Departure-Time Choice and Mode Choice for Nonwork Trips

Alternative Formulations of Joint Model Systems

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Modeling travel demand by time of day is gaining increasing attention in the practice of travel demand forecasting. The relationship between time-of-day (departure-time) choice and mode choice for nonwork trips is investigated. Two alternative causal structures are considered: one in which departure-time choice precedes mode choice and a second in which mode choice precedes departure-time choice. These two causal structures are analyzed in a recursive bivariate probit modeling framework that allows random error covariance. The estimation is performed separately for worker and nonworker samples drawn from the 1999 Southeast Florida Regional Household Travel Survey. For workers, model estimation results show that the causal structure in which departure-time choice precedes mode choice performs significantly better. For nonworkers, the reverse causal relationship, in which mode choice precedes departure-time choice, is found to be a more suitable joint modeling structure. These two findings can be reasonably explained from a travel behavior perspective and have important implications for advanced travel demand model development and application.

Departure-time choice and mode choice are important constituents of traveler behavior (*1*). Travel demand models designed to estimate travel not only for the average weekday but also for different periods within the day (referred to as time-of-day models) are increasingly required to analyze a broad range of transportation policies and initiatives (*2*). In addition to the temporal dimension of trip making, mode choice is another facet of trip making that has important implications in the transportation policy context. Understanding the relationships underlying these two facets of travel behavior will, in turn, assist planners in examining the potential effectiveness of policy measures aimed at alleviating traffic congestion and reducing automobile vehicle emissions (*3, 4*).

Early studies involving departure-time choice focused mainly on work or commuting trips. Indeed, commuting directly contributes to morning and afternoon peak-period congestion. The direct link between work trips and peak-period travel has provided researchers with the necessary impetus to undertake studies that aim at modeling departure-time choice of commuters and understanding the relationship between commuter departure-time choice and traffic congestion levels (*5–7*).

The interest in modeling nonwork trips also lies in their inherent nature of being more flexible than work trips in terms of individuals' time-of-day choice and mode choice. For certain types of nonwork activities, such as shopping, the departure-time flexibility is evident and therefore travelers may have a greater tendency to shift departure times than to shift modes in response to transportation control measures (*1*). Similarly, social-recreation trips may be pursued at various times of the day unless the activity involves rigid time and space constraints such as those associated with concerts, sporting events, and movies. With respect to mode choice, nonwork activities and trips tend to be undertaken jointly with other household members or friends (*8, 9*). Such joint coupling constraints may make mode switching quite difficult; however, departure-time shifts may still be feasible, particularly in today's context of real-time activity scheduling using cellular communications technology.

The causality between departure-time choice and mode choice is quite important from a transportation planning and policy analysis context. If mode choice precedes departure-time choice, strategies aimed at reducing peak-period travel should also focus significantly on people's mode choice behavior (because the departure-time choice is influenced by mode choice). However, if departure-time choice affects (and therefore precedes) mode choice, strategies aimed at reducing peak-period travel demand can focus primarily on departure-time aspects of behavior. Besides, strategies aimed at reducing single-occupancy-vehicle (SOV) use would have to focus significantly on departure-time choice aspects as well because mode choice is affected by departure-time choice. In addition to the causal relationship between these two aspects of behavior, attention must be paid to the potential simultaneity in their nature, in that unobserved factors affecting each of these may be correlated with one another. Thus, when the relationship between departure-time choice and mode choice is modeled, one needs to consider a rigorous simultaneous-equation modeling framework. By treating both mode choice (SOV versus vehicle other than SOV) and departure-time choice (peak period versus off-peak period) as a set of two binary choice variables, the recursive bivariate probit modeling methodology provides a rigorous flexible framework in which to analyze their causal relationship (*10*).

The central question addressed in this paper is, What is the causal relationship between departure-time choice and mode choice for nonwork trips? One may conjecture that people engaging in activities in the off-peak period may choose to travel by automobile because of the reduced traffic congestion and possibly poorer transit levels of service during such periods. Conversely, those who choose to travel by automobile may arrange their activities so that they can be performed in the off-peak periods to avoid congestion. Similar causal relationships may be considered in the context of peak-period travel, nonautomobile travel, or both. Thus, one may

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hypothesize causal relationships between departure-time choice and mode choice that are opposite one another. This study attempts to shed light on this issue by identifying the causal structure that is statistically supported by travel survey data collected in 1999 from a sample of households in the Southeast Florida region consisting of Miami-Dade, Broward, and Palm Beach Counties.

The model formulation and estimation methodology are presented in the next section. Then the Southeast Florida Regional Household Travel Survey is introduced and the survey sample is described. Model estimation results are presented, and a performance comparison between the models is furnished to help identify the causal structure or structures supported by the data set from a statistical standpoint. Finally, conclusions are drawn and some recommendations for future research are given.

MODELING METHODOLOGY

The recursive simultaneous bivariate probit model, which allows the analysis of one-way causal relationships between two choice behaviors, is employed in this study. In this formulation, the random error terms in the simultaneous-equation system are assumed to follow the bivariate normal distribution. The bivariate normality assumption implies that two endogenous dummy variables may not coexist in mutual functional relations. The existence of an endogenous dummy variable in either function corresponds to two different causal structures, as illustrated later in this section. Intuitively, this feature of the bivariate probit model provides an appropriate approach to distinguish the causality between departure-time choice and mode choice. However, it should be noted that this approach also entails an underlying assumption that an explicit unidirectional causal relationship (or at least the tendency for such a unidirectional causal relationship) exists in the population being studied. Thus, two possible causal structures are considered and compared:

1. Mode choice → departure-time choice (recursive bivariate probit model) and
2. Departure-time choice → mode choice (recursive bivariate probit model).

