

# **MODELING DEPARTURE TIME CHOICE FOR HOME-BASED NON-WORK TRIPS**

by

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## **ABSTRACT**

The existing literature on departure time choice has primarily focused on work trips. This thesis examines departure time choice for non-work trips, which constitute an increasingly large proportion of urban trips. Discrete choice models are estimated for four categories of home-based non-work trips using the 1996 activity survey data collected in the Dallas-Fort Worth metropolitan area. The effects of individual and household socio-demographics, employment attributes, and trip characteristics on departure time choice are presented and discussed. The results indicate that departure times for non-work trips are determined for the most part by individual/household socio-demographics and employment characteristics, and to a lesser extent by trip level-of-service characteristics. This suggests that departure times for non-work trips are not as flexible as one might expect and are confined to certain times of day because of overall scheduling constraints. The paper concludes by identifying future methodological and empirical extensions of the current research.

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## EXECUTIVE SUMMARY

There are many aspects of choice associated with individual trip-making. These choices include frequency, destination, mode, and route, and all of these components are explicitly modeled in the four-step Urban Transportation Model System (UTMS) procedure used by Metropolitan Planning Organizations (MPOs) in most cities. However, time-of-day choice is a fifth and equally important dimension of choice that has received relatively little attention in the trip-based modeling approaches adopted by MPOs. However, in the past decade there has become an increasing need to understand travel behavior responses to shorter term, time-of-day specific, congestion management policies such as peak period pricing and peak period high occupancy vehicle use incentives. In addition, air quality modeling requires temporal resolution in the number of vehicle trips.

The recognition of the need for temporal resolution in trip-making has led MPOs of some large metropolitan areas to apply fixed, aggregate-level, factors to apportion the predicted total daily travel to different times of the day. The use of such fixed factors in travel modeling represents an improvement over disregarding the time-of-day dimension entirely, however, it is still very simplistic. The importance of obtaining an accurate picture of the departure time decisions of individuals motivates the research in this thesis. Specifically, this thesis examines the effect of individual and household socio-demographic characteristics, employment-related attributes, and trip characteristics on departure time choices of individuals. The departure time alternatives are represented by six temporally contiguous discrete time periods that collectively span the entire day. The choice among these alternatives is modeled using a discrete choice model.

Within the context of departure time choice, the focus of this study is on non-work trips. This thesis concentrates on four types of trips within the broad category of non-work trips: home-based social/recreational, shopping, personal business, and community activity trips. The selected trip purposes comprise the largest proportion of non-work trips in most metropolitan areas.

Two model structures are explored for modeling departure time choice among the six discrete periods: the multinomial logit (MNL) and the ordered generalized extreme value (OGEV) structures. The latter is a generalization of the former and allows an increased degree of sensitivity (due to excluded factors) between temporally adjacent departure periods compared to

temporally non-adjacent periods. For all trip purposes, the analysis indicates that the MNL model is adequate to model departure time choice.

The empirical analysis in the paper uses the 1996 activity survey data collected by the North Central Texas Council of Governments (NCTCOG) in the Dallas-Fort Worth area, along with a level-of-service (LOS) data file obtained from NCTCOG that provided information on the Dallas-Fort Worth network. Several sets of variables were considered in the model specifications, including individual and household socio-demographics, employment-related attributes and trip-related characteristics. Important overall results from the empirical analysis are as follows:

- gender does not have an important role in departure time choice,
- older individuals are most likely to participate in non-work activities during the mid-day,
- high-income-earning individuals avoid the mid-day periods for shopping and personal business,
- individuals with very young children (under 5 years of age) in their households are unlikely to pursue most activities during the p.m. peak and evening, presumably because of the increased biological needs of young children during these late times of the day,
- individuals with children below 5 years of age are unlikely to participate in shopping activities during the mid-day,
- individuals with children above 5 years of age in their households, on the other hand, are most likely to pursue recreational activities during the p.m. peak period since this is the most convenient time to jointly participate in recreational activities,
- individuals with children above 5 years of age are unlikely to pursue recreational, personal, and community activities during the mid-day,
- employed individuals and students are most likely to participate in non-work activities during the latter parts of the day,
- self-employed individuals are more likely than externally employed individuals to “sandwich” a recreational, shopping, or personal activity between the a.m. and p.m. work periods,
- trips to a non-work activity from home tend to be made before the evening period,
- trips pursued together with others or by walk are likely to be undertaken during the p.m. peak and evening periods, and
- in the current empirical context, the only level-of-service variable that has a significant impact is trip travel time and even this applies only for recreational trips.

The empirical results indicate the strong impact of socio-demographic and employment-related characteristics on departure time choice for non-work trips. These results have substantial implications for transportation planning analysis. Specifically, the analysis suggests that ignoring the effects of these variables can lead to misinformed transportation planning and air quality decisions because of changing demographic and employment-related trends over the next few decades. The need to include socio-demographic and employment attributes is also important because of spatial differences in these variables within a metropolitan region. Applying fixed factors to apportion total daily travel to different times of the day assumes away the existence of spatial demographic variations and will, in general, lead to incorrect network assignment volumes by time of day. This, in turn, can lead to inaccurate VMT and speed estimates by time of day and, consequently, inaccurate transportation-air quality analysis.

An interesting finding from the research in this thesis is that level-of-service characteristics do not appear to substantially impact departure time for non-work trips. This has significant implications for time-of-day specific transportation control measures (such as peak-period pricing or converting a general-purpose lane to a high occupancy vehicle use lane). Specifically, the results imply that there will be little to no temporal displacements of non-work trips because of such policies. This suggests that non-work trips may not be as temporally flexible as one might think.

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## CHAPTER 1: INTRODUCTION

### TRAVEL DEMAND MODELING

Travel demand modeling is an essential component of the transportation planning process. It enables transportation planners to forecast future travel needs, to quantify the effects of changes in the transportation system, and to compare alternatives when making transportation-related decisions. Transportation systems comprise a complex set of interactions among travelers, infrastructure, and transport policy actions, and the mathematical modeling of these interactions constitutes an important component of overall efforts to analyze transportation systems.

Travel demand modeling is also necessary because of the *dynamic* nature of the factors that affect travel. Socio-demographics and land use patterns are constantly changing, and these shifts have substantial impacts on travel patterns. By forecasting these shifts in land-use and socio-demographic patterns, and using them as inputs to travel demand models, the resulting changes in travel patterns can be predicted.

Finally, travel demand models are important in assessing the effect that changes in infrastructure and transportation policy will have on travel patterns. Such changes have significant and far-reaching impacts, so it is imperative that they are supported by research and planning. Funding and urban space are scarce resources, so the decision on how to use them cannot be taken lightly (Ortuzar and Willumsen 1990). Furthermore, changes to the transportation system cannot be made instantaneously; rather, they are undertaken over a period of time. Therefore, it is necessary to plan changes far in advance of their actual need.

### THE URBAN TRANSPORTATION MODEL SYSTEM

The set of models developed for travel demand modeling and used by most Metropolitan Planning Organizations (MPOs) today is the Urban Transportation Model System (UTMS). The basic structure of the UTMS was developed during the 1950s in Chicago and Detroit (Pas 1995). The UTMS takes as inputs the transportation system characteristics, socio-demographic attributes, and land-use patterns in a region and provides as outputs the volume and level of service of network links.

Several preliminary steps must be undertaken before applying the UTMS. The first of these is to identify the study area. Next, the area is partitioned into a set of Travel Analysis

Zones (TAZs). The size of the TAZs often varies considerably, but is, in general, inversely proportional to the activity density within the zone. Then, the transportation network, including the major roads, collectors, and transit routes, but usually not the local roads, is superimposed onto the study area. Centroids are assigned to the zones, under the assumption that all activity in the zone is produced from/attracted to that centroid. Finally, “dummy links” are created for each zone. These links represent the average amount of time that it takes for an individual within the zone to get to the main network.

The UTMS may be employed once the preparatory steps have been completed. The UTMS structure, shown in Figure 1, comprises four steps: trip generation, trip distribution, modal split, and traffic assignment. Each of these steps is briefly discussed below.

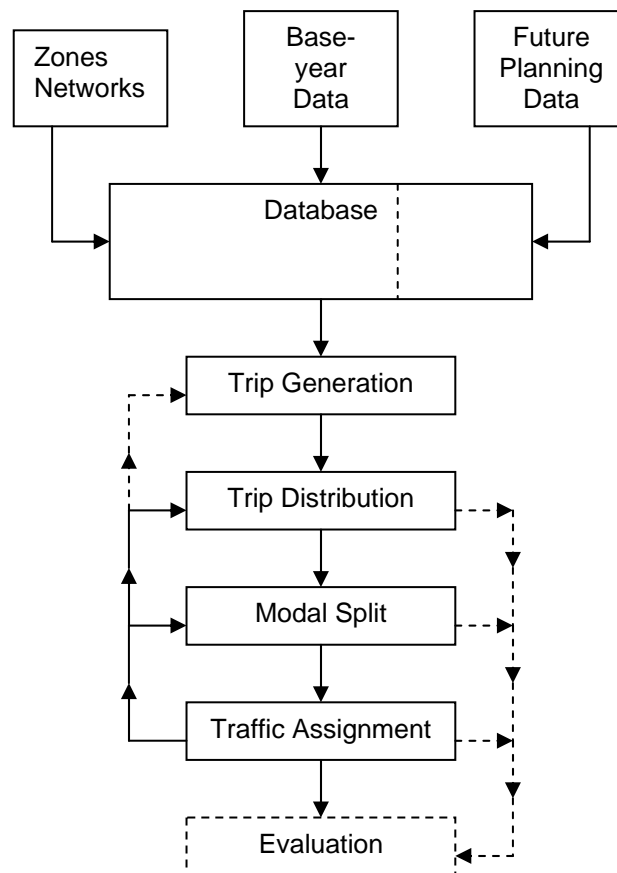


Figure 1: Four-step Urban Transportation Model System (source: Ortuzar and Willumsen 1990)

The first step of the UTMS, trip generation, is primarily concerned with predicting the number of trips produced by and attracted to each zone in the study area. The number of trips

produced at each zone is predicted by estimating a regression model, usually at the household level. In such a model, the number of trips per household is estimated as a function of household characteristics, and the household-level regression is aggregated over the entire zone to produce the total number of trips produced at the zone. The number of trips attracted to a zone is estimated as a function of the current or projected land use characteristics of the zone.

