Technical Report Documentation Page

1. Report No. 3 FHWA/TX-03/4080-3	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Activity-Based Travel-Demand Analysis for Metropolitan Areas in Texas: Data Sources, Sample Formation, and Estimation Results.		5. Report Date September 2002
7. Author(s) Chandra R. Bhat, Sivaramakrishnan Srinivasan, Jessica Y. Guo		6. Performing Organization Code
		8. Performing Organization Report No. 4080-3
9. Performing Organization Name and Address Center for Transportation Research The University of Texas at Austin 3208 Red River, Suite 200 Austin, TX 78705-2650		10. Work Unit No. (TRAIS)
		11. Contract or Grant No. 0-4080
12. Sponsoring Agency Name and Address Texas Department of Transportation Research and Technology Implementation Office P.O. Box 5080 Austin, TX 78763-5080		13. Type of Report and Period Covered
		14. Sponsoring Agency Code

15. Supplementary Notes

Project conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration, and the Texas Department of Transportation.

16. Abstract

The project aims to comprehensively model the activity-travel patterns of workers as well as nonworkers in a household. The activity-travel system will take as input various land-use, sociodemographic, activity system, and transportation level-of-service attributes. It will provide as output the complete daily activity-travel patterns for each individual in the household. In addition to the short-term activity-travel decisions, longer-term decisions of household location, employment, and auto-ownership are also considered. This report presents detailed frameworks for modeling both the medium-term and the short-term decisions. Models were estimated using data from the Dallas-Fort Worth area. These empirical model results are presented and discussed in detail

17. Key Words	18. Distribution Statement
Activity-Based Analysis, Analysis Frameworks, Econometric models, Empirical results	No restrictions. This document is available to the public through the National Technical Information Service, Springfield, Virginia 22161.

19. Security Classif. (of report)	20. Security Classif. (of this page)	21. No. of pages	22. Price
Unclassified	Unclassified	118	

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Activity-Based Travel-Demand Modeling for Metropolitan Areas in Texas: Data Sources, Sample Formation, and Estimation Results

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Research Report 4080-3

Research Project 0-4080
Activity-Based Travel-Demand Modeling for Metropolitan Areas in Texas

Conducted for the
Texas Department of Transportation
in cooperation with the
U.S. Department of Transportation
Federal Highway Administration
by the
Center for Transportation Research
The University of Texas at Austin

September 2002

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Acknowledgments

Research performed in cooperation with the Texas Department of Transportation and the U.S. Department of Transportation, Federal Highway Administration

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1. Introduction

Since the beginning of civilization, the viability and economic success of communities have been, to a major extent, determined by the efficiency of the transportation infrastructure. To make informed transportation infrastructure planning decisions, planners and engineers have to be able to forecast the response of transportation demand to changes in the attributes of the transportation system and changes in the attributes of the people using the transportation system. Travel-demand models are used for this purpose; specifically, travel-demand models are used to predict travel characteristics and usage of transport services under alternative socioeconomic scenarios, and for alternative transport service and land-use configurations.

The need for realistic representations of behavior in travel-demand modeling is well acknowledged in the literature. This need is particularly acute today as emphasis shifts from evaluating long-term, investment-based capital improvement strategies to understanding travel behavior responses to shorter-term, congestion management policies such as alternate work schedules, telecommuting, and congestion pricing. The limitations of the traditional *statistically oriented*, trip-based approach in evaluating demand management policies (Gordon et al. 1988; Lockwood et al. 1994; Hanson 1980) has led to the emergence of a more *behaviorally oriented*, activity-based approach to demand analysis.

The activity-based approach to travel-demand analysis views travel as a derived demand, derived from the need to pursue activities distributed in space (Jones et al. 1990; Axhausen et al. 1992). The approach adopts a holistic framework that recognizes the complex interactions in activity and travel behavior. The conceptual appeal of this approach originates from the realization that the need and desire to participate in activities is more basic than the travel that some of these participations may entail.

Activity-based travel analysis has seen considerable progress in the past couple of decades. Several studies have focused on the participation of individuals in single-activity episodes, along with one or more accompanying characteristics of the episode such as duration, location, or time window of participation. The effect of household interdependencies on individual activity choice is represented in these models in the form of simple measures such as presence of a working spouse, number of adults, and household structure. Significant attempts have also been made to broaden the scope of earlier studies to examine activity episode patterns, that is, multiple activity episodes and their sequence over a particular time span, typically a day. Some of these studies focus only on activity episode scheduling and consider the generation of activity episodes and their attributes as exogenous inputs. Other studies analyze both activity episode generation and scheduling, yielding more comprehensive activity-travel models. Such comprehensive models can potentially replace the conventional trip-based, travel-demand models (see Guo and Bhat, 2001, for a detailed review of state-of-the-art activity-based research).

The current project aims to advance the state of the art in daily activity-travel modeling. It represents one of the first attempts to comprehensively model the activity-travel patterns of workers, as well as nonworkers, in a household. The activity-travel system will take as input various land-use, sociodemographic, activity system, and transportation level-of-service attributes. It will provide as output the complete daily activity-travel patterns for each individual in the household.

Within the broader context of the research objective of the project, this report presents frameworks developed for modeling the daily activity-travel decisions and longer-term household decisions (such as household location and auto ownership). Detailed analysis frameworks are presented for developing models for the Dallas-Fort Worth (DFW) area. The empirical results for the model systems estimated are discussed.

This report is organized as follows. Chapter 2 discusses conceptual frameworks developed for modeling short-term, activity-travel decisions and medium-term household choices. Chapter 3 presents the sources of data used in model estimations and provides details on the data cleaning and sample formation procedures. Chapter 4 presents analysis frameworks developed for estimating models for the DFW area. Chapter 5 presents details on the empirical models developed for medium-term household choices model systems and Chapter 6 provides the empirical results for the short-term, activity-travel decisions. Chapter 7 provides the summary and conclusions.

2. Conceptual Frameworks

Modeling medium-term household decisions and short-term, individual activity-travel decisions were identified as a key objective of this research effort. In this chapter, detailed conceptual frameworks are provided for modeling these decisions. The framework for modeling medium-term decisions is discussed first, followed by the approach for modeling short-term decisions.

2.1 Conceptual Framework for Medium-Term Choices

The medium-term choices made by households and their members have a profound impact on individuals' daily activity and travel patterns. These choices, including housing, work, and automobile decisions, are also at the heart of understanding our urban structure (Clark and Withers 1999). Each of these three medium-term choices further encompasses many choice dimensions. Those that are considered important to the modeling of land-use and transportation interaction are listed in Figure 2.1. Drawing from past studies of relevance, the subsequent sections discuss these choice dimensions in detail. The discussion is more in depth than that presented in the earlier report and represents the foundation for developing our analysis frameworks.

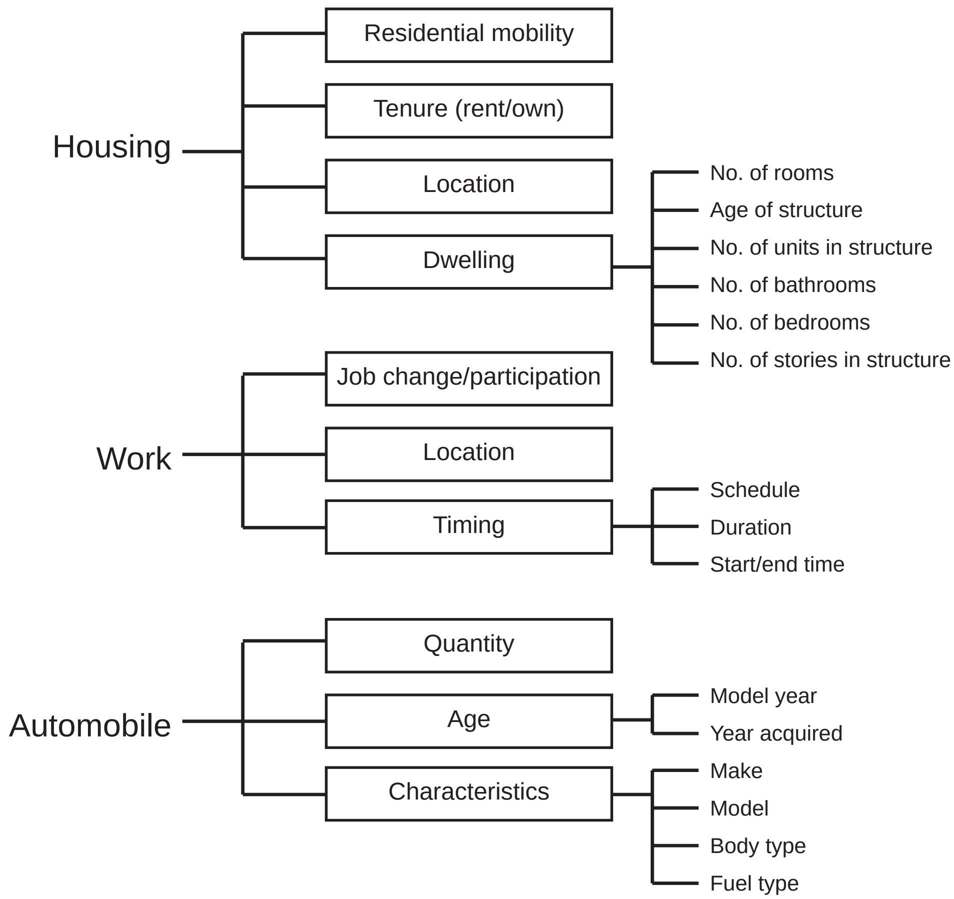

Figure 2.1 Dimensions of medium-term household decisions

2.1.2 Housing

Housing decisions are often considered as a bundle of related choices, including the decision to move (residential mobility choice), the selection of tenure, and the selection of dwelling. The choice of dwelling can be broken down further to the choice of location and the choice of the dwelling unit type (see Figure 2.1). The housing-related choice dimensions are examined in turn in the next few sections.

Mobility

Previous research identified having a child (Dieleman, Clark, and Duerloo 1995), getting married (Davis-Withers 1998) and divorce (Dieleman and Schouw, 1989) as triggers of residential relocation. Factors in addition to stage of life cycle that are also expected to influence the mobility choice include household income, number of full-time workers, and number of years each worker has held his or her current job (Waddell 1996). Older or low-income households are less likely to move. The presence of children might stimulate or inhibit a move, depending on whether the current residential neighborhood is suitable for children. The presence of multiple workers in a household may affect mobility in either way. On the one hand, more workers in a household implies a higher likelihood that one of them will change jobs, resulting in a higher probability of relocation. On the other hand, because of the ripple effects of relocation on all workers, one could argue that a multi-worker household will have a lower propensity to relocate. While the workplace of the primary worker imposes the dominant locational constraint, the secondary worker's place of employment and labor force attachment constitute additional constraints (Zax 1991). The hypothesis is supported by Clark and Withers' (1999) empirical findings that the distance between the workplaces of the two wage earners negatively influences the job search and housing search process. Furthermore, two-worker households are found to move less often than single-worker household. The length of employment represents the other link between work and residence. The longer the employment, the less likely a household is to move. The effect of employment may differ for males and females. Based on previous observation of females' higher sensitivity to commute distance, Clark and Withers (1999) argued that an employment change on the part of the husband will be less likely to trigger a residential relocation.

Tenure

Buying a dwelling is one of the most important decisions that a household makes. Not only is it one of the largest expenditures that a household makes, but it is also commonly regarded as an investment (Waddell 2001).

Economic theories of housing tenure choice stress the role of the relative costs of rental and owner-occupied housing, particularly the effect of the tax system on relative costs (Rosen 1979, King 1980). Housing demand is also closely related to tenure choice. People who want better quality housing are more likely to own. Thus, wealthier households can afford to buy housing and become homeowners more easily than can low-income households (Waddell 1993, Elder and Zumpano 1991). Another important point to note is that once the decision to rent is made, either on the basis of preference or of necessity, renters have fewer choices and less flexibility in regard to location and housing quality, as compared to homeowners (Elder and Zumpano 1991).

Family background also has an important influence on tenure choice. People whose parents are homeowners are more likely to become homeowners themselves, reflecting either the transfer of resources from parents to their adult children or the influence of the parents' attitudes toward home ownership (Di Salvo and Ermisch 1997). Demographic factors such as marital status, presence of children and age of household head are also positively related to home ownership (Waddell 1993, Elder and Zumpano 1991).

Location

Location choice is defined here as the choice of neighborhood characteristics as opposed to the choice of a specific dwelling location or administrative district. In the literature, the most cited factors are the price of housing and the distance to the workplace (Hunt, McMillan and Abraham 1994). However, residential location choice is much more complicated than a simple trade-off between cost and accessibility. Location preferences vary among households with different, and even with similar, socioeconomic and demographic characteristics (Bhat and Guo 2002). The choice depends on nonspatial factors, including socioeconomic status, stage of life cycle, and ethnicity (Berry 1981). The choice is also influenced by spatial factors such as the quality of nearby schools and proximity of parks. However, physical distance has become less and less important with the dispersion of employment centers and increased personal mobility. The information revolution with its computer networking and the Internet is fast reducing the dominance of physical distance on housing location selection (Harvey 1991; Dear and Flusty 1998; Phe and Wakely 2000). As Clark and Onaka (1985) argued, the traditional approaches of using distance-based measures of accessibility appear to have limited value today.

Other hard to quantify factors that also affect location choice include ethnic preferences, racial biases, family loyalty to specific neighborhoods, and preferences for architectural styles. Social status also has a significant role in the households' decision-making process (Maclennan 1982), especially in societies with a strong stratified structure.

Dwelling

Dwelling considerations include size and quality. Size can be measured by floor plan, number of rooms, number of bathrooms, etc. Quality can be measured by number of units in the building (house versus apartment), age of building, architectural style, and facilities available (e.g., swimming pool). Similar to the choice of location, preference for dwellings is expected to differ for different households and is determined by household taste and needs.

For the purpose of this project, dwelling choices are considered as exogenous and will not be explicitly modeled in the integrated land-use and transportation system.

2.1.3 Work

The participation of household members in the labor market is important in the context of land-use and transportation interactions for a couple of reasons. First, individuals supply their time and skills in the labor market in exchange for wages, which form the major source of income used to pay for housing and other goods and services. Second, work represents the most frequent destination of travel other than home and, therefore, plays an important role in determining an individual's daily activity and travel pattern. Yet to date, it appears that the labor market behavior of household members has not been incorporated theoretically or empirically into activity-based travel modeling (Waddell 2001). Below we examine three aspects of work decisions: labor participation, timing, and location choices.

Labor participation

One could either view labor participation as a binary choice or as a multiple choice among not working, full time, part-time, self-employment, or flexible forms of contract labor (Waddell 2001). The decision depends on the set of employment opportunities, which are influenced by the individual's education, training, skills, experience, and choice of occupation. Certain occupations are more generic and low wage but lead to more opportunities and lower risk of unemployment; other occupations are more specialized and high paying but involve limited opportunities and location choices. Individuals make labor supply decisions by comparing potential wages against job-related costs such as commute costs, day care costs, opportunity costs such as lost welfare benefits, and the value of leisure time (Bhat 1991).

Work timing

There are several dimensions to the timing of one's job in the market, including length (the number of hours that a job demands), structure (the part of the day and week in which the individual works), and flexibility (the degree of employee control over variation in their work hours). These key dimensions affect not only a firm's profitability but also the amount and ordering of employees' time for domestic and personal activities (Fagan 2001). While there has been little change in the national average work hour length in the past several decades, the structure and the flexibility of work hours have undergone significant changes. From the standpoint of travel-demand analysis, the effects of increased diversity and flexibility in work schedules are twofold. On the one hand, the flexibility of drivers with respect to commute time – in addition to route, mode, and origin-destination – will facilitate resolving the peak-period congestion problem (Emmerink and Beek 1997). On the other hand, the increase in the dynamics of work hours represents new hurdles for travel-demand analysts. In particular, the common assumption embedded in many activity-based travel studies that the commute patterns of workers are routine and repetitive is under challenge. It is, therefore, important to explicitly model this temporal nature of employment.

The variation between individuals' weekly work hours is primarily attributed to the status of their employment, that is, part-time or full-time. Race appears to be one of the most significant determining factors of workers' actual and preferred work hours. Bell (1998) found that, in the U.S., black men work 20 percent fewer annual hours than white men, while the difference between black and white women is small. Furthermore, a greater proportion of black than white workers are in disequilibrium, desiring more hours than they are actually working. This racial gap appears to be unrelated to the difference in actual hours worked, wages, or family income, and is independent of demographic factors likely to influence labor supply behavior.

Job and family characteristics are determining factors of work hour structure. Presser (1995) found that the predominant reason (58.7 percent) for working nonstandard (i.e., outside the traditional 9 to 5, Monday to Friday) shifts was involuntary and based on job requirements. One-fifth of all persons employed do not work a fixed daytime schedule on their principal job; about one-sixth do not work during the daytime, at either fixed or varied hours. Further, two-fifths of those employed do not work 5 days a week, Monday through Friday.

Flexible work hours are invariably viewed positively by employees. Increase in work flexibility gives family members more autonomy in meeting family needs such as child care. Despite recognition by some researchers such as Presser (1995) and Hamermesh (1999) that this temporal nature of daily labor supply matters, the dimension of flexibility has not been thoroughly explored (Golden, 2001a). Race appears to be a significant factor in influencing flexibility in work schedule. Beers (2000) found that whites are found more likely than blacks or Hispanics to have flexible work schedules. In a probit analysis, Golden (2001a, 2001b) also found that access to daily schedule flexibility is not equally shared, being less likely for individuals who are nonwhite, women, unmarried, relatively less educated, and employed in the public sector. In Golden's (2001a) cross-tab analysis, work access to flexibility is found positively correlated with the usual length of their workweek. Mean usual and actual hours are both significantly longer for full-time workers who indicate having flexible schedules. Education levels have virtually no measurable overall correlation with flexible schedules.

