal and state agencies; the application software created in the original research was intended for demonstration purposes only. A user's guide for this application software and documentation on the full implementation of the modeling framework will also be provided.

ACKNOWLEDGEMENTS

The authors want to acknowledge the Federal Highway Administration (Tianjia Tang and Brad Gudzinas) for their support throughout the exploratory research process. In addition, we appreciate the guidance and direction from the expert panel on this project (Robert Cochrane, Chad Baker, John Conlow, Rich Brancato, Richard Laferriere, William Sheridan, Kay Axhausen, and Doug Hunt). We have also had strong technical input from our colleagues at RSG (Thomas Adler, Colin Smith, and Åsa Bergman,), University of Texas (Marisol Castro and Subodh Dubey), Arizona State University (Sandeep Subramanian and Dae Hyun You) and Auburn University (Benjamin Bacon).

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