The second step of the UTMS, trip distribution, links the productions and attractions of the trips predicted by the trip generation model to develop a trip matrix describing inter-zonal production-attraction flows in the study area. The most common method used to assign trips between productions and attractions is the gravity model. The gravity model apportions the trips produced at a given zone to each attraction zone based on the attractiveness of the attraction zone and the cost of travel to the zone. The “cost” may be a combination of monetary cost and travel time cost. Higher cost for travel from a production zone to an attraction zone implies fewer trips to that attraction zone.

The third step of the UTMS, modal split, apportions the total number of trips between each zonal pair among the available travel modes. Prior to this step, the production-attraction interchanges between zones are converted to equivalent origin-destination interchanges. The proportion of trips assigned to each mode is then determined according to the utility for travel between the origin-destination pair for that given mode relative to the utilities of other available modes. At the end of the modal split step, the number of person-trips is converted to vehicle-trips, according to the occupancies of the various types of vehicles.

The final step in the UTMS is traffic assignment. The purpose of this step is to assign each vehicle trip to a specific route within the transportation system. The general goal is to maintain equal travel times for all routes between a given origin and destination. This method approximates how actual system users will choose routes. People will generally travel on the route they perceive to be the fastest; therefore, if all individuals travel on the fastest route, over time the travel times on all routes will tend to equalize over time.

The model parameters are estimated using base-year data gathered from household travel surveys. Projections of socio-demographic and land use data are then used to apply the calibrated models to possible future scenarios. This enables transportation planners to evaluate the scenarios and predict future demands on the transportation system.

## **TIME-OF-DAY CHOICE**

As the preceding discussion indicates, there are many aspects of choice associated with individual trip-making. These choices include frequency, destination, mode, and route, and all of

these components are explicitly modeled in the four-step UTMS procedure used by most planning organizations. However, time-of-day choice is a fifth and equally important dimension of choice that has received relatively little attention in the trip-based modeling approaches adopted by MPOs. The reason for this lack of attention to time-of-day may be traced back to the context in which the trip-based modeling framework was developed in the 1950s. The primary objective then was to evaluate alternative major capital improvements, so the focus was on predicting how alternative projects would affect overall daily travel demand levels and not on predicting shifts in travel within a day (Cambridge Systematics, Inc. 1994).

While evaluating capital improvements continues to remain an important objective of travel demand models, there has been a shift in emphasis in the past decade from evaluating long-term investment-based strategies to understanding travel behavior responses to shorter term, time-of-day specific, congestion management policies such as peak period pricing and peak period high occupancy vehicle use incentives. In addition, air quality modeling requires temporal resolution in the number of vehicle trips because a) the emissions factors (in grams per mile) to be applied to vehicle miles of travel (VMT) are sensitive to meteorological conditions (temperature and humidity) and vary considerably by time-of-day, b) the operating mode of trips are quite different across times of day (for example, a large proportion of trips in the morning and afternoon peak periods begin in the cold-start mode relative to other periods of the day), and c) photochemical dispersion models to determine ozone formation require mobile source emission levels of ozone precursor pollutants (i.e., Oxides of Nitrogen and Volatile Organic Compound) by time of day (see Chatterjee *et al.* 1997).

The recognition of the need for temporal resolution in trip-making has led MPOs of some large metropolitan areas to apply fixed, aggregate-level, factors to apportion the predicted total daily travel to different times of the day. The use of such fixed factors in travel modeling represents an improvement over disregarding the time-of-day dimension entirely. However, it is still very simplistic and inadequate for a number of reasons. First, fixed factors implicitly assume that trip departure times are unaffected by employment-related and socio-demographic characteristics. This is a rather untenable assumption since it is very likely that employment and socio-demographic attributes are associated with constraints/preferences regarding time-of-day of participation in activities. It is particularly critical to accommodate these effects at a time when there are substantial changes in employment and socio-demographic attributes of the population which can lead to trip timing patterns in the future that are very different from those existing today. Assuming that trip timing will remain the same in the future, therefore, can lead to inappropriate policy evaluations of congestion alleviation strategies and misinformed air quality plans (see Deakin, Harvey, Skabardonis, Inc. 1993). In addition, socio-demographics vary spatially within an

urban area, resulting in spatial variations in temporal travel patterns. Fixed factors are applied uniformly over the entire area, not accommodating these spatial differences. Second, applying aggregate-level factors to apportion trips to different times of the day does not accommodate departure time switching that might occur due to non-uniform (across time-of-day) variations in roadway conditions between the estimation and forecast years. Third, if time-of-day specific transportation control measures (such as congestion pricing or peak-period pricing) are implemented, the resulting temporal displacements of trips can be evaluated only by modeling level-of-service sensitivities in departure time decisions (Bhat 1998a).

## **OBJECTIVE AND THESIS ORGANIZATION**

The preceding discussion of the importance of modeling departure time decisions of individuals motivates the research in this thesis. Specifically, this thesis examines the effect of individual and household socio-demographic characteristics, employment-related attributes, and trip characteristics on departure time choices of individuals. The departure time alternatives are represented by several temporally contiguous discrete time periods such as early morning, a.m. peak, a.m. off-peak, p.m. off-peak, p.m. peak, and evening. The choice among these alternatives is modeled using a discrete choice model.

Within the context of departure time choice, the focus of this study is on non-work trips. The reason for the emphasis on non-work trips is three-fold. First, non-work trips constitute an increasingly large proportion of urban trips and, therefore, have a significant impact on traffic congestion and air quality (see Gordon *et al.* 1988). Second, individuals may have more temporal flexibility for pursuing non-work activities than they do for commuting to work. The implication of this greater flexibility for non-work trips is that socio-demographic changes and/or transportation control measures may have a more significant impact on such trips than on the less flexible work trips. Third, the existing literature on departure time choice has focused primarily on work trips. The lack of previous research points to a need for more study of departure time choice for non-work trips.

This thesis concentrates on four types of trips within the broad category of non-work trips: home-based social/recreational, shopping, personal business, and community activity trips (a home-based trip of any purpose refers to all trips which have that purpose at one trip end and home at the other trip end). The selected trip purposes comprise the largest proportion of non-work trips in most metropolitan areas.

The remainder of this thesis is organized as follows. Chapter 2 provides a review of the existing departure time choice literature. Chapter 3 presents an overview of the model structure

used in the analysis. Chapter 4 describes the data source and sample formation process as well as the variables considered in the model specification. Chapter 5 provides empirical results of departure time choice for each trip purpose and compares these results across trip purposes. Finally, Chapter 6 highlights the important findings from the study and their implications, and identifies future research directions.



## **CHAPTER 2: LITERATURE REVIEW**

The existing literature on departure time choice has primarily focused on work trips. This thesis, in contrast, focuses on departure time choice for non-work trips. Table 1 provides a summary of both work and non-work departure time research. The next two sections review these various studies.

### **WORK DEPARTURE TIME STUDIES**

Departure time for work trips is fairly well-represented in the literature. The first study listed in Table 1, by Small (1982), makes use of a multinomial logit formulation to model desired arrival time at work in the morning. The choice is modeled among 12 five-minute periods, ranging from 42.5 minutes before the individual's official work start time to 17.5 minutes after the work start time. Small found that travelers were willing to shift their schedules by one to two minutes toward the early side, or one-third to one minute toward the late side, in order to save a minute of travel time. He also concluded that many commuters prefer to travel to work during the peak period from schedule considerations, but avoid doing so because of traffic congestion problems; therefore, he suggests that congestion alleviation would encourage commuters to shift to the peak periods.

TABLE 1: SUMMARY OF DEPARTURE TIME CHOICE LITERATURE

Study (year)	Work/Non-work	Time Period	Methodology	Variables
Small (1982)	W	a.m. commute	MNL (5-min. intervals)	travel time, schedule delay, household structure, carpool, arrival flexibility, occupation type
Abkowitz (1981)	W	a.m. commute	MNL (5-min. intervals)	arrival flexibility, mode, occupation, location, income, age, travel time
Chin (1990)	W	a.m. commute	MNL, NL (15-min intervals)	schedule delay, occupation, income, travel cost, travel time, gender
McCafferty & Hall (1982)	W	p.m. commute	MNL (pre-peak, peak, post-peak)	travel time, income
Mannering (1989)	W	a.m. commute	Poisson regression (# departure time changes/month)	travel time, work time flexibility, age, marital status
Hendrickson & Plank (1984)	W	a.m. commute	MNL – joint mode & departure time (10-min. intervals)	free flow travel time, congestion time, cost/income, time early, time late, access time, wait time
Mannering & Hamed (1990)	W	p.m. commute	MNL, continuous Weibull survival function	peak/free-flow travel time, mode, route, distance, gender, income
Kumar & Levinson (1995)	N	full day	descriptive	trip type, employment status
Hunt & Patterson (1996)	N (rec)	hypothetical	Exploded logit (ranks alternatives)	travel time, time early, probability of lateness, parking cost, film newness
Bhat (1998a)	N (shopping)	full day	MNL-OGEV – mode & departure time	employment status, race, age, gender, location, cost, travel time, ovt/distance
Bhat (1998b)	N (soc/rec)	full day	Mixed MNL – mode & departure time	age, gender, presence of children, income, #vehicles/#adults, CBD, employment status
Levinson & Kumar (1993)	Both	p.m. peak	Binomial logit (peak & shoulder)	congested & free-flow travel time, distance
Hamed & Mannering (1993)	N	post-work	continuous Weibull survival function	age, income, # children, # workers, home arrival time
Bhat (1998c)	N	post-work	least-squares regression	age, gender, employment, presence of children, home arrival time

Abkowitz (1981) used the same data and travel time choices as Small, including additional socio-demographic variables and transit mode use as determinants of commute departure time choice behavior. His analysis indicates significant effects of income, age, occupation, and travel mode on preferred work arrival time.