Location

The choice of work location is closely related to the choice of residential location. Efficient commuting, resulting from working closer to home, is an important factor. However, workers who are more specialized have a lower number of suitable jobs in a given geographical area and tend to adopt a wider job search pattern. Furthermore, women have been found to work closer to home than men (Abraham and Hunt 1997). Wage maximization is another important factor. As Waddell (1993) pointed out, wage consideration has a more significant influence on workplace choice in the low and middle skill levels, where there is a high level of interchangeability between jobs. At the unskilled job level, wage maximization plays a smaller role and job supply plays a more significant role in the choice of workplace. At the highest skill level, wage maximization seems to have an even smaller influence, while job supply takes on much higher influence in the job search. Waddell (1993) also observed distinct avoidance by whites of workplaces with significant proportions of blacks, extending the findings of racial segregation in residential choice. This racial avoidance in the choice of workplace does not seem to extend to Hispanics, except at the highest skill level, which is the skill level at which white avoidance of workplaces with concentrations of blacks is the highest.

2.1.4 Automobile holdings

Auto ownership is a critical intermediate link between household location choices and subsequent activity-travel decisions. For instance, households who choose to live and/or work in low density suburban areas will of necessity (if not also preference) be "auto oriented", tend to have a high auto ownership level, and make most if not all trips of any significant distance by auto (Badoe and Miller 2000). Yet to date, vehicle ownership has been treated as an independent, exogenous choice within travel-demand systems, and assumed to be influenced principally by sociodemographic characteristics of households (Waddell 2001).
This may be inadequate for studies, such as those concerning emissions and energy use, that intend to gain understanding of how current policy issues relate to household decisions on the number and types of vehicles that they own, as well as on their (auto) travel activities. Thus, a strong case exists for including models of household automobile choice within the overall travel-demand modeling process (Bhat and Koppelman 1993).

The disaggregate approach to vehicle ownership modeling examines households' decisions regarding how many autos and what types of autos to own. In deciding how many autos to own, the household has a choice of zero, one, two, and so on. The decision is generally based on the affordability (reflected by cost and income) and the usefulness to the household of having vehicles (as reflected by household size, number of workers or availability of alternative mode). In deciding the type of autos to own, the choice is among all the available makes, models, and vintages of automobiles. In this case, the decision is influenced by factors such as the purchase price, fuel economy, and capacity for passengers, as well as luggage. There have been a large number of empirical studies on the subject (see Train (1993) for a review).

2.1.5 Summary

The discussion presented thus far in Chapter 2.1 suggests that the decision making of household medium-term choices is quite involved and complex. Some decisions of interest may be associated with households (e.g., residential choice), while others may be better associated with individuals (e.g., job changes), with interactions between both levels occurring continuously. For instance, the decision to change jobs may have ramifications for household income levels and hence the suitability/affordability of the current residential location. On the other hand, the decision on whether/where to move may be influenced by the impact of the move on commuting times and costs.

As depicted in Figure 2.2, the household medium-term choices are influenced by many different factors, including the characteristics of individuals in the household, the characteristics of the neighboring households (as reflected by the composite socio demographic characteristics), the physical environment (e.g., the land-use patter and the transportation system) and the economic environment (e.g., the housing and the labor market). Also shown in Figure 2.2 is the interrelationship among the many choice dimensions. This complex interdependency renders the task of uncovering and modeling the underlying choice hierarchy very difficult. For instance, the assumption underlying the standard urban economic theory that households' decisions about work places and residential locations are independent has come under increasing scrutiny (Waddell 1993). Although individuals would not be expected to make simultaneous decisions regarding their residence and work locations, some individuals will make workplace decisions based on predetermined residence locations, while others will make residence decisions on the basis of predetermined workplace locations. The degree to which residence location is driven by workplace location, or vice versa, may vary with the degree to which workplace locations are dispersed in a multinodal city, as well as household tenure, ethnicity, and socioeconomic status (Waddell 1993). Workplace-location choice is usually modeled as a decision conditional to a current home location. This makes the integration of such models with home-location choice models difficult because most home-location choice models are conditional on the current workplace location of one employed household member (Abraham and Hunt 1997).

There is also a close relation between residential mobility and employment mobility. Past research suggests that the likelihood of residential relocation subsequent to a change in employment is expected to differ significantly on the basis of housing tenure (Clark and Withers 1999). The costs of moving are greater for homeowners, and generally renters are more mobile and tend toward relatively lower place attachments. Among those who decide to change their residence, renters move sooner than owners because owners have the additional task of selling. A study by Ommeren et al. (2000) observed that workers will first accept a new job and then search for a new residence because finding a job is generally far more difficult than finding another residence. After a job move that increases the commuting distance, an individual would almost immediately move his residence to relocate closer to the new work place. On the other hand, after a residence move that increases the commuting distance, it may take considerable time before a worker will adjust the workplace location.

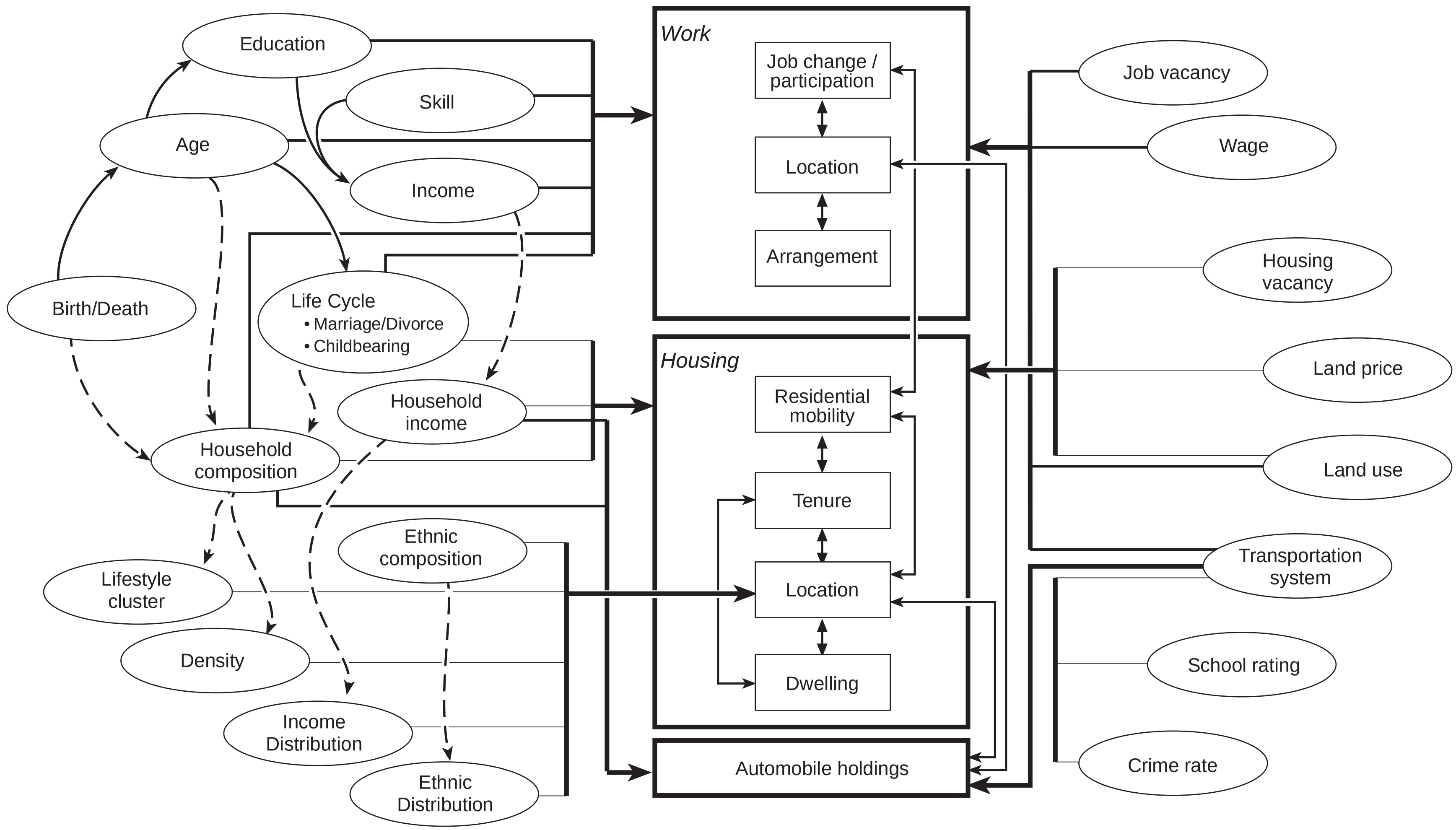

Figure 2.2 Path diagram illustrating factors influencing household medium-term choices.

2.2 Conceptual Framework for Short-Term Choices

This section presents a conceptual framework for modeling the daily activity-travel decisions of all adults in a household. Socio-demographics and medium-term choices of individuals and households, as well as the characteristics of the activity-travel environment, are taken as exogenous inputs to the model system.

The activity-travel pattern representations for workers and nonworkers are based on the work by Bhat and Singh (2000) and Bhat and Misra (2002). The conceptual framework presented generalizes the representation frameworks presented in Report 4080-2 (Bhat et al., 2001) and provides a more comprehensive approach to activity-travel modeling. Some of these key generalizations include: (1) Recognition of sleep as an important and essential daily activity (2) A generation-allocation model system that captures interpersonal interactions within a household in determining individual activity-travel patterns (the previous frameworks modeled some of these household interactions primarily as interactions in activity scheduling); and (3) Consideration of participation in both in-home and out-of-home activities. The conceptual framework is discussed here in the context of a two-adult household, but it can be naturally extended to households with any number of adults.

The overall framework is divided into three major components: (1) the generation-allocation model system, (2) the pattern-level model system and (3) the tour- and stop-level model system. Each of these is discussed in detail in the following subsections.

2.2.1 The generation-allocation model system

The generation-allocation model system (Figure 2.3) determines the set of all activities that an adult decides to pursue on any weekday. This model system explicitly recognizes that individual activity participation on any given day is motivated by both personal and household needs and influenced by interpersonal interactions within the household.

The first component in this system is the determination of the wake-up time and the bedtime of an individual. Sleep is an essential requirement for any human being and sleep duration limits the time available for participation in other activities during the day. The available time for an individual is determined as the time duration between wake-up time and bedtime.

The second component in the system is based on the employment status of the individual. Adults are broadly classified into workers, students, and nonworkers based on their employment status. Work is a mandatory activity for workers and is typically pursued for long hours and over several days in a week. Consequently, the decision of a person to work on a given day could substantially limit the available time for participation in other activities, either for personal or household needs, thereby influencing the daily activity-travel decisions of *all* household members. Therefore, the worker's decision to work is modeled immediately after determining the available time for the day and prior to modeling any other activity participation decisions. With advances in information-technology, it is becoming more and more feasible to work from home. Hence, the decision to work from home as opposed to traveling out-of-home to work is modeled. If the worker decides to work in-home, the total work duration for the day is determined. If the work activity is out-of-home, the work start and end times are determined.

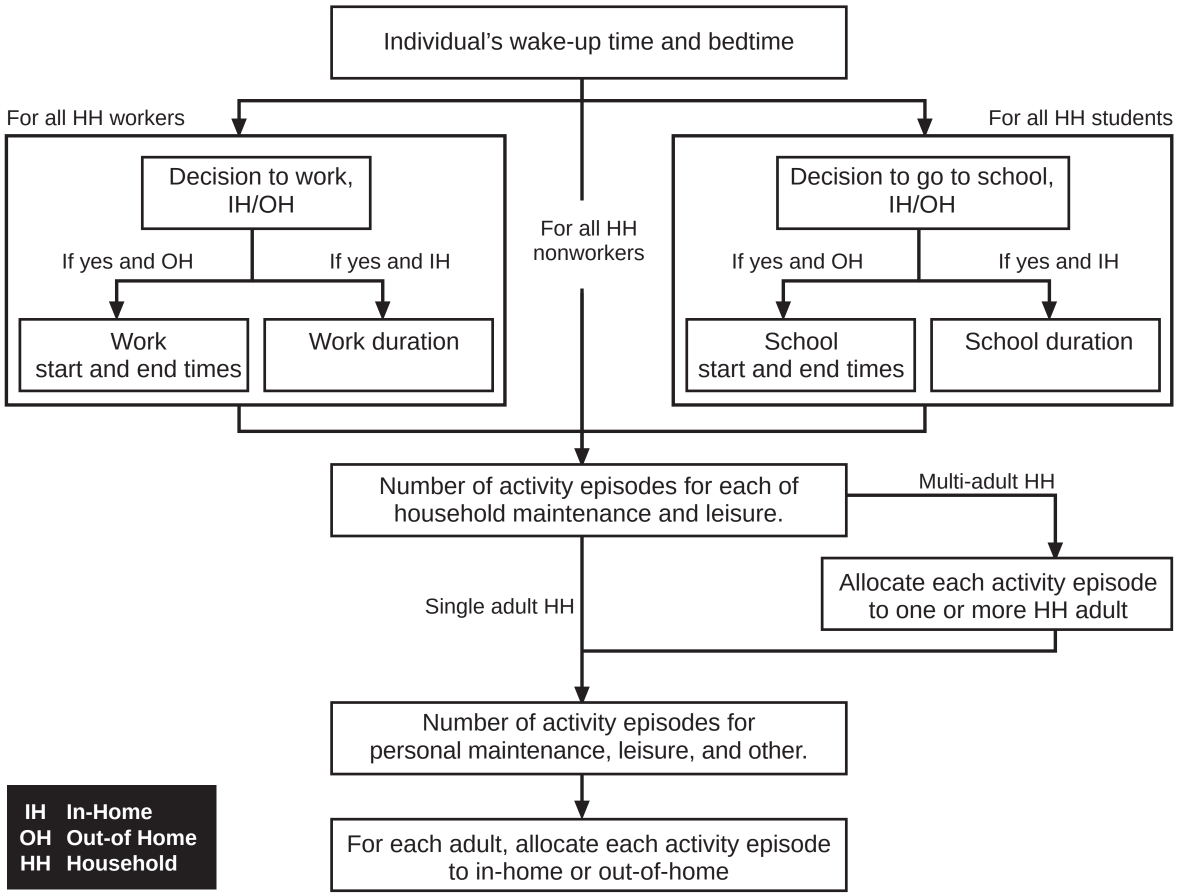

Figure 2.3 Conceptual framework for modeling daily activity-travel patterns: generation-allocation model system

Similarly, the decision to attend classes may limit a student's available time to participate in any other activity. Hence, akin to the decisions of workers related to work, the decision to go to school, whether it is in-home or out-of-home and the school duration or the school start and end times are modeled for students.

The decision of a household to participate in different kinds of maintenance (e.g., shopping) and leisure (e.g., social visits, recreation) activities and the number of episodes of each kind is modeled next. Such decisions are motivated by household needs and may be constrained by the decision of household members to pursue mandatory work or school activities. Hence, the household activity generation is modeled subsequent to the modeling of individual participation in mandatory activities.

If the household has only one adult, then all these activities (i.e., mandatory and leisure) have to be pursued by this single adult. If there are two or more adults in the household, each activity generated may be pursued by one or more of the household adults. The next model in the system allocates each activity episode to one or more of the household adults. Thus, this allocation model can capture both the sharing of responsibility by household members in taking care of household needs (allocation of an activity episode to a particular household member) and joint activity participation (allocation of an activity episode to multiple household members).

In addition to activities that an individual pursues for the sake of the household in general, a person may also wish to undertake activities for personal reasons. These could be personal maintenance, leisure, or any other type of activity. The next model in the system determines the number of episodes of different activity types that a person pursues for personal reasons. As structured, this assumes that the decision of an individual to participate in activities for personal reasons is constrained by the need to participate in activities for the sake of the household.

Finally, each activity episode is designated as in-home or out-of-home. Advances in the consumer goods industry and the Internet revolution is making it possible for in-home participation in a wide variety of activities without significantly compromising the quality of participation in the activity. For example, one can shop for almost anything on the Internet, or watch a movie at home with theater-quality, audio-video effects. In-home activity participation eliminates the need to travel, and hence it should be considered in any travel-demand modeling framework. The activity location choice (at the level of in-home versus out-of-home) is assumed to be made after deciding upon *all* the activities to be participated in during the day.

2.2.2 The pattern-level model system

Pattern-, tour- and stop-level models focus on scheduling decisions of individuals, given their overall activity participation decisions (as determined by the generation-allocation model system). Pattern-level attributes characterize the overall sequencing of out-of-home activities into tours and the in-home activities into periods between tours. Thus, pattern-level decisions are guided by the activity participation needs for the entire day and interpersonal interactions in scheduling of joint activity episodes. Hence, these are modeled as the highest level of scheduling decisions, prior to the modeling of more detailed tour- and stop-level decisions. Two different approaches are adopted in modeling the pattern-level attributes depending on whether the person decides to make out-of-home mandatory (work or school) activities or not. The model system is presented in Figure 2.4.

