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Alternative Formulations of Joint Model Systems of Departure Time Choice and Mode Choice for Non-Work Trips

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by

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ALTERNATIVE FORMULATIONS OF JOINT MODEL SYSTEMS OF DEPARTURE TIME CHOICE AND MODE CHOICE FOR NON-WORK TRIPS

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ABSTRACT

Modeling travel demand by time of day is gaining increasing attention in travel demand forecasting practice. This is because time of day choice has important implications for mode choice and for quantifying potential modal and time of day shifts in response to traffic congestion and peak period travel demand management strategies. In this context, understanding the causal relationship between time of day (departure time) choice and mode choice behavior would be useful in the development of time of day based travel demand modeling systems both within the four-step modeling paradigm and within newer tour-based and activity-based microsimulation paradigms. This thesis investigates the relationship between departure time choice and mode choice for non-work trips as work trips tend to be constrained with respect to time of day choice. Two alternative causal structures are considered in this thesis: one structure in which departure time choice is determined first and mode choice is subsequently influenced by departure time choice and a second structure in which mode choice is determined first and affects 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 non-worker 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 non-workers, 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.

CHAPTER 1

INTRODUCTION

1.1 Background

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 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 auto vehicle emissions. Such policies, motivated by recent legislation such as the Intermodal Surface Transportation Efficiency Act 1991 (ISTEA), Clean Air Act Amendments (CAAAs), and the Transportation Equity Act for the 21st Century (TEA-21), call for the deployment of travel demand models capable of assessing a range of transportation control measures (TCMs) such as congestion pricing, peak-period pricing, restrictions on single occupancy vehicle (SOV) use during certain time periods in certain places, and incentives that promote ride-sharing and transit use [3, 4].

1.2 Time-of-day Travel Demand Modeling

Travel demand modeling systems are increasingly being enhanced to incorporate time-of-day modeling capabilities. Regardless of whether one is implementing time-of-day modeling concepts in a four-step modeling paradigm or a newer tour- or activity-based modeling paradigm, the relationship between time-of-day choice or departure time choice and mode choice is an important one. In the four step modeling framework, should time-of-day based trip tables be obtained first and then mode choice models applied to different time-of-day based trip tables? Or should mode based trip tables be calculated first and then time-of-day choice models applied to each modal trip table? In tour-based or activity-based modeling systems, should time-of-day choice models precede, succeed, or be jointly combined with mode choice models?

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, then 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). On the other hand, if departure time choice affects (and therefore precedes) mode choice, then strategies aimed at reducing peak period travel demand can focus primarily on departure time aspects of behavior. Besides, strategies aimed at reducing 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 modeling the relationship between departure time choice and mode choice, one needs to consider a rigorous simultaneous equations modeling framework. Treating both mode choice (SOV vs non-SOV) and departure time choice (peak vs 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 the causal relationship between them [10].

1.3 Objective and Scope of the Study

The central question addressed in this study is: what is the causal relationship between departure time choice and mode choice for non-work 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, people choosing to travel by the automobile may arrange their activities such that they can do so in the off-peak periods to avoid congestion. Similar causal relationships may be considered in the context of peak period travel and/or non-auto travel. Thus, one may hypothesize causal relationships between departure time choice and mode choice that are opposite to 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.

1.4 Outline of Thesis

This thesis is composed of six chapters. This chapter has provided an introduction about the background and the purpose of the study as well as literature review. The rest of the thesis is organized as follows. Chapter 2 provides a summary of a literature review on the topic of interest. Chapter 3 presents the model formulation and estimation methodology for the two alternative causal structures. Chapter 4 introduces the Southeast Florida Regional Household Travel Survey and provides a description of the survey sample. Model estimation results are presented in chapter 5, including a performance comparison between the models to help identify the causal structure(s) supported by the data set from a statistical standpoint. Conclusions are drawn and some recommendations for future research are given in the sixth and final chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Need for Time-of-day Modeling Procedures

The need for incorporating time-of-day modeling into conventional travel demand models has been mentioned in the introduction of this thesis. This need for enhancing travel demand models to have the ability of analyzing travel conditions at different times of day is driven from the emerging requirements of recent transportation planning policies on the local and national level. These policies mainly focus on how to deal with the issues of congestion and air quality within the context of traffic management and transportation planning. It is widely recognized that the magnitude of congestion and vehicle emissions (and poor air quality) are very much related to the extent of peak period auto travel. Developing travel demand models that predict travel at different times of day by different modes of travel, including peak/ off-peak periods and SOV/ Non-SOV modes, may be a way to address the requirements of contemporary transportation policies. Some of the rising requirements of such policies are outlined below [2]:

- Vehicle Emissions and Air Quality Analysis. Strict air quality standards have been established by the Federal Clean Air Act Amendments (CAAA) and State Clean Air Acts. Travel demand models provide necessary variables required for the analysis of vehicle emissions (including traffic volumes, vehicle speeds, traffic compositions, vehicle-miles and hours of travel by facility type, by vehicle type, by hour of the day, and by vehicle starting mode). However, because emission levels change with different vehicle speeds, variables that describe vehicle volumes and speeds by time-of-day are also required.

- Congestion Management Programs. Travel demand models are required to be capable of precisely predicting travel speed, congestion, delay, and time-of-day to cope with the rigorous analytical standards of the Intermodal Surface Transportation Efficiency Act (ISTEA), and State Congestion Management Programs. In order to justify the replacement of capacity addition and improvement with traffic management strategies on existing transportation facilities, travel demand models must capture the effect of these strategies on time-of-day travel.
- Identification of Highway System Problems. Many urban areas are suffering from roadway problems such as route diversions caused by peak period congestion. In order to accurately estimate peak travel demands, travel demand models need to account for route diversions because the severity of the peaking and the congestion vary throughout the urban area and over time.
- Transit Analysis. Accurately capturing the amount of transit travel has long been a challenge for travel demand modeling in urban areas. Because mode choice models are commonly applied at the daily level, they do not account for variations in transit service availability throughout the day. As a result, these models are not able to forecast transit mode share in cases where

alternatives may considerably change transit ridership trends across peak and off-peak time periods.

- Analysis of Transportation Demand Management (TDM) Alternatives. TDM alternatives target such groups as peak period travelers (mainly home-to-work commuters) and are aimed at reducing peak traffic congestion, decreasing SOV travel dependency, and dealing with air quality and other environmental issues connected to auto travel. Parking charges, congestion pricing, transit subsidies, variable work hours, and telecommuting are some types of TDM policies that involve peak travel analysis capabilities.
- Time-of-Day Travel Choices. These alternatives are aimed at significantly changing the times and costs of traveling during peak periods. Models that deal with the above should be capable of capturing the effect of peak spreading, in which many travelers that are more temporary flexible than others try to avoid delays by shifting departure times away from peak hour.
- Analysis of Intelligent Transportation Systems (ITS). Many urban areas are considering ITS as a lower-cost alternative to capital improvements. ITS systems incorporate advanced traffic management systems, advanced traveler information systems, commercial vehicle operations, and advanced public transportation systems. In order to quantify the benefits of ITS, models should be enhanced to precisely measure changes in the operational context that includes traffic volumes, speed, delay, and queuing by time-of-day.

2.2 Time-of-day Modeling in Four-step Modeling Paradigm

There are various methods used for time-of-day modeling within the traditional four-step modeling framework. Commonly used methods throughout the United States are presented within the context of the Travel Model Improvement Plan (TMIP) of the U.S. Department of Transportation [2]. TMIP also documents the most innovative methods, and emerging methods to estimate time-of-day travel demands. This section summarizes time-of-day modeling procedures as presented in the TMIP program.

2.2.1 Standard Approaches

A first step in time-of-day modeling is to define the peak period or peak hour. This could be done for a weekday trip dataset from local or national surveys. During the average weekday, there are typically two dominant peak periods: morning (AM) peak and afternoon (PM) peak. A peak period is identified by its maximum trip rate in trips per unit time. On the other hand, peak hour is the hour of the day with the highest traffic. "Shoulders of the peak" is a term used to describe the segments of the peak before and after the peak hour.

In traditional four-step modeling, peaking and time of travel are incorporated in a greatly approximate fashion by producing time-of-day factors (TDOF) derived from observed data. The basic assumption, however, is that travel patterns will remain constant over the years. A TDOF is defined as "the ratio of vehicle trips made in a peak period (or peak hour) to vehicle trips in some given base period, usually a day" [2]. TDOF's, usually fixed and independent of congestion levels, are either determined separately for each trip purpose form household activity/travel or on-board transit and intercept auto surveys, or from traffic data from special surveys (travel surveys at workplaces or major businesses/ activity centers) depending on the point at which they are applied in the modeling process. Time-of-day factors may be assigned at four points in the four-step model:

- After trip assignment;
- Between mode choice and trip assignment;
- Between trip distribution and mode choice; and
- Between trip generation and trip distribution.

Time-of-day assignment after trip assignment is the most commonly used and simplest method and is used in smaller urban areas where there is limited congestion. This method requires minimal labor and data. Data requirements include peak period link-level peak hour factors and directional split factors. This method however, does not take into account peak travel times in assignments and congested times are not considered for trip distribution and mode split. Further, it does not account for localized effects of changes in demand.

Time-of-day assignment between mode choice and trip assignment is another broadly used method and may be applicable in areas that suffer from least congestion. It requires factors of the trips by purpose and by mode for each hour and direction (production-to-attraction or attraction-to-production) as well as directional split factors. Disadvantages of this method include failure to account for congested times in trip distribution and mode split and the lack of sensitivity to general policy changes, rising congestion, and corridor or subarea-specific changes.

Time assignment between trip distribution and mode choice is a limited use method applicable in the least congested areas. Data required to produce time-of-day factors involves hourly totals of trips by purpose for each direction (production-to-attraction or attraction-to-production) and directional split factors. This method fails to account for effects of time-of-day characteristics such as congestion or transit levels of service in the formation of time-period based trip tables. Another limitation of this method is that congested times are not accounted for in trip distribution and mode split.

Time-of-day assignment between trip generation and trip distribution is another limited use method and may be applied in urban areas with minimal congestion. Directional hourly time-of-day factors of trips by purpose and mode, and directional split factors are required for this method. A major advantage of this approach is its time efficiency in the model application. In addition, trip distribution and mode choice may be done according to differences in travel characteristics by time-of-day. On the other hand, this procedure can not capture the effects of changes in policies, increasing levels of congestion, or congestion management measures.

2.2.2 Innovative Approaches

Standard approaches of time-of-day modeling, described in the previous section, offer only approximate estimates of time-of-day effects on travel. Various agencies around the U.S. are using innovative methods, within the four-step modeling context, that offer a more realistic approach to time-of-day modeling. These methods incorporate peak spreading, a process that deals with the issue that in certain corridors projected demand exceeds capacity during the peak period and that ignoring the effects of excess demand yields to an inaccurate estimate of future travel conditions. TMIP presents three innovative approaches to improving the time-of-day modeling process:

- Link-based peak spreading
- Trip-based peak spreading
- System-wide peak spreading

Link-based peak spreading is a limited-use method developed in Phoenix, AZ that accounts for congestion at the link level and shifts trips to the shoulders of the peak period. The method includes peaking factor functions by facility type reflecting the peak hour to peak period volume ratio. These functions are derived by means of a decreasing function of the link three-hour volume-to-capacity ratio. This method, although providing more accurate estimates of regional travel performance measures, does not guarantee continuity of link flow in the peak hour prediction and does not account for further spreading of the peak beyond a three-hour period.

Used in Tri-Valley, CA, Boston, MA, and Washington, DC, the trip-based peak spreading method distributes the number of peak period or peak hour trips for an origin-destination interchange. The method requires interchange-specific peak hour factors, that may also be trip purpose-specific, that are applied to daily trip tables. A disadvantage of this method lies in the fact that it is not efficient in treating the reduced off-peak trips. Further, it fails to account for changes in traveler behavior associated with congestion.