Chin (1990) modeled morning commute departure time for workers in Singapore using multinomial logit and nested logit models. Instead of structuring the departure time choices around the individual's work start time (as done by Small and Abkowitz), the choice was modeled among eleven 15-minute clock-time periods (which, for the nested logit, were grouped into three nests). He found that journey time had an effect on travel time choice, and also that occupation and income affected propensity for switching departure times.

In contrast to the previous studies, which all focused on departure time to work in the morning, McCafferty and Hall (1982) modeled the time that individuals chose to leave work in the evening. McCafferty and Hall also used a multinomial logit, testing several different temporal partitioning schemes to represent discrete periods of departure time choice. Their preferred model used three alternatives: the p.m. peak period, pre-peak period, and post-peak period. However, they found that neither travel time nor the socio-economic variables considered had a significant effect on departure time.

Mannering (1989) adopted a different approach to studying the factors that affect an individual's propensity to switch departure times. He used a Poisson regression formulation to model the number of times individuals changed their departure time to work (morning commute) during a one-month period. The travel time on the individual's most frequently-used route, work time flexibility, age, and marital status were found to influence the frequency of departure time changes.

A joint model of mode and departure time choice for the morning commute was proposed by Hendrickson and Plank (1984). They used a multinomial logit with four mode choices and seven 10-minute intervals for departure time choice, resulting in 28 overall alternatives. Considerable effort was directed toward obtaining accurate time-varying level-of-service data in the study. The study found that travelers showed more flexibility in changing departure time than in changing mode.

The studies mentioned thus far have used discrete methods to model departure time choice. More recently, there has been some exploration into using continuous methods for the same purpose. Mannering and Hamed (1990) used a joint discrete/continuous method to model the decision to delay departure to home from work in order to avoid congestion. A discrete model was used for the decision of whether or not to delay departure, and then the duration of the delay was modeled using a continuous Weibull survival function. The duration of the delay was based

on the utility derived from the activity undertaken during the delay (which could be either work, or some non-work activity near the job site). It was found that the overall congestion level dominated the delay decision.

## **NON-WORK DEPARTURE TIME STUDIES**

There are only a handful of studies that focus on non-work departure time. One of these is by Kumar and Levinson (1995), who analyze the distribution and type of non-work trips during different times of the day. Their results suggest considerable variation in the temporal pattern of non-work trips between workers and non-workers, and between shopping and other non-work activities. The study is insightful, but is conducted at an aggregate descriptive level rather than at an individual choice level.

Hunt and Patterson (1996) analyze recreational trip departure time choice at the individual choice level. Their study is conducted in the context of a hypothetical recreational trip to the movies. The choice of the movie start time is pre-determined, and the emphasis is on understanding departure time choice (from home) based on factors such as automobile travel time, desired “cushion” time at the theatre before the movie begins, the probability of being late, parking cost, and whether the movie is a new or old release. Since the movie start time is considered fixed in the study, there is limited temporal flexibility in departure time (as in the case of the work departure time studies reviewed earlier).

More recently, in two separate papers, Bhat (1998a, 1998b) demonstrates the application of new discrete choice formulations for joint travel mode and departure time choice modeling for non-work trips in the Bay Area. The first paper (1998a) estimates a joint model of mode and departure time choice for shopping trips, while the second paper (1998b) formulates a joint mode-departure time choice model for social/recreational trips. The emphasis in these papers is on the formulation of new discrete choice model structures rather than on empirical specification analysis.

In an effort to update the commonly-used four-step Urban Transportation Model System, Levinson and Kumar (1993) propose a new six-step model for non-work trips as well as work trips. One of the new steps in the system is a model of departure time choice. The time choice model assumes a binomial logit structure where the decision modeled is between traveling during the middle hour of a three-hour peak period, or during one of the two one-hour “shoulders”.

Hamed and Mannering (1993) applied a continuous formulation to estimate the duration of individuals’ post-work home-stay prior to participating in non-work activities. Given the time of arrival back home from work, the home-stay duration determines departure time choice for the

non-work trip. The study found that the major factors influencing the home-stay duration included socio-economic characteristics of the individual and household, and the time of arrival home from work.

Similarly, Bhat (1998c) used a discrete/continuous methodology to model individuals' choice of activity type, home-stay duration, and activity duration following a return home from work. Home-stay duration was influenced by socio-economic characteristics and by the arrival time at home after work.

## **SUMMARY OF LITERATURE REVIEW**

The literature review indicates that departure time choice for work trips is a fairly well-researched topic, whereas non-work trips have received relatively little attention. However, for both trip types, the emphasis of the studies has generally been on narrow time periods during the day. While the results of these studies are useful, they are unable to represent time-of-day choice over the period of an entire day. Only two studies (Bhat 1998a, Bhat 1998b) model travel over the entire day; however, the emphasis in these papers is on model formulation rather than extensive empirical testing of the determinants of departure time choice. This research will focus on empirical specification of models to forecast time-of-day choice for a number of different non-work trip purposes.

## CHAPTER 3: MODEL STRUCTURE

### DISCRETE VERSUS CONTINUOUS MODEL STRUCTURES

An important issue in modeling departure time choice is the representation of the dependent variable. Time is intrinsically a continuous variable, and a decision must be made whether to retain the continuous structure, or to discretize the variable for modeling purposes. There are advantages and limitations to both a continuous model structure and a discrete model structure, as is discussed next.

Time has an underlying continuous structure, and retaining this continuous-time representation is appealing for at least two reasons. First, it does not require the rather ad hoc partitioning of the day into time intervals, as a discrete method would. Second, it provides departure time of trips at a fine temporal resolution rather than in aggregate intervals. However, there are several limitations to the use of continuous-time models. They have yet to find their way into practice, whereas discrete models are commonly used by MPOs. In addition, while researchers have used continuous-time models in the past for modeling departure time of trips, most of these studies have been confined to narrow time periods of the day, as noted in Chapter 2. Within such narrow time periods, it may be reasonable to assume that the effect of socio-demographic and employment characteristics do not change over time so that the familiar proportional hazard continuous-time model (which assumes that the covariates change the baseline hazard by a constant factor that is independent of duration; see Hensher and Mannering 1994) may be applied. However, assuming fixed effects of socio-demographics and employment characteristics is untenable when the time domain for consideration is the entire day, as is the case in the current research. For example, the effect of children on the termination of the activity duration preceding participation in recreational activity may be much more "accelerated" during the evening than in earlier times of the day because the evening is most convenient (from schedule considerations) for joint activity participation with children. Such sudden non-monotonic accelerations (or decelerations) in the effect of variables over the course of the day cannot be captured by the traditional proportional hazard or accelerated lifetime models (the accelerated lifetime model allows time-varying effects, but specifies the time-varying effects to be monotonic and smooth in the time domain). Further, level-of-service variables change during the course of the day and one must accommodate these time-varying covariates within the duration model framework. Incorporating such time-varying coefficients and time-varying covariates in duration

models poses an econometric challenge (specialized econometric software needs to be developed) and also presents specification and interpretational challenges (see Bhat 1999a).

Discrete choice models, on the other hand, have the advantage of being able to easily accommodate time-varying coefficients and covariates, even using commercially available software. In addition, discrete choice models are now commonly used in practice and a discrete departure time model can be relatively easily incorporated within the travel demand frameworks of MPOs, while continuous-time duration models are still used primarily for research purposes.

For the above reasons, and because of the widespread familiarity and use of discrete choice structures, a discrete choice representation of departure time choice is retained in this thesis. Within the context of a discrete choice formulation, two alternative structures are considered. The first is the multinomial logit (MNL) structure and the second is an ordered generalized extreme value (OGEV) structure.

## **THE MULTINOMIAL LOGIT (MNL) AND ORDERED GENERALIZED EXTREME VALUE (OGEV) STRUCTURES**

Both the MNL and the OGEV model structures are based on utility maximization theory. Each of the available alternatives (in this case, each of the departure time periods) has an associated utility that is a function of characteristics of the decision-making individual and attributes of the alternative. Utility theory states that an individual will tend to choose the alternative that maximizes his utility.

For a given observation, the utility of alternative  $i$  from the perspective of the decision-maker is given by the equation:

$$U_i = V_i + \varepsilon_i \quad (3.1)$$

where  $U_i$  is the utility of alternative  $i$  to the decision-maker,  $V_i$  is the deterministic, or observed, component of the utility, and  $\varepsilon_i$  is the error, or unobserved, component of utility. The error component is assumed to be a random variable (Koppelman *et al.* 1999).

The MNL and the OGEV both belong to the class of random utility choice models, which recognize that the analyst does not have information on all the factors that affect the choice decision under consideration. Thus, instead of attempting to predict with certainty each individual's choice, these models provide probabilities that the individual will choose each alternative.

## MULTINOMIAL LOGIT MODEL

The MNL structure relies on three basic assumptions. First, the error components of the utility function are extreme-value (Gumbel) distributed. The extreme-value distribution is one of several possible distributions that may be used. But it is the most commonly used distribution because it leads to a closed-form model for the choice probabilities. The second assumption of the MNL is that the error components are identically and independently distributed (IID) across alternatives. Finally, the MNL assumes that the error components are IID across observations. These last two assumptions imply that the variances of the error terms are the same for all individuals and all alternatives, and that there is no correlation between the error terms of various alternatives or between the error terms of various individuals (Koppelman *et al.* 1999).