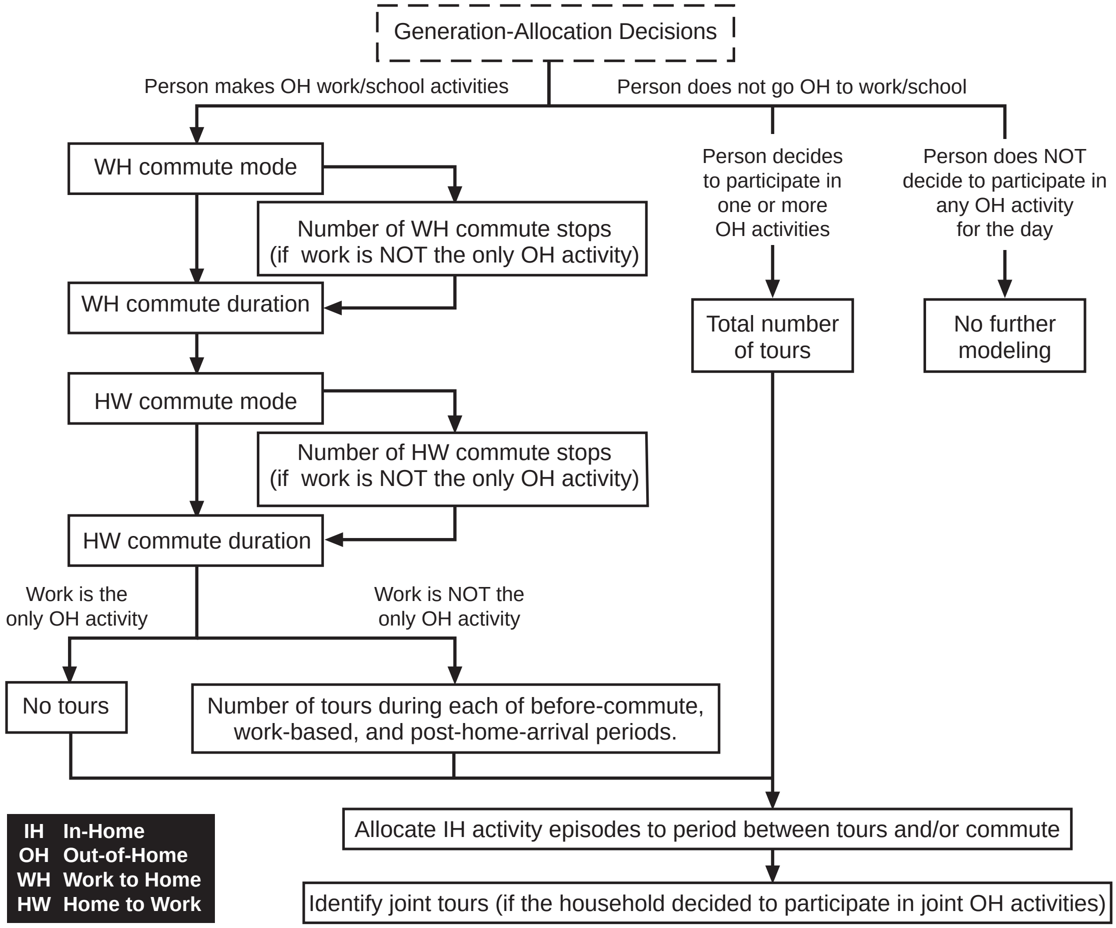

Figure 2.4 Conceptual framework for modeling daily activity-travel patterns: pattern-level model system

In the context of scheduling models, persons who decide to work out-of-home or attend school on any day are referred to as "workers." As the term "workers" also includes students, the term "work" also refers to "school," as appropriate, in all subsequent discussions. Commute forms a very important part of the daily activity-travel pattern of workers. Commute characteristics are constrained by the individual's need to be at work (or school) for a specific period of time (defined by work start and end times as determined in the generation-allocation model system). Consequently, scheduling decisions about the commute are modeled at the highest level, prior to modeling any other scheduling decision.

The work-to-home commute characteristics are first determined. This is motivated by empirical studies that indicate stop making to be typically in the latter part of the day (Bhat and Singh 2000). The commute is characterized by sequentially modeling the mode, number of stops, and duration. The number of work-to-home commute stops is determined only for persons who choose to participate in out-of-home activities other than work (and this is determined by the generation-allocation model system). The home-to-work commute characteristics are then determined in a similar, sequential manner.

The work start and end times along with the commute durations fix the time of departure to work and the time of arrival at home after work. These time pegs can be used to divide a worker's day into five parts: (1) the before-work period (from wake-up time until departure time to work); (2) the home-to-work commute (from departure-time to work-start time; (3) the work-based period (from work start time to work end time); (4) the work-to-home commute (from work end time to the arrival time at home); and (5) the after-work period (from the time of arrival at home from work until bed time). Subsequent to characterizing the commute, the next model in the system determines the number of tours a worker undertakes during each of the before-work, work-based, and after-work periods. Again, this is done only for persons who choose to participate in out-of-home activities other than work.

For nonworkers (this also refers to employed persons who did not decide to participate in out-of-home work activities and students who did not decide to participate in out-of-home school activities), there are no commute characteristics to be determined. For such individuals, the total number of tours is determined depending on their decision to participate in any other out-of-home activities.

Once the number of tours of all the different household adults has been determined, the next model identifies the joint tours from among all the tours made by the household members. This assumes that households that decide to participate in joint out-of-home activities do so by making joint home-based tours.

The final model in the pattern-level system focuses on the scheduling of in-home activity episodes. Since in-home activity participation does not require travel, scheduling involves the allocation of in-home activity episodes to periods between tours and/or commute. Further details such as the activity duration and the exact time of day of participation are not modeled for the in-home activity episodes. The periods during the day when the person is in-home are determined, once the tour- and stop-level attributes are modeled. The exact times of in-home activity participation within these home-stay periods are perhaps not critical from the standpoint of travel demand modeling.

The scheduling of in-home activities becomes trivial for persons who decide not to participate in *any* out-of-home activities and, hence, there are no pattern-level attributes or scheduling decisions to be modeled.

2.2.3 The tour- and stop-level model system

The tour-and stop-level model system determines more detailed scheduling decisions. Unlike pattern-level decisions, which are guided by overall activity participation needs for the entire day, tour- and stop-level decisions are guided by more short-term temporal and spatial constraints. Therefore tour- and stop-level attributes are modeled as the lowest level decisions, subsequent to the modeling of the pattern-level attributes. Figure 2.5 presents the tour- and stop-level model system schematically.

The pattern-level model system classifies each tour as either a joint tour or a solo tour. Since joint tours must fit in the overall schedule of multiple adults, characteristics of such tours and the stops in these tours are determined first. Subsequent to modeling the joint tours made by the household members, the characteristics of solo tours are determined independently for each adult. Finally, the attributes of each stop in every tour are modeled to complete the characterization of a person's activity-travel pattern for the day.

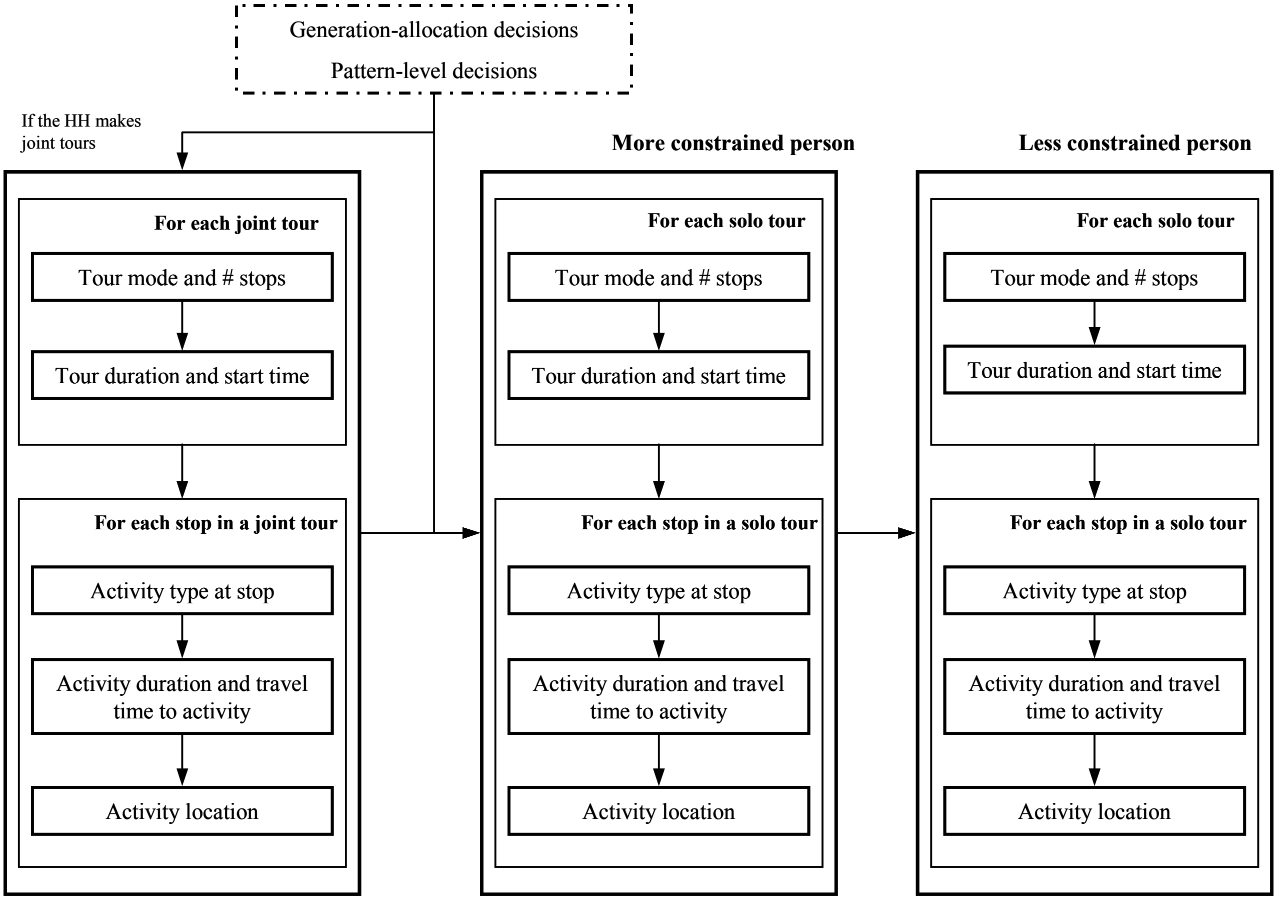

Figure 2.5 Conceptual framework for modeling daily activity-travel patterns: tour- and stop-level model system

In households that do not have as many vehicles as licensed adults, the same vehicle could be used by different household members during different periods in the day. Consequently, the activity-travel patterns of these adults will be interlinked. In such cases, a "more-constrained" and a "less constrained" person for the day are identified. The "more constrained" person is the one who has the least flexibility in making choices about overall activity-travel decisions on any day. For example, in a household with a single employed adult going to work on a day, this person may be labeled the "more constrained" person for that day. It is then assumed that household auto(s) are available for the use of the "more constrained" person at any time of the day and become available to the less constrained person(s) only if the "more constrained" person is not using them. Hence, in such cases, while modeling the solo tours and stops, the decisions of the "more constrained" person are determined prior to modeling the "less constrained" person.

For any tour (joint or solo) the attributes modeled are the tour mode, number of stops in the tour, total tour duration, and the tour start-time. These attributes are modeled sequentially for each tour. Any stop in a tour is completely characterized by sequentially modeling the activity type at the stop, activity duration, travel time to the activity, and the activity location. The characteristics of all stops in a tour are modeled independent of the characteristics of stops in other tours.

3. Data

This section of the report describes the data sources and the sample formation procedure. Sample characteristics of the data set used in the final modeling are also presented.

3.1 Activity-Travel Survey

The primary data set used in the modeling of both medium-term household choices and short-term activity-travel patterns was obtained from the 1996 DFW household activity survey. The data from this survey is available as three main files: (1) the household file, (2) the person file, and (3) the activity file. The household file contains sociodemographic characteristics of each household that responded to the survey. These include number of people in the household, number of household vehicles and characteristics of each of these vehicles, household location, etc. The person file has sociodemographic characteristics for each person from the households that responded to the survey. The person-level information includes age, gender, ethnicity, education level, employment status, etc. For employed people, work location, work schedule characteristics and income levels are available. The activity file contains sequential information on all the activities the surveyed individuals participated in on the diary day. Each data record in this file provides information for one particular activity. The available information includes the type of activity (classification), the location, duration, and the mode of travel (for travel activities only).

3.2 Public Use Microdata Samples

When conducting the census, the U.S. Census Bureau distributed the long-form questionnaires to a subsample of the full census sample (approximately 15.9 percent of all household units). These samples are collectively called the Public Use Microdata Samples (PUMS). The purpose of microdata is to allow users to prepare their own customized tabulations and cross tabulations of population and housing subjects, using specially prepared microdata files. These files are the actual responses to census questionnaires, but with names or addresses removed and the geography sufficiently broad to protect confidentiality. Table 3.1 lists the population and housing information collected in the data. This disaggregate data set is used to estimate some of the medium-term household choices.

Table 3.1 Information provided in PUMS

POPULATION	HOUSING
Place of birth, citizenship, and year of entry	Value of home or monthly rent paid
School enrollment and educational attainment	Units in structure
Ancestry	Year structure built
Migration (residence in 1995)	Number of rooms and number of bedrooms
Language spoken at home and ability to speak English	Year moved into residence
Veteran status	Plumbing and kitchen facilities
Disability	Telephone service
Grandparents as caregivers	Vehicles available
Labor force status	Heating fuel
Place of work and journey to work	Farm residence
Occupation, industry, and class of worker	Utilities, mortgage, taxes, insurance, and fuel costs
Work status in 1989	
Income in 1989	

The 1990 PUMS data are available for the United States and outlying areas that meet a 100,000 minimum-population threshold. The standard PUMS products are the 5 percent and 1 percent samples for the United States and Puerto Rico, and a special 3 percent sample dealing specifically with the elderly population. Besides the obvious difference in file size, the 5 percent and 1 percent files differ in the geography around which the files are constructed. For example, the Public Use Microdata Area (PUMA) is the lowest level of geography identified on any PUMS file. The 5 percent sample is basically a county-level file; that is, the PUMA can be a single county (or county equivalent), a group of counties, a place, or county/place parts if that county has more than 100,000 persons. On the other hand, the 1 percent sample is basically a metropolitan area file. For this, the PUMA will be a Metropolitan Statistical Area (MSA), groups of MSAs, parts of MSAs when the metropolitan area is larger than 100,000 persons, and groups of nonmetropolitan areas.

3.3 Land Use and Level of Service Data

Both the Level of Service (LOS) and the land-use files were obtained from the North Central Texas Council of Governments (NCTCOG). The LOS file provides information on travel between each pair of the 919 Transportation Analysis Process (TAP) zones in the North Central Texas region. The file contains the interzonal distances as well as peak and off-peak travel times (in-vehicle and out-of-vehicle), and costs for transit and highway modes. For the transit mode, additional information including means of accessibility to the transit stop and the number of transfers is provided.

The land-use coverage file contains acreage by land-use purposes (including water area, park land, roadway, office, retail, etc.) for each of the 5,938 traffic survey zones (TSZ) within the same region. The file also provides information on the characteristics of each of the zones in the

DFW area including total population, number of households, median income, basic employment levels, service employment levels, and retail employment levels.

3.4 Data Cleaning and Sample Formation for Medium-Term Choices

Ideally, one would like to model the medium-term choices using one single data set that contains all the information required for model estimation. However, neither the activity-travel survey nor the PUMS data includes all the medium-term choice variables identified in Chapter 2. As will be discussed in Chapter 4, this issue of data availability poses limitations on our choice of analysis frameworks as well as estimation methods. As a result, the medium-term choice model components are estimated independently using either the activity-travel survey data or the PUMS data, depending on the model requirements. Data is processed in different ways for different models. Thus, the size and the content of the sample vary from one model to the other. Details about the data cleaning and sample formation procedures are available from the authors.

3.5 Data Cleaning and Sample Formation for Short-Term Choices

The overall data cleaning and sample formation procedure for modeling short-term activity-travel patterns is presented schematically in . Though the original household file has records for 7,315 households, 2,632 households did not complete their travel diary. Further cleaning resulted in a household file with 4,677 household records. The raw person file had over 12,000 person records. Preliminary cleaning (includes deleting cases with missing data on age, employment status, etc.) resulted in a person file with about 9,500 person records. The activity file had over 119000 activity records. From this file, a "trip" file was created (with about 31,000 records) in which each record corresponds to a trip. This was subjected to preliminary cleaning and about 50 percent of the records were lost as a result of this cleaning process. The primary reason for the loss of this amount of data was missing information on activity location and activity types. It is to be noted that activity-based modeling requires complete information on *all* activities that an individual participated in. Thus, even if one piece of information about any one trip is missing, the entire person record has to be discarded for further analysis. From the activity file, another subset of persons who did not make any out-of-home activities was also created. This file had 1,048 person records.

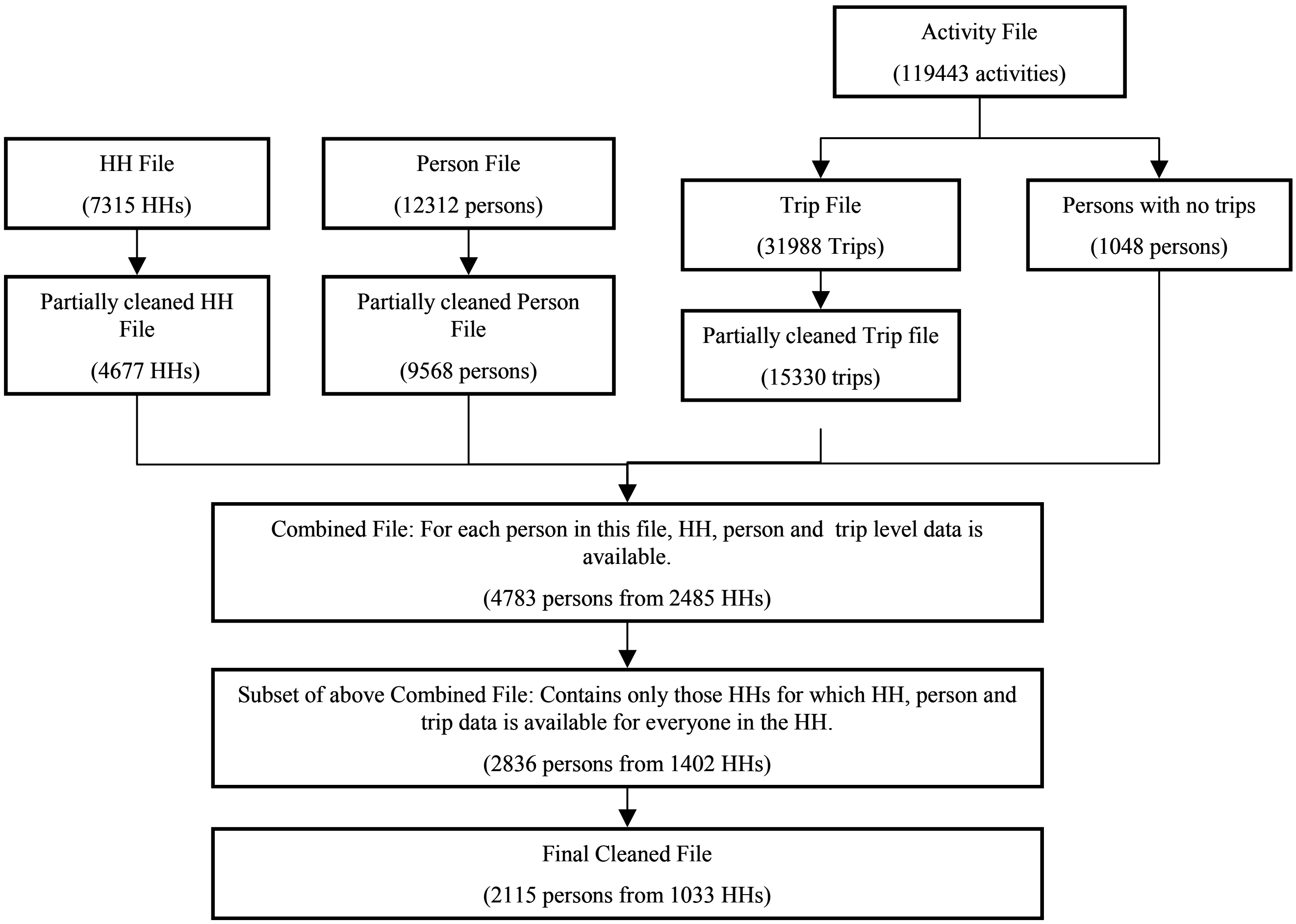

Figure 3.1 Data cleaning and sample formation: short-term activity pattern models

The person, household, and trip files were then matched to determine a data set in which for each person in the sample, all information is available. This resulted in a data set of over 4700 persons from 2,485 households. Because the current modeling effort focuses on all household members, the models require that data be available for *all* household members. Hence, a data set (2,836 persons from 1,402 households) was created in which data was available for all household members.

