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

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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 was demonstrated, with application software that simulate long distance travel for all U.S. households. This paper is a high-level overview of the exploratory research over 3 years.

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.

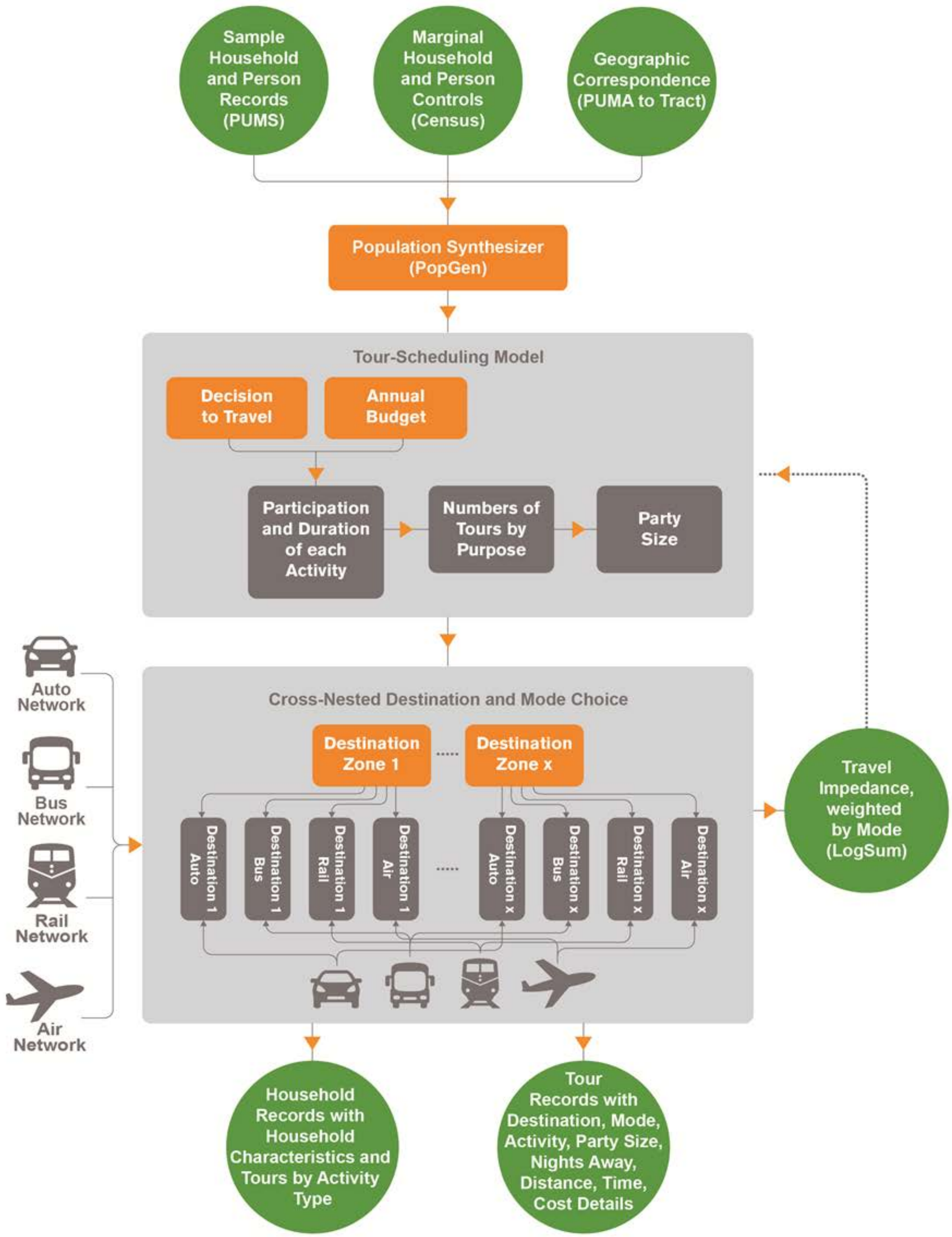
The goal of this research is to develop a framework for a long-distance passenger travel demand model that can be used to build a national model for the United States, one based on exploring new ways to simulate behavior of long-distance passenger movements. This framework includes model specifications based on statistical analysis of available data, recommendations for data collection that facilitate the development of the national model, and a demonstration that the framework can be reasonably implemented. In addition, this national model will be estimated, calibrated, and validated on current long-distance travel data in the United States during the next phase of work. 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 exploratory research was conducted from 2011 to 2014 and included a long term goal to develop long distance passenger models not constrained by traditional methods or existing data sources, in combination with making data recommendations to support these new models. An implementation phase was added to move the research into practice by calibrating and validating long-distance travel demand models that are practical for current use and implementing these models with software.