System-wide peak spreading takes into account the system-wide (rather link-specific or trip-specific) travel demand and delay surplus, and spreads excess travel demand between the separate travel hours of the peak period. It is a limited-use method implemented by the Volpe National Transportation System Center (VNTSC) for evaluating Intelligent Transportation Systems. The underlying assumption is that a considerable amount of travel information is available to travelers through ITS and their reaction to congestion can then be modeled on a system-wide basis. Disadvantages this method lies in the fact that it is not sensitive to different trip purposes or link-specific or origin-destination-specific congestion.

2.2.3 Emerging Approaches

The effects of policy changes and TDM procedures may not be fully captured by the peak spreading time-of-day procedures described in the previous section. The framework of emerging approaches is based on modeling traveler response to congestion in a very similar way that mode choice is modeled within the traditional four-step modeling paradigm.

A number of urban areas around the country (including San Francisco, Portland, Sacramento, Jacksonville, and Tampa Bay) are considering such methods and have proposed various approaches including the following:

- A time of day choice logit model applicable after mode choice and capable of predicting the period of travel as a function of variables that capture free flow and congested travel times, transit level of service, trip purpose, and area type variables.
- A model predicting whether peak period trips occur in the peak or off-peak hour. This could be in a form of a logit model as part of a “variable demand” multiple vehicle class assignment which guarantees that the outcome of the

peak hour models are in agreement with the congestion resulting from the assignment.

- A model based on the underlying assumption that relatively higher congestion levels during peak time tends to increase the propensity of choosing off-peak departure time. Such model would combine traditional time-of-day factors and a binary time-of-day choice model. The choice model would be estimated by congestion variables such peak/off-peak travel times, delays, etc.

2.3 Previous Studies on Departure Time Choice

Early studies involving departure time choice have 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 travel has provided researchers 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. Noland and Small [5] used models of commuting time-of-day choice to analyze the effect of uncertain travel times, relating this uncertainty in time-of-day choice to the cost of early or late arrival at work. It should be pointed out, however, that most researchers, e.g., Kumar and Levinson [6], do not omit to recognize the interaction of work-trips and non-work trips and the role of non-work trips in travel demand analysis. They state that, on weekdays, workers are more likely to pursue shopping and other non-work trips on the way home from work, while non-workers are more prone to execute such trips during off-peak periods. This study recognizes the rising importance of non-work trips as a major contributor to urban traffic congestion and automobile emissions and attempts to model the relationship between departure time choice and mode choice for such trips. As Lockwood and Demetsky [7] note, non-work travel accounts for more than three-quarters of the total trips in urban areas and are growing faster than work trips as suburbanization and changes in lifestyles alter travel behavior.

The interest in modeling non-work trips also lies in their inherent nature of being more flexible than work trips in terms of the individuals' time-of-day choice and mode choice. For certain types of non-work activities, such as shopping, the departure time flexibility is evident and therefore travelers may have a greater tendency to shift departure times than 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, non-work 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; on the other hand, departure time shifts may still be feasible, particularly in today's context of real-time activity scheduling using cellular communications technology.

CHAPTER 3

MODELING METHODOLOGY

3.1 The Recursive Simultaneous Bivariate Probit Model

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 of such a unidirectional causal relationship) exists in the population being studied.

3.2 Model Structure and Formulation

Two different possible causal structures are considered in this study:

- Mode choice → Departure time choice (recursive bivariate probit model)
- Departure time choice → Mode choice (recursive bivariate probit model)

Through a performance comparison of models between the two causal structures, it is envisaged that the relationship between departure time choice and mode choice may be discussed and clarified.

If the departure time choice (peak vs off-peak) and SOV/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:

$$\begin{cases} M_q^* = \gamma' z_q + \alpha T_q + \varepsilon_q \\ T_q^* = \beta' x_q + \eta M_q + \omega_q \end{cases} \tag{3.1}$$

where,

- q is an index for observations of trips (q = 1, 2, … , Q)
- M_q^* is a latent variable representing the mode choice for trip q
- T_q^* is a latent variable representing the departure time choice for trip q
- M_q = 1 if M_q^* > 0, = 0 otherwise, i.e., M_q is a dummy variable indicating whether trip q uses the SOV mode
- T_q = 1, if T_q^* > 0, = 0 otherwise, i.e., T_q is a dummy variable indicating whether trip q is made in the peak period
- z_q is a vector of explanatory variables for M_q^*
- x_q is a vector of explanatory variables for T_q^*
- γ, β are two vectors of model coefficients associated with the explanatory variables z_q and x_q, respectively

- α is a scalar coefficient for T_q to measure the impact of departure time choice on mode choice
- η is a scalar coefficient for M_q to measure the impact of mode choice on departure time choice
- ε_q and ω_q are random error terms, which are standard bivariate normally distributed with zero means, unit variances, and correlation ρ, i.e., ε_q, $\omega_q \sim \phi_2(0,0,1,1,\rho)$.

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

$$prob(M=0,T=0)=\Phi_2[-\gamma' z,-\beta' x,\rho] \tag{3.2}$$

$$prob(M=1,T=0)=\Phi_1[-(\beta' x+\eta)]-\Phi_2[-\gamma' z,-(\beta' x+\eta),\rho] \tag{3.3}$$

$$prob(M=0,T=1)=\Phi_1[-(\gamma' z+\alpha)]-\Phi_2[-(\gamma' z+\alpha),-\beta' x,\rho] \tag{3.4}$$

$$\begin{aligned} prob(M=1,T=1)=1-\Phi_1[-(\gamma' z+\alpha)]-\Phi_1[-(\beta' x+\eta)] \\ +\Phi_2[-(\gamma' z+\alpha),-(\beta' x+\eta),\rho] \end{aligned} \tag{3.5}$$

where,

- $\Phi_1[\cdot]$ is the cumulative distribution function for standard univariate normal distribution
- $\Phi_2[\cdot]$ is the cumulative distribution function for standard bivariate normal distribution.

The sum of the probabilities for the four combinations of two binary choices should be equal to one, i.e.,

$$prob(M=0,T=0)+prob(M=1,T=0)+prob(M=0,T=1)+prob(M=1,T=1)=1 \quad (3.6)$$

Substituting equations (3.2) through (3.5) into equation (3.6), it can be shown that

$$\Phi_2[-\gamma' z,-\beta' x,\rho]+\Phi_2[-(\gamma' z+\alpha),-(\beta' x+\eta),\rho]$$
$$=\Phi_2[-\gamma' z,-(\beta' x+\eta),\rho]+\Phi_2[-(\gamma' z+\alpha),-\beta' x,\rho] \quad (3.7)$$

This equation 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:

- $\alpha = 0$, $\eta \neq 0$ (Mode Choice $\rightarrow$ Departure Time Choice)

$$\begin{cases} M_q^* = \gamma' z_q + \varepsilon_q \\ T_q^* = \beta' x_q + \eta M_q + \omega_q \end{cases} \quad (3.8)$$

In this structure, mode choice is predetermined as per 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.

- $\alpha \neq 0$, $\eta = 0$ (Departure Time Choice $\rightarrow$ Mode Choice)

$$\begin{cases} M_q^* = \gamma' z_q + \alpha T_q + \varepsilon_q \\ T_q^* = \beta' x_q + \omega_q \end{cases} \quad (3.9)$$

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

3.3 Formulation of Likelihood Functions

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 (3.2) through (3.5) can be rewritten in a format including only the cumulative distribution function of the standard bivariate normal distribution.

$$prob(M=0,T=0)=\Phi_2[-\gamma' z,-\beta' x,-\rho] \tag{3.10}$$

$$prob(M=1,T=0)=\Phi_2[\gamma' z,-(\beta' x+\eta),-\rho] \tag{3.11}$$

$$prob(M=0,T=1)=\Phi_2[-(\gamma' z+\alpha),\beta' x,-\rho] \tag{3.12}$$

$$prob(M=1,T=1)=\Phi_2[\gamma' z+\alpha,\beta' x+\eta,\rho] \tag{3.13}$$

Equations (3.10) through (3.13) and the corresponding likelihood functions can be summarized by the following general formulations for the two different unidirectional causal structures [12]:

- $\alpha = 0$, $\eta \neq 0$ (Mode Choice $\rightarrow$ Departure Time Choice)

$$prob_q = \Phi_2[\mu_q \gamma' z_q, \tau_q(\beta' x_q + \eta M_q), \mu_q \tau_q \rho] \tag{3.14}$$

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

(3.15)

- $\alpha \neq 0$, $\eta = 0$ (Departure Time Choice $\rightarrow$ Mode Choice)

$$prob_q = \Phi_2[\mu_q(\gamma' z_q + \alpha T), \tau_q \beta' x_q, \mu_q \tau_q \rho] \tag{3.16}$$

$$L = \prod_{q=1}^{Q} \left\{ \Phi_2 \left[\mu_q(\gamma' z_q + \alpha T), \tau_q \beta' x_q, \mu_q \tau_q \rho \right] \right\} \tag{3.17}$$

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

As 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].

CHAPTER 4

DATA SET AND SAMPLE DESCRIPTION

4.1 The Southeast Florida Regional Household Travel Survey

The dataset used in this study is drawn from the Southeast Florida Regional Household Travel Survey which was conducted during 1999 in the Southeast Florida region consisting of Miami-Dade, Broward, and Palm Beach counties. The travel survey consisted of three parts: A CATI (computer aided telephone interview) recruitment, a mail-out of survey instruments and travel diaries, and a CATI retrieval of the survey responses. Households agreeing to participate in the survey were mailed a survey package including a travel diary for each member of the household. As with most household travel surveys, this survey collected detailed socio-demographic and trip information for each person in the household. The 24-hour travel diary was organized around tours to minimize potential under-reporting of short trips. A tour was defined as a series of trips that began at home, visited other locations, and ended at home. More details about the survey and sampling methodology and an extensive description and graphical presentation of the survey instruments are provided by The Corradino Group [14].

The sampling procedure employed was based on a geographically stratified random sampling methodology in order to ensure that the survey sample had adequate geographic coverage for the entire Southeast Florida region. Surveys were collected from households in Broward, Miami, and Palm Beach counties. Each of these counties was further subdivided into survey districts and a stratified random sample was drawn to obtain appropriate geographic coverage. A total of 5,168 households completed the survey, and out of these households, 5,067 had valid addresses within the tri-county region. Approximately 34 percent of the surveys were collected in Broward County, and 33 percent each in Miami-Dade and Palm Beach counties. The surveys provided a respondent sample of 11,426 persons reporting a total of 33,082 trips. The socio-economic, demographic, and travel characteristics of the respondent sample were generally consistent with those of the population in the region.

4.2 Household Characteristics of the Survey Sample

A summary description of household characteristics of the survey data is shown in Table 4.1. The average household size is about 2.6 persons per household with nearly 30 percent of the households reporting household sizes of 4 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 four percent reporting no vehicles. More than 60 percent have two or more vehicles in the household. Likewise, about 60 percent 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 the average household size and vehicle ownership figures. About 60 percent 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.