If the departure-time choice (peak versus off-peak) and SOV or non-SOV mode choice are treated as two binary choices, the bivariate probit model can be formulated at the trip level to simultaneously analyze their probabilities with accommodation of random error correlation. The general formulation is as follows:

$$\begin{cases} M_q^* = \gamma' z_q + \alpha T_q + \epsilon_q \\ T_q^* = \beta' x_q + \eta M_q + \omega_q \end{cases} \tag{1}$$

where

q = index for observations of trips ($q = 1, 2, \ldots, Q$);
M_q^* = latent variable representing the mode choice for trip q ($M_q = 1$ if $M_q^* > 0$, $M_q = 0$ otherwise; i.e., M_q is a dummy variable indicating whether trip q uses SOV mode);
T_q^* = latent variable representing departure time for trip q ($T_q = 1$ if $T_q^* > 0$, $T_q = 0$ otherwise; i.e., T_q is a dummy variable indicating whether trip q is made in the peak period;
z_q, x_q = vectors of explanatory variables for M_q^* and T_q^*, respectively;
γ, β = two vectors of model coefficients associated with the explanatory variables z_q and x_q, respectively;
α = scalar coefficient for T_q to measure impact of departure-time choice on mode choice;
η = scalar coefficient for M_q to measure impact of mode choice on departure-time choice; and
ϵ_q, ω_q = random error terms, which are standard bivariate normally distributed with zero means, unit variances, and correlation ρ [i.e., $\epsilon_q, \omega_q \sim \phi_2\,(0,0,1,1,\rho)$].

On the basis of this normality assumption, one can derive the probability of each possible combination of binary choices for trip q:

$$\text{prob}(M = 0, T = 0) = \Phi_2[-\gamma' z, -\beta' x, \rho] \tag{2}$$

$$\text{prob}(M = 1, T = 0) = \Phi_1[-(\beta' x + \eta)] - \Phi_2[-\gamma' z, -(\beta' x + \eta), \rho] \tag{3}$$

$$\text{prob}(M = 0, T = 1) = \Phi_1[-(\gamma' z + \alpha)] - \Phi_2[-(\gamma' z + \alpha), -\beta' x, \rho] \tag{4}$$

$$\text{prob}(M = 1, T = 1) = 1 - \Phi_1[-(\gamma' z + \alpha)] - \Phi_1[-(\beta' x + \eta)] + \Phi_2[-(\gamma' z + \alpha), -(\beta' x, \eta), \rho] \tag{5}$$

where $\Phi_1[\cdot]$ and $\Phi_2[\cdot]$ are the cumulative distribution function for standard univariate and bivariate normal distributions, respectively.

The sum of the probabilities for the four combinations of two binary choices should be equal to 1; that is,

$$\text{prob}(M = 0, T = 0) + \text{prob}(M = 1, T = 0) + \text{prob}(M = 0, T = 1) + \text{prob}(M = 1, T = 1) = 1 \tag{6}$$

By substituting Equations 2 to 5 into Equation 6, it can be shown that

$$\Phi_2[-\gamma' z, -\beta' x, \rho] + \Phi_2[-(\gamma' z + \alpha), -(\beta' x + \eta), \rho] = \Phi_2[-\gamma' z, -(\beta' x + \eta), \rho] + \Phi_2[-(\gamma' z + \alpha), -\beta' x, \rho] \tag{7}$$

Equation 7 does not hold unless either α or η is equal to zero. This requirement, known as the logical consistency condition, will lead to two different recursive simultaneous modeling structures (*11*), suggesting two different causal relationships:

For $\alpha = 0, \eta \neq 0$ (mode choice → departure-time choice),

$$\begin{cases} M_q^* = \gamma' z_q + \epsilon_q \\ T_q^* = \beta' x_q + \eta M_q + \omega_q \end{cases} \tag{8}$$

In this structure, mode choice is predetermined according to the first functional relationship. Then the choice of mode is specified as a dummy variable in the second functional relationship for departure-time choice to directly measure the impact of mode choice on time-of-day choice.

For $\alpha \neq 0, \eta = 0$ (departure-time choice → mode choice),

$$\begin{cases} M_q^* = \gamma' z_q + \alpha T_q + \epsilon_q \\ T_q^* = \beta' x_q + \omega_q \end{cases} \tag{9}$$

Conversely, one may consider the alternative structure in which departure-time choice is predetermined according to the second functional relationship. The trip departure time is specified as an explanatory variable influencing mode choice according to the first functional relationship.

Thus, the desirable feature of the bivariate probit model in which the coefficients of two endogenous dummy variables do not coexist in both functional relationships provides an appropriate modeling framework to analyze the unidirectional causality between trip departure time and mode choice.