The MNL structure is appealing because it has a simple formulation. It provides the probability that the individual will choose a given alternative based on the observable portion of the utility of the alternatives. Using the MNL, the probability that a given individual chooses alternative  $i$  from a set of  $J$  alternatives is

$$P(i) = \frac{\exp(V_i)}{\sum_{j=1}^J \exp(V_j)} \quad (3.2)$$

The main drawback of the MNL is that it is saddled with the Independence from Irrelevant Alternatives (IIA) property, which implies that, for any given individual, the ratio of the choice probabilities of two alternatives is independent of all other alternatives. One of the assumptions of the MNL leading to the IIA property is that the error terms are not correlated across alternatives. In the context of departure time modeling, this property implies that there is no increased degree of sensitivity (due to excluded exogenous factors) between adjacent departure time alternatives compared to non-adjacent departure time alternatives. Thus, for example, implementation of congestion pricing during the p.m. peak period will result in an equal proportionate increase in the probability of choice of the a.m. off-peak period and in the probability of choice of the p.m. off-peak period. However, individuals may be more likely to shift to the p.m. off-peak period than the a.m. off-peak period due to such a p.m. peak period congestion pricing policy. In an attempt to remedy this problem of the MNL, the OGEV structure is examined.



## ORDERED GENERALIZED EXTREME VALUE (OGEV) MODEL

The OGEV structure generalizes the MNL structure by allowing an increased degree of sensitivity (due to excluded exogenous factors) between adjacent departure time alternatives compared to between non-adjacent departure time alternatives. Thus, it is not limited by the IIA restriction. The OGEV is similar conceptually to the nested logit (NL) model, which allows for correlation between the error terms of alternatives that are in the same subset, or “nest”, within the tree structure of the model. The NL, however, is restrictive in that each alternative can belong to only one nest, and so each alternative’s error term can only be correlated with the error terms of other alternatives within the same nest (Small 1987).

The main difference between the OGEV and the NL is that with the OGEV structure, the subsets are allowed to overlap, so that an alternative can belong to more than one subset. With the NL, the subsets are mutually exclusive. The OGEV is designed for discrete choice decisions where the alternatives have a natural ordering, which may be the case with departure time. By including an alternative in nests with the alternatives that are before it and after it in the natural ordering, the OGEV allows for what Small (1987) terms “proximate covariance”, where alternatives that are close to each other in the ordering have error terms that are correlated.

This research uses the standard OGEV, a specific form of the general OGEV in which the degree of correlation is assumed to be equal across subsets of alternatives. The choice probability given by the standard OGEV for an alternative  $i$  from a selection of  $J$  alternatives is:

$$P(i) = \sum_{r=i}^{i+M} q(i|B_r) Q(B_r) \quad (3.3)$$

where

$$q(i|B_r) = \frac{w \exp\left(\frac{V_i}{\rho}\right)}{\exp(I_r)} \quad (3.4)$$

$$Q(B_r) = \frac{\exp(\rho I_r)}{\sum_{s=1}^{J+M} \exp(\rho I_s)} \quad (3.5)$$

$$I_r = \log \sum_{j \in B_r} w \exp\left(\frac{V_j}{\rho}\right) \quad (3.6)$$

$$w = \frac{1}{M+1} \quad (3.7)$$

$$B_r = \{j \in \{1, \dots, J\} | r - M \leq j \leq r\} \quad (3.8)$$

$$0 < \rho \leq 1 \tag{3.9}$$

$B_r$  represents the subsets of alternatives  $J$  such that there are  $(J+M)$  subsets, each containing anywhere from 1 to  $(M+1)$  elements.  $\rho$  is called the dissimilarity parameter, and indicates the degree of correlation between the alternatives in the same subset.  $\rho = 1$  indicates perfect correlation between the alternatives within a subset (i.e. the choice between alternatives in the same subset is deterministic), while  $\rho = 0$  indicates no correlation between the alternatives in the same subset (in which case the model collapses to the MNL).

### **CHOICE BETWEEN THE MNL AND OGEV MODEL STRUCTURES**

For all trip categories, a preferred model specification was developed based on the MNL structure and then the OGEV structure was tested using this preferred specification. The OGEV structure used had  $M = 1$ , resulting in up to two alternatives in each subset. Therefore, the error term of each departure time alternative is correlated only with the error terms of the immediately adjacent departure time alternatives. With this structure, implementation of congestion pricing in the p.m. peak, for example, will result in a larger proportionate increase in the p.m. off-peak choice probability relative to the a.m. off-peak choice probability. A determination of the preferred model type was made after examination of both the MNL and OGEV structures.

## **CHAPTER 4: SAMPLE FORMATION AND VARIABLE SPECIFICATION**

### **DATA SOURCE**

The primary data source used for this analysis was the 1996 activity survey conducted in the Dallas-Fort Worth metropolitan area by the North Central Texas Council of Governments (NCTCOG). This survey included an activity diary to be filled out by all members of the household. The activity diary collected information on all activities undertaken during the diary day. For non-travel activities, information on the activity type, start and end times of participation, and location was collected. For travel activities, information on the mode of travel used, costs incurred, and trip duration was collected. In addition, the survey elicited individual and household socio-demographic information.

The secondary data source for this analysis was a level-of-service (LOS) data file obtained from NCTCOG which provided information on times, costs and distances for travel between each pair of the 919 Transportation Analysis Process (TAP) zones in the Dallas-Fort Worth metropolitan planning area. The LOS data varied by travel mode (drive alone, shared-ride and transit) and by time of day (peak and off-peak).

### **SAMPLE FORMATION**

The process of developing the sample for analysis involved several steps. First, the raw composite (travel and non-travel) activity file was converted into a corresponding trip file. In doing so, information was retained on the type of activity pursued at, and the TAP zone identifier for, the origin and destination ends of each trip. The start and end times of each trip were also retained from the activity file.

Second, the 36-category typology used in defining activity types in the original survey was collapsed into a broader eight-category classification. These eight broad activity categories were home, work, school, personal business, community activities, social/recreational, shopping, and other (for ease in presentation, the social/recreational category will henceforth be referred to simply as the recreational category, the personal business category as the personal category, and the community activities category as the community category). Table 2 provides the disaggregate activity types that were combined into the broader activity categories used in this analysis.

TABLE 2: NON-WORK ACTIVITY TYPE CLASSIFICATIONS

<b>Activity Category</b>	<b>Activity Types</b>
Social/Recreational	Dining out Gym/health club Exercise and recreation Entertainment Visiting friends/relatives
Shopping	Grocery (including housewares, medicine) Non-Grocery (furniture, clothes, appliances)
Personal Business	Medical visits Buying gas Banking, post office, utilities
Community	Community meetings Political and civic events Volunteer work Religious services and meetings

Third, those trips that were home-based recreational, shopping, personal business, or community activity trips were identified and selected using the activity type designations at each end of the trip. Home-based trips include all trips from home to an activity, as well as trips from an activity to home. As indicated earlier, the analysis in this paper is confined to trips of these four purposes because they constitute a major fraction of total home-based non-work trips (in the Dallas-Fort Worth data these four trip purposes together represent about three-fourths of all home-based non-work trips).

Fourth, the departure time of each trip was associated with one of the following six time periods of the day: early morning (midnight-6:30 a.m.), a.m. peak (6:30 a.m.-9:00 a.m.), a.m. off-peak (9:00 a.m.-noon), p.m. off-peak (noon-4:00 p.m.), p.m. peak (4:00 p.m.-6:30 p.m.), and evening (6:30 p.m.-midnight). The time periods for the a.m. and p.m. peaks were based on the peak periods definitions employed by NCTCOG in the Dallas-Fort Worth area. The times for the off-peak periods were determined by splitting the remaining blocks of time at noon and midnight. The dependent variable in the analysis was the choice of departure time among these six time periods.

Fifth, the trip data was matched with the appropriate socio-demographic characteristics of the individual pursuing the trip, and his household.

Sixth, the appropriate LOS data was appended to each trip record based on the origin/destination TAP zones and the mode used for the trip (almost all trips for shopping,

recreational, personal, and community activity were pursued using the drive alone, shared-ride or walk modes, and the analysis is restricted to trips using one of these modes; interestingly, there was not a single home-based shopping, recreational, personal, or community trip in the sample that used public transportation). The drive alone and shared-ride LOS information was obtained from the TAP zone-level LOS data file provided by NCTCOG. The walk LOS information was computed from the distance between TAP zones and an assumed walk speed of 3 miles per hour.

Finally, several screening and consistency checks were conducted on the resulting data set from the previous steps. Figure 2 shows a flowchart of this screening process and the resulting number of sample observations for each trip purpose. As part of the screening process, observations that had missing data on departure times and/or on the location of the origin/destination ends of the trip were eliminated (the latter information is needed to obtain the level-of-service information for the trip). Several observations had missing income information and income for such observations was imputed based on a relationship between income and relevant socio-demographic attributes estimated from the sample of individuals who provided income information. Socio-demographic attributes that were significant predictors of income in the regression model included race, age, gender, educational level, status as a student, status as a homemaker, disability, and number of work hours per week.