Table 4.1. Household Characteristics of Southeast Florida Household Travel Survey

Characteristic	Statistic
Sample Size	5067
Household Size	2.66
1 person	17.7%
2 persons	34.2%
3 persons	18.3%
≥ 4 persons	29.8%
Annual Income	
$15 K or less	12.2%
$15 K - $30 K	19.9%
$30 K - $50 K	27.8%
Greater than $50 K	40.1%
Vehicle Ownership	1.80
0 auto	3.9%
1 auto	33.3%
2 autos	45.5%
≥ 3 autos	17.3%
Dwelling Unit Type	
Single-family dwelling unit	59.4%
Apartment	27.1%
Mobile Home	1.8%
Condo	11.1%
Other	0.5%
Average No. of Licensed Drivers	1.95
0 licensed drivers	1.6%
1 licensed driver	27.0%
2 licensed drivers	53.8%
3 licensed drivers	12.8%
4+ licensed drivers	4.8%
Average No. of Children (under 18)	0.75
0 children	58.3%
1 child	18.0%
2 children	15.9%
3+ children	7.8%
Average No. of Workers	1.6
0 workers	18.7%
1 worker	30.2%
2 workers	38.2%
3+ workers	12.9%

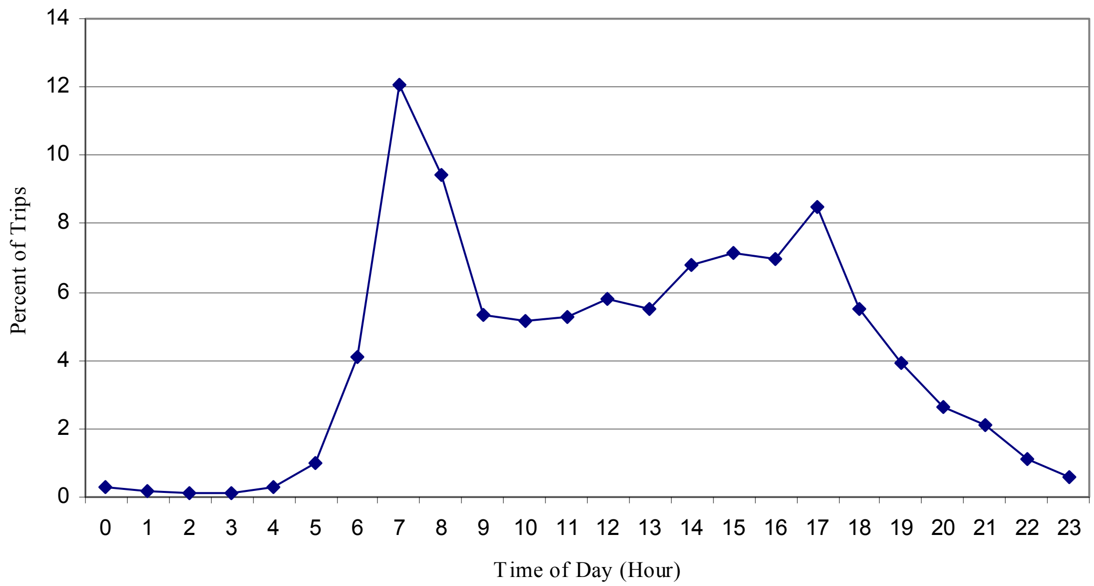
4.3 Departure Time, Mode Choice, and Travel Patterns of the Sample

A set of figures and tables, describing the nature of trips, time-of-day and mode choice population characteristics of the Southeast Florida Region are presented in this chapter. These figures are useful in understanding the travel patterns of the particular region of interest. Further, they are important in understanding and comparing travel patterns between different population groups within the dataset and have helped in drawing useful conclusions for the further time-of-day/ mode choice analysis of this study.

4.3.1 All Trips

Figures 4.1 through 4.4 and Table 4.2 show characteristics for all trips drawn from the original trip file (33,082 trips). A distribution of trips by purpose (Figure 4.2) shows that the majority of trips are work related (home-based work) and home-based other, each having a share of about 23%. SOV combined with car-pool constitute of the highest mode share (81%) with an almost negligible percentage of public transit trips (1%) (Table 4.2). A time-of-day distribution (Figure 4.1) shows two peaks, as expected, representing morning (7:00 am – 9:00 am) and afternoon (4:00 pm – 6:00 pm) peak periods. The afternoon peak period seems to be not as distinct as the morning peak extending two hours to the left shoulder of the peak (2:00 pm – 4:00 pm). This is indicative of the peak-spreading phenomenon explained in Chapter 2 and later in Chapter 5 of this thesis. In Figure 4.3 the peak periods are clearer for SOV and car-pool modes as opposed to non-motorized and “other” travel modes in which afternoon trips peak in the early afternoon rather than during the typical 4:00 pm – 6:00 pm period. The distribution of public transit trips indicate service staring at 5:00 am and ending at 11:00 pm with a better service during morning commute. Generally, non-SOV trips demonstrate a longer afternoon peak period (2:00 pm – 6:00 pm) than SOV trips (Figure 4.4).

Figure 4.1. Time-of-Day Distribution of All Trips (N = 28889)



Note: missing values are excluded

Table 4.2. Mode Share of All Trips (N = 33082)

Mode	Share
SOV	46.2
Pool	35.1
Public Transit	1.1
Non-Motorized	3.4
Other	1.5
Missing	12.7
Total	100.0

Note: modes are categorized: SOV (car, motor-cycle), Pool (car/van pool, multi-passenger auto), Public Transit (bus, train, jitney), Non-motorized (walk, bike, run, roller-blade), Other (taxi, school-bus, airplane), and Missing (don't know, refused and missing)

Figure 4.2. Distribution of All Trips by Purpose (N = 33082)

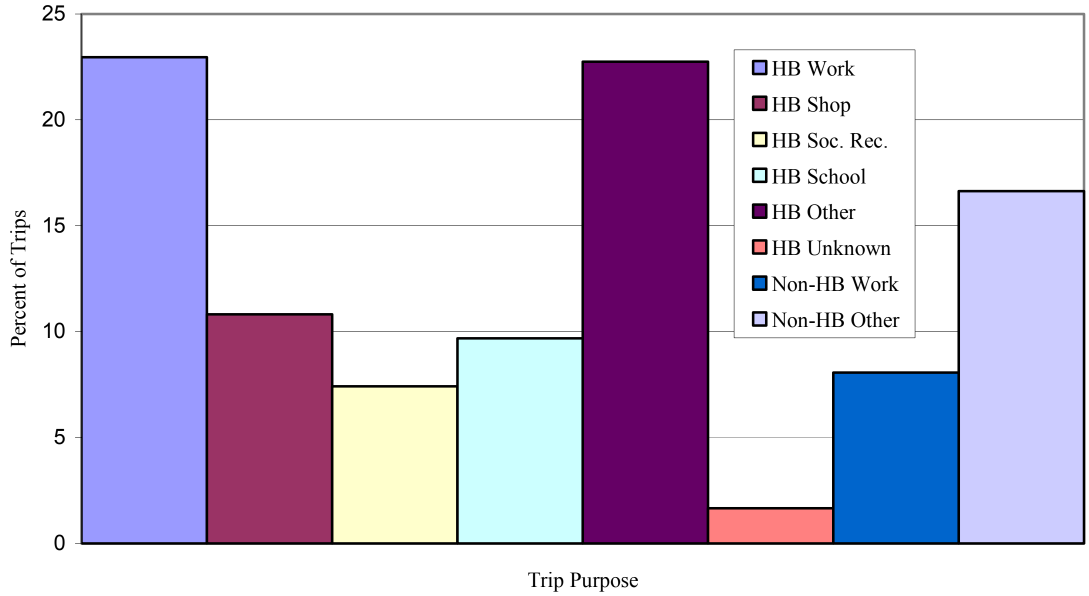
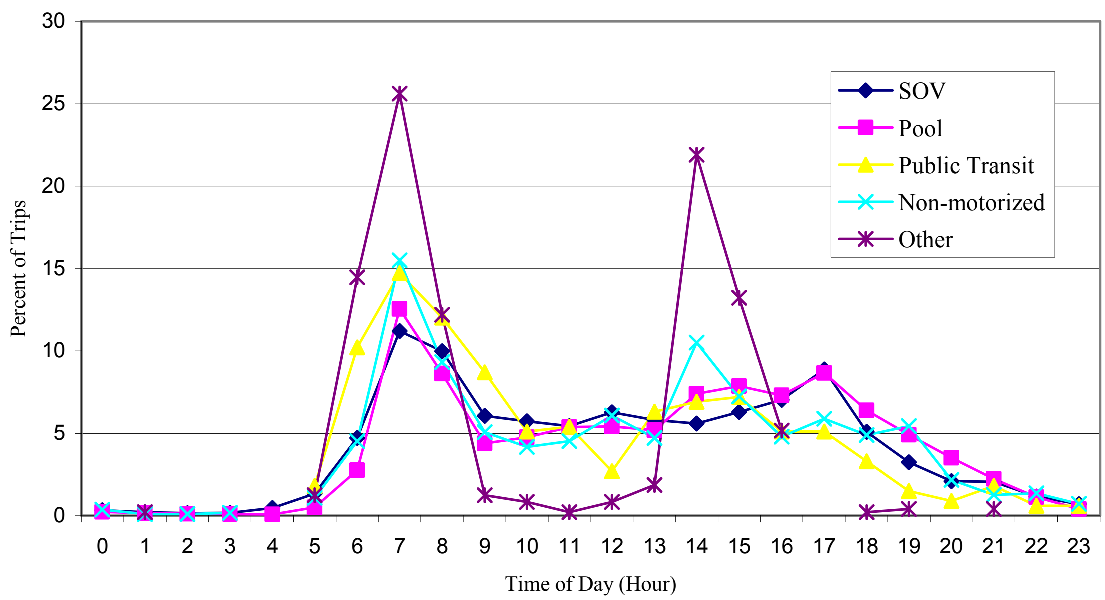
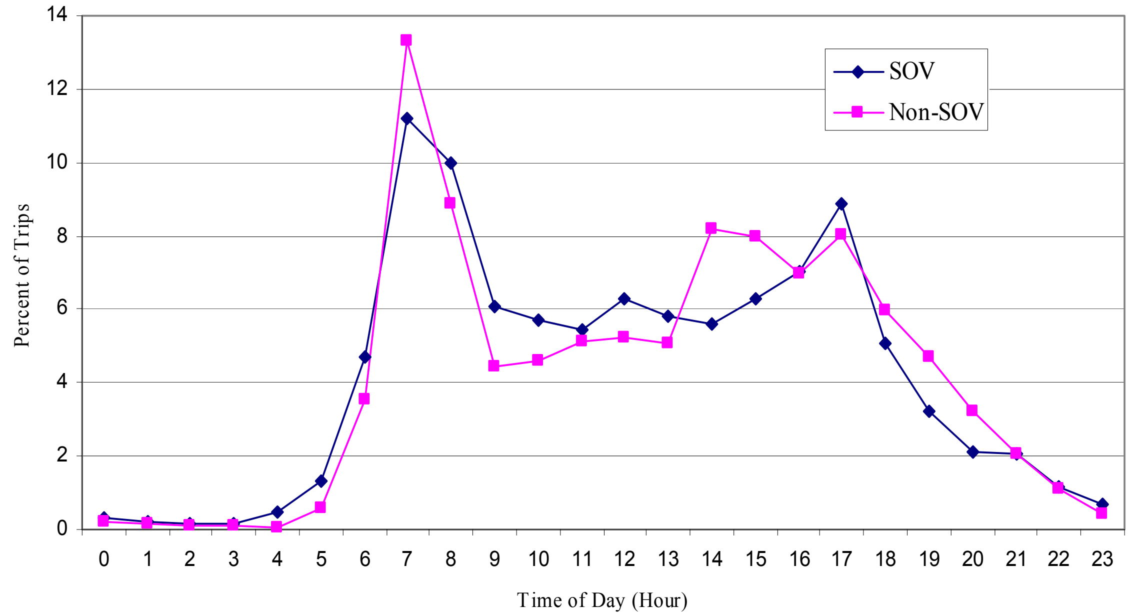


Figure 4.3. Time-of-Day Distribution of All Trips by Mode (N = 24677)



Note: missing values are excluded

Figure 4.4. Time-of-Day Distribution of All Trips by Mode: SOV vs Non-SOV (N = 24677)