The long-distance passenger travel demand forecasting modeling system (Figure 1) synthesize 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

Figure 1. National Long Distance Passenger Travel Demand Modeling System



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).

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. The details of the characteristics of these models, data used, and lessons learned are available *(1)*, but were too detailed for this paper. A summary of our findings is provided below:

- Many models were found to evaluate long-distance rail travel or high-speed rail *(2) (3) (4) (5) (6) (7)*
- Several models were found to primarily evaluate long-distance air travel *(8) (9) (10)*.
- One model was found to primarily evaluate ferry options to islands off the coast of the United Kingdom *(11)*
- Several European national-scale long-distance models *(12) (13) (14) (15) (16) (17) (18)* 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 *(19) (20) (21) (22) (23) (24)*.
- The remainder were international models *(25) (26) (27) (28) (29) (30)* 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).

The literature review informed the definition of a long distance tour, the model structures and forms, as well as segmentation, considered for the exploratory research. A summary is provided below.

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. Tours are selected as the basis for travel rather than trips, due to the representation of round trips as linked with the demographic and network characteristics underlying these tours.

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 long distance travel in New York state
  - Add-on for long distance travel in 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 long distance surveys for New York, Wisconsin, Ohio, Colorado, and California were used in estimating the destination, mode, and frequency models, individually and as a merged dataset. The 2001 NHTS did not include a long distance survey, but New York and Wisconsin conducted add-ons for long distance travel. Household data from all five states were used to better represent behavior across the United States, combined with national data on multimodal travel times and costs for 2010. The advantages of this combined dataset were seen to outweigh the disadvantages of combining multi-year datasets, but geographical and scale differences were addressed with the national data constructed for travel times and costs.

The exploratory nature of this project provided some flexibility in the use of available data sources with limitations for the purposes of this project. These limitations include the age of the dataset and the lack of spatial data for to represent accessibility (e.g., ATS), the short timeframe for data collection (4-8 weeks for the 5 state surveys) and various other minor data issues described in more detail (*31*).

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 *(32)*, 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. TOUR GENERATION, SCHEDULING AND PARTICIPATION

Tour generation, scheduling, and 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 because choices are made jointly by household members, rather than individually. This is particularly true for leisure travel, where long distance travel is often undertaken bv all members of the household, but is also true for business travel undertaken by an individual, since it still affects the other members of the household.

Nonbusiness travel is divided into six activity categories, including:

- Visiting friends;
- Relaxation;
- Sightseeing;
- Recreation, including sports, hunting, fishing, boating, camping, etc.;
- Entertainment, including attending the theater or sports events, etc.; and
- Personal business, including weddings, funerals, health treatments, family gatherings, and other personal matters.

Business travel is divided into three activity categories, including:

- Business;
- Business/pleasure; and
- Convention/conference/seminar.

The following sequential decision-making process was used in this analysis:

1. The household decides whether to make a tour (either business or nonbusiness).
2. If the decision is "yes," the household allocates an annual budget for time spent on nonbusiness and business activities.
3. The household further splits the total annual budget into various tour purposes. To illustrate, assume a household decides to engage in nonbusiness travel (step 1) and allocates a 30-day budget (step 2) for it. Then, in step 3 (the current step), the household will further split the 30-day budget into various nonbusiness purposes. The same process is followed for business purposes.
4. The household decides the number of tours to make in a given year based on the budget allocated for various nonbusiness and business purposes. That is, if a household allocates eight days for recreational purposes, the household may make more than one tour to consume their total recreational budget.
5. The household decides the tour-party composition (i.e., number of people in the tour).

The above-described decision-making steps reflect a top-down approach, where the third step (allocation of total annual budget in various nonbusiness and business purposes) is modeled using Bhat's MDCEV model *(33)*. The MDCEV model simultaneously estimates the participation and duration of a tour. Households first decide whether to make a specific kind of tour, followed by determination of tour-specific characteristics, such as duration, number of tours, party size, and composition. The first and second step (decision to make a nonbusiness or business tour followed by the determination of total annual budget) is modeled using a sample selection model (*34*). The fourth step (number of tours by tour purpose) is modeled using a traditional zero truncated

Poisson regression (*34*). Finally, the fifth step (party size and composition) is modeled using a multinomial logit model (MNL).

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 scheduling models. Parameters affecting the decision to make a tour are presented in Table 1. Additional details of other model forms tested in model estimation *(35)* and other models included in the framework *(36)* are available.

The 1995 ATS was used to estimate the 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 47,931 households for this analysis. The households participating in long distance tours by purpose and quarter is presented in Figure 2. 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). 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%).These data have only coarse spatial resolution, so accessibility was not considered. Commute travel was not included in this dataset. These data limitations were overcome with the tour frequency models described in the next section.

Figure 2. Participation of Long Distance Tours by Purpose and Quarter

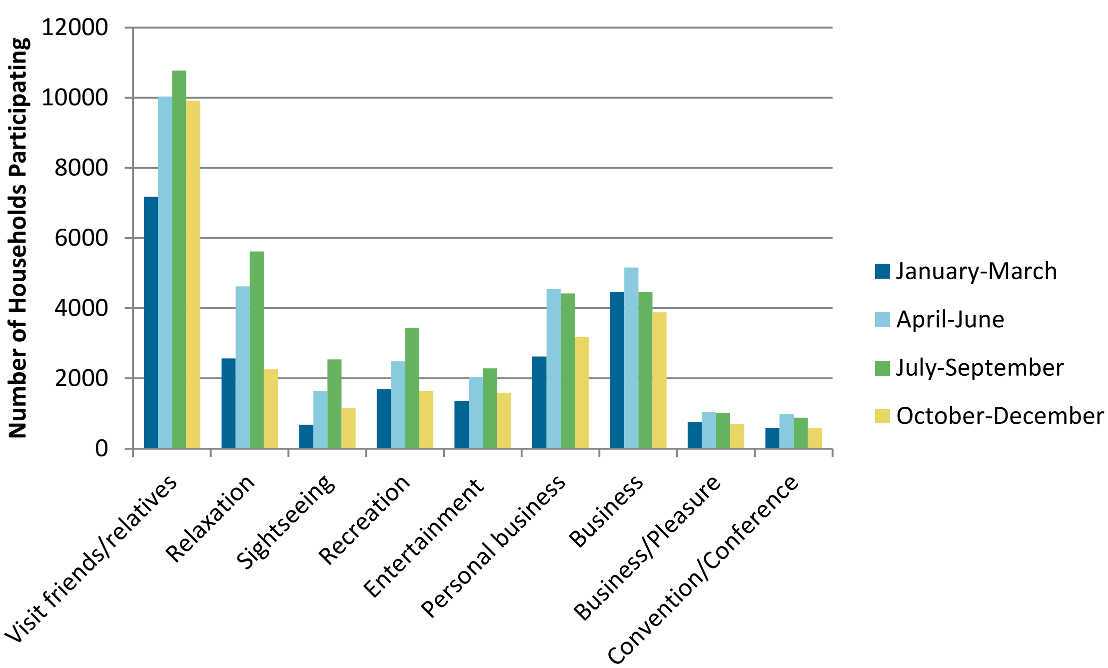


Table 1. Parameters Affecting Selected Business and Leisure Scheduling Models

	NonBusiness Travel		Business Travel	
Variables	**Coeff**	**T-Stat**	**Coeff**	**T-Stat**
Alternative Specific Constant	1.626	46.212		
Income (base: 25K-49K)				
Less than 25K	-0.202	-9.662	-0.374	-19.596
50K-74K	0.189	9.068	0.291	16.137
75K-99K	0.189	9.068	0.606	21.769
100k and more	0.389	9.114	0.910	27.627
Business tour (base: zero tours)				
1 or more tours	-0.583	-33.784		
Family composition				
Presence of Children (less than 17 Years Old)	-0.215	-6.121	-0.263	-7.643
# of individuals between 17 and 49 years old	-0.087	-8.546	-0.023	-2.685
# of individuals between 50 and 64 years old	-0.017	-1.483	-0.070	-6.752
# of individuals >= 65 years old	-0.017	-1.483	-0.197	-18.147
Working status				
# of full-time workers	0.017	1.989	0.110	14.764
# of part-time workers	0.033	2.315	0.110	14.764
Vehicle ownership (base: Three or more vehicles)				
Zero Vehicle	-0.085	-2.842		
One or Two Vehicles	-0.141	-7.071		
Household residential location (base: Mountain)				
New England	-0.174	-5.867	-0.328	-13.033
Atlantic	-0.163	-4.120	-0.416	-12.391
East-North Central	-0.165	-5.008	-0.337	-11.805
West-North Central	-0.095	-3.207	-0.122	-4.858
South Atlantic	-0.087	-3.011	-0.165	-6.920
East-South Central	-0.238	-7.231	-0.184	-6.345
West-South Central	-0.120	-3.335	-0.103	-3.326
Pacific	-0.062	-1.825	-0.097	-3.554

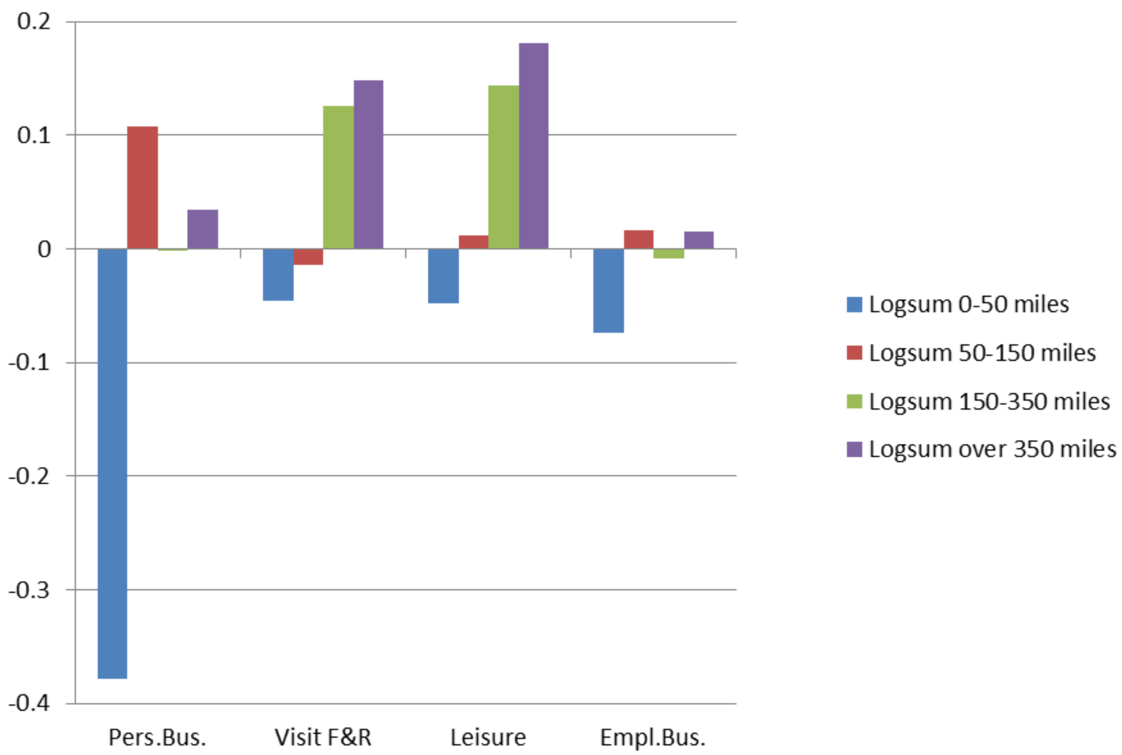
Tour Frequency

Tour-frequency models were estimated to address three limitations of the business and leisure scheduling models:

- Spatial detail is limited to states;
- Temporal detail is limited to seasons; and
- 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 3). Accessibility has a minimal impact on business travel.

Figure 3. 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. Details of model estimation *(35)* and final models *(36)* used in the framework are available.

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:

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

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

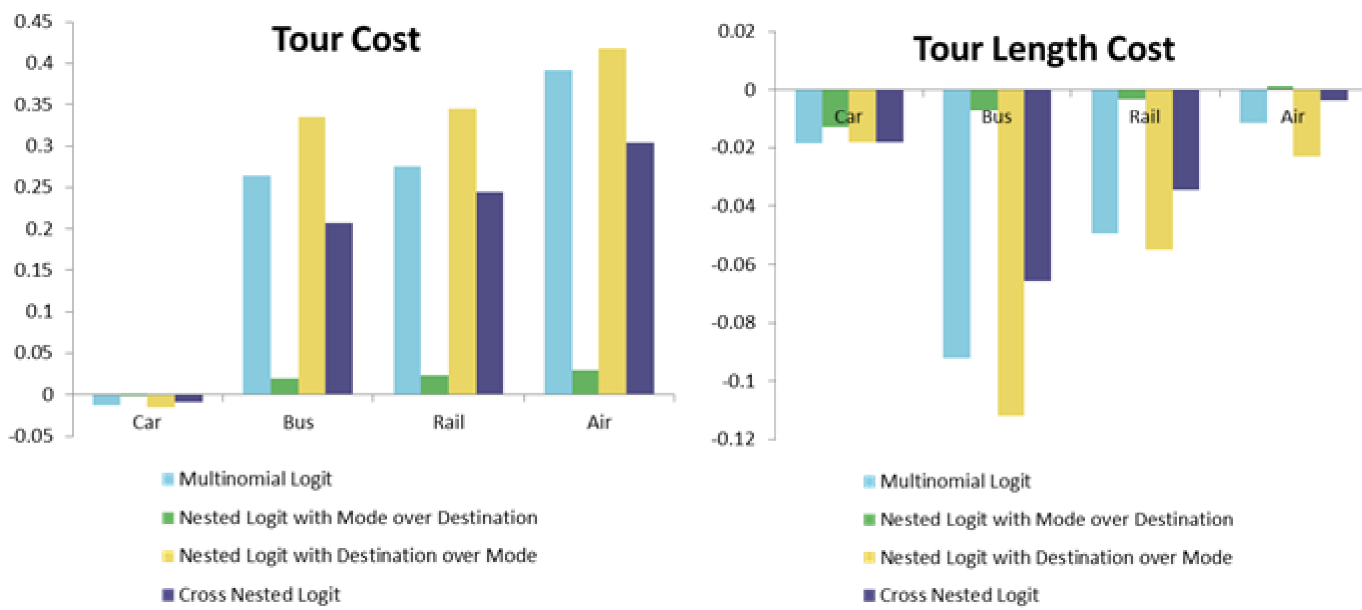
The changes in time and cost are unrealistic, and the estimation sample may not be representative, but the intention of these tests is only to indicate the degree of responsiveness of the model.

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 4. 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 development of the Long-Distance Passenger Travel Demand Modeling Framework included research into new methods for estimating long-distance passenger model components and implementation of selected methods to produce long-distance passenger travel demand on a national scale. The parallel paths were conducted to allow research to include methods that may not be immediately implementable, but should be considered for future efforts. The research has demonstrated that a disaggregate tour-based approach to predicting annual long distance passenger travel demand model for all households in the U.S. is feasible. Initial results are intuitive, despite some of the challenges in the research phase, due to limitations in available data for model estimation. The focus of this initial research was on developing a framework that could be re-estimated with more robust and comprehensive data sources when these data are collected. In summary, the paper presents 3 years of exploratory research to develop models unconstrained by current available data or practice (a long term goal) and to demonstrate that these models can be implemented with current hardware and software capabilities (a short term goal).

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. This work will also include improvement of the performance of the application software to facilitate wider use by federal and state agencies. A user's guide for this application software and documentation on the full implementation of the modeling framework will also be provided.

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