Using the above data set, the descriptors for the activity-travel patterns were determined. This involved identification of the different tours and commute, and the determination of the tours to which each stop belongs (detailed procedures can be obtained from the researchers). Further consistency checks were performed and the final data sample contains 2,115 persons from 1,033 households.

4. Analysis Frameworks

4.1 Analysis Framework for Medium-Term Choices

Ideally, we would like to model all the choice dimensions identified in Figure 2.1. In so doing, not only the relevant household demographics need to be modeled, the market process (supply) also needs to be considered at the same level of detail as the demand. Such a comprehensive system would also need to capture the complex choice hierarchies that vary for households of different characteristics. For example, the hierarchy of residential and work location choices may differ for households with different tenure status and stages of life cycle. For homeowners and households with multiple workers and school children, the work location choice is more likely to be conditional to residential location choice because the cost and impact of moving would be greater. Change of housing is more likely to trigger change of work. On the contrary, renters and single-person households have relatively higher mobility and are more likely to condition housing choice on work location choice. Change of work is more likely to trigger change of housing. Ideally, we would like to encapsulate all these choice dimensions in one model to allow the empirical testing of different nesting choice structures.

In reality, the availability and the quality of data available to us impose major obstacles for developing the ideal system. Furthermore, for modeling studies, the reduction of system complexity is often necessary to yield better forecasting capability. Therefore, a number of assumptions have been made to yield a simplified framework for analysis and modeling. First, the modeling of market behavior is not included in the current stage of this study. As we do not attempt to accurately predict the housing and job market, it is not very useful to model the household choice behaviors to a high level of detail. Hence, choices such as dwelling type and vehicle type will not be explicitly considered in the proposed framework. Second, we assume that households do not consider every possible bundle of choice alternatives that is available, and they also must find a way to simplify the evaluation of groups of alternatives. Joint decisions are therefore represented by the proposed hierarchical analysis frameworks, as shown in Figure 4.1 to Figure 4.3. The three hierarchical structures correspond to households with zero, one, and two workers, respectively. For households with no workers, the work related choices become irrelevant, yielding a simple hierarchy of three tiers. As the set of available residential location and dwelling choices usually differs for renters and owners, the location choice is placed below the tenure choice in the choice hierarchy. For single-worker households, it is assumed that they are more likely to condition housing choice on work location choice. Change of work is more likely to trigger change of housing than vice versa. In the case of multiworker households, change of employment for the primary worker is more likely to trigger change of housing. The ripple effects of residential relocation on the other workers are then reflected by conditioning the work choices of these workers on the housing choice. It is important to note that the sequence assumed in the hierarchical modeling frameworks does not necessarily reflect the sequence of a household's decision-making process. Rather, the sequencing of the choice dimensions is simply a convenience to the modeling process and an aid to exposition.

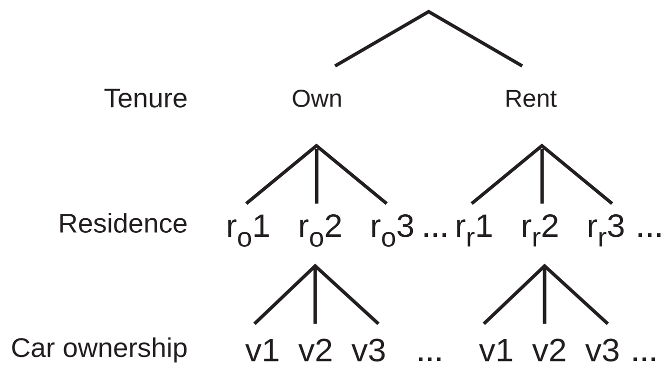

Figure 4.1 Choice hierarchy for no-worker households

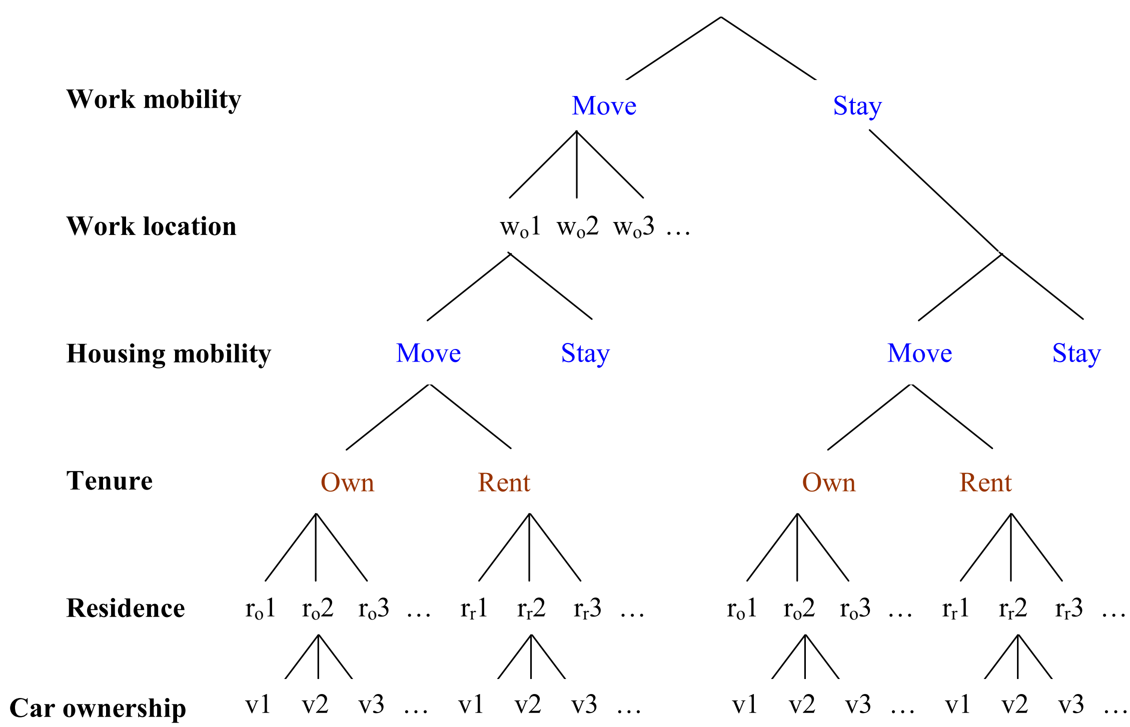

Figure 4.2 Choice hierarchy for single-worker households.

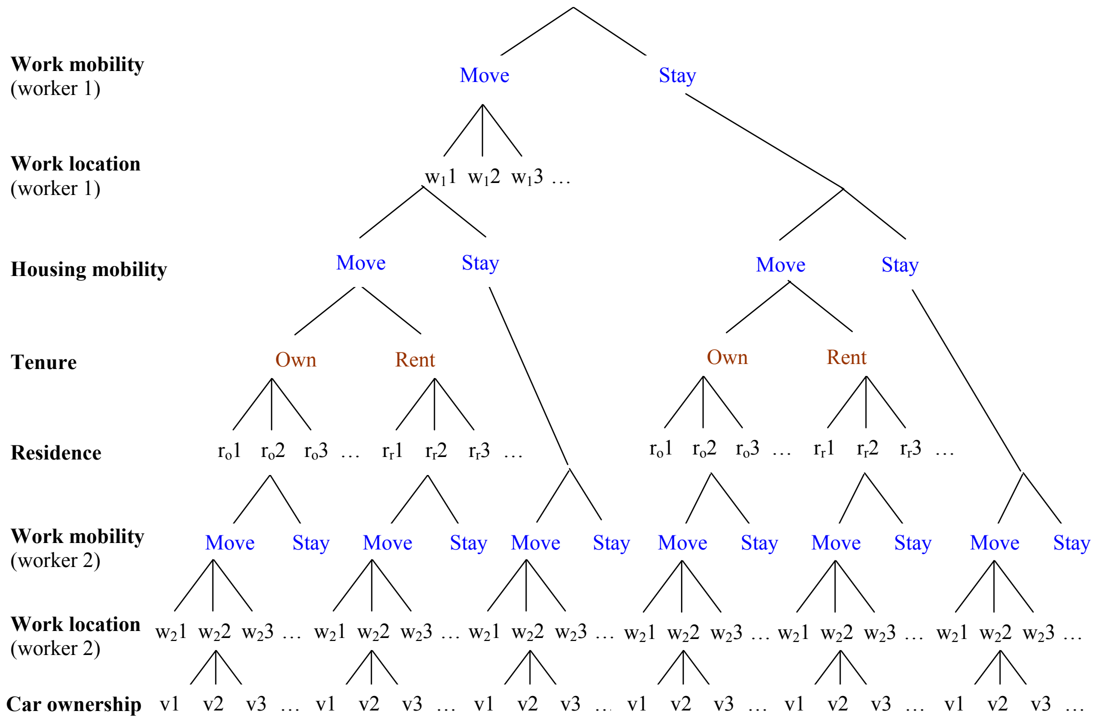

Figure 4.3 Choice hierarchy for dual-worker households.

The third assumption embedded in the analysis framework is that households make rational decisions by choosing the alternative that has the maximum utility value. For instance, the utility of a residential location is measured by considering the relevant locational attributes as well as household preferences. The neighborhood with the highest utility value will be chosen.

In the subsequent sections, we describe the modeling framework for each of the choice components.

4.1.2 Residential mobility model

The residential mobility model predicts the probability that households of each type will move from their current residential location or stay during a particular year. Since it is possible that the household's choice of tenure and of location may influence its decision to move, an alternative structure for the mobility model could use the marginal choice in a nested logit model with a conditional choice of tenure and location. In this way, the model could exploit information about the relative utility of alternative tenure status and locations compared to the utility of the current status in predicting whether households will move. Although this might be more theoretically sound than the proposed specification, the data available to us does not support calibration of such nested model structure. Instead, the mobility decision is treated as an independent choice.

The mobility probabilities are estimated based on the migration data in the Current Population Survey, which provides a cross-sectional tabulation of general mobility by various household characteristics.

4.1.3 Residential tenure choice model

Housing tenure choice is modeled using a binary logit model, with rent or own being the two choice alternatives. We let y_i be a dummy variable such that

$$y_i = \begin{cases} 1 \text{ if household } i \text{ is a homeowner} \\ 0 \text{ if household } i \text{ is a renter} \end{cases}$$

The probability that a household is a homeowner is then given by:

$$P(y_i = 1) = \frac{e^{\beta' X_i}}{1+e^{\beta' X_i}}$$

where the β are model parameters and X_i are household attributes.

Since homeownership information is not recorded in the DFW activity-travel survey, we have to resort to the PUMS data of the census to estimate the above model. For each household in the PUMS data, the tenure status is recorded as one of the economic characteristic variables. The original variable has four possible values: (1) owned with a mortgage or loan, (2) owned free and clear, (3) rented for cash rent, and (4) occupied without payment of cash rent. For the purpose of estimating our binary model, the first two categories are combined as owning and the last two are combined as renting.

4.1.4 Residential location choice model

In this model, we predict the probability that a household that is either newly formed or has decided to move within the region will choose a particular zonal location. The model structure used is the multinomial logit (MNL) model, which is based on the random utility theory. The probability that a household n would choose zone j from the set C_n for residence is formulated as:

$$P_{nj} = \frac{e^{V_{nj}}}{\sum_{j \in C_n} e^{V_{nj}}}$$

which follows from the definition of the utility, U_{nj}, for household n choosing zone j for residence:

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \alpha' Z_j + \beta' X_{nj} + \varepsilon_{nj}.$$

In this expression, Z_j is a vector of zonal attractiveness, whereas X_{nj} represents the interaction terms of sociodemographic characteristics of household n with attractiveness measures of zone j. The error term, ε_{nj}, is identically and independently Gumble distributed across zonal alternatives and households; α and β are parameter vectors to be estimated.

An important element of location choice modeling is the definition of the residential alternatives. The proposed location model predicts the individual household's choice of residence to aggregated zones rather than specific dwelling units. Had individual dwelling units been used, the number of choices in each household's choice set would be enormous. Furthermore, for the purpose of this study, which is to understand the association between household and locational characteristics, the use of aggregated spatial units should suffice.

In theory, the elementary dwelling units can be aggregated in many different arbitrary ways at different levels of spatial scale to give different definitions of location choice alternatives. For this application, the Transport Analysis Processing (TAP) zones have been chosen because population, land-use and network information are available at this spatial level and because conformity between TAP zones and other spatial units, such as the census tracts, allows easy access to information.

The choice of TAP zones as the choice alternative results in over 900 TAP zones in the universal choice set for the chosen study region. Inclusion of this large choice set for each household would make the model difficult to estimate. However, by assuming an identically and independently distributed structure for the error terms across the alternatives in the universal choice set, the residential location model can be consistently estimated with only a subset of the choice alternatives (McFadden 1978). One way of drawing a choice subset from the universal set without jeopardizing the consistency of the parameter estimates is the random sampling technique (Ben-Akiva and Lerman 1993). The approach involves combining the chosen alternative with a subset of nonchosen alternatives, randomly sampled from the universe of zones without replacement. For our purpose, in addition to the chosen location, four random alternatives are sampled for each household to give a choice set of five alternatives per household.

4.1.5 Labor participation model

The labor participation model predicts the probability that an individual will enter the labor market. The choice considered here is binary: being a worker or not. The model structure will take the form of a binary logit model identical to that specified in 4.1.3 for residential tenure choice.

4.1.6 Employment mobility model

As for the residential mobility model, one could use a nested logit model with location choice conditional to the mobility choice. However, data is not available for calibration, hence the mobility decision is treated as an independent decision. Furthermore, because no longitudinal data are available for estimating a duration model, we opted for a simple probability model based on cross-sectional distributions.

4.1.7 Employment arrangement model

The present modeling effort adopts the view that workers seek a reasonable level of income in combination with a convenient, individualized work schedule to fulfill household, family, and other responsibilities (Golden 1996). Their observed choice of schedule is assumed to be one that maximizes a utility function reflecting their greatest well-being.

A MNL model is developed to identify the factors that explain the cross-sectional variation among individuals in their access to different levels of variability and flexibility in their work schedules. The six choice alternatives are: (1) variable at own choice , (2) variable depending on work, (3) allowed to vary within fixed limits, (4) fixed start, variable end depending on work, (5) fixed but not the same everyday, and (6) fixed and the same everyday. The probability of a worker *n* having schedule type *i* is expressed as:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{i'} e^{V_{ni'}}},$$

where V_{ni} is a linear-in-parameter function as follows:

$$V_{ni} = \beta' X_{ni}.$$

In the above expression, X_{ni} represents a set of observed sociodemographic and job characteristics specific to worker *n* and schedule type *i*. These include characteristics that appear to be related to the dependent variable in the prior cross-sectional analysis. The β parameter vector is estimated using the maximum likelihood approach. Based on the hypothesis that the driving factors behind part-time and full-time workers are different, separate models are developed for the respective employment statuses. This hypothesis is well supported by the improvement to the overall explanatory power of the models.

4.1.8 Employment location choice model

In this model, we predict the probability that an employee, who is either new to the job market or has switched jobs, will locate at a particular zone. The model is specified as a MNL model similar to the residential location choice model. Calibration of the model is based on the activity-travel survey. A sample of individuals who recorded their employment TAP zone is used to estimate the coefficients of the location choice model. Again, owing to the large number of work zone choices, sampling of alternatives is required. The choice set for each household is formed by four randomly selected zones plus the observed choice.

4.1.9 Vehicle ownership level model

Modeling auto ownership at the disaggregate level usually takes the form of either the ordered-response models or the unordered response models. The ordered-response approach is based on the hypothesis that a single continuous variable, C_i^*, represents the latent auto ownership propensity of household i. The observed auto ownership level, C_i, for household i is assumed as:

$$C_i = k \text{ if and only if } \psi_{k-1} < C_i^* < \psi_k,\ k = 0,1,\ldots,K,\ \psi_{-1} = -\infty,\ \psi_K = +\infty,$$

where the ψ_K terms represent the threshold values of the latent propensity demarcating the discrete outcomes (Bhat and Pulugurta 1998). The unordered-response approach is based on the random utility maximization principle that assumes that households associate a utility value with each auto ownership level and select the auto ownership level that provides the highest utility. The utility of car ownership level k for household i is defined as:

$$U_{ik} = \beta_k' X_i + \varepsilon_{ik}$$

where X is a vector of household attributes and β_k is a vector of parameters to be estimated for each auto ownership level k. It should be noted that because of identification problems the parameter vector corresponding to one of the (K+1) car ownership levels needs to be normalized to zero.

Based on the findings from Bhat and Pulugurta (1998), who concluded that the unordered-response modeling approach better represents households' auto ownership decision process than the ordered-response approach, we opted for the unordered-response model structure for the current project.