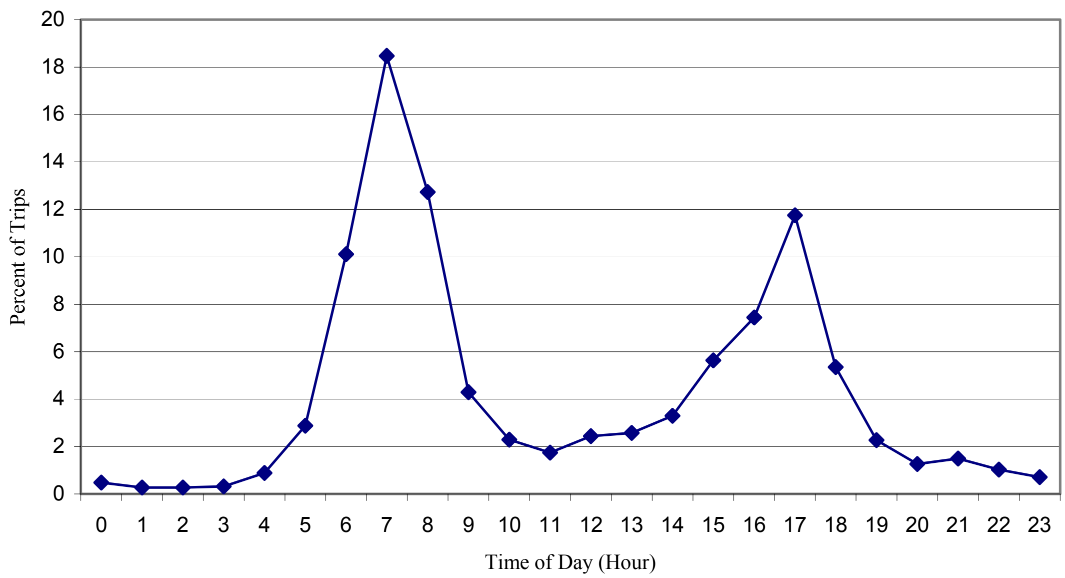
Note: missing values are excluded

4.3.2 Work Trips

Figure 4.5 shows a time-of-day distribution of all work trips made by adults of 18 years of age or older. By looking at the chart someone can clearly distinguish both morning and afternoon peak periods associated with commute travel. The 7th and 17th hours combined constitute of more than 30% of trips indicating highest commute activity during those hours. The mode share of work trips (Table 4.3) also appears to be in agreement with expectations. The vast majority of work trips (more than 75%) are made by drive-alone mode while car-pooling falls far behind with only around 11%. It is not a surprise that public transit and non-motorized travel are almost negligible and in accord with national numbers. Considering the fact that Southeast Florida is a very autodependant region and public transit service is limited (despite the existence of the relatively new Miami metro) the above numbers make sense.

As indicated in the above discussion and corresponding figures, work-related travel behavior seems to be rather predictable in nature. Work travel is auto-oriented revolving around the typical peak periods. This is one reason for choosing to analyze non-work travel behavior for the purposes of this study, as mentioned in the introduction. Since this thesis is not aimed in analyzing work trip patterns, the discussion on work trips is limited.

Figure 4.5. Time-of-Day Distribution of Work Trips (N = 6638)



Note: missing values are excluded

Table 4.3. Mode Share of Work Trips
(N = 9788)

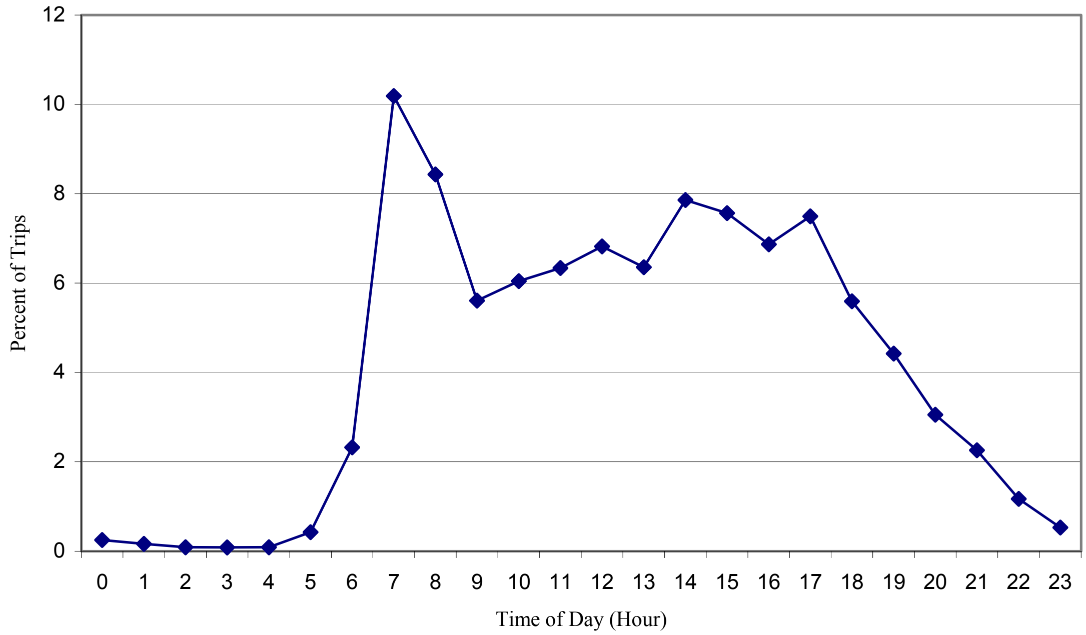
Mode	Share (%)
SOV	75.4
Pool	12.3
Public Transit	1.3
Non-Motorized	1.8
Other	0.02
Missing	9.2
Total	100.0

Note: modes are categorized: SOV (car, motor-cycle), Pool (car/van pool, multi-passenger auto), Public Transit (bus, train, jitney), Non-motorized (walk, bike, run, roller-blade), Other (taxi, school-bus, airplane), and Missing (don't know, refused and missing)

4.3.3 Non-work Trips

Figures 4.6 through 4.8 and Table 4.4 present general characteristics of all non-work trips made by adults of 18 years of age or older. Unlike work trips, the distribution of non-work trips by time-of-day (Figure 4.6) is described by one major peak point (morning peak period) and a substantial concentration of trips along the early to late afternoon hours. The majority of non-work trips are made by SOV mode (Table 4.6). However, there is a substantial percentage of ride-sharing trips (46%) which may be explained by the general tendency of non-work trips to be undertaken jointly in accommodating obligations of households of different auto-availability. A time-of-day distribution by SOV vs. Non-SOV modes (Figure 4.8) shows a strong morning peak for car-pooling trips. This peak may be associated with the presence of drop-off school trips and other non-work trips linked with the morning commute. On the other hand, drive-alone non-work travel seems to be more temporally flexible with most trips occurring uniformly during the course of the day.

Figure 4.6. Time-of-Day Distribution of Non-Work Trips (N = 22251)



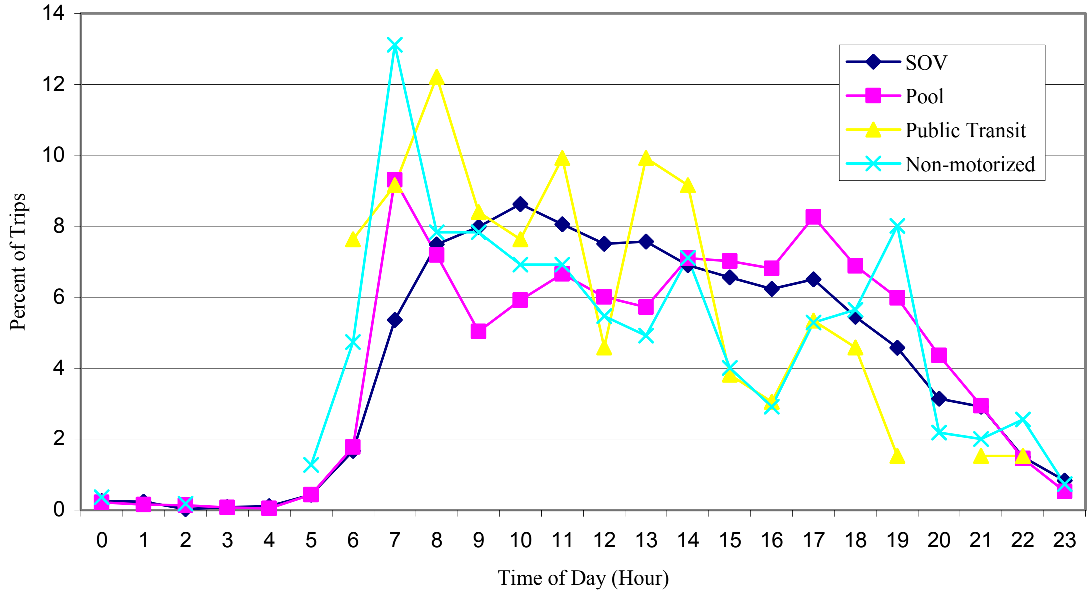
Note: missing values are excluded

Table 4.4. Mode Share of Non-Work Trips (N = 14727)

Mode	Share (%)
SOV	49.9
Pool	45.0
Public Transit	0.9
Non-Motorized	3.9
Other	0.3
Total	100.0

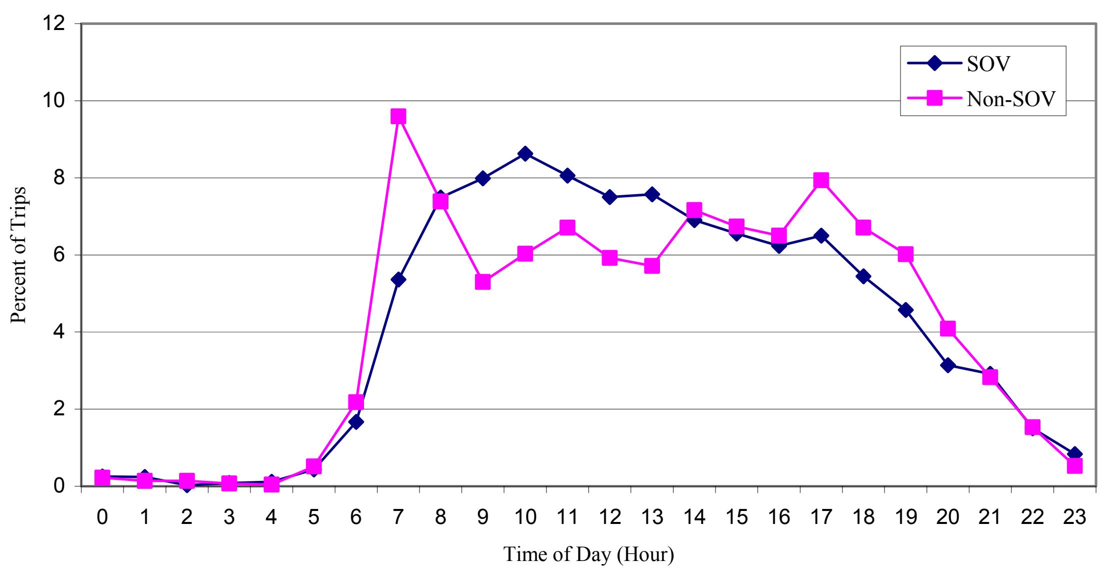
Note: modes are categorized: SOV (car, motor-cycle), Pool (car/van pool, multi-passenger auto), Public Transit (bus, train, jitney), Non-motorized (walk, bike, run, roller-blade), Other (taxi, school-bus, airplane), and Missing (don't know, refused and missing)

Figure 4.7. Time-of-Day Distribution of Non-Work Trips by Mode (N = 22251)



Note: missing values are excluded

Figure 4.8. Time-of-Day Distribution of Non-Work Trips by Mode: SOV vs Non-SOV (N = 14727)



Note: missing values are excluded

4.4 Preparation of Datasets for Modeling

In preparing the available survey data for modeling, all origin and destination locations in the original trip file were geocoded to latitude/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 secondary data. Modal level of service (LOS) data was extracted from the Southeast Regional Planning Model. This data provided information on travel times, distances, and costs between each pair of TAZ's in the Southeast Florida Region for both peak and off-peak periods. The LOS data was merged into the trip file producing a new dataset with added modal LOS characteristics by time-of-day for each origin-destination TAZ pair. The merging process as well as the descriptive analysis of the data was performed with the aid of SPSS Version 11.5 statistical software [18].

This study focuses on the relationship between time-of-day choice and mode choice for non-work trips made by adults. For this reason, all non-work trips made by persons 18 years of age or older were extracted from the original dataset. In addition, this study distinguishes between workers (employed) and non-workers (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 non-work trips to the commute while non-workers might make use of their travel flexibility to avoid congestion during peak hours. From the original trip data set, all non-work trips that had complete information including household and person socio-economic data, trip attribute data, and modal LOS data were extracted. This subsample of trips included a total of

14,410 non-work trips of which 7,947 were made by 2,710 workers and 6,463 were made by 1,741 non-workers.

Non-work trips include the following trip categories:

- Home-based Shopping/Personal Business
- Home-based Social Recreation
- Home-based School
- Home-based Other
- Non-home-based Non-work

4.5 Workers and Non-workers Sample Characteristics

Table 4.5 offers a description of person characteristics for the subsamples of workers and non-workers used in this study. In general, the non-worker sample includes a large proportion of elderly and retired people, thus pushing the average age up to 57 years. The corresponding average age for workers is 41 years. About 80 percent of the worker sample is employed full time while the remainder is employed part time. A vast majority of the persons in both samples are full time residents of the area. As expected, average daily trip rate for workers is slightly higher than non-workers presumably due to the presence of commute trips for workers. On average, workers make about five trips per day while non-workers make a little over four trips per day.

Time-of-day distributions of non-work trips are shown in Figure 4.9 for both worker and non-worker samples. The differences between the two graphs are rather striking. The time-of-day distribution for workers shows two peaks that are coincident with the commute peak periods. This distribution suggests that workers may be more inclined to link their non-work 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 there is a substantial portion of non-work travel occurring during off-peak hours as well. The time-of-day distribution pattern for non-workers is consistent with expectations and quite different from that of workers. The distribution shows that non-workers tend to make non-work 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. A time-of-day distribution by mode (Figure 4.10) shows that workers may utilize the better transit service during the morning and afternoon peak periods to accommodate non-work activities within their commute. Further, the majority of non-motorized trips by workers tend to be associated with the morning commute while a significant amount of such trips is concentrated in the early evening hours. In general, workers traveling alone tend to take on their non-work trips throughout the course of day looking to avoid the peak hour, while those who use alternative modes (mostly ride-sharing) are more temporally constraint around the commute peak periods (Figure 4.11). On the other hand, non-workers, being more temporally flexible than workers due to the absence of work schedule, are more likely to try to avoid the peak hour weather they are driving alone, ride-sharing, or walking/ bicycling (figures 4.12 and 4.13). There seems to be an exception for transit use however, where more frequent service during the morning hours may be a stronger factor than peak traffic for special groups of non-workers who are dependent on transit (Figure 4.12).

Table 4.5. Person Characteristics of Southeast Florida Household Travel Survey

Characteristic	Statistics	
	Workers	Non-workers
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+	4.2%	45.4%
Employment Status		
Full time	81.3%	-
Part time	18.6%	-
Resident 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.
Non-workers are defined as those who indicated that they are unemployed.

Figure 4.9. Time-of-day Distribution of Non-Work Trips: Workers vs Non-Workers

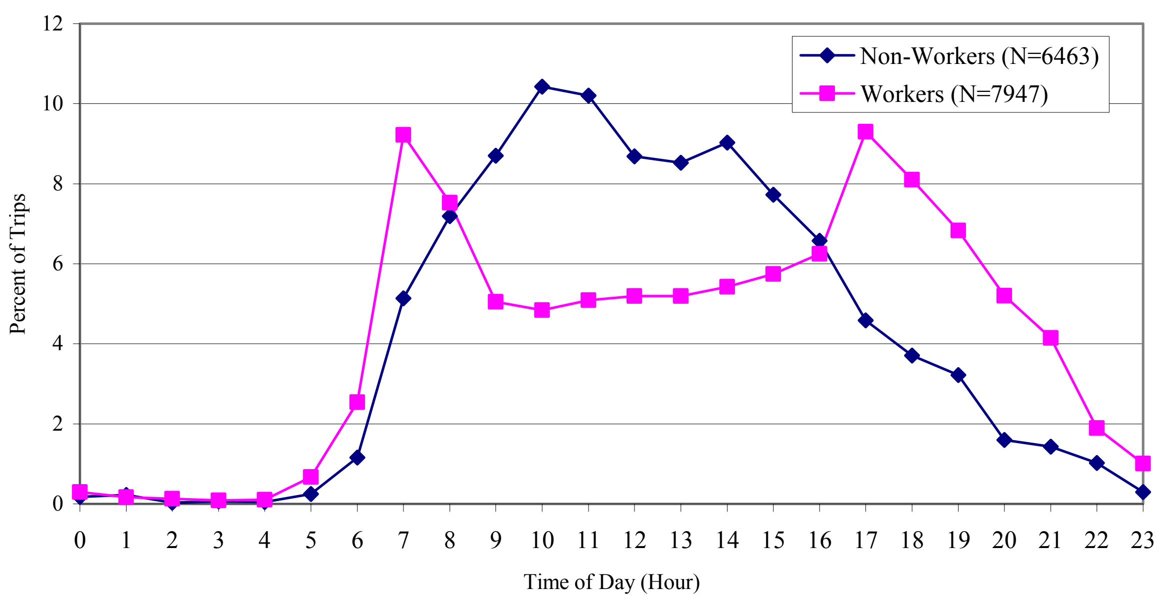


Figure 4.10. Time-of-Day Distribution of Workers Non-Work Trips by Mode (N = 7947)

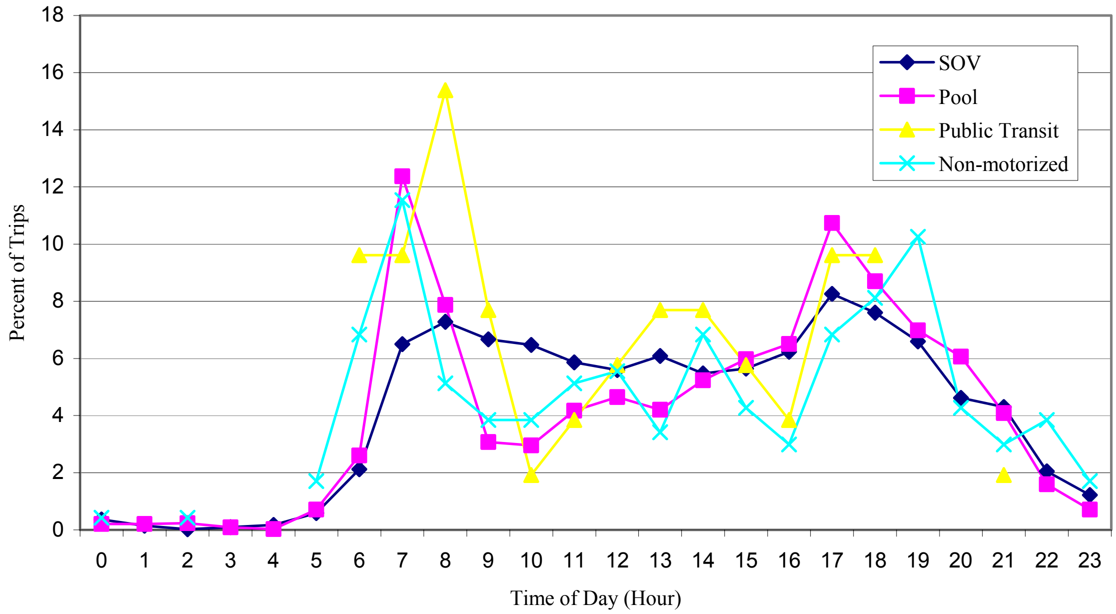


Figure 4.11. Time-of-Day Distribution of Workers Non-Work Trips by Mode: SOV vs Non-SOV (N = 7947)

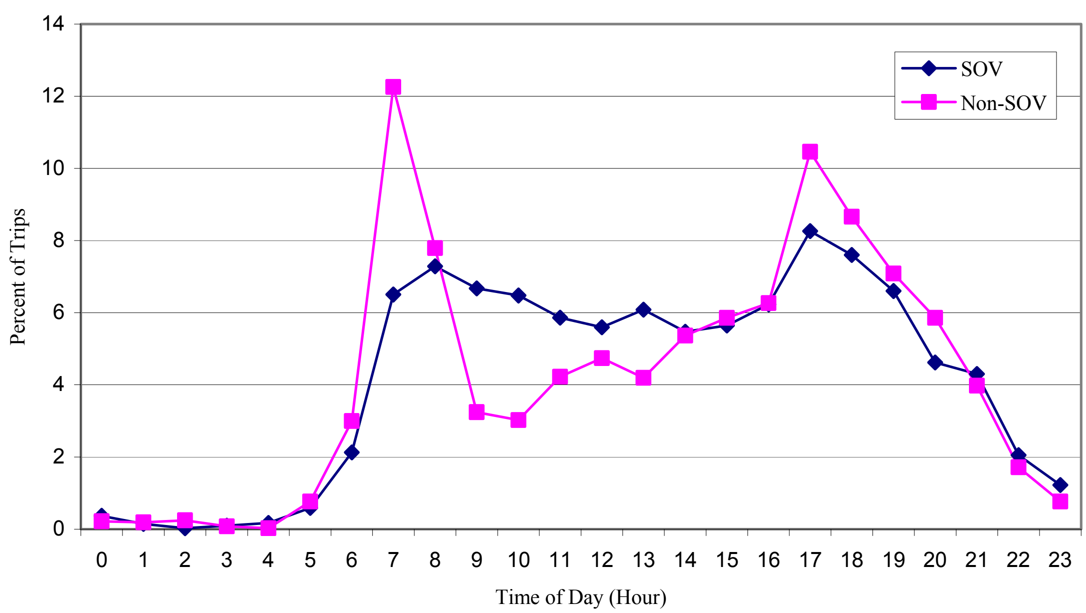


Figure 4.12. Time-of-Day Distribution of Non-Workers Non-Work Trips by Mode (N = 6463)