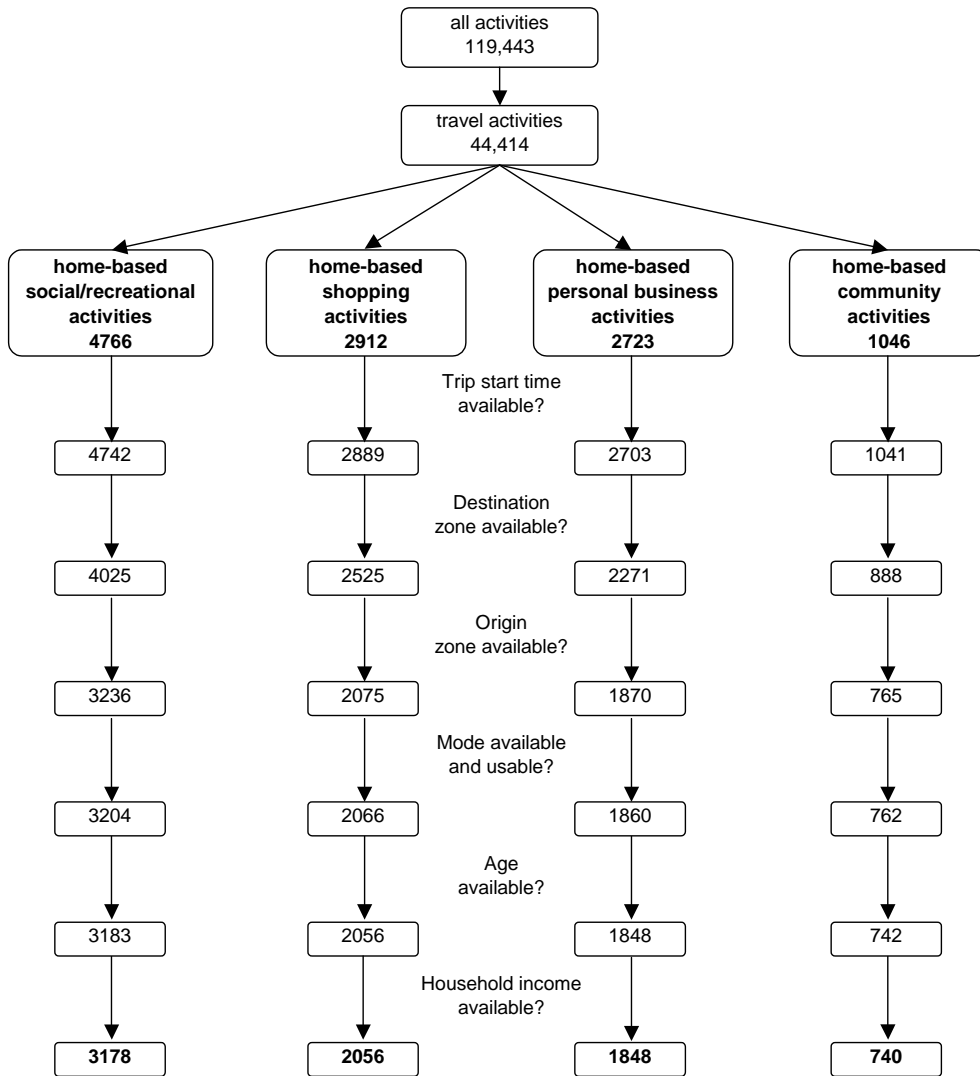


Figure 2: Flowchart of data screening process

The final samples for analysis included 3178 observations for the home-based recreational trip category, 2056 observations for the home-based shopping trip category, 1848 observations for the home-based personal trip category, and 740 observations for the home-based community activity category. These final samples represent approximately two-thirds of the total number of trips in the corresponding trip categories in the original raw data. The primary reason for the substantial reduction was the lack of origin/destination TAP zone data for many trips (because of which LOS information for these trips could not be determined). However, the

observed split of trips among the six time periods was approximately the same in the final sample as in the original raw data.

## SAMPLE DESCRIPTION

The distribution of departure times for the four trip categories in the final samples is presented in Figure 3. For both the recreational and shopping categories, the number of trips increases as the day progresses, while personal and shopping trips show a non-monotonic trend during the day. The temporal differences in trip-making among the categories highlight the need to separate non-work trips into more specific categories for analysis.

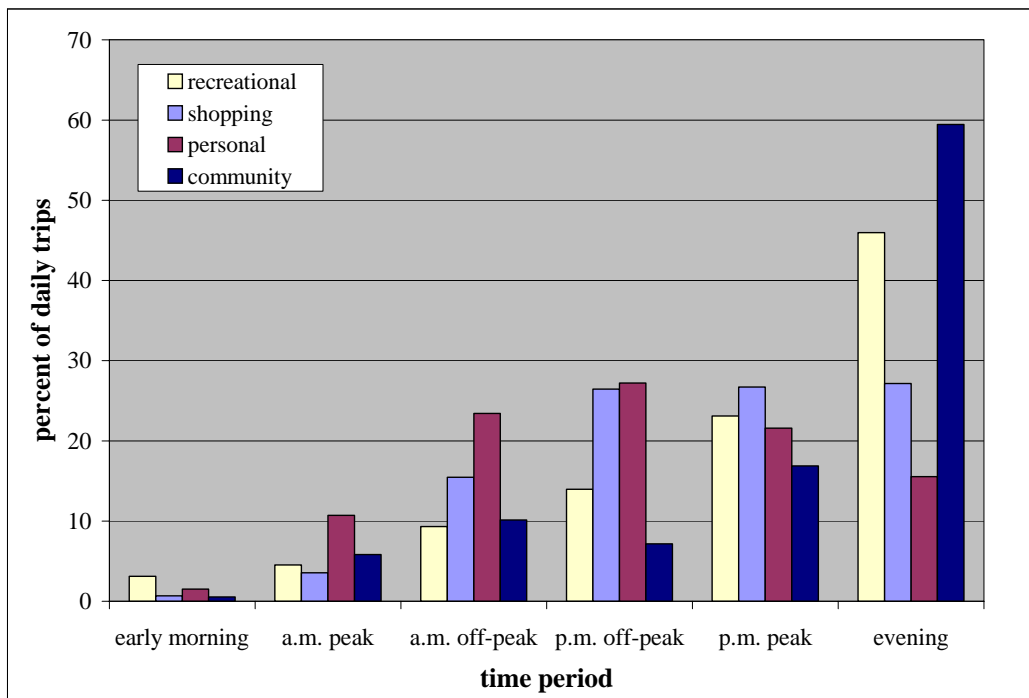


Figure 3: Temporal distribution of home-based recreational, shopping, personal, and community trips

The increase in trip-making as the day progresses is very noticeable for recreational trips, which have by far the greatest number taking place in the evening. For shopping trips, there is little variation in the percentage of trips among the later periods of the day (i.e., the p.m. peak, p.m. off-peak and evening periods). Personal trips experience their maximum in the p.m. off-peak, and subsequently decrease; this is quite reasonable since most businesses attracting trips classified as personal would be closed during the p.m. peak period and after. Community trips experience a minor crest in the a.m. off-peak and an overwhelming maximum in the evening. As

might be expected, very few trips of any type occur in the early morning or morning peak hours. Overall, the temporal distributions of recreational and community trips are quite similar, as are the temporal distributions of shopping and personal trips. Table 3 shows the distribution of trips among the drive alone, shared-ride and walk modes. The dominant mode for recreational and community trips is shared-ride, indicating joint activity participation by several family members. The dominant mode for shopping and personal trips is drive alone. This suggests less joint activity participation for shopping and personal trips than for recreation and community trips. Finally, recreational trips are more likely to be pursued using the walk mode compared to shopping or personal trips. Community trips using the walk mode were excluded from the sample, as there were not enough trips in the sample to justify the inclusion of the walk mode as an independent variable in the model.

TABLE 3: DISTRIBUTION OF MODES USED FOR RECREATIONAL, SHOPPING, PERSONAL, AND COMMUNITY TRIPS

Trip Category	Mode Used		
	Drive Alone	Shared Ride	Walk
Recreational	33.7%	59.9%	6.4%
Shopping	55.3%	42.2%	2.5%
Personal	63.8%	34.0%	2.2%
Community	43.6%	56.4%	N/A

An important note must be made here about travel mode choice. For this analysis, mode choice was considered as being exogenous to departure time choice. This decision is based on the observation that almost all non-work trips are pursued using a personal automobile (see Table 3). The distinction between drive alone and shared-ride modes is likely to be a reflection of how many individuals choose to participate jointly in the activity, not a conscious decision of which travel mode to use for the trip. It was assumed that the decision to engage in an activity with other individuals is made prior to the decision of what time to travel, and therefore it is assumed that travel mode choice between the drive alone and shared-ride modes is pre-determined. Also, there is little variation in walk mode characteristics across different times of the day and hence it is quite reasonable to consider the choice of the walk mode to be exogenous to departure time choice. That is, individuals are likely to first make a decision to walk or not for a recreational/shopping activity, and then determine the time of day to pursue the activity.



## VARIABLE SPECIFICATION

Several types of variables were considered in the four models of departure time choice. These include individual socio-demographics, household socio-demographics, individual employment-related attributes, and trip-related characteristics.

Individual socio-demographic characteristics explored in the specifications included dummy variables for sex, ethnicity and education level, and continuous representations (both linear and spline) of income and age. Household socio-demographic characteristics considered in the model included household size, the number and age distribution of children, the number and employment status of household adults, and the continuous value of household income. Individual employment-related attributes included dummy variables for employed individuals, self-employed individuals, students, homemakers and retired persons, as well as a continuous variable indicating the number of hours worked per week. The final category of variables was the trip-related characteristics, including whether the trip was to or from the given activity, the mode used for the trip, the trip travel time and trip travel cost.

For many of the variables discussed above, there were strong a priori expectations regarding the direction of their impact on departure time choice. For example, employed individuals are unlikely to undertake non-work trips during the mid-day periods. Similarly, it was anticipated that individuals whose households have very young children would be likely to avoid the evening periods because of the biological needs of young children toward the end of the day. However, for some of the variables we considered in the specification, there were no strong a priori expectations about the directionality of their effect. These variables were included to explore their effects on temporal trip-making patterns using empirical data.

The final model specifications were determined by adopting a systematic process of introducing new variables to the market shares model (i.e., the constants only model), eliminating statistically insignificant variables, and combining variables when their effects were not significantly different. This systematic statistical process was informed by intuitive considerations and parsimony in the representation of variable effects.