The endogenous nature of one of the dependent variables in the simultaneous-equation system can be ignored in formulating the likelihood function. To facilitate formulating likelihood functions, Equations 2 to 5 can be rewritten in a format that includes only the cumulative distribution function of the standard bivariate normal distribution (*12*). And the corresponding likelihood functions can be summarized by the following general formulations for the two different unidirectional causal structures:

For $\alpha = 0$, $\eta \neq 0$ (mode choice $\rightarrow$ departure-time choice),

$$L = \prod_{q=1}^{Q} \{\Phi_2[\mu_q \gamma' z_q, \tau_q(\beta' x_q + \eta M_q), \mu_q \tau_q \rho]\} \tag{10}$$

For $\alpha \neq 0$, $\eta = 0$ (departure-time choice $\rightarrow$ mode choice),

$$L = \prod_{q=1}^{Q} \{\Phi_2[\mu_q(\gamma' z_q + \alpha T_q), \tau_q \beta' x_q, \mu_q \tau_q \rho]\} \tag{11}$$

where $\mu_q = 2M_q - 1$ and $\tau_q = 2T_q - 1$.

Since the likelihood functions of the recursive bivariate probit model and the common bivariate probit model are virtually identical, parameter estimation can be accomplished using readily available software such as LIMDEP 8.0 (*13*).

DATA SET AND SAMPLE DESCRIPTION

The data set used in this study is drawn from the Southeast Florida Regional Household Travel Survey, which was conducted during 1999 in Miami-Dade, Broward, and Palm Beach Counties. Households agreeing to participate in the survey were mailed a survey package including a 24-h travel diary for each member of the household. As with most household travel surveys, this survey collected detailed sociodemographic and trip information for each person in the household. More details about the survey and sampling methodology and an extensive description and graphical presentation of the survey instruments are provided elsewhere (*14*).

The survey provided a respondent sample of 11,426 persons reporting a total of 33,082 trips. The socioeconomic, demographic, and travel characteristics of the respondent sample were generally consistent with those of the population in the region. A descriptive analysis of the sample shows that the average household size is about 2.6 persons per household with nearly 30% of the households reporting household sizes of four or more persons. About two-thirds of the households have annual incomes greater than $30,000 per year. On average, households own about 1.8 vehicles per household with only 4% reporting no vehicles. More than 60% have two or more vehicles in the household. Likewise, about 60% of the households live in a single-family dwelling unit. The average number of licensed drivers, at nearly two drivers per household, is consistent with average household size and vehicle ownership figures. About 60% of the households report having no child under the age of 18 years. The average number of workers is about 1.6 workers per household.

All origin and destination locations in the trip file were geocoded to latitude and longitude and to the traffic analysis zone (TAZ) of the Southeast Regional Planning Model. The household travel survey trip data set was therefore augmented with modal level-of-service (LOS) data extracted from the Southeast Regional Planning Model. Variables augmented to the trip data set included interzonal travel times, distances, and costs for both peak and off-peak periods.

This study focuses on the relationship between time-of-day choice and mode choice for nonwork trips made by adults. For this reason, all nonwork trips made by persons 18 years of age or older were extracted from the original data set. In addition, this study distinguishes between workers (employed) and nonworkers (unemployed) in an attempt to capture the effect of potential differences in temporal and modal choice flexibility between these two groups. For example, workers might link their nonwork trips to the commute, whereas nonworkers might use their travel flexibility to avoid congestion during peak hours. From the original trip data set, all nonwork trips that had complete information including household and person socioeconomic data, trip attribute data, and modal LOS data were extracted. This subsample of trips included a total of 14,410 nonwork trips, of which 7,947 were made by 2,710 workers and 6,463 were made by 1,741 nonworkers. Nonwork trips include the following categories:

- Home-based shopping or personal business,
- Home-based social recreation,
- Home-based school,
- Home-based other, and
- Non-home-based.

Table 1 offers a description of person characteristics for the subsamples of workers and nonworkers used in this study. In general, the nonworker sample includes a large proportion of elderly and retired people, thus pushing the average age up to 57. The corresponding average age for workers is 41. About 80% of the worker sample is employed full time, and the remainder is employed part

TABLE 1 Person Characteristics of Southeast Florida Household Travel Survey Sample

Characteristic	Statistics	
	Workers	Nonworkers
Sample Size	2710	1741
Average Age (in years)	41	57
18 to 24 years	10.2%	8.0%
25 to 54 years	73.9%	29.4%
55 to 64 years	9.9%	14.2%
65+ years	4.2%	45.4%
Employment Status		
Full time	81.3%	-
Part time	18.6%	-
Residence Status		
Full time	98.7%	92.0%
Part time	1.3%	7.9%
#Trips per day	5.08	4.32

NOTES: Workers are defined as those who indicated that they are employed. Nonworkers are defined as those who indicated that they are unemployed.

time. A majority of the persons in both samples are full-time residents of the area. As expected, the average daily trip rate for workers is slightly higher than that for nonworkers, presumably because of the presence of commute trips for workers. On average, workers make about five trips per day, and nonworkers make a little over four trips per day.

The time-of-day distribution of nonwork trips is shown in Figure 1 for both worker and nonworker samples. The differences between the two plots are rather striking. The time-of-day distribution for workers shows two peaks that coincide with the commute peak periods. This distribution suggests that workers may be more inclined to link their nonwork trips with their work trips. However, the peaks are not as well defined as one might encounter in the case of work trips, suggesting that a substantial portion of nonwork travel occurs during off-peak hours as well. The time-of-day distribution pattern for nonworkers is consistent with expectations and quite different from that of workers. The distribution shows that nonworkers tend to make nonwork trips during the midday period. There may be several reasons for this distributional pattern, including the desire to avoid traveling in the peak periods for trips that are flexible in the temporal dimension.