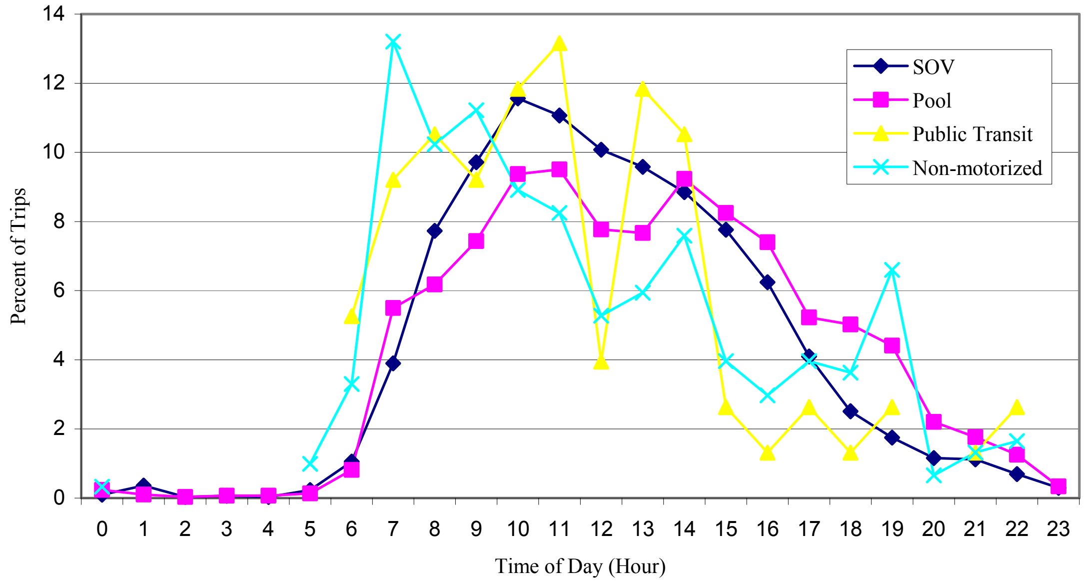
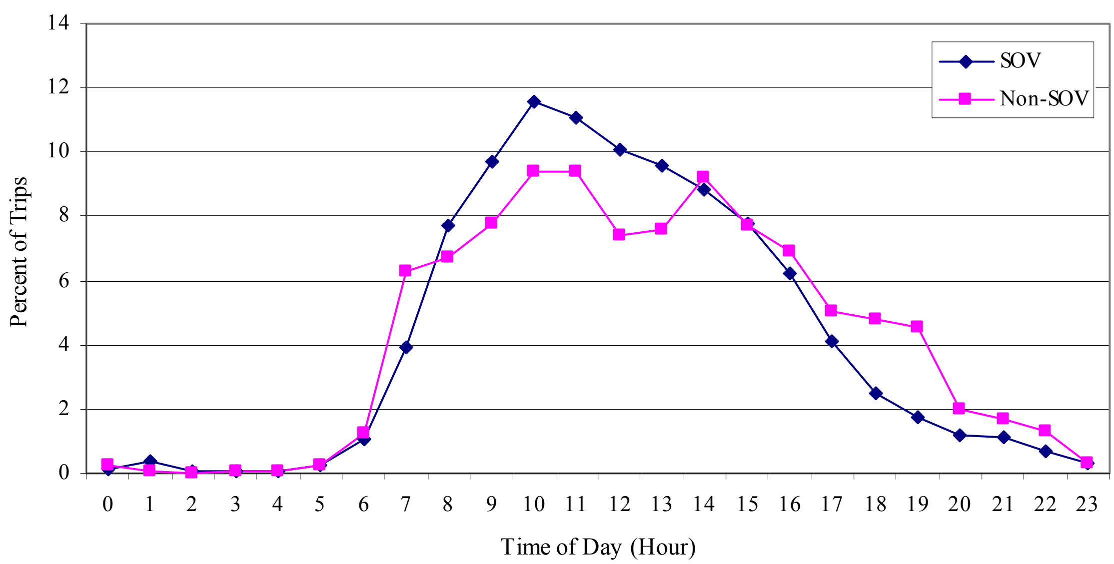


Figure 4.13. Time-of-Day Distribution of Non-Workers Non-Work Trips by Mode SOV vs Non-SOV (N = 6463)



Crosstabulations of time-of-day choice with mode choice are shown in Tables 4.6 and 4.7. Both choice variables are represented in a binary format to facilitate the development of the crosstabulation in a manner consistent with the treatment of the variables in the model specification. In Table 4.6, it is found that a majority of off-peak non-work trips (56 percent) by workers are made by SOV mode. On the other hand, a majority of peak non-work trips (54 percent) are made by non-SOV mode. An examination of the row percentages shows that while 72 percent of SOV trips are made in the off-peak period, the corresponding percentage for non-SOV trips is only 64 percent. These tendencies suggest that there is a negative relationship between SOV mode choice and travel in the peak period.

Similar trends are seen in Table 4.7 for non-workers, although the tendencies do not appear to be as strong. More than 75 percent of non-workers trips occur in the off-peak period. A slightly higher percentage of SOV trips occur in the off-peak period. Similarly, it is found that about 48 percent of off-peak trips are made by SOV while a slightly smaller percent of peak period trips (44 percent) are made by SOV. Thus, even for non-workers, it appears that there is a slight inverse relationship between SOV mode choice and peak period travel.

Table 4.6. Crosstabulation of Departure Time Choice by Mode Choice: Worker Sample (N = 7947)

Mode Choice	Departure Time Choice		Total
	Non-Peak	Peak	
Frequency			
Non-SOV	2399	1350	3749
SOV	3041	1157	4198
Total	5440	2507	7947
Column Percent			
Non-SOV	44.1	53.8	47.2
SOV	55.9	46.2	52.8
Total	100	100	100
Row Percent			
Non-SOV	64.0	36.0	100
SOV	72.4	27.6	100
Total	68.5	31.5	100

Table 4.7. Crosstabulation of Departure Time Choice by Mode Choice: Non-worker Sample (N = 6463)

Mode Choice	Departure Time Choice		Total
	Non-Peak	Peak	
Frequency			
Non-SOV	2563	831	3394
SOV	2404	665	3069
Total	4967	1496	6463
Column Percent			
Non-SOV	51.6	55.5	52.5
SOV	48.4	44.5	47.5
Total	100	100	100
Row Percent			
Non-SOV	75.5	24.5	100
SOV	78.3	21.7	100
Total	76.9	23.1	100

CHAPTER 5

RESULTS

5.1 Model Estimation Results

Model estimation results are presented in this section. Tables 5.1 and 5.2 offer descriptions of the variables used in the models. The variables constitute a series of dummy variables describing socio-economic characteristics on the household and person levels as well as modal LOS's. 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 non-worker samples.

Table 5.1. Description of Variables Used in Workers Non-work Trip Models (Sample Size = 7947)

Variable Name	Variable Description	Mean	Std Dev
AGE18_24	Person is between 18 and 24 years of age	0.09	0.29
CHILD2P	Number of children in the household is equal to or greater than 2	0.31	0.46
COMMUT15	One-way commute time for person is equal to or greater than 15 minutes	0.36	0.48
FT_JOB	Person has a full-time job	0.77	0.42
HHSIZE1	Single person household	0.10	0.30
HHSIZE3P	Household size is equal to or greater than 3	0.61	0.49
HWRUN30	Peak-period highway run time without HOV lane is equal to or greater than 30 minutes	0.13	0.34
INC_100K	Annual income of household is equal to or greater than $100,000	0.15	0.35
NOCHILD	Household has no children	0.48	0.50
PEAK	Departure time of trip is in peak period (7:00am-9:00am or 4:00pm-6:00pm)	0.32	0.53
PT_RES	Person is a part-time resident	0.02	0.14
SCHOOL	Primary purpose of trip is “school”	0.05	0.22
SOV	Trip mode is single-occupancy vehicle (SOV)	0.46	0.50
TERMTI2P	Peak-period highway terminal time is equal to or greater than 2 minutes	0.20	0.40
VEHICL2P	Number of autos owned by household is equal to or greater than 2	0.74	0.44
WALK5	Peak-period transit walk time is equal to or less than 5 minutes	0.34	0.48

Table 5.2. Description of Variables Used in Non-workers Non-work Trip Models (Sample Size = 6463)

Variable Name	Variable Description	Mean	Std Dev
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
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
HHSIZE1	Single person household	0.14	0.35
HHSIZE2	Household size is equal to two persons	0.47	0.50
INC_100K	Annual income of household is equal to or greater than $100,000	0.12	0.32
NOCHILD	Household has no children	0.70	0.46
NOVEHICL	Household has no autos	0.02	0.15
PALM_BCH	Person is a resident in Palm Beach	0.46	0.50
PEAK	Departure time of the trip is in peak period (7:00am-9:00am or 4:00pm-6:00pm)	0.23	0.42
SOV	Trip mode is single-occupancy vehicle (SOV)	0.47	0.50
T1WAIT30	Peak-hour transit first wait time is equal to or greater then 30 minutes	0.24	0.42
TERMTI2P	Peak-period highway terminal time is equal to or greater than 2 minutes	0.22	0.41
VEHICL2P	Number of autos owned by the household is equal to or greater than 2	0.56	0.50
WALK15	Peak-hour transit walk time is equal to or less than 15 minutes	0.59	0.49

5.1.1 Estimation Results for Workers Non-work Trips

Tables 5.3 and 5.4 offer estimation results of the bivariate probit model for both causal structures for the worker sample. In Table 5.3, 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 SOV as the mode for non-work trips. The coefficient is negative indicating that a departure time choice in the peak period tends to lower the propensity to drive alone for non-work trips. There are two important possible explanations for this. First, it is possible that peak period non-work trips primarily serve passenger trips where a worker is dropping off or picking up a child at school or daycare on the way to and from work. As 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 non-work 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, thus supporting the paradigm of simultaneity embodied in the bivariate probit model specification adopted in this study.

The constant term in the departure time choice model is negative indicating that the general propensity is to pursue non-work trips in the off-peak period. Younger workers and those without children tend to pursue their non-work 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 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 level of service 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 non-work trips in the off-peak period. This finding is suggestive of the presence of peak spreading where 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 towards the use of the SOV mode for non-work trips. As expected, larger households contribute to a lower propensity to use SOV for non-work trips presumably due to ride sharing and serving passenger trips associated with larger households. 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 SOV mode for non-work 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 six months of the year are found to show a negative propensity to drive alone. This 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 auto 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 SOV as the travel mode.

Table 5.4 shows model estimation results 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 Table 5.3.

All of the other variables provide indications in Table 5.4 that are very similar to those found in Table 5.3. The signs of the coefficients are virtually identical for the different explanatory variables in the two models. Model estimation results suggest that those with full time jobs tend to make their non-work trips in the peak period as evidenced by the positive coefficient. This is possibly due to the desire to efficiently link non-work activities with the commute trip that typically tends to take place in the peak period. Another noteworthy finding is that the constant term in the SOV mode choice model shows a negative value. This is indicative of a general tendency in the worker sample to avoid using the SOV mode for non-work trips. However, an examination of Table 4.6 shows that a majority of the non-work trips by workers are made by SOV (53 percent). While the constant term in the SOV mode choice model of Table 5.3 is positive and consistent with this higher percentage of SOV non-work trips, the negative constant term seen here in Table 5.4 is not easily explained. In addition, the random error correlation term is not as statistically significant as in Table 5.3. These findings provide 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 are more constrained with respect to their departure time choice due to scheduling constraints imposed by the work activity. Thus, workers determine their time-of-day choice for non-work activities (around the work activity/schedule) and then determine the mode choice based on a host of factors including the time-of-day choice.

Table 5.3. Workers Non-work Trip Model
(Departure Time Choice → Mode Choice)

Variable	Parameter	t-test
Peak Period Departure Choice Model		
Constant	-0.2997	-14.124
AGE18_24	-0.2171	-4.514
SCHOOL	0.59023	8.693
NOCHILD	-0.3226	-11.288
TERMTI2P	-0.2129	-6.459
HWRUN30	-0.0806	-2.163
SOV Mode Choice Model		
Constant	0.2960	7.0560
HHSIZE1	0.5640	10.3350
HHSIZE3P	-0.2263	-6.5660
CHILD2P	-0.1077	-3.5230
SCHOOL	0.6113	9.1220
PT_RES	-0.3617	-4.5200
FT_JOB	0.0470	1.7110
VEHICL2P	0.3769	10.9840
INC_100K	0.1198	3.6240
WALK5	-0.0786	-3.2420
PEAK	-1.4558	-22.1550
ρ (Error Correlation)	0.8275	16.2600
Sample Size	7947	
Number of parameters	18	
Log-likelihood		
At convergence	-9912.779	
At market share	-10417.222	
At zero	-11016.881	

Table 5.4. Workers Non-work Trip Model
(Mode Choice → Departure Time Choice)

Variable	Parameter	t-test
Peak Period Departure Choice Model		
Constant	-0.1907	-2.9210
AGE18_24	-0.2447	-4.3740
SCHOOL	0.6850	9.5990
FT_JOB	0.1309	3.5800
NOCHILD	-0.1958	-4.9510
TERMTI2P	-0.2339	-6.0030
HWRUN30	-0.1035	-2.3430
SOV	-0.4903	-3.9000
SOV Mode Choice Model		
Constant	-0.1668	-4.0040
HHSIZE1	0.7390	12.4890
HHSIZE3P	-0.3913	-10.2100
CHILD2P	-0.2273	-6.2310
COMMUT15	0.2044	6.7360
SCHOOL	0.4177	6.0930
PT_RES	-0.3588	-3.5030
VEHICL2P	0.5154	13.7610
INC_100K	0.1525	3.6790
WALK5	-0.0897	-2.9330
TERMTI2P	0.1043	2.8350
ρ (Error Correlation)	0.1975	2.4680
Sample Size	7947	
Number of parameters	20	
Log-likelihood		
At convergence	-9908.679	
At market share	-10417.222	
At zero	-11016.881	

5.1.2 Estimation Results for Non-workers Non-work Trips

Estimation results for non-workers non-work trips are shown in Tables 5.5 and 5.6. In Table 5.5, estimation results correspond to the model where departure time choice is predetermined and affects mode choice. 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 model 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 non-work trips made by non-workers. As these findings are quite counter-intuitive, the authors feel that this causal structure is not appropriate to describe the behavior of non-workers.

As far as the other explanatory variables are concerned, the model offers plausible and reasonable indications. The constant term in the departure time choice model is negative indicating a negative propensity to undertake non-work trips in the peak period. As non-workers are not constrained by the schedule of work activities, this is consistent with expectations. Those with no children tend to avoid the peak period; this may be due to the fact that people with children 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. While shopping trips tend to be outside the peak period (negative coefficient associated with HB_SHOP), recreational trips tend to be occurring 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, non-workers 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 minutes 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 non-work trips. Smaller household sizes and the absence of children positively influence SOV mode choice, presumably due to the lower possibility of sharing rides with other household members. As expected, vehicle ownership affects mode choice for non-work trips. Consistent with the findings in the departure time choice model, home-based shopping trips show a greater propensity to be drive-alone while home-based recreational trips show a greater propensity to be non-SOV trips. Once again, this may be due to the tendency to pursue recreational trips together with other household members leading to more shared ride trips. Three LOS variables appear to affect the mode choice of non-workers. A highway distance greater than 30 miles appears to discourage driving-alone when pursuing non-work trips. It is possible that longer trips are 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 positive impact on SOV mode choice.

In Table 5.6, estimation results correspond to the model where mode choice is predetermined and affects time-of-day choice. The most noteworthy finding in this table 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 of significance. In addition, the random error correlation is positive and statistically significant at the 0.05 level of significance. In general, the model indicates that non-workers are likely to avoid traveling in the peak period (negative constant in the departure time choice model) and using the SOV mode further contributes to avoiding the peak period. In general, it appears that non-workers 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 Table 5.5.

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 non-work trips while the opposite causal structure in which mode choice precedes departure time choice is more applicable to the non-worker sample.

Table 5.5. Non-workers Non-work Trip Model (Departure Time Choice → Mode Choice)

Variable	Parameter	t-test
Peak Period Departure Choice Model		
Constant	-0.4935	-12.1370
NOCHILD	-0.3299	-8.6340
INC_100K	0.0933	1.7550
PALM_BCH	-0.1010	-2.8240
HB_SHOP	-0.1807	-3.9670
HB_REC	0.0932	1.7620
WALK15	0.0676	1.8970
SOV Mode Choice Model		
Constant	-0.8498	-3.5730
HHSIZE1	1.2405	15.3950
HHSIZE2	0.1207	2.2890
NOCHILD	0.2809	2.9340
NOVEHICL	-2.4143	-11.6130
VEHICL2P	0.7036	16.8100
HB_SHOP	0.2404	4.0300
HB_REC	-0.1167	-2.0960
DIST30	-0.3676	-3.1500
T1WAIT30	0.0707	1.7140
FARE150	0.2108	2.8660
PEAK	-0.2655	-0.4110
ρ (Error Correlation)	0.1439	0.3800
Sample Size	6463	
Number of parameters	20	
Log-likelihood		
At convergence	-7448.404	
At market share	-7964.838	
At zero	-8959.620	

Table 5.6. Non-workers Non-work Trip Model
(Mode Choice → Departure Time Choice)

Variable	Parameter	t-test
Peak Period Departure Choice Model		
Constant	-0.3666	-6.2420
NOCHILD	-0.2824	-6.8980
INC_100K	0.1255	2.3540
PALM_BCH	-0.0992	-2.7880
HB_SHOP	-0.1746	-3.8270
TERMTI2P	-0.1551	-3.6200
WALK15	0.0634	1.7790
SOV	-0.2431	-2.3260
SOV Mode Choice Model		
Constant	-0.9562	-20.9490
HHSIZE1	1.2587	17.2300
HHSIZE2	0.1350	2.5560
NOCHILD	0.3088	5.7960
NOVEHICL	-2.4405	-12.6390
VEHICL2P	0.7055	18.4520
HB_SHOP	0.2554	6.1560
HB_REC	-0.1239	-2.3640
DIST30	-0.3365	-2.9250
T1WAIT30	0.0821	2.1010
FARE125	0.1565	3.1790
ρ (Error Correlation)	0.1372	2.0430
Sample Size	6463	
Number of parameters	20	
Log-likelihood		
At convergence	-7440.233	
At market share	-7964.838	
At zero	-8959.620	

5.2 Performance Comparisons

The model estimation results presented in section 5.1 of this chapter generally offer plausible indications for alternative causal paradigms. The only model that may be rejected on qualitative grounds is that in Table 5.5 where the departure time choice decision precedes the mode choice decision for the non-worker sample. The statistically insignificant random error correlation which implies that there are no correlated unobserved factors between mode choice and departure time choice appears difficult to explain and defend in light of the simultaneity shown by the other models. In addition, the coefficient reflecting the influence of departure time choice on mode choice is also statistically insignificant. In order to further help clarify the causal structure(s) most supported by the data, this section presents a more rigorous comparison across models 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 non-nested relationships in discrete choice models. The indices are given as follows:

$$\bar{\rho}_0^2 = 1 - \frac{L(\beta) - K}{L(0)} \tag{5.1}$$

$$\bar{\rho}_c^2 = 1 - \frac{L(\beta) - K}{L(c)} \tag{5.2}$$

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)
- K: the number of parameters in model.

The adjusted likelihood ratio indices for all of the models are presented in Tables 5.7 and 5.8.

To choose between two models (say, 1 and 2), Ben-akiva and Lerman [15, p. 172] provide a test where under the null hypothesis that model 1 is the true specification, the following holds asymptotically:

$$\Pr(\bar{\rho}_2^2 - \bar{\rho}_1^2 > z) \leq \Phi\{-[-2zL(0) + (K_2 - K_1)]^{1/2}\}, z > 0 \tag{5.3}$$

where

- $\bar{\rho}_i^2$ = the adjusted likelihood ratio index at zero for model i = 1, 2
- K_i = the number of parameters in model i
- Φ = the standard normal cumulative distribution function
- $L(0)$ = 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 (5.3) above. If the model with the greater $\overline{\rho}^2$ is selected, then this bounds the probability of erroneously choosing the incorrect model over the true specification. Using this procedure, models of alternative causal structures can be compared against one another.

Table 5.7 shows the comparison between the two models for the worker sample. The difference between the adjusted likelihood ratio indices for the two models is 0.0002 with the model in which departure time choice precedes mode choice showing the better fit. Applying equation (5.3) yields a bounding probability of almost zero; therefore, it can be said with a high degree of confidence (99 percent confidence or better) that the model of Table 5.3 better fits the data than the model of Table 5.4. The significantly better goodness-of-fit measure suggests that the causal structure "departure time choice → mode choice" is statistically dominant in the worker sample (for non-work trips). This may be behaviorally explained by considering the typical work schedule constraints faced by workers. As workers tend to link their non-work trips with the commute to and from work, the departure time choice is predetermined in conjunction with the work schedule that takes precedence over all else. The mode choice is then simply determined by the mode that has been chosen for the commute trip as the non-work trips are part of a larger trip chaining mechanism.

Table 5.7. Likelihood Ratio Comparison for Worker Models (Sample Size = 7947)

Model	Number of Parameters (K)	ρ_0^2	ρ_c^2	$\bar{\rho}_0^2$	$\bar{\rho}_c^2$
Departure Time → Mode	18	0.1002	0.0484	0.0986	0.0467
Mode → Departure Time	20	0.1006	0.0488	0.0984	0.0465

For non-workers, the model presented in Table 5.5 in which departure time choice precedes mode choice may be considered suspect on qualitative intuitive reasoning as explained earlier. In addition, Table 5.8 shows that the model where mode choice precedes departure time choice exhibits a higher adjusted likelihood ratio index. The difference between adjusted likelihood ratios is 0.001 and the non-nested test shown in equation (5.3) rejects the joint structure of Table 5.5 at the 0.01 level of significance. That the most appropriate causal structure for non-workers is opposite to that of workers is also quite reasonable. For non-workers, work-related scheduling constraints are not there. However, mode availability constraints may occur. If the worker has taken the automobile, then auto availability may be constrained particularly in multi-person households. Then, the non-worker must first think about the decision regarding mode and can then determine the most suitable time-of-day for pursuing the non-work activity.

Table 5.8. Likelihood Ratio Comparison for Non-worker Models (Sample Size = 6463)

Model	Number of Parameters (K)	ρ_0^2	ρ_c^2	$\bar{\rho}_0^2$	$\bar{\rho}_c^2$
Departure Time → Mode	20	0.1298	0.0648	0.1664	0.0623
Mode → Departure Time	20	0.1308	0.0659	0.1674	0.0634

In summary, this study points to the possible behavioral mechanism where 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, while for non-workers, 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.

5.3 Model Application

Travel demand models are important tools in forecasting future travel demand. In order to make educated decisions regarding transportation infrastructure planning, travel demand models must be capable of predicting the response of the transportation system and its users to changing demand. It is quite challenging however, for travel demand models to accurately predict future demand. In order to achieve that, travel demand models should incorporate realistic representations of individual and household activity and travel decision making [17].

The traditional urban transportation modeling system (UTMS), widely used in regional-level studies, incorporates aggregate trip making levels, rather than trip making on the individual level. As all discrete choice models, the bivariate probit model is based on the concept of utility maximization which assumes that the traveler will select the alternative that maximizes his or her benefit. In this sense, discrete choice attributes such as mode choice and departure time choice can be modeled on the aggregate trip level. In terms of forecasting however, probit models are much less applicable compared to logit models and very limited literature exists that discusses incorporating probit models in travel demand forecasting.

5.3.1 Comparison of Predictions between Causal Structures

In the context of this study, estimating predictions of traveler mode choice and departure time choice based on the estimated structural models may be useful in further supporting the validity of the models. Comparing predicted values across the two different directional relationships featured in this study can be helpful in assessing the importance of the proposed causal relationships for workers and non-workers. If the predictions are very different across the two opposite causal structures for workers or non-workers, then it can be stated that the outcome of this study makes a major contribution in the context of time-of-day modeling. That is to say, in order to have a realistic representation of traveler behavior in terms of time-of-day and mode choice, the modeling effort must be capable of achieving the right causal structure.

In achieving predictions, for each subsample (workers and non-workers) of non-work trips, new random seeds must be generated that reflect randomness for all cases in the dataset and produce independent random variables with standard normal distribution. For this purpose, the Monte-Carlo method is used to generate the bivariate normal random seeds for the error terms that are independent random variables with a standard normal distribution [12]. The methodology is illustrated below:

The Monte-Carlo method will generate independent random variables, suppose U and V, each with the standard normal distribution.

Based on the normal distribution the random error terms are defined by:

$$X = \mu_1 + d_1 U$$

$$Y = \mu_2 + d_2 \rho U + d_2 \sqrt{(1-\rho^2)} V \tag{5.4}$$

The joint distribution of (*X, Y*) is called the bivariate normal distribution with zero means (μ_1, μ_2 = 0), unit variances (d_1, d_2 = 1), and correlation ρ in [-1, 1]

Based on the specifications of this study, the error terms definition becomes:

$$\begin{cases} \varepsilon_q, \omega_q = U \\ \omega_q, \varepsilon_q = \rho U + V\sqrt{(1-\rho^2)} \end{cases} \tag{5.5}$$

where, ε_q and ω_q are random error terms, which are standard bivariate normally distributed with zero means, unit variances, and correlation ρ which is an estimator of correlation in the different estimated bivariate probit models, i.e. $\varepsilon_q, \omega_q \sim \phi_2(0,0,1,1,\rho)$.

The two different causal structures for prediction then become as follows:

- $\alpha = 0$, $\eta \neq 0$ (Mode Choice $\rightarrow$ Departure Time Choice)

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

In the first functional relationship, if M_q^* > 0, i.e. the predicted probability $\Phi(M_q^*)$ > 0.5 then M_q = 1 (otherwise equal to zero), and the *mode choice model* is selected.

Accordingly, in the second functional relationship, if $T_q^* > 0$, i.e. the predicted probability $\Phi(T_q^*) > 0.5$ then $T_q = 1$ (otherwise equal to zero), and the *departure time choice model* is selected.

- $\alpha \neq 0$, $\eta = 0$ (Departure Time Choice $\rightarrow$ Mode Choice)

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

In the first functional relationship, if $M_q^* > 0$, i.e. the predicted probability $\Phi(M_q^*) > 0.5$ then $M_q = 1$ (otherwise equal to zero), and the *mode choice model* is selected.
Accordingly, in the second functional relationship, if $T_q^* > 0$, i.e., the predicted probability $\Phi(T_q^*) > 0.5$ then $T_q = 1$ (otherwise equal to zero), and the *departure time choice model* is selected.

Given the above model definitions, prediction estimations can be computed using LIMDEP 8.0 [13].

5.3.2 Prediction Results

Tables 5.9 through 5.12 illustrate crosstabulations of predicted values and percentages of departure time choice with mode choice. A first look in the tables indicates four fairly different causal relationships across workers and non-workers samples. In tables 5.9 and 5.10 there seems to be a strong indication of two very different casual structures. The values across the two causal relationships are indeed dissimilar. For example, the predicted number of workers non-SOV trips made in the off-peak hour is 1679. On the other hand, only 512 of the off-peak hour trips are made by non-SOV mode.

A comparison of tables 5.11 and 5.12 shows that, even in the case of non-workers there seems to be a notable difference between the two causal structures, although this difference is not as evident as in the case of workers. For example, the predicted number of workers SOV trips made in the peak hour is 3844. On the other hand, 3175 of the total peak hour trips are made by SOV mode.

Table 5.9. Crosstabulation of Departure Time Choice → Mode Choice: Worker Sample
Predicted Values
(N = 7947)

Mode Choice	Departure Time Choice		Total
	Non-Peak	Peak	
Frequency			
Non-SOV	1679	2928	4607
SOV	2131	1209	3340
Total	3810	4137	7947

Table 5.10. Crosstabulation of Mode Choice→ Departure Time Choice: Worker Sample
Predicted Values
(N = 7947)

Mode Choice	Departure Time Choice		Total
	Non-Peak	Peak	
Frequency			
Non-SOV	512	1860	2372
SOV	2260	3315	5575
Total	2772	5175	7947

Table 5.11. Crosstabulation of Departure Time Choice → Mode Choice: Non-worker Sample
Predicted Values
(N = 6463)

Mode Choice	Departure Time Choice		Total
	Non-Peak	Peak	
Frequency			
Non-SOV	220	732	952
SOV	1667	3844	5511
Total	1887	4576	6463

Table 5.12. Crosstabulation of Mode Choice→ Departure Time Choice: Non-worker Sample
Predicted Values
(N = 6463)

Mode Choice	Departure Time Choice		Total
	Non-Peak	Peak	
Frequency			
Non-SOV	439	922	1361
SOV	1927	3175	5102
Total	2366	4097	6463

As a conclusion, it can be stated that at least in the case of workers, the evident distinct differences of the prediction results across the two different causal relationships further support the advocated variability between mode-choice/ departure-time-choice patterns of this group. Hence, when modeling workers non-work trips by time-of-day, one should be very careful in achieving the correct causal structure that portrays the relationship of mode choice and departure time choice. In the case of non-workers, the above can not be stated with high level of confidence. However, a dominant causal relationship between mode choice and departure time choice for non-workers still seems to hold as supported by the model estimation results of this study.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions and Future Research

New microsimulation models of travel and activity behavior attempt to predict travel and activity patterns at the level of the individual decision-maker or traveler. The development of such models calls for a deeper understanding of the causal decision mechanisms that govern travel and activity participation decisions. Two major elements of travel and activity behavior include departure time choice and mode choice as planners would undoubtedly expect such advanced model systems to offer information about travel demand by mode and time-of-day. This study attempts to shed considerable light on the relationship between these two elements of behavior by considering alternative formulations of joint model systems of departure time choice and mode choice for non-work trips. As 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/departure time window sizes. On the other hand, less attention has been paid to the issue of departure time choice for non-work trips, a growing segment of trip making that is accounting for a larger share of trips at all times of day.

This study considers two alternative formulations of joint model systems indicating two possible alternative causal relationships between departure time choice and mode choice for non-work trips. The analysis employs the 1999 Southeast Florida Regional Travel Characteristics Study household travel survey data. The model estimation effort was conducted separately for workers and non-workers due to 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 make decisions on choice variables that are more constrained first. For the worker sample, it was found that the data better supporting the causal relationship where departure time choice preceded mode choice. For the non-worker sample, on the other hand, the analysis and modeling results suggested that the data support the causal relationship where mode choice decisions preceded departure time choice. These findings are consistent with the notion that choices on constrained dimensions are made first. Workers are time constrained due to work activity schedules. Then, workers first determine when they can pursue their non-work activities and trips and then choose the mode for those trips depending on the time-of-day, modal availability, and other factors. Non-workers, on the other hand, are not as time constrained as workers. They may be more mode constrained than time-of-day constrained due to the modal availability issue, need to engage in non-work activities that serve household members and other household obligations (leading to more shared ride trips), and the absence of typically rigid work schedules. Models of activity and travel behavior should incorporate relationships such as those identified in this study to more accurately portray the decision mechanisms that may be driving traveler patterns.

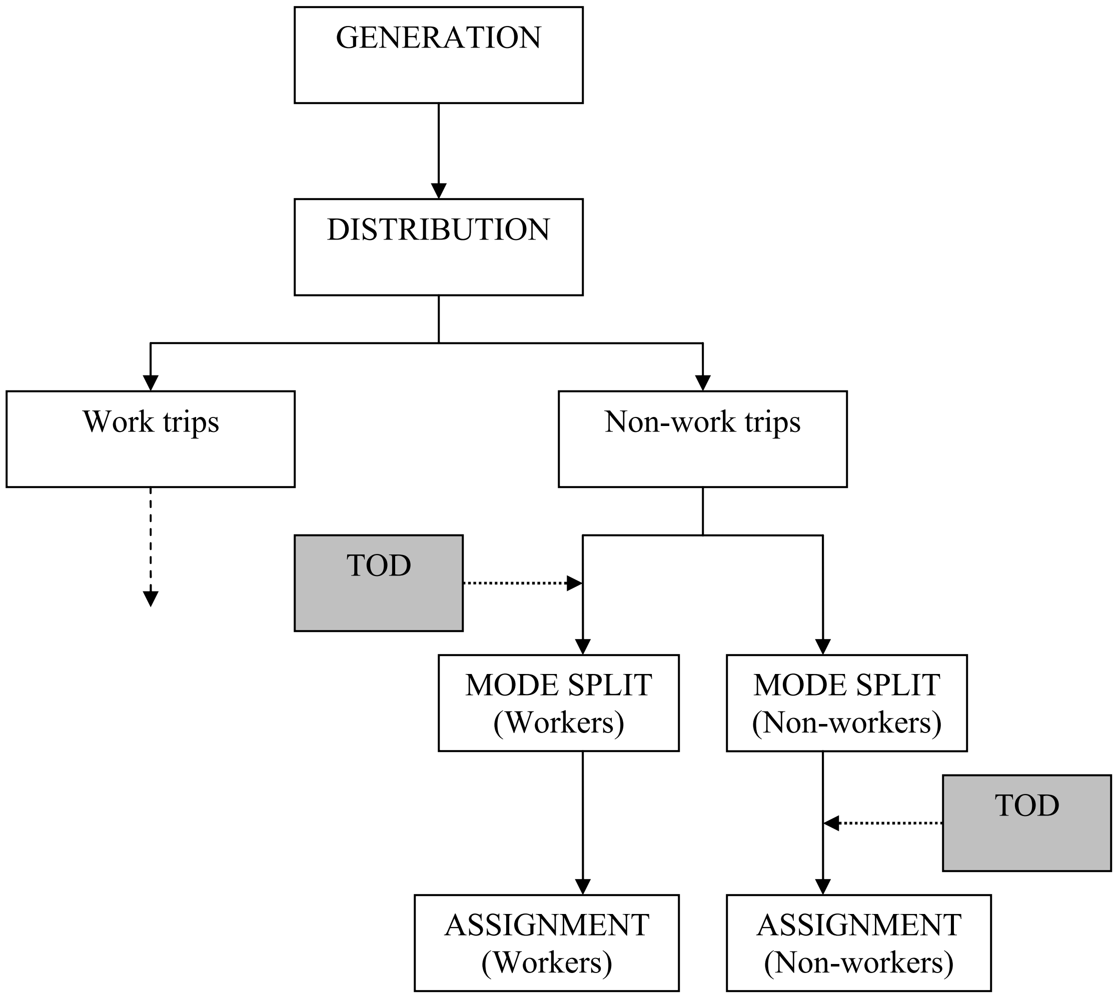
As with most research efforts of this type, limitations apply to this study and additional research is warranted. First and foremost, it must be recognized that the identification of true causal relationships based on a statistical analysis of revealed behavior data is extremely difficult and challenging. 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 collects information about the thought process that went into a certain decision or behavioral choice. Also, despite the best efforts of the author, 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.

6.2 Implications on Four-step Modeling Paradigm

Application on time time-of-day based factors within the traditional UTMS four-step modeling process has been discussed in the introduction of this thesis. Based on the outcome of this study someone could consider applying time-of-day factors at two different points in the four-step process. If indeed departure time choice precedes mode choice then time-of-day modeling could be performed before mode choice (between trip distribution and mode choice) to account for variations of traveler mode choice across peak/off-peak periods. On the other hand, if the opposite scenario is true, that is, mode choice precedes departure time choice, then TDOF's may well be applied after mode choice (between mode choice and traffic assignment). Two important problems seem to arise however: First and foremost, the implications of this study are constrained to non-work trips. Non-work travel may indeed account for the majority of all trips in an urban area, but commuting has its own share in urban daily travel. Second, the findings of this study are contradicting across two equally important market segments: workers and non-workers. Applying TDOF's before mode choice would not account for non-worker departure time travel patterns while the opposite may be conjectured for workers. Deciding how time-of-day assignment should be treated in the context of the four-step process, given the implications of this study, is therefore a challenge.

Essentially, someone may consider different models for different trip purposes and different market segments across an area-wide dataset. A common dataset including all person trips may be used for the first two steps of the modeling process: trip generation and trip distribution. Then, non-work trips may be separated from work trips and treated differently for worker and non-worker subsets. This process would eventually yield different link-level non-work trip assignments for workers and non-workers. The procedure could be implemented within the four-step modeling process as illustrated in Figure 6.1.

Figure 6.1. Time-of-Day Modeling Procedure for Non-work Trips



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