4.2 Analysis Framework for Short-Term Choices

This section of the report presents the analysis framework adopted for modeling short-term activity-travel patterns using data from the Dallas-Fort Worth (DFW) area. Although the approach mostly follows the conceptual framework described in Chapter 2, suitable modifications have been made to accommodate data availability and limitations. Some of these key modifications are discussed first. The framework is then presented in detail.

First, the wake-up time and bedtime are not modeled. In order to maintain simplicity, it is assumed that a person's "day" starts at 3 a.m. and ends at 3 a.m. on the next day and that the individual is at home at both of these times. Second, survey data from the DFW area does not provide detailed description of in-home activities. Hence, in-home activity episodes are not modeled. Third, the sample does not provide adequate data instances for modeling joint activity participation. Therefore, it is assumed that all activity episodes are pursued independently. Fourth, it is also assumed that every adult with a driver's license always has access to a vehicle. This is again because of data limitations; the sample did not provide adequate data instances in which different household members used the same household vehicle at different times in the day. Consequently, all scheduling decisions are assumed to be made independently by each adult. This negates the need to identify a "more-constrained" and a "less-constrained" adult in the scheduling models.

The following subsections present the details of the analysis framework. The framework is divided into four major components: (1) the generation-allocation mode system, (2) the pattern-level model system, (3) the tour-level model system, and (4) the stop-level model system.

4.2.1 The generation-allocation model system

The generation-allocation model system is presented in Figure 4.4. The first set of models focus on the individual's decision to participate in mandatory activities such as work or school. For workers, the decision to go to work is first modeled using a binary-logit model and for those who decided to go to work, hazard-duration models are estimated to determine the work-based duration and the work start time. The work-based duration includes the work duration and the time invested in all activities performed based at work (e.g., time spent in going out for lunch). Analogous to the workers, the decision of students to go to school is modeled as a binary-logit model. For students who decided to go to school, the school-based duration and the school start time are each modeled using linear regression. Work (or school) related decisions of any worker (or student) are assumed to be independent of work (or school) related decisions of any other household worker (or student).

The household's decision to participate in maintenance and leisure activities is modeled next. Shopping and personal business are classified as maintenance activities and social/recreational activities are classified as leisure. A multinomial-logit (MNL) model is developed to determine the household's decision to participate in one or more of the three above-mentioned activity types. This activity-generation model, therefore, captures the trade-offs made by a household in choosing to participate in different types of activities for the day.

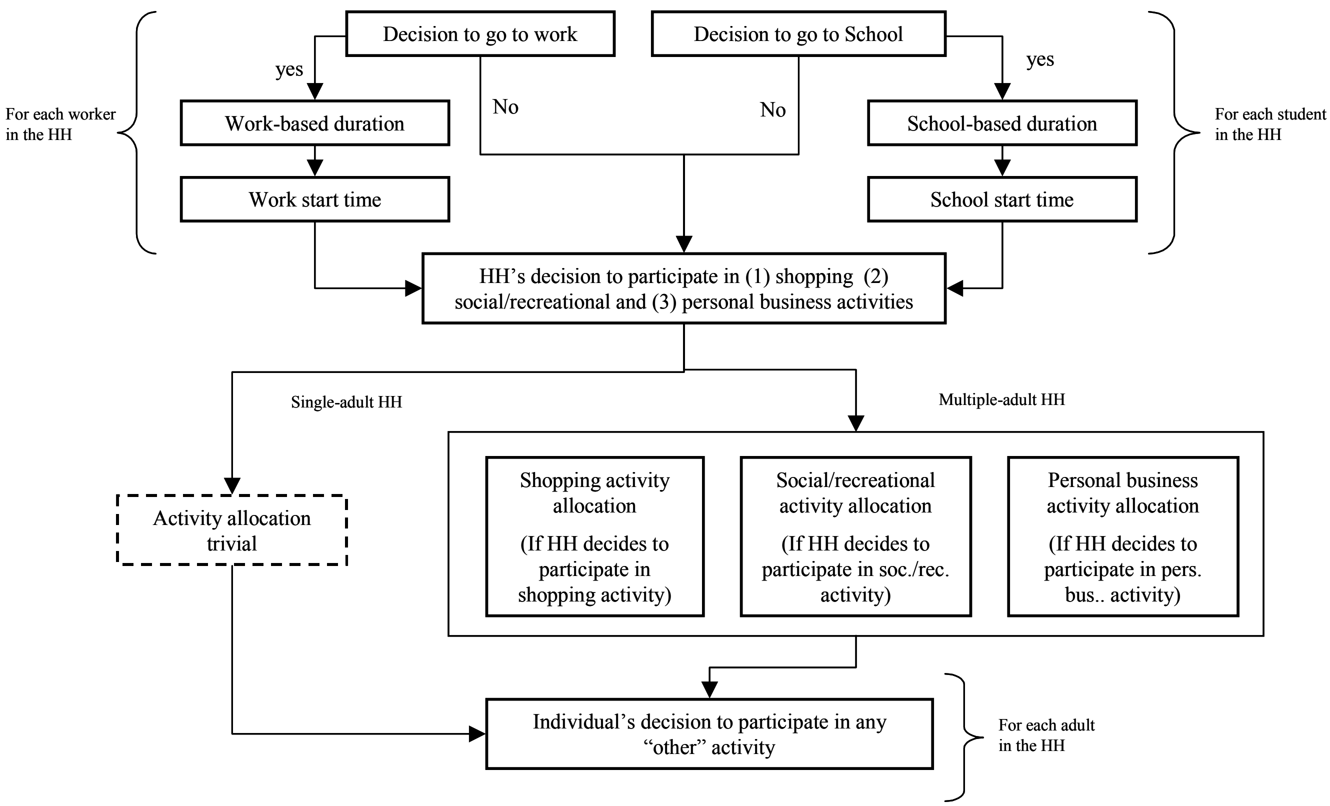

Figure 4.4 Analysis framework for modeling daily activity-travel patterns: generation-allocation model

The next set of models in the system is the activity-allocation models. For households with two or more adults, the decision of an individual to participate in an activity, given that the household has decided to participate in it, is modeled as a binary-logit model. Separate models are developed for shopping, personal business, and social/recreational activities. The allocation models assume that each individual independently decides whether or not he/she will undertake an activity (of a particular type), given that it is required that someone from the household undertakes it on that day. Although it would be ideal to jointly model the decision of all household adults, data limitations do not permit such an approach.

The conceptual framework distinguishes between the activities that a person undertakes for the sake of the household and those that a person undertakes for personal reasons. However, for the activities reported in the travel survey, it was not possible to make this distinction. It is, therefore, assumed that all maintenance and leisure activities are generated at the household level and allocated to one or more of the household adults. However, it is not intuitive to assume that activities such as eating out, work-related activities, and volunteer services are generated at the household level. These activity types are all bundled into a single activity category called "other activities." Serve-passenger is also classified along with these "other activities" primarily because the data set does not provide enough data to model generation-allocation of this activity type. The final model of the generation-allocation model system determines the individual's decision to participate in such "other activities" given the person's decision to participate in mandatory, maintenance, and leisure activities. The methodology adopted is a binary- logit model.

4.2.2 The pattern-level model system

The pattern-level model system is presented in Figure 4.5. The pattern-level attributes to be modeled depend on the person's decision to participate in different activity types (especially the mandatory activities such as work or school) during the day. For all scheduling models, the workers who undertook work activities and students who undertook school activities are treated identically, as there are not enough cases in the data sample to examine the students separately. Hence, in all subsequent discussions, the term "worker" refers to persons who pursued work or school activities during the day and "nonworkers" refers to all persons who did not pursue work or school activities during the day.

The first pattern-level model for workers is a MNL model for work-to-home commute mode choice. Given the commute mode, the total number of commute stops is modeled using an ordered-response model. For those that chose to participate in only work activities, the number of commute stops is necessarily zero. Therefore, the model is developed only for those that chose to participate in activities other than work. Given the mode and the number of commute stops, the total commute duration is determined using a linear-regression model. Similarly, the home-to-work commute characteristics (i.e., mode, number of stops, and duration) are modeled next. Modeling the home-to-work commute mode choice is simplified by recognizing that the home-to-work commute mode is, in most cases, the same as the work-to-home commute mode.

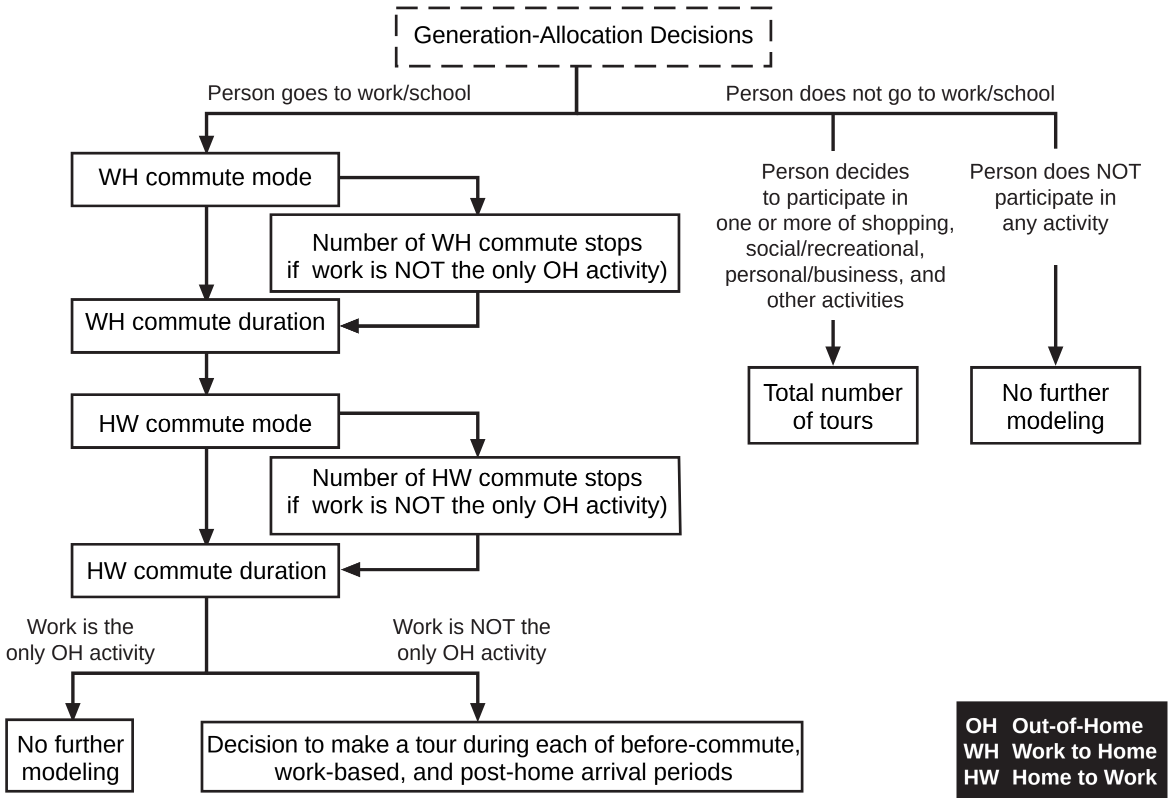

Figure 4.5 Analysis framework for modeling daily activity-travel patterns: pattern-level models

If work is the only activity for the person during the day, there are no further scheduling decisions to be modeled, as the person's complete activity-travel pattern for the day is determined by the work duration and commute characteristics. For workers that chose to participate in activities other than work, the decision to make a tour during each of the before-work, work-based, and after-work periods is modeled using a MNL model. The assumption that a person does not make more than one tour in any period is guided by empirical data examination.

For nonworkers who chose to participate in one or more activities, the only pattern-level attribute is the total number of tours. An ordered-response model structure is used to model the total number of tours made in the day. For adults who chose not to participate in any activity for the day, there are no scheduling decisions to be modeled.

4.2.3 The tour-level model system

The tour-level model system comprises four models that sequentially determine the mode, number of stops, duration, and the home-stay duration before the tour (or work-stay duration in the case of work-based tours). The home-stay duration before a tour is defined as the time between the end of the previous tour and the start of the current tour. For the first tour in the day, the home-stay duration is computed from 3 a.m. The tour mode is modeled as a MNL model and the number of stops is modeled as an ordered-response model. The tour and home-stay durations are modeled as linear-regression models.

Separate models are developed for workers and nonworkers. The sequence in which the tours are modeled for the workers and the nonworkers is presented in Figure 4.6 and Figure 4.7, respectively. In the case of workers, the characteristics of the tours during each period are modeled independently of tours made in other periods. In the case of the nonworkers, the tours are modeled sequentially from the first to the last. Consequently, it is assumed that while modeling any tour the characteristics of all previous tours are known.

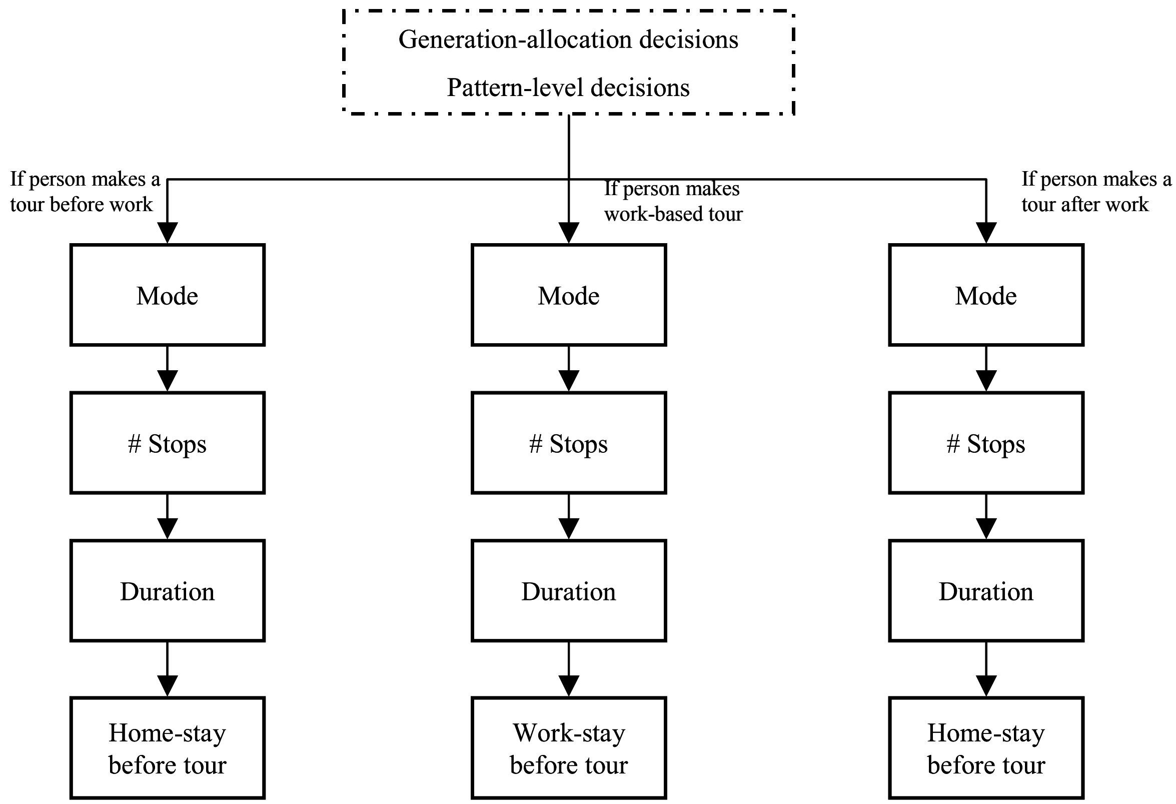

Figure 4.6 Analysis framework for modeling daily activity-travel patterns: tour-level models for workers

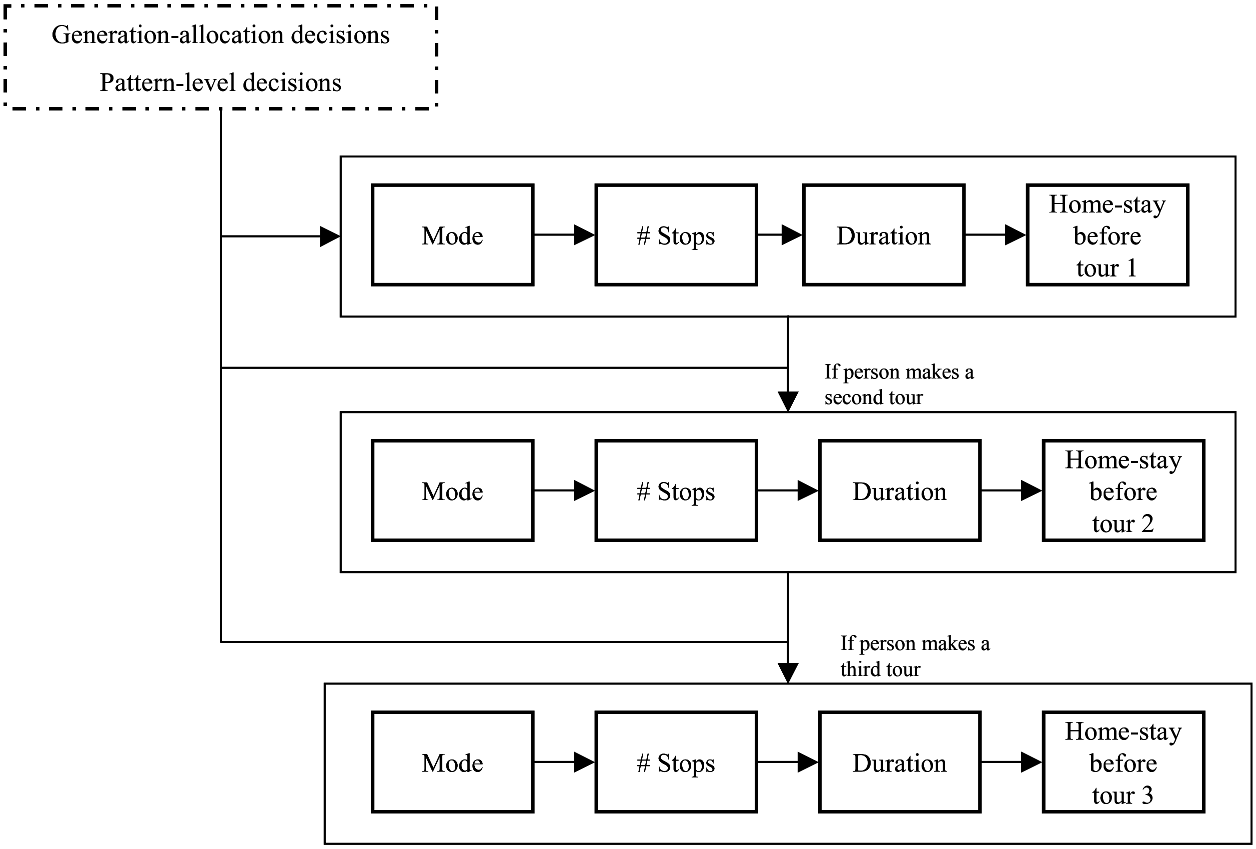

Figure 4.7 Analysis framework for modeling daily activity-travel patterns: tour-level model for nonworkers

4.2.4 The stop-level model system

The stop-level model system comprises four models that sequentially determine the activity type, activity duration, travel time to activity, and the location of the stop. The activity type is modeled using a MNL model. For any person, the candidate activity types in the choice set are the different activities that a person decided to participate in during the day (this is determined by the generation-allocation model system). Activity duration and travel time to the activity are modeled using linear-regression models. The activity location is determined using a disaggregate spatial location choice model (see Misra 1999 for an application of this method to modeling location choice of activity stops for nonworkers). This methodology first identifies the set of all destinations that can be reached by the travel mode for the tour (determined by the tour-level models) of which the stop is a part and within the travel duration estimated earlier. The choice of the location from this candidate set of locations is modeled as a MNL model. Thus, the model system accommodates spatial-temporal interactions in stop making.