## **CHAPTER 5: EMPIRICAL RESULTS**

This chapter presents the empirical results of departure time choice for four non-work trip purposes: home-based recreation, home-based shopping, home-based personal business, and home-based community activities.

The chapter is organized in six sections. The next section presents the results of statistical tests comparing the performance of the two alternative model structures considered for departure time choice modeling: the MNL model and the OGEV model. Section 5.2 evaluates the performance of the departure time models proposed in this thesis with the commonly used practice of applying fixed factors to apportion daily travel to different time periods of the day. Sections 5.3 through 5.6 discuss the effect of each category of variables on departure time choice for the different trip purposes.

### **MNL STRUCTURE VERSUS OGEV STRUCTURE**

For all trip categories, the empirical results indicated that the MNL structure is adequate in representing departure time choice in terms of data fit. For the recreational, shopping, and personal business trip purposes, the dissimilarity parameter in the OGEV model was greater than 1, implying inconsistency with utility-maximizing theory (for the recreational purpose, the dissimilarity parameter was 1.489 with a t-statistic of 1.18 for testing the parameter against the null of 1.0; for the shopping purpose, the corresponding parameter value and t-statistic were 1.451 and 0.91, respectively; finally, for the personal business purpose, the parameter value and t-statistic were 2.148 and 1.75, respectively). For community trips, the dissimilarity parameter was less than 1, but not significantly different from 1.0 (the parameter value and t-statistic were 0.671 and 1.57, respectively). Hence, we chose the MNL structure in the current analysis.

### **PROPOSED MODELS VERSUS FIXED FACTOR APPROACH**

The current practice in many MPOs of applying fixed factors to apportion daily travel to various time periods is equivalent, in this analysis framework, to a model specification with only constants. For each trip purpose, this restrictive model can be statistically tested against the model proposed in this paper using a standard likelihood ratio test.

Table 4 presents the log-likelihood value at market shares (corresponding to the application of fixed factors) and the log-likelihood value at convergence for the best MNL specification. For each trip purpose category, the table also computes the likelihood ratio test value for testing the restrictive “fixed factor” model with the more general model proposed in this thesis. As can be clearly observed, the likelihood ratio test values far exceed the appropriate chi-squared values at any reasonable level of significance. Thus, the tests strongly reject the fixed factor models in favor of the models proposed in this thesis.

TABLE 4: SUMMARY OF MODELS

	Recreational	Shopping	Personal	Community
Number of Observations	3178	2056	1848	740
Log Likelihoods				
Market Shares	-4576.52	-3082.98	-2988.56	-905.69
Convergence	-4056.22	-2767.12	-2671.45	-715.45
Likelihood ratio test value	1040.60	631.72	634.23	370.48
Degrees of freedom	19	17	18	19
$\chi^2$ value at 99% confidence	36.19	33.41	34.81	36.19

The next four sections present and discuss the effects of each category of variables on the different trip purposes. For all alternative-specific variables (*i.e.*, for all variables except the total time variable), the evening time period is the base. In instances where only a few time periods appear for a variable, all of the excluded time periods, including the evening period, form the base. One additional point must be made about the model specification for community trips; because there were so few trips observed in the early morning time period, no alternative-specific variables were estimated for that period (it is included in the base for all variables).

The alternative-specific constants for all four models are presented in Table 5 and will not be discussed in this analysis because they have no intrinsic meaning. Rather, they adjust for the range of variable values in the sample and capture overall intrinsic preferences for departing during each time period.

TABLE 5: ALTERNATIVE-SPECIFIC CONSTANTS

Variables	Recreational		Shopping		Personal		Community	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Constant								
Morning	-3.673	-22.18	-5.216	-13.79	-3.338	-11.38	-4.700	-9.36
a.m. peak	-4.295	-15.41	-2.757	-8.75	-3.096	-10.36	-3.995	-7.85
a.m. off-peak	-3.002	-14.59	-0.991	-4.08	-0.863	-3.89	-2.391	-7.50
p.m. off-peak	-2.227	-11.66	-0.260	-1.11	-0.252	-1.18	-4.393	-8.04
p.m. peak	-1.051	-10.57	-0.402	-2.57	0.201	0.74	-2.923	-9.32

## INDIVIDUAL SOCIO-DEMOGRAPHIC VARIABLES

Table 6 presents the parameter estimates for the individual socio-demographic variables in the final model specification. The first individual socio-demographic variable in the table is a female dummy variable. The results indicate that gender does not appear to play a very important role in departure time choice. Only in the personal business category is it a significant variable, and even then, only for the early morning period, in which women are less likely than men to make personal trips. This may reflect the family-associated responsibilities of women in the morning.

The age variables, in general, indicate a preference of older individuals (independent of work status) to pursue non-work trips during the middle of the day, and especially during the off-peak periods. This may be a reflection of their physiological need for more time to start the day and a desire to arrive home early because of safety/security considerations among older individuals. While there is a generic trend to stay away from the early and late parts of the day for any trip purpose, there are some differences across trip purposes. For recreational trips, the coefficients suggest that older individuals avoid the early morning, p.m. peak, and late evening periods. The effect of age on departure time for shopping trips is similar, except that the p.m. peak is preferred to the a.m. peak for these trips. Age effects for personal business activities indicate that older individuals stay away from travel during the evening period, and also prefer the earlier times of the day (morning through p.m. off-peak) to the p.m. peak. Finally, age has only a marginal effect on community trips, indicating a preference of older individuals for the p.m. off-peak. For all trip purposes, the p.m. peak is one of the favored time periods for travel for older individuals (in addition to the linear effect presented in the table, non-linear spline effects of age and dummy variables for age categories were also explored; however, these non-linear effects did not dramatically improve data fit and were also difficult to interpret).

Several ethnicity variables appear to affect departure time choice. These results are rather difficult to explain, but are retained because of the rapidly changing racial composition of the Texas and U.S. populations. The variables tested (with the base race being Caucasian) included indicators for Asian, African-American, Native American, mixed race, and "other" race (this category contains a high percentage of Hispanic individuals). For recreational trips, the only ethnicity variable having a significant effect is the variable identifying if a person is of mixed race or not. The parameter on the mixed race variable indicates that individuals with such a family heritage are more likely to pursue recreational activities during the mid-day periods. Two ethnicity variables, African-American and "other", significantly affect departure time for personal

TABLE 6: INDIVIDUAL SOCIO-DEMOGRAPHICS

Variables	Recreational		Shopping		Personal		Community	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Female								
Morning	-	-	-	-	-1.014	-2.30	-	-
Age								
Morning	-	-	-	-	0.033	7.31	-	-
a.m. peak	0.020	6.83	-	-	0.033	7.31	-	-
a.m. off-peak	0.020	6.83	0.027	6.63	0.033	7.31	-	-
p.m. off-peak	0.020	6.83	0.027	6.63	0.033	7.31	0.028	3.20
p.m. peak	-	-	0.020	5.80	0.016	2.86	-	-
Ethnicity								
Mixed race								
a.m. off-peak, p.m. off-peak	0.918	3.84	-	-	-	-	-	-
Black								
p.m. off-peak, p.m. peak	-	-	-	-	-0.510	-2.34	-	-
Asian								
p.m. peak	-	-	-	-	-	-	2.767	2.41
Other								
a.m. peak, a.m. off-peak	-	-	-	-	-0.662	-2.17	-	-
p.m. off-peak	-	-	-	-	-0.662	-2.17	1.606	2.49
Income (thousands)								
a.m. peak, a.m. off-peak, p.m. off-peak	-	-	-0.055	-2.56	-0.042	-2.84	-	-

trips. The parameter on the African-American variable indicates that these individuals are less likely to choose the p.m. off-peak for personal business activities. Individuals in the “other” race category are less likely to pursue personal activities in the a.m. peak, a.m. off-peak, or p.m. off-peak periods. The effect of ethnicity on community trips shows a preference by Asians for travel in the p.m. peak, and a preference by individuals in the “other” race category for travel in the p.m. off-peak.

The final socio-demographic variable in the table is individual income. Individual income affects departure time choice for shopping and personal trips only. For both of these categories, the effect of income indicates that individuals with higher income tend to avoid trip-making during the a.m. peak and mid-day periods. This may be the result of tighter schedule constraints of high-income-earning individuals during the mid-day. As with the age variable, spline effects were tested for the income variable to see if its effect on departure time was non-linear. However, the spline representation did not improve the model significantly, and the results were difficult to interpret.

## **HOUSEHOLD-LEVEL SOCIO-DEMOGRAPHIC VARIABLES**

Several household socio-demographic attributes were tested; however, the majority of the variables appearing in the final specifications are those associated with the presence and age distribution of children. The parameter estimates for the household socio-demographics are shown in Table 7.

The presence of young children (less than 5 years of age) in the household affects the timing of recreational, personal, and community activities in a similar manner. The results show that individuals whose households have young children are more likely to pursue recreational trips during the earlier periods of the day (early morning through p.m. off-peak) than in the p.m. peak or evening periods. This may be related to the biological needs of young children toward the end of the day. A similar result can be observed for personal trips; the p.m. peak is the least preferable time of day for these trips. For community trips, the a.m. peak and a.m. off-peak are the preferred travel periods for households with young children. Shopping activities, however, differ from the other non-work activity types with regard to the effect of young children. The presence of young children in the household suggests a lower likelihood of participation in shopping trips during the mid-day (a.m. and p.m. off-peak) hours. Perhaps this is a result of the tendency to shop alone by an adult who must remain at home in the mid-day to take care of the

TABLE 7: HOUSEHOLD-LEVEL SOCIO-DEMOGRAPHICS

Variables	Recreational		Shopping		Personal		Community	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Presence of children age 5 or under								
Morning	0.988	8.09	-	-	-	-	-	-
a.m. peak	0.988	8.09	-	-	-	-	1.522	4.36
a.m. off-peak	0.988	8.09	-0.407	-2.41	-	-	1.522	4.36
p.m. off-peak	0.988	8.09	-0.407	-2.41	-	-	-	-
p.m. peak	-	-	-	-	-0.724	-3.57	-	-
Presence of children age 6 to 11								
morning, a.m. peak	-0.421	-2.27	0.640	2.54	-	-	-	-
Presence of children age 12 to 15								
a.m. off-peak	-	-	-	-	-0.371	-2.57	-	-
p.m. off-peak	0.384	3.85	-0.332	-1.88	-0.371	-2.57	-	-
p.m. peak	0.384	3.85	-	-	-	-	-	-
Presence of children age 6 to 15								
a.m. peak, a.m. off-peak	-	-	-	-	-	-	-0.932	-3.12
Income (thousands)								
a.m. peak, a.m. off-peak, p.m. off-peak, p.m. peak	-	-	-	-	-	-	0.061	2.78



needs of the young children. Instead, the individual may choose to shop at other times of the day when another adult is available to care for the children.

The effect of older children on trip timing is, in most cases, opposite of the effect of young children. Individuals whose households have children between the ages of 6 and 15 tend to pursue recreational trips during the p.m. off-peak and p.m. peak. This is quite intuitive since these periods offer convenient times for joint activity participation in recreational activities with school-going children, and are also the times when children are most likely to be participating in recreational activities that may require a ride from a parent. However, members of households with older children are less likely to pursue shopping and personal trips during the mid-day. This may be because individuals in these households tend to have other commitments during the day that preclude shopping and personal trip-making. Members of households with older children also tend not to make community trips in the a.m. peak and a.m. off-peak, likely for much the same reason.

Overall, it appears that recreational, personal, and community activities are likely to be pursued jointly with children and so participation in such activities appears to be organized around the schedule availability of children (*i.e.*, during the day for households with young children and late in the day for households with older children). However, shopping activities may be pursued alone and so these activities are scheduled in periods when young children have fewer biological needs or during times when older children are at school. For all four categories, the number of children in the household does not have any significant impact beyond that of the presence of children.

The final household level characteristic examined was household income. Interestingly, community trips are the only category for which household income, rather than individual income, affects departure time. The parameter on household income indicates that members of higher-income households are more likely to participate in community activities during the day than in the late evening or early morning time periods. This may result from members of higher-income households (although not perhaps the high-wage earners themselves) having, in general, more schedule freedom during the day and choosing to participate in community activities then. The parameter effect obviously must be applied to working members of the household as well, but its strength may be overshadowed by the effects of some of the other, work-related variables.

## INDIVIDUAL EMPLOYMENT-RELATED ATTRIBUTES

Employment-related attributes make such a substantial contribution to departure time decisions that they are considered in this analysis as a separate category of variables. The parameter estimations for the employment-related variables are given in Table 8.

The effect of the number of hours of work variable is quite consistent across all trip categories. It indicates that individuals who are employed and have a substantial work commitment are very unlikely to participate in non-work activities during the mid-day periods (i.e., the a.m. and p.m. off-peak periods). This is a reasonable result since employed individuals are typically at work during these times. These individuals are also less likely to participate in non-work activities in the peak periods (especially the a.m. peak) relative to the evening period. Overall, individuals who are employed and work many hours are likely to participate in non-work activities during the evening period because of work schedule constraints during the earlier times of the day (technically speaking, the results suggest that working individuals are as likely to participate in activities during the early morning period as in the evening period; however, this result is simply a statistical manifestation of the extremely few number of working individuals who choose the early morning period).

The parameter indicating whether an individual was self-employed, as opposed to externally (non-self) employed, also exhibits considerable consistency across categories. Self-employed individuals are more likely to participate in recreational, shopping, and personal activities during the mid-day (a.m. off-peak and p.m. off-peak) than externally employed individuals. That is, self-employed individuals are able to “sandwich” an activity from home between periods of a.m. and p.m. work because of lesser schedule rigidity. For personal trips, this effect also carries over into the a.m. and p.m. peak periods, indicating that self-employed individuals are more likely than externally employed persons to make personal trips during the peak periods. Across trip purposes, the greatest difference in the effect of the self-employed variable is for community trips. In this category, self-employment affects only the p.m. peak period, again increasing the likelihood of participation. This may be due, in part, to the temporal distribution of community activities; very few take place prior to the p.m. peak, so the self-employment effect may be statistically negligible during those periods.

Like the employment variables, the student variable is also reasonably consistent across categories. The coefficients on this variable suggest a preference by students for the p.m. peak and evening periods for participation in recreational and shopping activities, an intuitive result because students are generally free from academic obligations at these times. Students tend to

TABLE 8: INDIVIDUAL EMPLOYMENT-RELATED ATTRIBUTES

Variables	Recreational		Shopping		Personal		Community	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Hours worked per week								
a.m. peak	-0.029	-6.43	-0.021	-3.43	-0.017	-4.90	-0.033	-3.64
a.m. off-peak	-0.049	-12.09	-0.057	-12.18	-0.042	-11.81	-0.061	-6.23
p.m. off-peak	-0.041	-12.70	-0.048	-12.71	-0.042	-11.81	-0.046	-3.26
p.m. peak	-0.016	-6.97	-0.016	-5.68	-0.017	-4.90	-0.026	-3.83
Self-employed								
a.m. peak	-	-	-	-	0.568	1.83	-	-
a.m. off-peak, p.m. off-peak	0.994	6.18	0.721	3.49	1.108	3.66	-	-
p.m. peak	-	-	-	-	0.568	1.83	1.028	2.50
Student								
a.m. peak, a.m. off-peak	-0.768	-5.24	-1.204	-4.89	-	-	-2.079	-4.48
p.m. off-peak	-0.768	-5.24	-0.907	-4.06	-	-	-	-
p.m. peak	-	-	-	-	0.392	1.92	-	-
Homemaker								
p.m. off-peak	-	-	-	-	-	-	0.997	2.49
p.m. peak	-	-	-	-	-	-	-1.082	-2.22
Retired								
p.m. off-peak, p.m. peak	-	-	-	-	-	-	0.783	2.88

prefer the p.m. peak period for personal trips, and they avoid the a.m. peak and a.m. off-peak periods for participation in community activities. The reasoning behind this is much the same as for recreational and shopping trips. An interesting difference between students and employed individuals (externally-employed or self-employed) is that students are equally likely to participate in non-work activities (with the exception of personal trips) during the p.m. peak and evening periods, while employed individuals are more likely to choose the evening period than the p.m. peak. This difference may be attributed to the increased flexibility of students during the p.m. peak, since the typical school day of a student ends earlier than the typical workday of an employee.

In addition to the above variables, there were two attributes that had significant effects for the personal business category, but were not significant in any of the other trip categories. Individuals who were primarily occupied as homemakers prefer the p.m. off-peak for personal activity participation, while avoiding the p.m. peak. These individuals probably have more schedule freedom in the early afternoon than in the p.m. peak, when children are arriving home from school. However, it is interesting that the personal business category is the only one in which this effect was exhibited.

Finally, retired persons prefer the p.m. off-peak and p.m. peak for personal activity participation. As with the homemaker variable, this variable is present only in the personal business model.

For each trip purpose, a specification was considered that also included a dummy variable corresponding to external-employment in addition to the number of hours and self-employment variables. Such a variable would add a generic effect (i.e., independent of hours of work) of being externally employed. The resulting specification showed a marginal (though statistically significant) improvement in data fit, but also led to results that were quite difficult to interpret. Therefore, the external-employment dummy variable was excluded from the model. An alternative specification that replaced the hours of work variable with the external-employment dummy variable also performed well and provided easy-to-interpret results, but was statistically inferior to the current specification (however, this alternative specification might offer forecasting advantages since it only requires forecasting employment status, not hours of work).

## **TRIP-RELATED ATTRIBUTES**

The trip-related attributes make up the final group of variables, and their parameter estimates are provided in Table 9. The first variable indicates whether a trip was from home to an

TABLE 9: TRIP-RELATED ATTRIBUTES

Variables	Recreational		Shopping		Personal		Community	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Home to activity								
Morning	0.848	4.03	1.251	5.35	-	-	-	-
a.m. peak	2.386	10.35	1.251	5.35	2.926	11.69	2.593	5.27
a.m. off-peak	1.495	10.50	0.577	4.51	1.165	8.65	1.593	5.39
p.m. off-peak	0.610	5.16	-	-	0.548	4.29	-	-
p.m. peak	1.323	13.71	-	-	-	-	2.323	8.43
Drive alone mode								
Morning	1.247	12.08	1.199	4.66	-	-	-	-
a.m. peak	1.247	12.08	1.199	4.66	-	-	0.934	4.17
a.m. off-peak	1.247	12.08	0.437	3.94	0.515	3.75	0.934	4.17
p.m. off-peak	1.247	12.08	0.437	3.94	0.361	2.78	0.934	4.17
p.m. peak	0.296	2.68	-	-	-	-	-	-
Total travel time	-0.022	-2.37	-	-	-	-	-	-

activity (as opposed to from the activity back home). The home-to-activity variable proves to be highly significant in all four models. For recreational trips, the results indicate that trips from home to an activity are likely to be pursued before the evening periods, and especially in the a.m. peak period. This is expected, since most trips originating in the a.m. peak are likely to be leaving home. The same is true, though to a lesser extent, for the a.m. off-peak period. The increased likelihood of trips from home to a recreational activity in the p.m. peak compared to the morning and p.m. off-peak periods can be attributed to the temporal “resurgence” in recreational participation during the p.m. peak period; on the other hand, a sizable fraction of home-based recreational trips in the early morning period are late return home trips from the previous evening’s recreational engagement and many p.m. off-peak home-based recreational trips are return home trips after recreational participation in the a.m. periods. The parameters on the home-to-activity variable for community trips indicate a pattern similar to that for recreational trips, with an overall preference for the a.m. peak period, and a temporal resurgence in the p.m. peak. The home-to-activity variable exhibits a different effect for shopping and personal trips. For these trip types, the impact is fairly straightforward; there is a strong preference to leave for shopping and personal activities during the earlier parts of the day (morning through a.m. off-peak for shopping trips, and a.m. peak through p.m. off-peak for personal trips).

The drive-alone dummy variable effects in the table indicate a general trend, over all trip purposes, toward the use of the drive alone mode during the earlier periods of the day and the use of non-drive alone modes (shared-ride and walking) during the later periods of the day. This is a rather intuitive result; trips during the day are more likely to be pursued alone, while the late afternoon and evening periods are times that are most convenient for joint activity participation and for walking. The differences between trip categories are slight; for personal trips, the preference is to pursue drive-alone trips during the mid-day, while for shopping trips, the morning and a.m. peak are preferred. Both recreational and community trips show a consistent preference for the daytime (p.m. off-peak and earlier), but drive-alone recreational trips are more likely to be made in the p.m. peak than in the evening. The overall preference for making drive-alone trips early in the day supports the hypothesis that trips made later in the day are more family-oriented, while trips made early in the day are individually-oriented.

Total travel time is the only LOS variable that demonstrates any significance whatsoever, and even that is only for recreational trips (a travel cost variable was also considered, as were separate representations of in-vehicle and out-of-vehicle travel time). The negative effect of travel time in the recreational trip model is consistent with a priori expectations; individuals prefer departure times that result in shorter travel times. However, the lack of any significant effect of trip travel time on departure time choice for the other purposes is interesting. Two related issues

may be at work here. First, many of these activities are organized around work constraints and other household schedule considerations, and are pursued at the most convenient time within these schedule considerations. Travel time may therefore not play a substantial role in the departure time decision. Second, in the current data set the average lengths of shopping, personal, and community trips are shorter than the average length of recreational trips. In the context of the shorter lengths of these trips, there is likely to be smaller variation in travel times across time periods (in this data, the travel time variation across time periods is lower for shopping, personal, and community trips than for recreational trips). This may be manifesting itself in the form of the lack of any travel time effect on departure time decisions for shopping, personal, and community trips. Nonetheless, it is a somewhat unexpected result that travel time has such a minor effect on departure time choice.

## CHAPTER 6: CONCLUSIONS

### SUMMARY

This thesis presents models for home-based recreational, shopping, personal business, and community trip departure time choice. The departure time alternatives are represented by six temporally contiguous discrete time periods that collectively span the entire day.

Two model structures are explored for departure time choice among the six discrete periods: the multinomial logit (MNL) and the ordered generalized extreme value (OGEV) structures. The latter is a generalization of the former and allows an increased degree of sensitivity (due to excluded factors) between temporally adjacent departure periods compared to temporally non-adjacent periods. For all trip purposes, our analysis indicates that the MNL model is adequate to model departure time choice.

The empirical analysis in the paper uses the 1996 activity survey data collected by the North Central Texas Council of Governments (NCTCOG) in the Dallas-Fort Worth area. Several sets of variables were considered in the model specifications, including individual and household socio-demographics, employment-related attributes and trip-related characteristics. Important overall results from the empirical analysis are as follows:

- gender does not have an important role in departure time choice,
- older individuals are most likely to participate in non-work activities during the mid-day,
- high-income-earning individuals avoid the mid-day periods for shopping and personal business,
- individuals with very young children (under 5 years of age) in their households are unlikely to pursue most activities during the p.m. peak and evening, presumably because of the increased biological needs of young children during these late times of the day,
- individuals with children below 5 years of age are unlikely to participate in shopping activities during the mid-day,
- individuals with children above 5 years of age in their households, on the other hand, are most likely to pursue recreational activities during the p.m. peak period since this is the most convenient time to jointly participate in recreational activities,
- individuals with children above 5 years of age are unlikely to pursue recreational, personal, and community activities during the mid-day,



- employed individuals and students are most likely to participate in non-work activities during the latter parts of the day,
- self-employed individuals are more likely than externally employed individuals to “sandwich” a recreational, shopping, or personal activity between the a.m. and p.m. work periods,
- trips to a non-work activity from home tend to be made before the evening period,
- trips pursued together with others or by walk are likely to be undertaken during the p.m. peak and evening periods, and
- in the current empirical context, the only level-of-service variable that has a significant impact is trip travel time and even this applies only for recreational trips.

Due to the use of a trip-based approach and the choice of the familiar MNL model structure, the current modeling effort can be incorporated relatively easily within the travel demand model system used by most MPOs for transportation planning. The results show the models proposed in this thesis to be an improvement over the fixed-factor approach generally used to accommodate the time-of-day dimension of travel choice.

## **IMPLICATIONS OF THE EFFECT OF SOCIO-DEMOGRAPHIC AND EMPLOYMENT-RELATED ATTRIBUTES**

The empirical results indicate the strong impact of socio-demographic and employment-related characteristics on departure time choice for non-work trips. These results have substantial implications for transportation planning analysis. Specifically, the analysis suggests that ignoring the effects of these variables can lead to misinformed transportation planning and air quality decisions because of changing demographic and employment-related trends over the next few decades. For instance, 18% of the population will be 60 years or older in 2020 compared to about 13% today in the State of Texas, according to projections by the Texas State Data Center. Similarly, there is a rise in inter-racial marriages, and trends suggest a consequent steep rise in individuals with a mixed race heritage over the next few decades (Census Bureau 1999a). The percentages of the population of Texas that are black and Asian are also expected to rise in the coming years (Census Bureau 1999b). The structure of the household is also changing rapidly with an increase in households with no children (projections suggest that households with no children below 18 years of age will increase from about 53% today to about 60% in the next decade (Census Bureau 1999c). The number of employed individuals in the household, and the number of self-employed individuals, are on the rise (Census Bureau 1999d) and this trend is

likely to continue. All of these demographic and employment changes will have an effect on departure time choices, and the departure time model in this paper can be used to assess these impacts and provide reliable information regarding the temporal distribution of trips for input to transportation policy and air quality analysis. Of course, application of this model for forecasting would require regional socio-demographic and employment forecasts of ethnicity, household structure, and employment arrangements in addition to the age and income forecasts that are commonly used by MPOs. These additional forecasts may be obtained from supplementary data sources, and the results presented here suggest that it is important for MPOs to pursue such an effort (see also Deakin, Harvey, Skabardonis, Inc. 1993 for a discussion of the importance of including socio-demographic and lifestyle issues in forecasting travel behavior).

The need to include socio-demographic and employment attributes is not only important because of changes in such variables over time, but also because of spatial differences in these variables within a metropolitan region. Applying fixed factors to apportion total daily travel to different times of the day assumes away the existence of spatial demographic variations and will, in general, lead to incorrect network assignment volumes by time of day. This, in turn, can lead to inaccurate VMT and speed estimates by time of day and, consequently, inaccurate transportation-air quality analysis.

## **IMPLICATIONS OF THE EFFECT OF LEVEL OF SERVICE RESULTS**

An interesting finding from the research in this thesis is that level-of-service characteristics do not appear to substantially impact departure time for non-work trips. This has significant implications for time-of-day specific transportation control measures (such as peak-period pricing or converting a general-purpose lane to a high occupancy vehicle use lane). Specifically, the results imply that there will be little to no temporal displacements of non-work trips because of such policies. This suggests that non-work trips may not be as temporally flexible as one might think. That is, an individual considers participation in non-work activities within the larger spectrum of daily activities that need to be pursued based on his individual circumstances and household structure characteristics, and this narrows down the time-of-day of non-work pursuits. Thus, scheduling issues may be so overpowering in activity participation that they render individuals insensitive to level-of-service changes. However, a couple of comments are in order here. First, the lack of sensitivity to level-of-service may be a result of little variation in times and costs across time periods in the sample. In other metropolitan areas where there are substantial time/cost differences across time periods (for example, because of congestion-pricing controls which are absent in the Dallas-Fort Worth area), the results may be different.

Second, the seeming lack of sensitivity to level-of-service may be partially attributable to the use of zone-to-zone network data where the same times and costs are assigned to all trips between a particular zonal pair. Zone-to-zone impedance is considered an attribute of each individual trip, resulting in a confounding of individual heterogeneity (variations in impedance measures across trips between the same zonal pair) and place heterogeneity (variations in impedance measures across zonal pairs). This can lead to incorrectly estimated parameters on the level-of-service variables. An approach to handle this issue would be to use a multi-level cross-classified model of the type proposed recently by Bhat (1999). However, despite the cautionary notes above, there is a suggestion in these results that trips for non-work purposes may not, after all, be as temporally flexible as widely perceived.

## **EXTENSIONS**

This thesis has presented models of departure time choice for recreational, shopping, personal business, and community activities. While this encompasses a broad range of non-work activities, one empirical extension of this work would be to estimate models for other trip purposes. School trips are a possible category of trips that, in some ways may resemble work trips, but may be different in other ways. In addition, it would be useful to break the current trip categories down into more disaggregate groupings. For example, instead of analyzing social and recreational trips together, these two purposes could be separated. Likewise, it would be interesting to investigate the differences between grocery shopping trips and other types of shopping trips.

Another useful empirical extension of the current work would be to estimate a model of departure time choice using a data set collected in an area where there are congestion-pricing or peak-period pricing control strategies. This would enable further analysis into the effect that level-of-service variables have on departure time choice. As mentioned before, the temporal variation in the level of service variables in the current data set was limited, and using a data set with greater temporal variation could provide some very insightful results.

A possible methodological extension of the current work would involve the use of a continuous-time hazard duration model for analyzing departure time choice decisions, as discussed in Chapter 3. This approach would obviate the need for the rather ad hoc boundaries associated with classifying the day into discrete time periods.

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