MODEL ESTIMATION RESULTS

Table 2 offers descriptions of the variables used in the models. The variables constitute a series of dummy variables describing household and person socioeconomic characteristics in addition to modal LOS variables. Both causal structures (i.e., mode choice affects departure-time choice and departure-time choice affects mode choice) are estimated separately for the worker and nonworker samples.

Workers' Nonwork Trips

Table 3 offers estimation results of the bivariate probit model for both causal structures for the worker and nonworker samples. Starting from left to right, in the first worker model, departure-time choice is hypothesized to affect mode choice. First, it is found that the dummy variable representing peak-period departure-time choice (PEAK) significantly affects the choice of the SOV mode for nonwork trips. The coefficient is negative, indicating that a departure-time choice in the peak period tends to lower the propensity to drive alone for nonwork trips. There are two important possible explanations for this finding. First, it is possible that peak-period nonwork trips primarily serve passenger trips in which a worker is dropping off or picking up a child at school or daycare on the way to and from work. Since nearly one-half of the households in the sample have at least one child, this is likely to be a strong explanation for this relationship. Second, it is possible that some workers are choosing to use alternative modes of transportation for their nonwork trips to avoid the frustration of driving alone in congested conditions during the peak period. Thus, the negative coefficient associated with the peak-period departure-time variable in the mode choice model is both reasonable and plausible. In addition, it is found that the random error correlation is statistically significant, which supports the paradigm of simultaneity embodied in the bivariate probit model specification adopted for this study.

The constant term in the departure-time choice model is negative, indicating that the general propensity is to pursue nonwork trips in the off-peak period. Younger workers and those without children tend to pursue their nonwork trips in the off-peak period as demonstrated by the negative coefficients associated with these variables. The finding that absence of children contributes to more off-peak

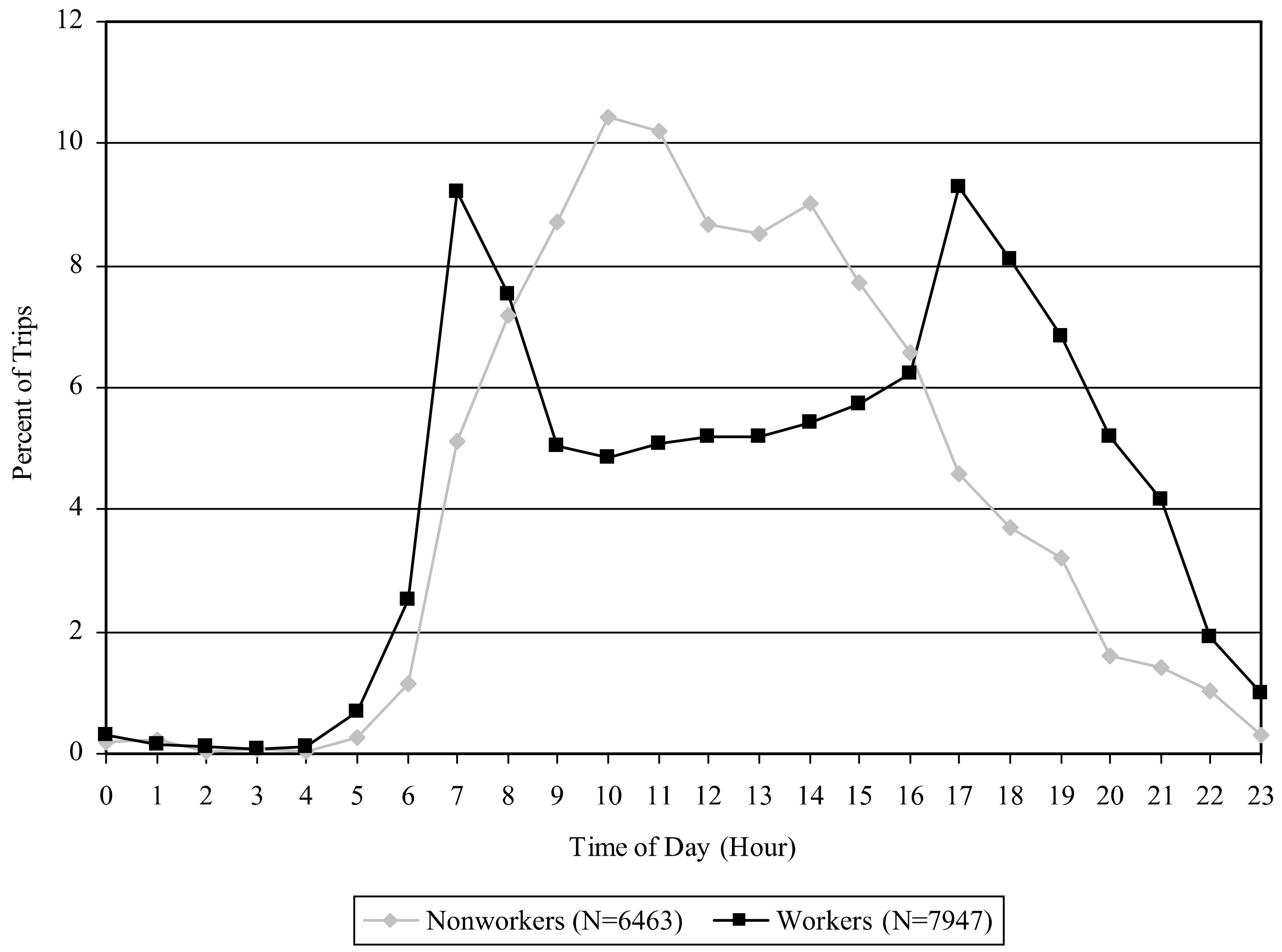

FIGURE 1 Time-of-day distribution of nonwork trips for workers and nonworkers.

TABLE 2 Variables Used in Models

Variable Name	Variable Description	Workers (N=7947) Mean	Workers (N=7947) St. Dev.	Nonworkers (N=6463) Mean	Nonworkers (N=6463) St. Dev.
Household Sociodemographics					
HHSIZE1	Single person household	0.10	0.30	0.14	0.35
HHSIZE2	Household size is equal to two persons	-	-	0.47	0.50
HHSIZE3P	Household size is equal to or greater than 3	0.61	0.49	-	-
NOCHILD	Household has no children	0.48	0.50	0.70	0.46
CHILD2P	Number of children in the household is equal to or greater than 2	0.31	0.46	-	-
NOVEHICL	Household has no autos	-	-	0.02	0.15
VEHICL2P	Number of autos owned by household is equal to or greater than 2	0.74	0.44	0.56	0.50
INC_100K	Annual income of household is equal to or greater than $100,000	0.15	0.35	0.12	0.32
Person Sociodemographics					
AGE18_24	Person is between 18 and 24 years of age	0.09	0.29	-	-
FT_JOB	Person has a full-time job	0.77	0.42	-	-
PT_RES	Person is a part-time resident	0.02	0.14	-	-
PALM_BCH	Person is a resident in Palm Beach	-	-	0.46	0.50
COMMUT15	One-way commute time for person is equal to or greater than 15 minutes	0.36	0.48	-	-
Trip Variables					
HB_REC	Trip purpose is home-based social recreation	-	-	0.07	0.25
HB_SHOP	Trip purpose is home-based shopping	-	-	0.11	0.31
SCHOOL	Primary purpose of trip is "school"	0.05	0.22	-	-
LOS Variables					
DIST30	Peak-period highway distance without HOV lane is equal to or greater than 30 minutes	-	-	0.02	0.13
FARE125	Peak-period one-way transit fare is equal to or greater than $1.25	-	-	0.13	0.33
FARE150	Peak-period one-way transit fare is equal to or greater than $1.50	-	-	0.05	0.22
HWRUN30	Peak-period highway run time without HOV lane is equal to or greater than 30 minutes	0.13	0.34	-	-
T1WAIT30	Peak-period transit first wait time is equal to or greater than 30 minutes	-	-	0.24	0.42
TERMTI2P	Peak-period highway terminal time is equal to or greater than 2 minutes	0.20	0.40	0.56	0.50
WALK15	Peak-period transit walk time is equal to or less than 15 minutes	0.34	0.48	-	-
WALK5	Peak-period transit walk time is equal to or less than 5 minutes	-	-	0.59	0.49
Choice Variables					
PEAK	Departure time of trip is in peak period (7:00am-9:00am or 4:00pm-6:00pm)	0.32	0.53	0.23	0.42
SOV	Trip mode is single-occupancy vehicle (SOV)	0.46	0.50	0.47	0.50

(-) Variables not used in the models of respective group.

departure-time choice lends credence to the explanation offered in the previous paragraph. As expected, school trips also tend to occur in the peak period. The model also indicates that highway LOS affects departure-time choice. Peak-period travel time variables (HWRUN30 and TERMTI2P) are found to have negative coefficients, indicating that higher peak-period travel times lead to a greater propensity to engage in nonwork trips in the off-peak period. This finding is suggestive of the presence of peak-spreading, in which individuals pursue their trips outside the peak period to avoid the worst congestion.

With respect to the mode choice model, it is found that the constant term is positive, indicating a general tendency toward the use of the SOV mode for nonwork trips. As expected, larger households contribute to a lower propensity to SOV use for nonwork trips presumably because of ridesharing and serve-passenger trips associated with larger households. A longer commute, holding a full-time job, having access to more vehicles (higher car ownership levels), and high income are all found to contribute positively to the use of the SOV mode for nonwork trips. All of these indications are consistent with expectations. School trips show a propensity to be undertaken by SOV mode. Young adults driving to college and university may do so alone, possibly because they are from small one- and two-person households. Also, part-time residents who live in the area for less than 6 months of the year are found to show a negative propensity to drive alone. This finding may be due to the fact that these residents tend to be elderly retired people whose driving abilities may be diminished. They may also have limited automobile availability, thus contributing to a greater propensity to use transit or share rides with others. The model also suggests that small transit walk access times contribute negatively to the choice of the SOV mode.

The next model in Table 3 shows estimation results for the model in which mode choice is assumed to affect departure-time choice. The results show that the SOV mode choice contributes negatively to peak-period departure-time choice as evidenced by the negative coefficient associated with the SOV choice variable in the departure-time choice model. In addition, it is found that the random error correlation is statistically significant. These indications are consistent with those found in the first causal structure.

All other variables provide indications that are similar to those found in the first model. The signs of the coefficients are virtually identical for the different explanatory variables in the two worker models. Model estimation results suggest that those with full-time jobs tend to make their nonwork trips in the peak period, as shown by the positive coefficient. This finding is possibly due to the desire to link nonwork activities efficiently with the commute trip, which typically tends to take place in the peak period. The constant term in the mode choice model shows a negative value, indicating a general tendency in the worker sample to use non-SOV modes for nonwork trips. This finding is inconsistent with the survey sample data, in which it was found that a higher percentage of workers used the SOV mode for their nonwork trips. The constant term in the mode choice model of the first causal structure is positive and consistent

TABLE 3 Bivariate Probit Model Estimation Results

Variable	Workers		Workers		Nonworkers		Nonworkers	
	Dep Time→Mode		Mode→Dep Time		Dep Time→Mode		Mode→Dep Time	
	β coef	t-stat	β coef	t-stat	β coef	t-stat	β coef	t-stat
Departure Time Choice Model (Peak period = 1)								
Constant	-0.300	-14.12	-0.191	-2.92	-0.494	-12.14	-0.367	-6.24
AGE18_24	-0.217	-4.51	-0.245	-4.37	-	-	-	-
FT_JOB	-	-	0.131	3.58	-	-	-	-
SCHOOL	0.590	8.69	0.685	9.60	-	-	-	-
NOCHILD	-0.323	-11.29	-0.196	-4.95	-0.330	-8.63	-0.282	-6.90
TERMTI2P	-0.213	-6.46	-0.234	-6.00	-	-	-0.155	-3.62
HWRUN30	-0.081	-2.16	-0.104	-2.34	-	-	-	-
INC_100K	-	-	-	-	0.093	1.76	0.126	2.35
PALM_BCH	-	-	-	-	-0.101	-2.82	-0.099	-2.79
HB_SHOP	-	-	-	-	-0.181	-3.97	-0.175	-3.83
HB_REC	-	-	-	-	0.093	1.76	-	-
WALK15	-	-	-	-	0.068	1.90	0.063	1.78
SOV	-	-	-0.490	-3.90	-	-	-0.243	-2.33
Mode Choice Model (SOV = 1)								
Constant	0.296	7.06	-0.167	-4.00	-0.850	-3.57	-0.956	-20.95
HHSIZE1	0.564	10.34	0.739	12.49	1.241	15.40	1.259	17.23
HHSIZE2	-	-	-	-	0.121	2.29	0.135	2.56
HHSIZE3P	-0.226	-6.57	-0.391	-10.21	-	-	-	-
NOCHILD	-	-	-	-	0.281	2.93	0.309	5.80
CHILD2P	-0.108	-3.52	-0.227	-6.23	-	-		
COMMUT15	-	-	0.204	6.74	-	-	-	-
SCHOOL	0.611	9.12	0.418	6.09	-	-	-	-
PT_RES	-0.362	-4.52	-0.359	-3.50	-	-	-	-
FT_JOB	0.047	1.71	-	-	-	-	-	-
NOVEHICL	-	-	-	-	-2.414	-11.61	-2.441	-12.64
VEHICL2P	0.377	10.98	0.515	13.76	0.704	16.81	0.706	18.45
HB_SHOP	-	-	-	-	0.240	4.03	0.255	6.16
HB_REC	-	-	-	-	-0.117	-2.10	-0.124	-2.36
INC_100K	0.120	3.62	0.153	3.68	-	-	-	-
WALK5	-0.079	-3.24	-0.090	-2.93	-	-	-	-
TERMTI2P	-	-	0.104	2.84	-	-	-	-
DIST30	-	-	-	-	-0.368	-3.15	-0.337	-2.93
T1WAIT30	-	-	-	-	0.071	1.71	0.082	2.10
FARE125	-	-	-	-	-	-	0.157	3.18
FARE150	-	-	-	-	0.211	2.87	-	-
PEAK	-1.456	-22.16	-	-	-0.266	-0.41	-	-
ρ (Error Correlation)	0.828	16.26	0.198	2.47	0.144	0.38	0.137	2.04
Log-Likelihood								
At convergence	-9912.779		-9908.679		-7448.404		-7440.233	
At market share	-10417.222		-10417.222		-7964.838		-7964.838	
At zero	-11016.881		-11016.881		-8959.620		-8959.620	
Likelihood-Ratio Comparison								
No. of parameters (K)	18		20		20		20	
ρ_0^2	0.1002		0.1006		0.1298		0.1308	
ρ_c^2	0.0484		0.0488		0.0648		0.0659	
$\bar{\rho}_0^2$	0.0986		0.0984		0.1664		0.1674	
$\bar{\rho}_c^2$	0.0467		0.0465		0.0623		0.0634	

(-) Variable not included in model

with the higher observed percentage of SOV nonwork trips in the worker sample. The negative constant term seen here in the second causal structure (in which mode choice precedes departure-time choice) is not easily explained. This finding provides the first indication that the model in which mode choice affects departure-time choice may not be as well supported by the data as the one in which departure-time choice affects mode choice. Indeed, one would expect that workers would be more constrained with respect to their departure-time choice because of scheduling constraints imposed by the work activity. Thus, workers determine their time-of-day choice for nonwork activities (around the work activity schedule) and then determine the mode choice based on a host of factors including the time-of-day choice.

Nonworkers' Nonwork Trips

Estimation results for nonworkers' nonwork trips are also shown in Table 3. First, estimation results corresponding to the model in which departure-time choice precedes mode choice are presented. This model appears to reject the paradigm of simultaneity in the relationship between departure-time choice and mode choice. The coefficient of the dummy endogenous variable (PEAK) in the modal choice model is negative but not at all statistically significant. Moreover, the random error correlation is also not statistically significant at all. Both of these findings indicate that this model specification does not support the notion of simultaneity in departure time and mode choice for nonwork trips made by nonworkers. Since these findings are quite counterintuitive, the authors believe that this causal structure is not appropriate to describe the behavior of nonworkers.

As to the other explanatory variables, the model offers plausible and reasonable indications. The constant term in the departure-time choice model is negative, indicating a negative propensity to undertake nonwork trips in the peak period. Since nonworkers are not constrained by the schedule of work activities, this finding is consistent with expectations. Those with no children tend to avoid the peak period, perhaps because of their need to drop off and pick up children at school and daycare, and these serve-child trips may occur in or around the peak periods. Although shopping trips tend to be outside the peak period (negative coefficient associated with HB_SHOP), recreational trips tend to occur in the peak period (positive coefficient for HB_REC). These findings are also plausible in that recreational trips may involve household member participation and therefore occur in the peak periods depending on the availability and constraints of the household worker and school children. As far as LOS variables are concerned, nonworkers seem to be sensitive to transit walk time in their departure-time choice. The variable representing a peak-period transit walk access time of less than 15 min has a positive influence on peak-period departure-time choice. This finding may be attributed to the better transit service that is provided during the peak period.

The mode choice model shows a negative constant, indicating an overall tendency to avoid using the SOV mode for nonwork trips. Smaller household sizes and the absence of children positively influence SOV mode choice, presumably because of the lower possibility of sharing rides with other household members. As expected, vehicle ownership affects mode choice for nonwork trips. Consistent with the findings in the departure-time choice model, home-based shopping trips show a greater propensity to be drive-alone trips, whereas home-based recreational trips show a greater propensity to be non-SOV trips. Once again, this result may be due to the tendency to pursue recreational trips together with other household members, which leads to more shared-ride trips. Three LOS variables appear to affect the mode choice of nonworkers. A highway distance greater than 30 mi appears to discourage driving alone when nonwork trips are pursued. It is possible that longer trips may be recreational trips undertaken with other household members and friends, thus contributing to a lower proportion of drive-alone mode usage. Greater transit waiting times and higher fares appear to discourage transit use and have a positive impact on SOV mode choice.

Finally, estimation results corresponding to the model in which mode choice precedes time-of-day choice are presented for nonworkers. The most noteworthy finding in these data is that this model (causal structure) supports the hypothesis of simultaneity between departure-time choice and mode choice. The coefficient of mode choice (SOV) in the departure-time choice model is negative and statistically significant at the 0.05 level. In addition, the random error correlation is positive and statistically significant at the 0.05 level. In general, the model indicates that nonworkers are likely to avoid traveling in the peak period (negative constant in the departure-time choice model) and that using the SOV mode further contributes to avoiding the peak period. In general, it appears that nonworkers undertake shopping and personal business trips using the drive-alone mode during the off-peak periods. The positive coefficient associated with HB_SHOP variable in the mode choice model further supports this conjecture. In the departure-time choice model, a longer out-of-vehicle travel time has a negative effect on peak-period departure-time choice. This finding is consistent with that observed in the worker models. All of the other findings in this model are consistent with those reported in the first nonworker model, in which departure-time choice precedes mode choice, except for the finding that the random error correlation term is statistically significant. The significant error correlation supports the notion of a simultaneous relationship between time-of-day choice and mode choice and is intuitively more consistent with travel behavior hypotheses.

Thus, from a qualitative and intuitive standpoint, it appears that the causal model in which departure-time choice precedes mode choice is more applicable to workers' nonwork trips, whereas the opposite causal structure, in which mode choice precedes departure-time choice, is more applicable to the nonworker sample.

PERFORMANCE COMPARISONS

The model estimation results presented in the previous section generally offer plausible indications for alternative causal paradigms. The only model that may be rejected on qualitative grounds is the nonworker model in which departure-time choice precedes mode choice. The insignificance of the random error correlation and coefficient reflecting the influence of departure-time choice on mode choice is difficult to explain and defend in light of the simultaneity shown by the other models. A more rigorous comparison across models is presented in this section to better understand the relationship between mode choice and departure-time choice.

A goodness-of-fit comparison among the models of different causal structures is conducted first. The adjusted likelihood-ratio index as a goodness-of-fit measure can be used for testing and comparing nonnested relationships in discrete choice models. The indexes are given as follows:

$$\bar{\rho}_0^2 = 1 - \frac{L(\beta) - K}{L(0)} \tag{12}$$

$$\bar{\rho}_c^2 = 1 - \frac{L(\beta) - K}{L(c)} \tag{13}$$

where

$\bar{\rho}_0^2$ = adjusted likelihood-ratio index at zero,
$\bar{\rho}_c^2$ = adjusted likelihood-ratio index at market share,
$L(\beta)$ = log-likelihood value at convergence,
$L(0)$ = log-likelihood value at zero,
$L(c)$ = log-likelihood value at market share (model including only the constant term), and
K = number of parameters in model.

The adjusted likelihood-ratio indexes for all of the models are presented at the bottom of Table 3.

To choose between two models (say, Models 1 and 2), Ben-Akiva and Lerman (*15*, p. 172) provide a test in which under the null hypothesis that Model 1 is the true specification, the following holds asymptotically:

$$\Pr\left(\bar{\rho}_2^2 - \bar{\rho}_1^2 > z\right) \leq \Phi\left\{-[-2zL(0) + (K_2 - K_1)]^{1/2}\right\} \qquad z > 0 \tag{14}$$

where

$\bar{\rho}_i^2$ = adjusted likelihood-ratio index at zero for model $i = 1, 2$,
K_i = number of parameters in model i,
Φ = standard normal cumulative distribution function, and
$L(0)$ = log-likelihood value at zero.

If all N observations in the sample have all J alternatives, $L(0) = N \ln(1/J)$.

The probability that the adjusted likelihood-ratio index of Model 2 is greater by some $z > 0$ than that of Model 1, given that the latter is the true model, is asymptotically bounded by the right-hand side of Equation 14. If the model with the greater $\bar{\rho}^2$ is selected, this bounds the probability of erroneously choosing the incorrect model over the true specification. With this procedure, models of alternative causal structures can be compared against one another.

The difference between the adjusted likelihood-ratio indexes for the two worker models is 0.0002 with the model in which departure-time choice precedes mode choice, showing the better fit. Applying Equation 14 yields a bounding probability of almost zero; therefore, it can be said with a high degree of confidence (99% confidence or better) that the model corresponding to the causal structure "departure-time choice → mode choice" is statistically dominant in the worker sample (for nonwork trips). This finding may be behaviorally explained by considering the typical work schedule constraints faced by workers. Since workers tend to link their nonwork trips with the commute to and from work, the departure-time choice is predetermined in conjunction with the work schedule, which takes precedence over everything else. The mode choice is then simply determined by the mode that has been chosen for the commute trip since the nonwork trips are part of a larger trip-chaining mechanism.

For nonworkers, the model in which departure-time choice precedes mode choice may be considered suspect on qualitative intuitive reasoning, as explained earlier. In addition, Table 3 shows that the model in which mode choice precedes departure-time choice exhibits a higher adjusted likelihood-ratio index. The difference between adjusted likelihood ratios is 0.001, and the nonnested test shown in Equation 14 rejects the joint structure of departure-time choice preceding mode choice at the 0.01 level of significance. That the most appropriate causal structure for nonworkers is the opposite of that of workers is also quite reasonable. For nonworkers, work-related scheduling constraints are not involved. However, mode availability constraints may occur. If the worker has taken the automobile, then automobile availability may be constrained, particularly in multiperson households. Then the nonworker must first think about the decision regarding mode and then determine the most suitable time of day for pursuing the nonwork activity.

In summary, this study points to the possible behavioral mechanism by which people tend to first make choices that are subject to constraints and then make choices that are less constrained. Thus, for workers, departure-time choice is determined first because of work schedule constraints, whereas for nonworkers, mode choice is determined first because of possible modal availability constraints and greater departure-time flexibility. These conclusions are reasonable and consistent with expectations regarding travel behavior.

CONCLUSIONS AND RECOMMENDATIONS

This study attempts to shed light on the relationship between departure-time choice and mode choice behavior for nonwork trips. Since departure-time choice for work trips tends to be governed largely by work schedules and constraints, studies of work trip departure-time choice have largely examined the issue with respect to traveler sensitivity to congestion, travel time reliability, and arrival- or departure-time window sizes. In contrast, less attention has been paid to the issue of departure-time choice for nonwork trips, a growing segment of trip making that is accounting for a larger share of trips at all times of day.

Two alternative formulations of joint model systems are considered indicating two possible alternative causal relationships between departure-time choice and mode choice for nonwork trips. The analysis employs the 1999 Southeast Florida Regional Household Travel Survey data. The model estimation effort was conducted separately for workers and nonworkers because of the different scheduling and time constraints under which these demographic groups make activity and travel decisions. Both mode choice and departure-time choice were treated as binary choice variables, with mode represented as a choice between SOV and non-SOV and departure time represented as a choice between peak and off-peak periods. Under this scheme, the bivariate probit modeling framework was applied to estimate the model systems and clarify the direction of causal relationships between these dimensions of behavior. Undoubtedly, this effort can be extended in future research efforts to treat departure time as a continuous choice process (along the continuous time axis) and mode as a multinomial choice among several modes.

The model results suggest that people generally first make decisions on choice variables that are more constrained. For the worker sample, it was found that the data better supported the causal relationship in which departure-time choice preceded mode choice. For the nonworker sample, however, the analysis and modeling results suggested that the data support the causal relationship in which mode choice precedes departure-time choice. These findings are consistent with the notion that choices on constrained dimensions are made first. Workers are time constrained because of work activity schedules. Thus, workers first determine when they can pursue their nonwork activities and trips and then choose the mode for those trips depending on the time of day, modal availability, and other factors. Nonworkers, on the other hand, are not as time constrained as workers. They may be more mode constrained than time-of-day constrained because of the modal availability issue, the need to engage in nonwork activities that serve household members and other household obligations (leading to more shared-ride trips), and the absence of rigid work schedules. Models of activity and travel behavior should incorporate relationships such as those identified here to more accurately portray the decision mechanisms that may be driving traveler patterns.

As with most research efforts of this type, limitations apply to this study, and additional research is warranted. First and foremost, it must be recognized that the identification of true causal relationships based on a statistical analysis of revealed behavior data is extremely difficult and challenging. This study provides a framework by which alternative hypotheses regarding causal relationships can be tested, but true causal relationships may be best identified by collecting and analyzing behavioral process data that provide information about the thought process that went into a certain decision or behavioral choice. Also, despite the best efforts of the authors, research results may be sensitive to model specification and choice of explanatory variables. Finally, additional research should examine whether the relationships found to be more suitable in this study extend to other data sets and geographical contexts.

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