Again, separate models are estimated for workers and nonworkers. The stops in any tour or commute are modeled sequentially from the first to the last (Figure 4.8). Therefore, it is assumed that while modeling any stop, the characteristics of all previous stops are known. Further, the characteristics of all stops in a tour are determined independently of the characteristics of stops in other tours.

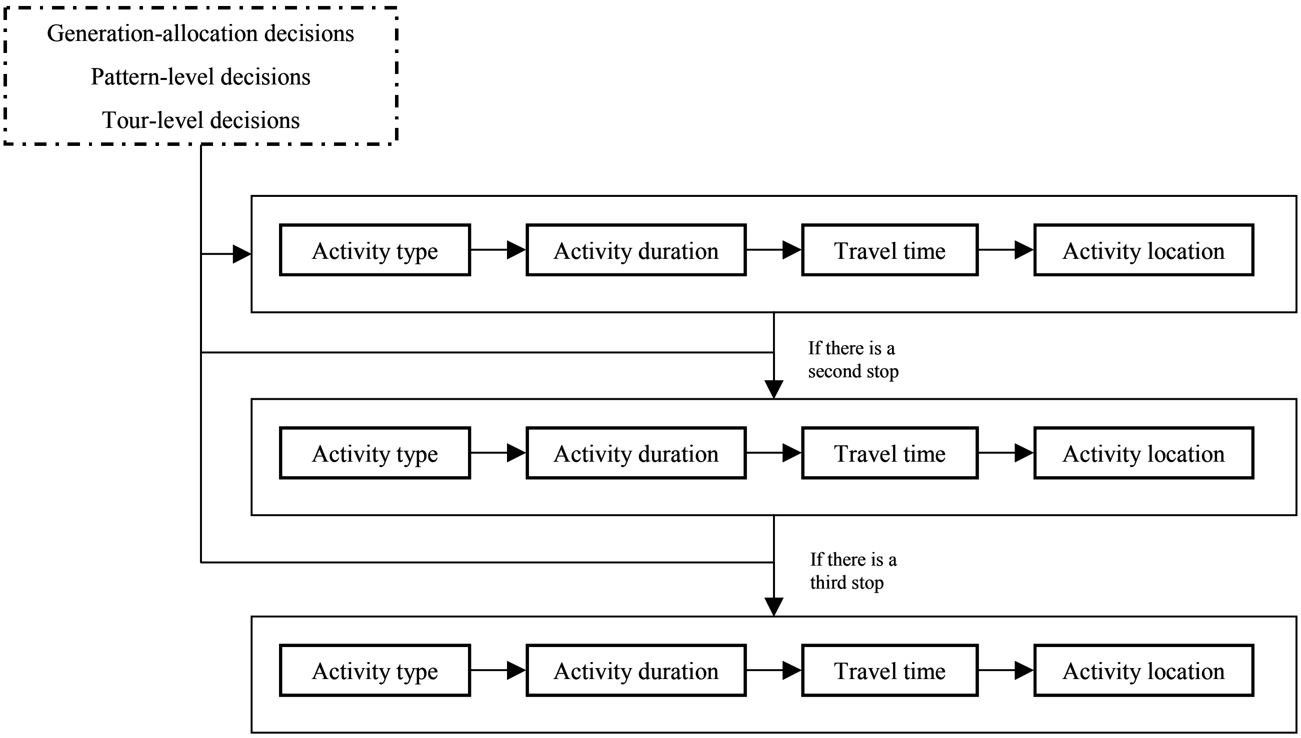

Figure 4.8 Analysis framework for modeling daily activity-travel patterns: Stop-level model system

5. Empirical Results: Medium-Term Choices

The medium-term household choice models described in Section 4.1 have been estimated for the DFW area. The empirical results for each of these models are discussed in detail in this chapter.

5.1 Residential Mobility Model

Data from the current population survey (CPS) provide cross-tabulation of general mobility by various sociodemographic characteristics. Shown in Figure 5.1 is the distribution based on tenure status. Here, movers are defined as those who were living in a different house or apartment one year prior to the survey. Movers are categorized as to whether they were living in the same or different county, state, or region, or were movers from abroad. The figures suggest that while 9 out 10 homeowners stayed in their original residences only 2 out of 3 renters did so. Also, about half of the moves take place within the same county or state.

Table 5.1 Probability distribution of household mobility by tenure and type of move

Type of Move	Total	Non-mover	Same County	Diff. County, Same State	Diff. State, same division	Diff. Division, same region	Diff. Region	Abroad
Total	100.00%	83.94%	9.03%	3.26%	1.50%	0.47%	1.15%	0.65%
In an Owner-Occupied Unit	70.09%	63.75%	3.48%	1.50%	0.56%	0.19%	0.44%	0.18%
In a Renter-Occupied Unit	29.91%	20.20%	5.55%	1.77%	0.94%	0.27%	0.71%	0.47%

5.2 Residential Tenure Choice Model

Residential tenure choice model is estimated using samples drawn from the PUMS data. The data provides 70,094 valid observations, of which approximately 62 percent are homeowners (Table 5.2). The final specification of the binary logit model is shown in Table 5.3.

Table 5.2 Observed market shares of tenure choice

	No. of Observations	Percentage
Rent	26333	37.57
Own	43761	62.43
Total	70094	100.00

Table 5.3 Estimation results of the tenure choice model

Tenure	Own	
	Coeff.	t-stat
Constant	-4.565	-68.94
Family income ($10K)	0.305	55.73
Household size	-0.030	-2.98
Household type (non-family being base)		
Household head is single	0.323	9.61
Married-couple family	1.205	40.00
Presence of person under 18	0.301	9.95
Presence of person 60 years and over	-0.039	-1.42
Age of household head	0.064	67.80
Household head's years of education	0.043	11.57

The parameter estimate for family income is positive and statistically highly significant. This concurs with the conventional wisdom that wealthier households are more likely to buy housing and become homeowners. Household size is found to have a negative effect on home ownership. The result is not very intuitive and should perhaps be interpreted together with the composition of the household. When compared to nonfamily households, households that are families are more likely to own their own residence. Moreover, families with married couples are more likely to own than are families with a single household head. The presence of children under 18 years of age has a positive effect on ownership, whereas the presence of seniors in the household is not a statistically significant factor. Finally, age and years of education of household head are also positively related to home ownership.

5.3 Residential Location Choice Model

Separate MNL models have been estimated for households with zero, one and two workers. The final specifications are summarized in Table 5.4.

Table 5.4 Estimation results of the residential location models

	No-Worker HH		Single worker HH		Dual-worker HH	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Log of zonal area	-0.047	-0.95	0.157	2.95	0.347	4.18
Accessibility to employment	0.332	0.72	-1.928	-3.66	-4.103	-4.29
Accessibility to shopping	-1.444	-1.15	4.479	3.22	11.926	4.33
Accessibility to recreation	2.045	1.28	-1.723	-1.02	-5.036	-1.69
Income dis-similarity	-1.377	-3.37	-0.916	-2.48	0.339	0.55
Percentage zonal Caucasian population interacted with Caucasian dummy variable	-0.284	-1.42	0.161	0.79	0.734	2.11
Percentage zonal Hispanic/Black population interacted with Hispanic/Black dummy variable	1.692	3.55	1.593	3.69	2.017	2.40
Commute distance of primary worker			-0.128	-6.59	-0.073	-9.26
Commute distance of secondary worker					-0.090	-11.97

For households with one or more workers, the coefficient on the logarithm of zonal area has the expected positive sign, indicating that households are more likely to locate in larger zones than smaller zones. In the case of households with no workers, though this coefficient has an unexpected negative sign, the corresponding t-value (-0.95) suggests that the estimate is not statistically significant. The coefficients on the accessibility measures indicate that households with workers prefer locations that offer good accessibility to shopping. Accessibility to employment opportunities is associated with negative signs, which appears counterintuitive. The income dissimilarity measure, captured by the absolute difference between the zonal median income and household income, confirms the income segregation phenomenon observed in previous studies (Waddell 1993).

The interaction effect of the percentage of Hispanic or African-American population with the dummy variable identifying if the head of the household is Hispanic or African-American indicates that Hispanic/African-American households tend to locate in zones with a high percentage of Hispanic/African-American population. This consistent observation of racial segregation across all three models may be attributed to one or more of the following factors: (a) racial discrimination in the housing market, (b) differences between racial groups in preferences for neighborhood attributes, or (c) a preference to be with others of the same ethnic background. Such an effect also applies to Caucasian households of dual workers.

The effect of commute distance has the expected negative sign; that is, proximity to the employment location of the worker in the household is an important factor in residential location choice. In the case of dual worker households, the effect of commute distance is greater for the secondary worker than for the primary worker (defined as the worker with the highest earnings).

5.4 Labor Participation Model

Person records drawn from the PUMS data have been used to estimate a binary logit model for labor participation. Table 5.5 presents the final model specification.

Table 5.5 Estimation results of labor participation model

	Coeff.	t-stat
Constant	1.124	18.61
Age	-0.058	-75.63
Years of education	0.025	2.27
Years of education squared	0.008	12.89
Presence and age of own children (male as base)		
Female with own children under 6 years only	0.742	17.56
Female with own children 6 to 17 years only	-1.319	-41.62
Female with own children under 6 and 6 to 17 years	-0.072	-2.74
Female with No own children	-1.253	-37.47
Marital status (Now married, except separated as base)		
Widowed	1.293	56.05
Divorced	0.976	22.58
Separated	2.206	60.80
Never married or under 15 years old	1.743	32.33

Age has the expected negative effect on participation in the labor market. Years of education, on the other hand, have positive but nonlinear effect, as suggested by the years-of-education squared term. Gender and stage of life cycle also has significant effect on labor participation. Specifically, compared to males, females with no own children, or with children between 6 and 17 years, are less likely to work. On the other hand, females with young kids under 6 years are more likely to work. Individuals who are separated, single, widowed or divorced all have a higher likelihood, but in a decreasing degree, to participate in the job market than those who are married.

5.5 Employment Mobility Model

Data are being acquired for the estimation of this model.

5.6 Employment Arrangement Model

After appropriate data processing, 5,241 valid observations remain in the DFW data set for model estimation. Of these observations, 14 percent reported having the highest level of autonomy in their work schedule, i.e., variable at own choice. Seventeen percent have schedules that are largely work dependent. Fourteen percent indicated having flextime schedules while 16 percent have fixed starting times and variable end times based on work. Respondents who have fixed schedules that involve either irregular or rotating shifts take up about 9 percent of the sample. Thirty percent of the respondents follow fixed schedules every day without any variation or flexibility.

The final MNL model specifications for the work arrangement of part-time and full-time workers are presented in Table 5.6 and Table 5.7, respectively. The parameter estimates represent the effect of exogenous variables on the utility of each work schedule alternative relative to the fixed and the same everyday alternative. Some of the key results are highlighted below.

Table 5.6 Estimation results of the work schedule choice model for part-time workers

Work Arrangement	ALT1 Variable at my choice		ALT2 Variable depending on work		ALT3 Allowed to vary within fixed limits		ALT4 Fixed start, variable end based on work		ALT 5 Fixed but not the same everyday	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	-0.894	-3.54	-0.258	-1.04	-1.460	-5.22	-1.263	-5.90	-1.588	-6.93
Ethnicity										
White	0.635	2.90	0.703	3.31	1.101	3.83	0.476	1.94	0.865	3.52
Gender & interaction										
Female	--	--	-0.583	-4.01	--	--	--	--	--	--
Female & having children	0.202	1.50	--	--	--	--	--	--	--	--
Employment										
Self-employed	2.963	14.30	1.867	8.45	--	--	--	--	--	--
Weekly work hours	-0.026	-4.03	-0.025	-4.11	--	--	--	--	--	--
Industry										
Retail	0.947	4.49	0.863	4.27	--	--	--	--	1.141	5.49
Service	--	--	--	--	-0.602	-3.10	--	--	--	--
Education										
Bachelor +	--	--	--	--	--	--	--	--	--	--
Master's +	--	--	--	--	0.459	1.66	--	--	--	--

Table 5.7 Estimation results of the work schedule choice model for full-time workers

Work Arrangement	ALT1 Variable at my choice		ALT2 Variable depending on work		ALT3 Allowed to vary within fixed limits		ALT4 Fixed start, variable end based on work		ALT 5 Fixed but not the same everyday	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	-6.544	-17.07	-6.544	-17.07	-7.158	-7.31	-6.488	-11.84	-5.126	-9.02
Ethnicity										
White	--	--	--	--	0.831	5.54	0.431	3.67	--	--
Age										
Age	--	--	--	--	0.095	2.72	--	--	--	--
Age squared	--	--	--	--	-0.001	-3.25			--	--
Presence of children							--	--		
Kids under 16	--	--	--	--	0.279	3.26	--	--	--	--
Gender & interaction										
Female & having children	-0.463	-2.70	-0.463	-2.70	-0.260	-1.97	--	--	--	--
Employment										
Self-employed	2.571	18.04	2.571	18.04	--	--	--	--	--	--
Weekly work hours	0.097	11.73	0.097	11.73	0.050	5.57	0.087	11.30	0.060	5.98
Industry										
Retail	--	--	--	--	--	--	--	--	1.334	7.78
Service	--	--	--	--	-0.374	-3.76	--	--	0.386	2.65
Education										
Bachelor +	0.798	5.90	0.798	5.90	0.991	8.38	0.275	2.49	--	--
Master's +	0.526	2.96	0.526	2.96	0.901	5.79	0.326	2.28	--	--
Income	1.375	6.70	1.375	6.70	1.196	5.77	0.894	4.25	0.478	1.63

Race plays a significant role in determining work schedule variability and flexibility. A Caucasian is more likely to have flextime or variable-end work schedules than an otherwise observationally identical full-time employee of another race. Full-time employees' access to flextime work schedules increases with age, possibly suggesting that flextime comes as a benefit with job tenure or seniority in an organization. However, as indicated by the negative sign associated with age-squared, this positive effect diminishes at older age.

All else being equal, a full-time worker who has children under 16 years of age is more likely to have a flextime schedule than one who does not. This result is intuitive, as flexibility in work start and end times would be favorable for those who need to juggle work and parenting responsibilities. While this holds for both male and female workers, the effect is lesser for the females. The gender difference with regard to having children also is observed for work schedules variable at employee's own choice or variable depending on work. In both cases, the presence of children does not have significant effect for full-time male workers. For females, however, the likelihood of having either schedule type decreases.

Among part-time workers, the presence of children alone does not have any effect on work schedule variability and flexibility. However, females with children are more likely to have work schedules variable to their own choice than ones without children, suggesting the appeal of the combination of part-time employment status and full-time autonomy of work hours in view of child care responsibilities. Discounting the factor of children, gender difference is not observed for all flexibility/variability alternatives except work-dependent schedules. For both full-time and part-time workers, females are less likely than males to engage in work schedules that are variable depending on workload.

Being self-employed rather than a payroll employee has significant positive effect on having a work schedule of high variability – either based on his or her own choice or depending on work. This applies to both part-time and full-time workers. As indicated by parameters relating to weekly work hours, for full-time employees, the effect of work hour duration is highest for work-dependent schedules, followed by schedules that are variable at own choice and that involve fixed starts but variable ends. Evidently, full-time workers' level of education influences their access to variable and/or flexible work schedules. The dummy variable Bachelor's+ in Table 5.7 indicates an individual having attained a bachelor's degree, with or without some graduate studies; whereas the variable Master's+ indicates the completion of a Master's degree or above. The parameter estimates indicate that, the higher the education level is, the more likely a worker has a work schedule that either entirely depends on the workload or has a fixed start but work-dependent end. Workers with a Bachelor's degree, on the other hand, are more likely to have access to some level of flexibility – either full control or within fixed limits (flextime) – than those with higher or lower levels of education. These education- related findings are possibly attributed to the nature of individuals' occupations, although the parameters corresponding to 14 occupation types fail to show statistical significance when introduced to the models.

Although the effect of occupation is inconclusive, the industry in which an individual works is a determining factor to certain types of work schedules. Three industry sectors are examined in the present study. These are retail, service, and basic employment. When the aforementioned personal characteristics are controlled for, the likelihood of a full-time employee having employer-specified rotating/varying shifts is highest for the retail sector, followed by the service sector, and then others. Being in the service industry sector, on the other hand, reduces the likelihood for a full-time worker to have access to flextime or work-dependent schedules. For part-time workers, employment in the retail industry increases the likelihood of having variable schedules, either by own choice or work-dependent, but also the likelihood of engaging in fixed work shifts that may vary across days.

With regard to individuals' income levels, the effect is significant and positive for full-time workers across all five alternatives but consistently insignificant for part-time workers. The degrees of effect of income on work schedule alternatives, from the highest to lowest, are variable at own choice, variable within fixed limits, variable depending on work, fixed start with work-dependent end, and, lastly, fixed shifts that may vary over days. Hence, high-income earners have greater freedom of choice for not only work start time, as concluded by Emmerink and van Beek (1997), but the overall schedule variability and flexibility. It should be noted at this point that the previous discussions in the present paper relate to employees' access to variable and/or flexible schedules, but not the actual variation observed in their schedules. That is, access to flexibility is an option but not necessarily taken advantage of by everyone who has it.

5.7 Employment Location Choice Model

Table 5.8 provides the estimation results for the MNL model for employment location choice. The coefficients on the logarithm of number of employment opportunities in a zone all have the expected positive sign, indicating that individuals are more likely to work in zones with more jobs than those with fewer jobs. The coefficient on the employment accessibility indicates that proximity to other employment activities is a positive determining factor. Similarly, good accessibility to recreational opportunities is also preferred. On the other hand, after accounting for the number of retail employment, accessibility to shopping has a negative effect on employment location choice. Finally, workers are less likely to choose zones with high land-use coverage by office buildings.

Table 5.8 Estimation results of the employment location choice model

	Coeff.	t-ratio
Log of number of basic employment	0.006	0.32
Log of number of retail employment	0.088	2.22
Log of number of service employment	0.072	3.26
Accessibility to employment	2.775	9.39
Accessibility to shopping	-4.787	-6.30
Accessibility to recreation	2.432	2.84
Percentage of zonal area covered by office buildings	-1.523	-3.83

5.8 Vehicle Ownership Model

Samples drawn from the DFW activity-travel survey are used to estimate the MNL models of car ownership choice. The parameter estimates are shown in Table 5.9. The coefficient estimates represent the effect of exogenous variables on the utility of each auto ownership alternative relative to the zero car alternative. Where the t-statistic is significant, the signs of all parameters are consistent with a priori expectations. Except for households with one car, households tend to prefer higher car ownership as the number of workers in the household increases. Similarly, the higher the number of driver's license holders in the household, the more cars the household is likely to have. The number of household members without a driver's license, on the other hand, has a negative effect. Higher household income is associated with higher levels of car ownership, a finding consistent with microeconomic theory of consumer choice.

Table 5.9 Estimation results of the vehicle ownership models

Number of Vehicles	1		2		3		4		5 or more	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	-0.577	-2.76	-5.469	-21.03	-10.716	-30.93	-13.937	-30.34	-17.059	-25.56
No. of workers	-0.049	-0.34	0.288	1.85	0.433	2.62	0.320	1.73	0.414	1.90
No. of members with license	2.122	10.72	4.766	21.85	6.509	27.27	7.201	27.81	7.809	26.41
No. of members without license	-0.270	-4.28	-0.183	-2.55	-0.321	-3.83	-0.233	-2.10	-0.382	-2.15
HH income	0.028	5.08	0.040	7.20	0.040	7.31	0.041	7.35	0.041	7.31
Model fit										
Log-likelihood	-4018.712									
# Cases	4563									

6. Empirical Results: Short-Term Choices

The short-term, activity-travel model system developed for the Dallas-Fort Worth (DFW) area is divided into four major components: (1) the generation-allocation model system, (2) the pattern-level model system, (3) The tour-level model system, and (4) the stop-level model system. All model components were coded in the matrix programming language GAUSS. The empirical results for each of the above-mentioned model components are discussed in detail in this section.

6.1 The Generation-Allocation Model System

The generation-allocation model system models the decision of each adult in a household to undertake different activity types for the day. The decision of individuals to participate in mandatory activities such as work and school is modeled first. The household's decision to pursue maintenance and leisure activities is modeled subsequently. The activity-allocation models are developed for multiadult households. A model to capture an individual's decision to participate in any other activity type forms the last model of the generation-allocation model system.

6.1.1 Decision to go to work, work-based duration, and work start times

Of the 1,198 employed persons in the sample, 1,000 (83.45 percent) made out-of-home work activities on the diary day. The decision to make out-of-home work activities on any day is modeled using a binary-logit model (Table 6.1). If there are multiple workers in a household, their decisions are assumed to be independent.

Table 6.1 Worker's decision to make out-of-home work activities

	Coefficient	t-statistic
Constant	1.4449	3.12
Sociodemographics		
Age	-0.0189	-2.73
Female	0.1718	0.94
African-American (Base = Caucasian)	-0.6046	-1.84
Other race	-0.4281	-1.56
Graduate education (Base = high school)	0.3806	1.65
Income as a fraction of HH income	0.9849	3.26
Number of kids between ages 0 and 4 in the HH	-0.2386	-0.91
Interaction term: Female and number of kids between ages 0 and 4 in the HH	-0.8863	-2.28
Work characteristics		
Partially flexible work schedule	1.5274	6.71
Fixed work schedule	1.128	6.08
Characteristics of the HH zone		
Median income	-0.0119	-1.74
Model fit		
Log-likelihood	-485.04	
Number of Cases	1198	

The model indicates that elderly people are less likely to go to work on any day when compared to younger adults. Caucasians are more likely to make work trips than people of any other race. College graduates are more likely to make work trips. Among the different household members who are workers, the one that earns more is also more likely to make work trips. Females with very young kids in the household are less likely to make work trips when compared to males, as the females are generally the ones to take care of the children.

Work characteristics are also found to significantly affect the decision to make work trips. People with flexible work schedules (those that indicated "variable at my choice," "variable depending on work," and "allowed to vary within fixed limits" as a description of their work schedule) are less likely to make work trips when compared to workers who have partially flexible ("fixed start but variable end based on work" and "fixed but different hours on different days") or fixed ("fixed and the same for several days or weeks" and "fixed and the same every day") schedules. The type of industry (retail, basic, or service) that the person works in was not found to influence the decision to go to work on any day. Finally, workers in areas of high median income are estimated to be less likely to make work trips.

Work location characteristics could not be used in this model, as the work location was not available for workers who did not make work trips on the diary day. Aggregate zonal accessibility measures were examined, but were not found to be statistically significant.

For adults who went to work, the work start and end times are determined. This is achieved by first modeling the total work-based duration and then the work start time. Work-based duration is defined as the total time between arrival at the work place for the first time in the day to the time of departure from work for the last time in the day. Thus, it includes the total time spent at work and in any tours based at work. The mean work-based duration in the sample is 525.74 minutes (or approximately 8.5 hours), with a standard deviation of 128.81 minutes. Work start time is defined as the time between 3 a.m. and the time of first arrival at the work place for the day. The mean work start time in the sample is 315.6 minutes from 3 a.m. (or approximately 8:15 a.m.) with a standard deviation of 120.3 minutes.

Both work-based duration and work start times are modeled as hazard-duration models (see, for example, the work by Bhat 1996 and 2000, for methodological details and applications of hazard-duration models in transportation engineering). A proportional-hazard specification with a nonparametric baseline hazard (recognizing a natural tendency to round off time to the nearest 5 minutes) and parametric control for unobserved heterogeneity (to capture the effect of unobserved individual effects on the duration) are adopted. The model developed for work-based duration is presented first, followed by the model developed for the work start time.

Table 6.2 presents discrete-period sample hazards for work-based duration. Failures, F_k, represent the number of individuals whose work-based duration ended in discrete period k. Number at risk, R_k, refers to the number of individuals whose work-based duration has lasted until the beginning of discrete period k. One observes substantially high hazards corresponding to discrete periods 15, 21 and 25. These correspond to durations of approximately 9, 9.5, and 10 hours respectively. Since the typical work duration is about 8 hours, it is quite intuitive that several people are found to have a work-based duration of 9, 9.5, or 10 hours.

Table 6.3 presents the effects of covariates. The model indicates that females are likely to work shorter durations than males. Adults with a driver's license are estimated to work longer than those without a license. As expected, individuals who earn more are likely to work longer durations. Individuals with a partially flexible work schedule and those that work in the basic industries are found to work longer. Perhaps people with partially flexible schedules can make more work-based trips, leading to an increase in work-based time. Finally, the variance of the heterogeneity term is estimated to be statistically very significant. This indicates the presence of unobserved effects significantly impacting work-based duration.

Table 6.2 Discrete period sample hazard for work-based duration

Discrete period (k)	Time (mins.)	Failures (F_k)	Number at risk (R_k)	Discrete period hazard
1	0 - 239.5	33	1000	0.033
2	239.5 - 299.5	24	967	0.025
3	299.5 - 359.5	26	943	0.028
4	359.5 - 419.5	21	917	0.023
5	419.5 - 449.5	18	896	0.020
6	449.5 - 479.5	28	878	0.032
7	479.5 - 494.5	53	850	0.062
8	494.5 - 509.5	48	797	0.060
9	509.5 - 514.5	59	749	0.079
10	514.5 - 519.5	20	690	0.029
11	519.5 - 524.5	33	670	0.049
12	524.5 - 529.5	33	637	0.052
13	529.5 - 534.5	16	604	0.026
14	534.5 - 539.5	17	588	0.029
15	539.5 - 544.5	87	571	0.152
16	544.5 - 549.5	27	484	0.056
17	549.5 - 554.5	26	457	0.057
18	554.5 - 559.5	28	431	0.065
19	559.5 - 564.5	20	403	0.050
20	564.5 - 569.5	22	383	0.057
21	569.5 - 574.5	44	361	0.122
22	574.5 - 579.5	14	317	0.044
23	579.5 - 584.5	20	303	0.066
24	584.5 - 599.5	47	283	0.166
25	599.5 - 614.5	53	236	0.225
26	614.5 - 629.5	40	183	0.219
27	629.5 - 659.5	52	143	0.364
28	659.5 - 689.5	29	91	0.319
29	689.5 - 749.5	32	62	0.516
30	>=749.5	30	30	1.000

Table 6.3 Covariate effects: hazard model for work-based duration

	Coefficient	t-statistic
Sociodemographics		
Female	-0.4081	-3.043
Have driver's license	0.766	1.911
Income	0.0022	1.806
Income as a fraction of household income	0.5546	2.53
Work Characteristics		
Partially flexible work schedule	0.4083	2.96
Basic industry	0.5334	3.614
Heterogeneity		
Variance	1.0661	5.997
Model Fit		
Log-likelihood	-3258.27	
Number of cases	1000	

The shape of the estimated continuous-time baseline hazard is presented in Figure 6.1. The figure indicates a general trend of increasing hazard with time.

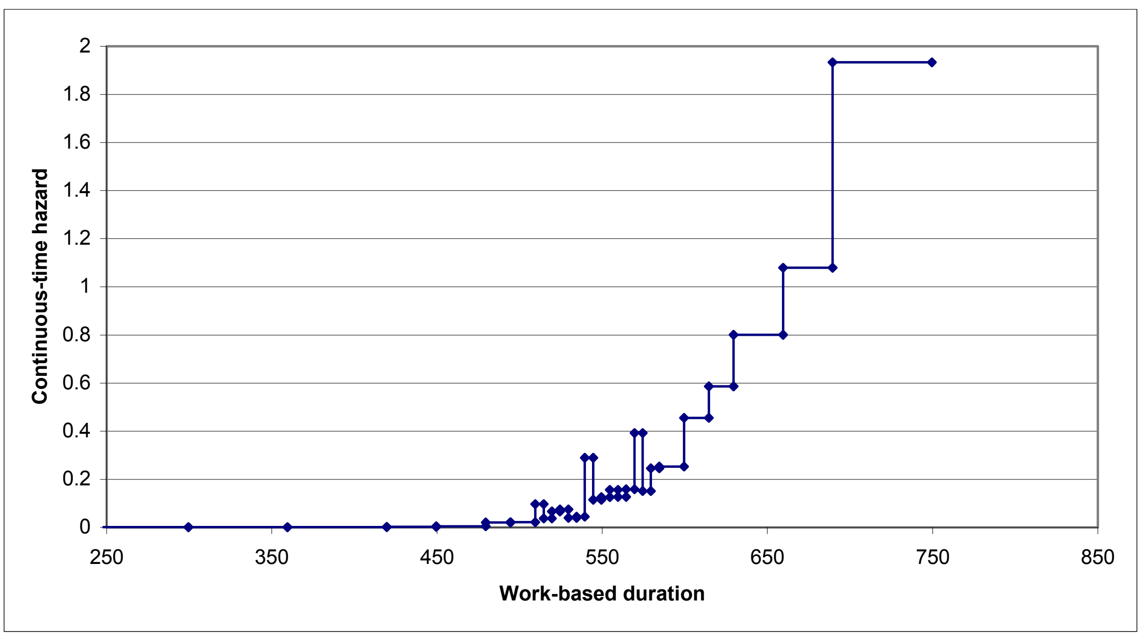

Figure 6.1 Continuous-time baseline hazard for work-based duration

Table 6.4 presents discrete-period sample hazards for work start time. One observes substantially high hazards corresponding to discrete periods 17, 23, and 25. These correspond to durations of approximately 5, 5.5, and 6 hours from 3 a.m. (or 8, 8:30, and 9 a.m.) respectively. Since the typical work start time is around 8 a.m. this observation is quite intuitive.

Table 6.4 Discrete-time sample hazard for work start time

Discrete time period	Time (mins.)	Failures	At risk	Discrete period hazard
1	0 - 179.5	36	1000	0.036
2	179.5 - 209.5	36	964	0.037
3	209.5 - 224.5	45	928	0.048
4	224.5 - 239.5	60	883	0.068
5	239.5 - 244.5	55	823	0.067
6	244.5 - 249.5	15	768	0.020
7	249.5 - 254.5	12	753	0.016
8	254.5 - 259.5	26	741	0.035
9	259.5 - 264.5	23	715	0.032
10	264.5 - 269.5	9	692	0.013
11	269.5 - 274.5	56	683	0.082
12	274.5 - 279.5	18	627	0.029
13	279.5 - 284.5	34	609	0.056
14	284.5 - 289.5	29	575	0.050
15	289.5 - 294.5	31	546	0.057
16	294.5 - 299.5	26	515	0.050
17	299.5 - 304.5	101	489	0.207
18	304.5 - 309.5	26	388	0.067
19	309.5 - 314.5	25	362	0.069
20	314.5 - 319.5	18	337	0.053
21	319.5 - 324.5	18	319	0.056
22	324.5 - 329.5	15	301	0.050
23	329.5 - 344.5	60	286	0.210
24	344.5 - 359.5	29	226	0.128
25	359.5 - 374.5	47	197	0.239
26	374.5 - 404.5	37	150	0.247
27	404.5 - 434.5	28	113	0.248
28	434.5 - 494.5	23	85	0.271
29	494.5 - 544.5	11	62	0.177
30	544.5 - 604.5	7	51	0.137
31	604.5 - 694.5	16	44	0.364
32	>=694.5	28	28	1.000

Table 6.5 presents the effects of covariates. The model indicates that elderly people and African-Americans are likely to start work early. Among the work characteristics, work-based duration was found to significantly impact the work start time. Workers who spend longer time at work are also more likely to start work early. Individuals with a partially flexible work schedule and those who work in the basic industries are estimated to start work earlier. Finally, the variance of the heterogeneity term is estimated to be statistically very significant. This indicates the presence of unobserved effects significantly impacting work start time.

Table 6.5 Covariate effects: model for work start time

	Coefficient	t-statistic
Sociodemographics		
Age	-0.0163	-3.69
African-American	-0.5763	-2.56
Work characteristics		
Fixed work schedule	-0.2671	-2.45
Basic industry	-0.6789	-5.66
Work-based duration	-0.0064	-11.54
Heterogeneity		
Variance	0.8939	10.46
Model Fit		
Log-likelihood	-3180.05	
Number of cases	1000	

The shape of the continuous-time baseline hazard for work start time is presented in Figure 6.2. The graph indicates a general trend of increasing hazard with time. As in the sample, one also observes a spike in the hazard corresponding to 8 a.m.

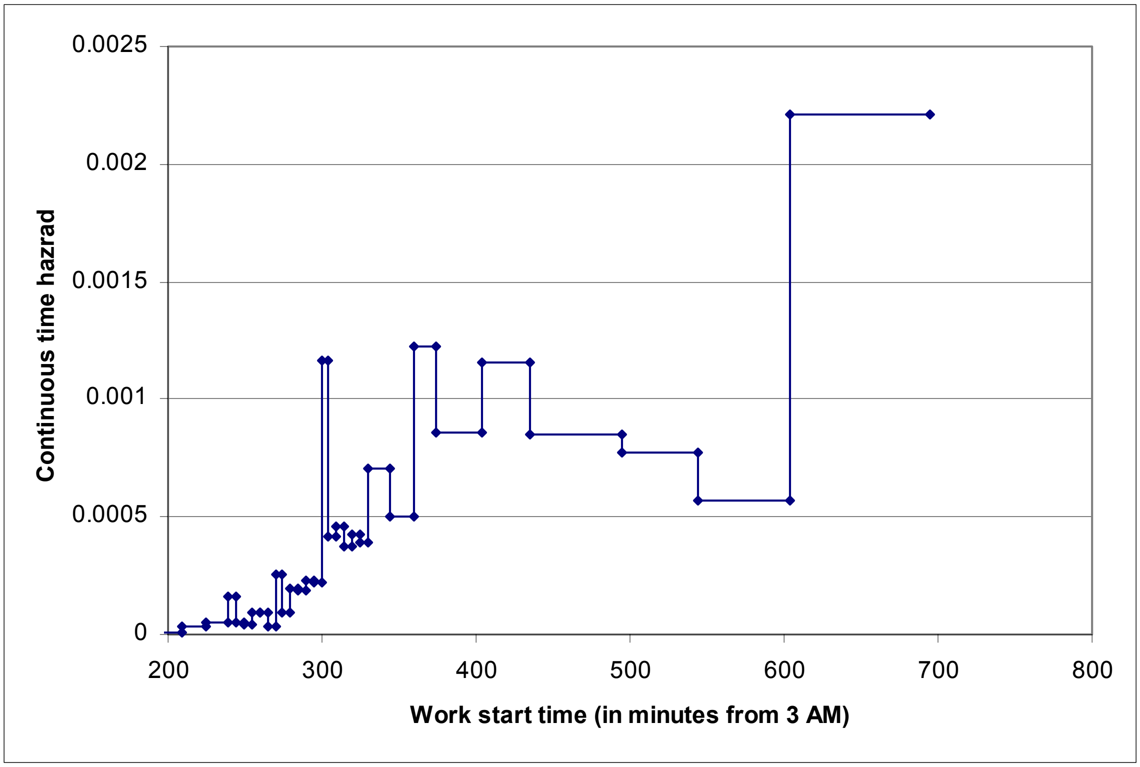

Figure 6.2 Continuous-time baseline hazard for work start time

6.1.2 Decision to go to school, school-based duration and school start times

Of the 104 adults in the sample who are students, 84 (80.77 percent) made school trips on the diary day. Table 5.6 presents the binary-logit model estimated to model a student's decision to go to school on any day. The model indicates that females are less likely to attend school on any day than males. The education level completed is also found to significantly affect the decision to make school trips. Students who have completed a graduate degree are less likely to make school trips than students who have completed high school. This is probably because high school and college (undergraduate study) have more regular schedules that warrant daily school trips. Presence of very young children in the household is also found to adversely impact the decision to make school trips.

Table 6.6 Student's decision to go to school

	Coefficient	t-statistic
Constant	2.8932	4.48
Sociodemographics		
Female	-1.0148	-1.61
College education	-1.0791	-1.85
Graduate education	-1.1565	-1.41
Number of kids between ages 0 and 4 in the HH	-0.8627	-1.69
Model fit		
Log-likelihood	-45.21	
# Cases	104	

School-based duration and the school start times are defined in the context of students and are analogous to the work-based duration and work start times for workers. The mean school-based duration for the students in the sample is 412.64 minutes (approximately 7 hours) with a standard deviation of 172.45 minutes. The mean school start time in the sample is 356.12 minutes from 3 a.m. (or approximately 9 a.m.) with a standard deviation of 157.57 minutes (2.5 hours). The natural logarithm of the school-based duration and start times are each modeled using linear regression for the 84 students who decided to attend school. The model results are discussed next.

The regression model for school-based duration (Table 6.7) suggests that school-based duration of students with a college degree is less than that for students with a high-school degree. Students with a graduate degree spend even less time based at school. The education level completed is perhaps indicative of the education underway. High school and college (undergraduate study) hours typically tend to be longer than graduate school hours. Females with young children are found to have lesser school-based time.

Table 6.7 School-based duration

	Coefficient	t-statistic
Constant	6.10	53.14
Sociodemographics		
Female	-0.12	-0.89
College education	-0.29	-2.07
Graduate education	-0.49	-2.14
Number of kids between ages 0 and 4 in the HH	0.22	0.85
Interaction term: Female and number of kids between ages 0 and 4 in the HH	-0.64	-1.74
Model fit		
Number of Cases	84	
Sum of squares (regression)	3.94	
Sum of squares (residual)	26.80	
Sum of squares (total)	30.74	
R^2	0.13	
$R^2_{adj.}$	0.07	

The results of the regression model estimated to determine school start time are presented in Table 6.8. The education level attained by the student is found to be a significant determinant of the school start time for the day. School tends to start later for students with graduate education when compared to students with college education. The longer the school-based duration, the earlier the person goes to school. Adults with a driver's license who do not have their own auto have earlier start times for school. Perhaps such people have to depend on others for a ride and so end up at school earlier than needed.

Table 6.8 School start time

	Coefficient	t-statistic
Constant	6.1587	69.36
Sociodemographics		
Have driver's license	-0.2914	-2.85
College Education	0.1862	2.79
Graduate Education	0.2405	2.34
Personal vehicle availability	0.3085	3.49
School-based duration (in minutes)	-0.0010	-6.24
Model fit		
Number of cases	84	
Sum of squares (regression)	4.93	
Sum of squares (residual)	4.98	
Sum of squares (total)	9.91	
R^2	0.50	
$R^2_{adj.}$	0.47	

6.1.3 Household activity generation

Subsequent to the modeling of an individual's participation in mandatory activities, the household's decision to participate in one or more of shopping, social-recreational, and personal-business activities is modeled. The sample shares are first presented, the modeling methodology is described next, and finally, the estimation results are discussed.

Table 6.9 indicates that most of the households did not undertake any maintenance or leisure activities on their diary day. This is quite intuitive, as one does not have to participate in such maintenance or leisure activities daily. About 34 percent of the households participated in one of the activity types and 18 percent in two of the three different activity types. Only 6 percent of the household participated in all of the three activity types.

Table 6.9 Sample shares: household activity participation

	Freq.	%
None	420	40.66
Only shopping	146	14.13
Only social/recreational	77	7.45
Only personal business	139	13.46
Shopping and social/recreational	39	3.78
Shopping and personal business	107	10.36
Social/recreational and personal business	43	4.16
All three	62	6
Total	1033	100

The decision to participate in one or more of the three activity types is modeled as a MNL model. Let U_{shop}, U_{soc}, and U_{pers} be the respective utilities derived by a household in participating in shopping, social/recreational, and personal-business activities. If the household participates in more than one activity, the total utility derived by the household is defined as the sum of the utilities derived by participating in each of the activities:

$$U = \delta_{shop} U_{shop} + \delta_{soc} U_{soc} + \delta_{pers} U_{pers}$$

where,

δ_{shop} =1, if the household decides to participate in shopping, 0 otherwise

δ_{soc} = 1, if the household decides to participate in social/recreational activities, 0 otherwise

δ_{pers} =1, if the household decides to participate in personal business, 0 otherwise

A household is assumed to choose the combination of activity types that would maximize the total utility, *U*. An alternative-specific constant is estimated for each of the seven combinations of activity participation to capture the utility associated with that activity combination. This approach helps preserve degrees of freedom and makes interpretation of results easier. The model results are presented in Table 6.10

Table 6.10 Household activity-generation model

	Coefficient	t-statistic
Constants		
Shopping	-8.0917	-2.53
Social/Recreational	-7.8954	-2.04
Personal business	-1.5118	-5.63
Shopping and Social/Recreational	-15.7748	-3.23
Shopping and Personal business	-9.0518	-2.82
Social/Recreational and Personal business	-9.0478	-2.33
Shopping, Social/Recreational, and Personal Business	-16.1683	-3.31
Specific to shopping		
Number of HH vehicles	0.1768	1.75
Number of nonworkers in HH	0.5586	4.51
One adult in HH goes to work	-0.5958	-3.25
Two adults in HH go to work	-0.6421	-2.56
Median income of HH zone	0.0155	2.59
Accessibility to retail businesses	0.6954	2.07
Specific to social/recreational		
Number of HH vehicles	0.2919	2.71
Median income of HH zone	0.0166	2.61
Accessibility to all businesses	0.5138	1.49
One adult in HH goes to work	-0.0438	-0.22
Work duration of primary worker	-0.0011	-2.92
Specific to personal business		
Number of children between ages 5 and 15 in the HH	-0.2675	-2.11
Number of HH vehicles	0.4392	4.39
HH income (1000s of $$)	0.0034	1.95
Median income of HH zone	0.0108	1.76
One adult in HH goes to work	-0.5889	-2.71
Two adults in HH go to work	-1.1302	-4.22
Commute duration of primary worker	-0.005	-1.57
Model fit		
Log-likelihood	1715.51	
Number of Cases	1033	

The model indicates that number of household vehicles positively influences the household's participation in each of the three activity types. Households in areas of high income are also more likely to make activities of each of the three types.

Households with more nonworkers are more likely to participate in shopping. This is possibly because the nonworkers have much more time available to invest in shopping than workers or students. The greater the number of adults that go to work on a day, the less likely the household is to undertake shopping activities. Better accessibility to retail businesses from the household zone is estimated to improve a household's likelihood of making shopping activities. Accessibility to retail industries from zone j is defined as the following log-sum measure:

$$Access_j^{retail} = \ln\left(\sum_{all\ zones\ i} \frac{retail\ emp_i}{IVTT_{ij}^{peak,auto}}\right).$$

$IVTT_{ij}$ is the in-vehicle travel time between zones i and j

The work duration of the primary worker (the one with the highest income) is found to negatively impact the household's participation in social/recreational activities. Further, a household's decision to participate in social/recreational activities is influenced positively by overall accessibility to all businesses. Accessibility to all businesses from zone j is defined as the following log-sum measure:

$$Access_j^{all} = \ln\left(\sum_{all\ zones\ i} \frac{total\ emp_i}{IVTT_{ij}^{peak,auto}}\right).$$

Households in which there are one or more adults going to work are less likely to undertake personal business on any day when compared to households that do not have an adult going to work. In addition, the expected commute duration (IVTT by auto based on work start and end times) of the primary worker also negatively influences participation in personal business. Higher income households are more likely to participate in personal-business activities. Finally, the presence of children is estimated to negatively influence the household's decision to participate in personal-business activities.

The alternative-specific constants are all negative. The constants corresponding to a household's participation in two or three different activity types is more negative indicating the household's disutility in participating in many different activities on the same day due to time constraints.

6.1.4 Activity allocation for multiadult households

This section presents the activity allocation model results. In these models, an individual's decision to participate in an activity is determined, given that the household has decided to participate in it. Models are developed separately for each of shopping, social/recreational, and personal-business activity types. The data sample for the allocation model for any activity type comprises all adults from multiadult households that decided to participate in that activity type (238 households for shopping, 156 for social/recreational, and 239 for personal business). Decisions of the different individuals in a household are assumed to be independent. The sample shares (of individual's decisions to participate in each activity, given that the household has decided to participate in the activity) are presented in the Table 6.11.

Table 6.11 Individual's decision to participate in an activity given household's decision to participate in the activity

	Shopping		Social/recreational		Personal business	
	Freq	%	Freq	%	Freq	%
No	215	41.03	134	39.3	223	42.08
Yes	309	58.97	207	60.7	307	57.92
Total	524	100	341	100	530	100

The model for shopping (see the first major column in Table 6.12) indicates that females are more likely to participate in shopping than males. Individuals with a driver's license are more likely to shop than individuals without a driver's license. The possibility that any individual will undertake shopping activity decreases with increasing number of nonworkers in the household. Workers and nonworkers are more likely to participate in shopping than students. However, the longer the worker spends at work (or student at school), the less likely he/she is to make shopping activities. The work duration of another worker in the household positively influences a person's decision to undertake shopping activities.

Table 6.12 Activity allocation models for multiadult households

	Shopping		Social/Recreational		Personal business	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Constant	-1.5713	-2.7	0.3374	0.8	-1.3249	-2.7
Sociodemographics						
Female	0.6291	3.08	-0.5902	-2.39	0.3091	1.66
Have driver's license	1.0397	2.38			1.0311	1.71
Is the person a worker	1.5509	3.34	0.0738	0.2	-0.1162	-0.5
Is the person a nonworker	1.8889	3.67				
Number of nonworkers in the HH	-0.4598	-2.05				
Personal vehicle availability			0.5637	1.52	0.8574	2.33
Work characteristics						
Work duration	-0.0031	-5.29	-0.0025	-3.8		
Expected commute time					-0.0134	-3.43
Work duration of the other HH worker	0.0008	1.75	0.0017	3.78		
Model fit						
Log-likelihood	-306.12		-208.52		-339.56	
Number of cases	524		341		530	

Females are less likely to participate in social/recreational activities (see the second major column in Table 6.12). Personal vehicle availability (defined as the ratio of the number of household vehicles to the number of household adults with licenses, if the person has a license, and 0 otherwise) positively influences participation in social/recreational activities. The longer a worker works, the less likely the person is to undertake social activities. However, the work duration of another worker in the household is found to positively influence any person's participation in social activities.

Females are more likely to participate in personal business than males (see the third major column in Table 6.12). Having a driver's license and personal vehicle availability make a person more likely to make personal-business activities. For workers, the expected auto commute time (total auto IVTT for work-to-home and home-to-work travel based on work start and end times) is found to have a negative influence on the individual's decision to participate in personal-business activities. Perhaps persons who have to commute longer do not have the time to undertake personal-business activities during the day.

6.1.5 Decision to participate in "other" activity

As described in the analysis framework, some activity types that could not be classified as maintenance or leisure (or did not have enough cases to explicitly model the generation and allocation) are termed as "other" activities. About 38 percent of these "other" activity episodes are eat out; 30 percent are serve-passenger, 13 percent work-related and another 13 percent are community-related activities. This section presents a binary-logit model for an individual's decision to participate in such "other" activities. Of the 1,764 adults in the data set, 637 (36.11 percent) participated in "other" activities. The model is presented in Table 6.13

Table 6.13 Decision of an adult to participate in "other" activities

	Coefficient	t-statistic
Constant	-1.9663	-6.27
Sociodemographics		
Female	-0.1214	-1.06
Have driver's license	0.6661	2.34
Income (in 1000$)	0.0033	2.03
Is the person a worker	0.7225	4.25
Number of kids between ages 0 and 4 in the HH	-0.4133	-1.91
Number of children between ages 5 and 15 in the HH	0.6368	7.65
Does the HH have more than one adult	0.0388	0.29
Interaction term: female and number of kids between the ages of 0 and 4 in HH	0.5185	1.82
Work characteristics		
Work duration	-0.0014	-4.14
Expected commute time	0.0043	1.75
Activity participation characteristics		
Person has decided to make social/recreational activities	0.4937	3.32
Person has decided to make personal-business activities	0.8079	6.54
Another HH adult has decided to make social/recreational activities	0.3812	2.36
Model fit		
Log-likelihood	-1059.92	
Number of cases	1764	

Having a driver's license positively influences an individual's decision to undertake "other" activities. Higher income individuals are also more likely to undertake "other" activities. When very young kids are present in the household, females are more likely to undertake "other" activities when compared to males. When children between ages 5 and 15 are present, the adults are likely to undertake "other" activities including driving the children to school, etc.

Workers are more likely to undertake "other" activities (possibly work-related activities) when compared to nonworkers and students. However, their propensity to undertake such activities decreases with increase in work-based duration. Further, workers who may have to commute longer are more likely to participate in "other" activities.

An individual's decision to participate in "other" activities is also positively influenced by the person's decision to participate in social/recreational and personal-business activities, and the decision of any other household adult to participate in social activities. Perhaps, when multiple household adults go out for social/recreational activities, they also tend to eat out.

6.2 The Pattern-Level Model System

This section of the report presents the models developed to determine the pattern-level choices, which form the highest level of all scheduling decisions. The pattern-level attributes for workers include the commute characteristics and the decision to make a tour during each of the before-work, work-based and after-work periods. The models developed to characterize the work-to-home commute are presented first. The models for home-to-work commute are presented next. The last pattern-level model for the workers focuses on the decision of the worker to make tours. The model estimated to determine the total number of tours for a nonworker, the only pattern-level attribute for nonworkers, is the final model presented in this section. It is noted, again, that in all scheduling models the term "worker" refers to adults who pursued work activities during the day and the term "nonworker" includes non-employed adults as well as employed adults who did not go to work.

6.2.1 Work-to-home commute characteristics

The mode, number of stops, and total commute duration together characterize the work-to-home commute of workers. This section presents models that sequentially determine the above characteristics. The number of adult students in the sample is too few to be examined separately. Hence, students are also treated as workers and their school activity is assumed to be synonymous with the work activity of the workers. Wherever appropriate, an indicator variable (student, which takes the value 1 if the adult is a student, and 0 otherwise) has been used to distinguish students from employed adults.

The first pattern-level characteristic modeled for workers is the work-to-home commute mode. The different modes available are auto, transit, and non-motorized modes (walk/bike). The auto mode is further classified into drive-alone and shared-ride based on vehicle occupancy (in the case of shared-ride, the characteristics of the other person(s) with whom the auto is being shared could not be determined from the survey data). In most cases, a single mode was used for the entire commute. However, for people who made pick-up or drop-off activities during their commute, the mode could be drive-alone for a part of the commute and shared-ride for the rest of the commute. This combination of drive-alone and shared-ride is classified as a separate mode and subsequently referred to as the DA-SR mode.

Thus, one or more of five different modes are assumed to be available to any person. These are drive-alone, shared-ride, transit, walk/bike, and DA-SR. Drive-alone is assumed to be available for all individuals with a driver's license. Shared ride is assumed to be available for all. Transit is assumed to be an available mode if transit service is available from the work zone to the home zone at work end time and is also available from the home zone to the work zone at the work start time. Walk/bike is assumed to be available if the distance between the home and the work zones is less than 10 miles (empirically derived threshold, based on the maximum distance traveled by individuals in the sample who used a non-motorized mode to work). As defined, the DA-SR mode is chosen only if the person has to make serve-passenger activities. Hence, it is assumed that adults who do not choose to perform any serve-passenger activities in the day do not consider this mode as an option. However, as the decision to participate in serve-passenger activities is not determined explicitly in the generation-allocation model system, the DA-SR mode is an option for all individuals who have a driver's license and choose to do "other" activity during the day (serve-passenger is classified under "other" activities).

The availability of the different modes and the sample shares are presented in Table 6.14. The table indicates that most of the people choose the drive-alone mode to work. The number of cases in the sample observed to choose transit or non-motorized modes is very few.

Table 6.14 Availability and sample shares for work-to-home commute mode

	Availability		Sample Shares	
	Freq.	%	Freq.	%
Drive-alone	1036	96.64	886	82.65
Shared-ride	1072	100.00	87	8.12
Transit	581	54.20	20	1.87
Walk/bike	514	47.95	21	1.96
DA-SR	365	34.05	58	5.41
Total			1072	100

The MNL model developed for mode choice is presented in Table 6.15. The alternative specific constants are all negative indicating a generic dispreference for all modes other than drive-alone. The model indicates that older people are less likely to share a ride when compared to younger people. A person who has access to his/her own vehicle is less likely to share-ride as indicated by the negative coefficient on the personal vehicle availability variable. It is also found that adults from households with multiple adults are more likely to share-ride. Further, if there is another household adult going to work on the same day, the propensity to share-ride increases. This is probably because multiple adults going to work from the same household provides a very good situation for making joint commute trips. Personal vehicle availability was found to be the most significant determinant of the choice of transit or walk as a commute mode. