Transferability of Time-of-Day Choice Modeling for Long-Distance Trips

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ABSTRACT

Time-of-day models deals with the time at which travel occurs throughout the day. This paper presents a study in time-of-day choice modeling for long-distance trips, with special interest in the transferability of the model. Two datasets from the 2001 National Household Travel Survey and the 2001 California Statewide Household Travel Survey were employed to explore the effects of various factors on time-of-day choice making and to test the transferability the behavior findings and model parameters. Although there are remarkable differences in data composition between the two datasets, comparative analysis of the models developed from the two datasets reveals consistent results, suggesting the potential for transferability of the behavior pattern across spatial locations.

INTRODUCTION

During the past two decades, it has become increasingly apparent that it is necessary to incorporate the temporal nature of trip making into the demand modeling process. The need to forecast traffic throughout the day has been motivated by the emerging issues that require detailed temporal resolution of trip making, such as estimating vehicular emissions and air quality, since vehicle speeds and warm-up characteristics vary widely by time-of-day; assessing the effectiveness of time-of-day specific congestion management programs – congestion pricing; and evaluating the effect of travel demand management strategies on peak spreading.

A fair amount of research has been conducted and various approaches have been proposed for time-of-day modeling. At an aggregate level, there are simple time-of-day factors and peak spreading procedures (*1*), and equilibrium-based models that account for interactions between network supply and demand (*2, 3, 4, 5*). At a disaggregate level, choice behavior modeling has been used to examine the underlying causality of individual time-of-day choice (*6, 7, 8, 9, 10, 11*). Time-of-day modeling is also an important element in the activity-based framework that involves comprehensive daily travel activity scheduling (*12, 13, 14, 15, 16, 17*).

While time-of-day modeling has been drawing considerable attention in research, almost all studies have focused on urban daily trips. It could be argued that choice behavior for long-distance trips is far more complicated than that for urban trips, since most urban trips are made on daily routines while long-distance trips are rather occasional and exceptional. Time-of-day analysis for long-distance trips will not only improve the forecasts of rural/intercity travel, but also supplement urban forecasts for vehicular emission and traffic congestion.

This paper presents a study in time-of-day choice modeling for long-distance trips, with special interest in the transferability of the model. Transferability is critical to assessing the validity of behavior models. As travel demand is derived from the needs to pursue activities at different spatial locations, travel behavior can be altered by changing spatial and socioeconomic structures. Transferability can be defined as how well a model developed in a particular specific spatial, transportation and institutional context can be applied to another context. In previous study a multinomial logit (MNL) model was developed to examine the time-of-day choice behavior on the 2001 National Household Travel Survey (NHTS) data (*18*). The general methodology for developing the model was applied to the 2001 California Statewide Household Travel Survey data to test the transferability of the behavior findings and model parameters.

LONG-DISTANCE TRIPS

This section provides general background information about the characteristics of long-distance trips as determined from the latest nationwide survey on long-distance travel – 2001 NHTS (19). Of all long-distance trips made in the United States in 2001, fewer

than half (43 percent) were made by women; the majority (approximately 55 percent) were made by individuals living in households with annual household incomes of $50,000 or more; and nearly two-thirds of all long-distance trips were made by persons aged 25 to 64. About 90 percent of the long-distance trips were made by personal vehicle, with the remaining trips split into air (7 percent) and bus or train (3 percent). Almost all trips (97 percent) less than 300 two-way miles were made by personal vehicles. For shorter daily trips, in comparison, there were no differences across genders in the total number of trips; and daily trips had smaller mode share for personal vehicles (about 87 percent).

An interesting finding from the NHTS data is that nearly one out of 200 commute trips were more than 50 miles one way. For commute trips between 50 miles and 99 miles, two-thirds of them occurred at least four days a week. These findings point to the need for more attention to long-distance trips. While not as frequent as urban trips, long-distance trips are critical to congestion and vehicular emission issues, since 90 percent of the long-distance trips are made by personal vehicles, long-distance trips account for about one-third of the total person-miles traveled in the US, and considerable portions of long-distance trips occur in urban areas, which would directly affect congestion management programs.

DATA DESCRIPTION

The first set of data used for this analysis was extracted from the 2001 NHTS daily-travel survey records if the trip was 50 miles or longer in distance and 60 minutes or longer in travel time. For the second set of data from the 2001 California Statewide Household Travel Survey, long-distance trips were defined as 60 minutes or longer in travel time. Information on trip distance was not available for the California dataset. Trips made by travelers younger than 16 were removed from both data sets. Sixteen years was used as the break point since this is the legal age for a driver's license in California.

In total, 3322 and 4527 long-distance trips were identified from the NHTS and CA data sets, respectively. Table 1 below provides some basic characteristics of travel activities in the data. Compared to the NHTS sample, households in the CA data had a slightly smaller size, slightly fewer workers, slightly fewer vehicles, but made far fewer daily trips per day on average. Households in California made on average slightly fewer long distance trips, which cannot be reasonably attributed to looser definition of a long distance trip used by California.

TABLE 1 Comparison of Basic Characteristics of NHTS and CA Data

Measurements	NHTS	CA
Total Households	1,924	2,795
Average HH Size	2.84	2.74
Average Number of Workers per HH	1.58	1.45
Average Number of Vehicles per HH	2.5	2.44
Total Long Distance Trips	3,322	4,527
Average Daily Trip Rate per HH per Day	12.19	8.69

The two data sets were prepared in a consistent way. The same categorization method was applied to both data, since they have very detailed and only slightly different classifications for mode, purpose, household income, etc. However, the California data had no variable indicating household structure. The entire day is aggregated into six time periods: early morning (0:00 -6:29), am peak (6:30-8:59), am off-peak (9:00-11:59), pm off-peak (12:00-15:59), pm peak (16:00-18:29), and evening (18:30-23:59).

The two data sets differed markedly as to departure time for long-distance trips, as seen in Figure 1. The NHTS data showed fewer trips during the two traditional peak periods than the am off-peak period, while the California data showed otherwise. There may be several possible reasons. The California sample might have greater shares of work/school trips or return home trips, which are more likely to happen during the traditional peak periods. In addition, if the two data sets had different shares for weekday and weekend trips, the distributions by departure time might be different. Further examination of the data by purpose and travel day type is presented below.

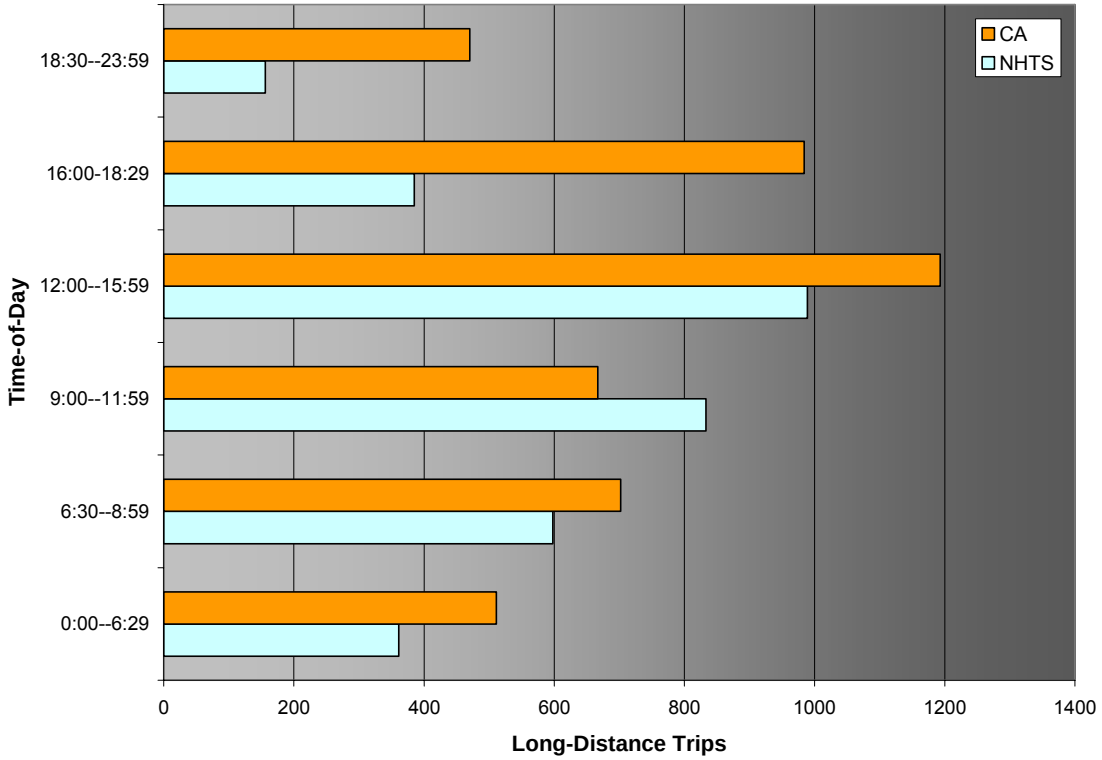

FIGURE 1 Distribution of departure time.

Both samples have about the same portion of work/school trips (about 26%), but the California data captured a larger share of return home trips than the NHTS data (37.5% compared to 10.9 %). Figure 2 shows the breakdown of trip purpose by departure time. The bars represent the percentages of work/school and return home trips by each time period in the NHTS data, while the lines represent similar shares for the California sample. For work/school trips the two data sets had a consistent pattern, although work/school trips in the California sample had a slightly bigger share in the am peak

periods than they did in the NHTS sample. A noticeable difference is that more than 50 percent of return home trips from the NHTS sample took place during the afternoon non-peak hours and only about 20 percent were taken in the pm peak period; while in the California sample, about 38 percent and 33 percent of return home trips occurred in the afternoon peak and non-peak hours, respectively. This difference may be partly due to the CA sample having much less of a share of weekend trips (only about 3.5%) compared to the NHTS sample (about 31%). Apparently return home trips in weekdays are more likely to take place in pm peak hours compared to weekend trips.

The above analysis indicates the influence of trip purpose and travel day type on the departure time choice. On the other hand, it could also be argued that the differences in departure time distribution in the two datasets are partly due to the different sampling composition in trip characteristics. Whether there are distinctions in choice behavior under different geographical and socioeconomic contexts still cannot be established at this point based on simple classifications. Multinomial logit (MLN) modeling analysis, a more sophisticated method of looking at behavioral patterns, would be able to provide some insights in this perspective, which is presented later in this paper.

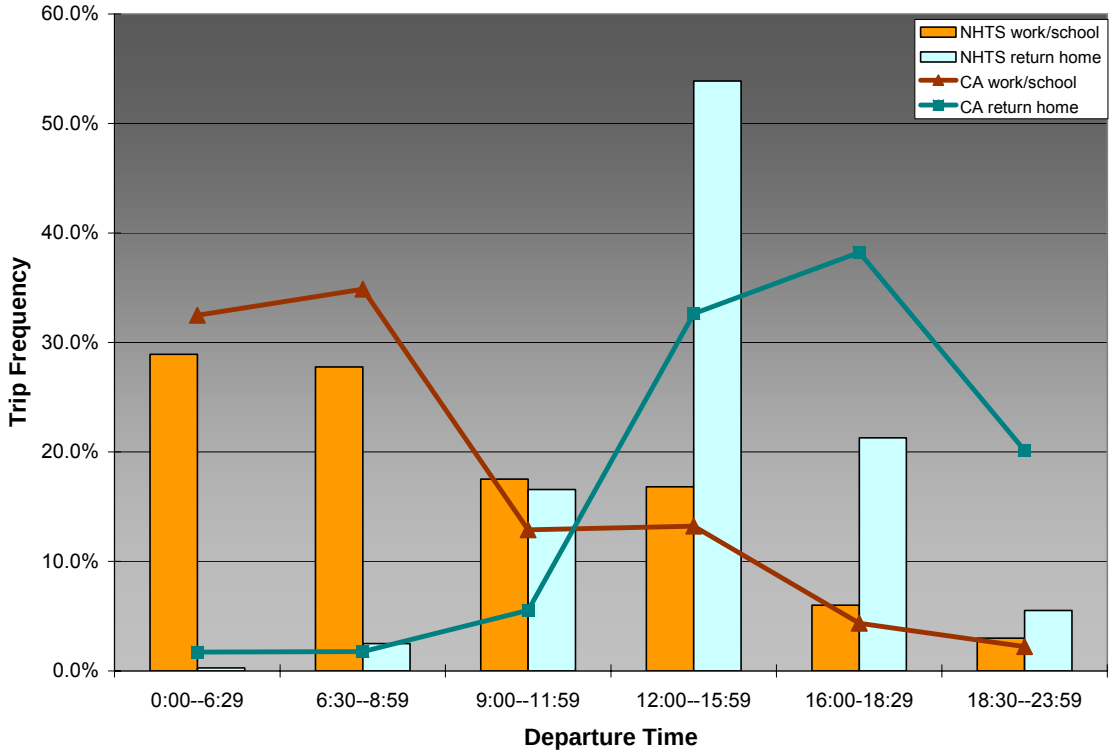

FIGURE 2 Distribution of departure time by purpose.

Figure 3 and Figure 4 are prepared in a similar fashion as Figure 2. Figure 3 below presents a comparison between the two datasets in departure time distribution by travel day type. As for weekend long trips, the California sample had fewer trips being taken in the morning off-peak period and more trips in the evening hours compared to the NHTS sample. Interestingly, in the NHTS sample weekend trips had higher share in the pm peak period than weekday trips.

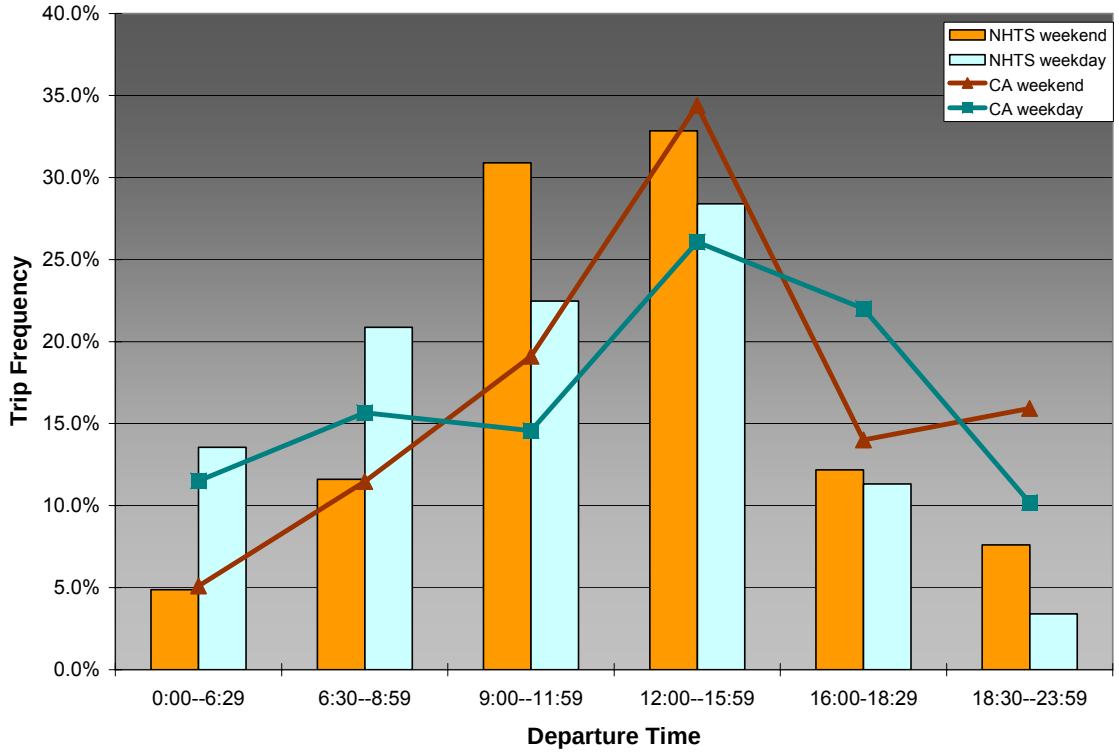

FIGURE 3 Distribution of departure time by travel day type.

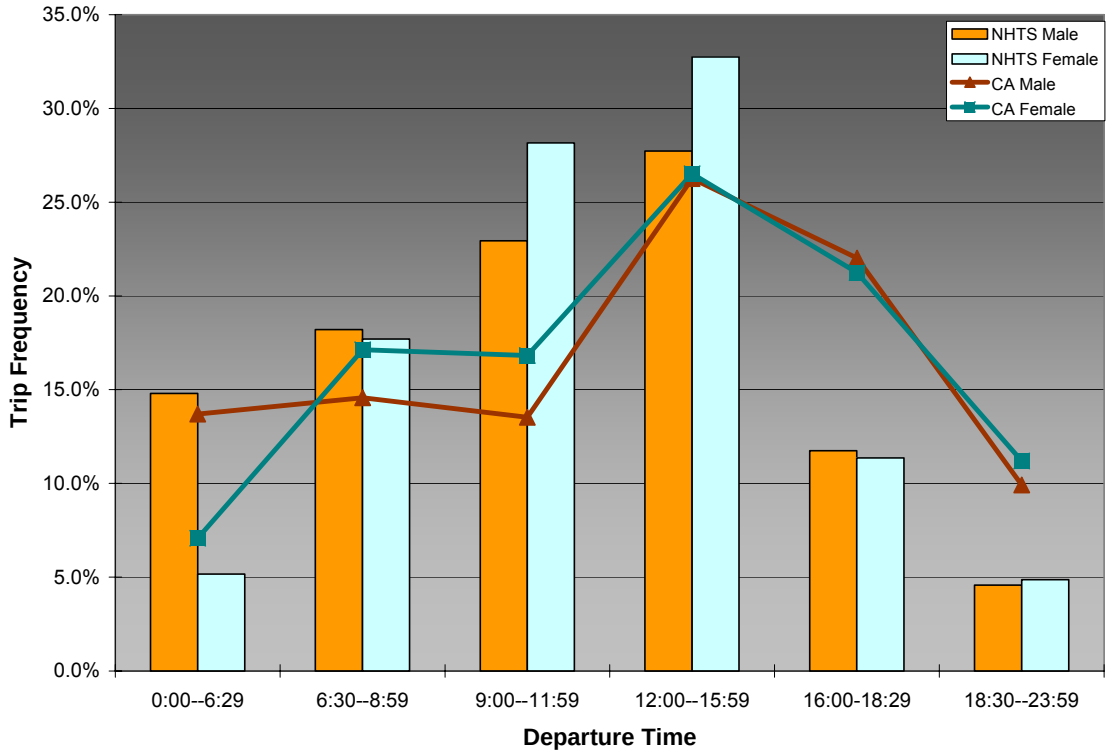

FIGURE 4 Distribution of departure time by gender.

Figure 4 shows the distribution of departure time by gender for both datasets. In general, the two datasets showed consistent patterns in comparing the departure time choices between male and female. Males made more long trips in early morning and fewer trips in morning off-peak hours than females. Again, households in the California sample made more long-distance trips in the pm peak period and fewer trips in the morning off-peak periods, compared to the NHTS sample. This can be partly explained by the California sample having a larger share of weekday trips, but MNL analysis can provide more robust reasoning behind the scene.

MNL MODELING ANALYSIS AND RESULTS

MNL Modeling

Multinomial logit modeling provides the opportunity to examine the effects of various factors on long-distance trip time-of-day choice, and to better understand the underlying causality of the choice behavior. The procedure forecasts the probability of one time-of day (TOD) being chosen for each long-distance trip based on a set of taste parameters and the attributes of the alternatives and the decision-maker. The model used in this study is described in the equation below:

$$\Pr(TOD) = f(T, A, P, H)$$

where

TOD =	TOD period choice for the long trip,
T =	trip related factors such as purpose, mode, travel time, traveling companions,
A =	activity related factors such as activity duration,
P =	personal characteristics such as age, gender, education level,
H =	household characteristics such as income, size, auto-ownership, presence of young child.

The last time period (18:30-23:59) served as the reference category, for interpreting the MNL model, since long-distance trips were least likely to happen in this time period. Among the many results, an MNL model gives an estimate the probability of departing at each of the time periods relative to the evening period, separately. Similarly, for each categorical independent variable the last category served as the base category, so the coefficients were calculated relative to these arbitrary base categories.

Model Specifications

The initial model developed on the 2001 NHTS data was modified to exclude trips made by non-automobile modes, because all long-distance trips extracted from the 2001 California data were made by automobiles. Various types and combinations of explanatory variables were examined in MNL analysis to determine whether and to what extent these variables affect time-of-day choice for long-distance trips.

Table 2 below presents the factors being tested in the models, and the final sets of model specifications being chosen. As shown in the table, some variables played an important

role in the choice behavior and were irreplaceable; some variables had influence on the decision-making and could be included into the model when other related variables were not available; while the other variables did not reveal significant relationship with the departure time choice in all three models. In general the behavioral findings are consistent between the NHTS models and the California model. The main difference is that number of non-household member in travel was significant in the NHTS models, while number of household member in travel was significant in the California model, and the two variables were not interchangeable in any model.

TABLE 2 Various Factors Tested in MNL Models

	NHTS All Modes	NHTS Auto Only	CA Auto Only
Activity duration	▲	▲	▲
Trip duration	▲	▲	▲
Purpose	▲	▲	▲
Weekend	▲	▲	▲
Mode	Δ	–	–
Driver or passenger	×	▲	Δ
Whether HH vehicle used	×	▲	×
Total number of people in travel	×	×	Δ
Number of HH member in travel	×	×	▲
Number of non-HH member in travel	▲	▲	×
Whether the travel was overnight	×	×	×
Gender	▲	▲	▲
Age	▲	▲	▲
Education level	▲	▲	Δ
Whether has a job	▲	▲	▲
Multi-job status	Δ	Δ	Δ
HH income	×	×	Δ
HH size	Δ	Δ	×
Number of HH worker	▲	▲	Δ
Number of HH vehicle	×	×	▲
Number of HH student	–	–	×
HH life cycle	▲	▲	–
Housing unit owned or rented	×	×	×
Household in urban or rural area	×	×	×
# of cases	3322	3106	4524
-2 log likelihood - intercept only	10943.245	10190.167	15699.053
-2 log likelihood - final	9325.567	8668.975	12807.416
R square	0.400	0.402	0.487

▲ significant and chosen in model × not significant
Δ significant at less degree – N/A

Model Parameter Coefficients

The logit coefficient is used to describe the effect of a single variable on predicting the dependent variable—in this study, travelers' time-of-day choice. To better explain the results of logit regression, another form of logit regression – exp(B) was used:

$$\text{odds } (p) = \frac{p}{1-p} = \exp(a + b_1 x_1 + b_2 x_2 + b_3 x_3 + \cdots)$$

The left hand side of the equation indicates the odds ratio (the probability of something is true divided by the probability of it not being true) for choosing a specific departure time period; the right hand side is the exponential of the regression predictor. Controlling for other variables constant, when the independent variable x_i increases by one unit, the odds that the dependent variable equals to a choosing time period increases by a factor of exp(B).

The NHTS –all modes model has been previously presented (*18*) and is not included in this paper. The estimated results for the NHTS auto-only model and the California model are presented in Table 3 and Table 4. The numbers in gray indicate that the coefficients were not statistically significant at 0.2 level.

TABLE 3 Parameter Coefficients for NHTS – Auto Model

		0:00--6:29	6:30--8:59	9:00--11:59	12:00--15:59	16:00--18:29
N_NonHH		0.848	0.914	0.803	0.864	1.002
Trip Duration		1.014	1.010	1.007	1.004	1.000
Activity Duration		1.017	1.014	1.011	1.009	1.007
Weekend (1 if weekend)		0.295	0.283	0.527	0.421	0.357
Sex (1 if male)		1.540	0.847	0.744	0.931	1.296
Dr_Pass (1 if driver)		0.830	0.883	1.070	0.925	0.626
hhveh_used (1 if used)		2.021	1.988	1.279	1.213	1.442
Worker (1 if worker)		0.827	0.592	0.588	0.514	0.883
Purpose	Work/School	7.177	4.608	1.992	1.475	0.727
	Return	0.042	0.190	0.712	1.972	1.341
	Persn Busin	1.280	1.954	1.558	1.157	0.693
	Soci Recrt	0.521	0.930	1.300	1.274	0.691
	Others	.	.	.	.	.
Education	HS or less	4.694	1.968	1.520	1.009	1.086
	HS	2.284	1.271	1.168	1.041	1.038
	College	3.498	2.358	2.129	2.162	1.466
	Graduate	.	.	.	.	.
LifeCycle	no child	0.543	0.882	0.884	1.057	1.119
	child 0-5	0.489	0.499	0.724	0.709	0.542
	child 6-15	0.453	0.519	0.815	0.995	0.723
	child 16-21	0.304	0.568	0.683	0.757	0.705
	retired	.	.	.	.	.

TABLE 4 Parameter Coefficients for California Model

		0:00--6:29	6:30--8:59	9:00--11:59	12:00--15:59	16:00--18:29
Num_HH		0.606	0.755	0.906	0.857	0.789
Trip Duration		1.008	1.006	1.007	1.004	1.000
Activity Duration		1.004	1.002	1.001	1.001	1.001
Weekend (1 if weekend)		0.373	0.565	0.767	0.887	0.414
Sex (1 if male)		1.905	0.914	1.026	1.187	1.140
Age		1.020	1.021	1.034	1.020	1.010
HHveh		1.007	0.904	0.873	0.914	0.954
Purpose	Work/School	4.538	5.675	3.073	1.550	0.533
	Return	0.007	0.013	0.072	0.267	0.383
	Persn Busin	0.916	1.798	2.306	2.103	1.458
	Soci Recrt	0.187	0.534	0.947	0.683	1.048
	Other	.	.	.	.	.
Work Status	Employed	3.229	2.224	0.545	1.755	3.738
	Work Home	1.898	2.935	1.112	2.106	3.303
	Non-worker	3.349	3.361	1.235	2.628	2.255
	other	.	.	.	.	.

The two MNL models are consistent in their behavioral interpretations, with a few distinctions at a fine level. In detail, the findings from the MNL models are summarized as follows:

- Trip duration, activity duration, trip purpose, and whether the trip took place on a weekend were the most powerful factors in determining the TOD choice for long-distance trips. The longer the trip itself or the longer the time to be spent at the destination, the earlier the trip would be taken. Weekend long-distance trips had higher possibility of happening in the evening period, followed by the mid-day periods compared to weekday long trips.
- Travelers taking different types of long trips exhibited various preferences on the departure time. Work or related trips most often took place in the early morning and am peak periods. Return home trips had the highest probability of occurring in the afternoon periods as indicated by the NHTS models, and in the evening period as shown in the California model. Travelers from the NHTS sample were more likely to depart in the morning for personal business trips, and in the afternoon for recreation trips. Travelers from the California were more likely to depart during the mid-day and the evening.
- Travel mode in general was not statistically significant to the TOD choice in the original NHTS analysis. However, for automobile long trips, whether the traveler drove or rode along had impacts on the departure time choice. Drivers had higher chances of making long trips in the morning off-peak period and fewer chances in the pm peak hours compared to passengers.
- Generally, traveling with other people, whether with household members or non-household members, would increase the probability of making long-distance trips in the evening.

- The traveler's age, gender, work status and education level all presented significant impacts on the TOD choice for long-distance trips. Older travelers would depart for long trips more often in the morning. Consistent with the NHTS models, the California model indicates that males were more likely to make long-distance trips in early morning period than females. The California model shows that males had higher possibility of making long trips in the mid-day periods relative to the evening period, while the NHTS models indicated the opposite. Workers had less probability of departing for long trips in the mid-day periods compared to non-workers.
- Household characteristics including household income, household size, number of workers, and number of vehicles revealed various impacts on the TOD choice for long-distance trips, depending upon the model. Only number of household workers showed significant effects in all models.

CONCLUSIONS

The 2001-2002 NHTS and the 2000-2001 California Statewide Travel Survey provided good data to examine the time-of-day choice behavior for long-distance trips and to test the possible spatial transferability of the behavior findings and models. A wide range of factors were explored, and the results indicated that departure time choice behavior for long, occasional and exceptional trips are more complicated than that for urban short trips. Trip/activity duration, trip purpose, travel day type and various personal and household characteristics all exhibited significant relationship with departure time choice-making. A closer look at the travel demands at certain times of the day would help better evaluate the impacts on the performance of the transportation network, and develop appropriate improvement programs to better serve regional or statewide transportation needs. Although there are remarkable differences in data composition between the two datasets, comparative analysis of the models developed from the two datasets reveals consistent results, suggesting the potential for transferability of the behavior pattern across spatial locations.

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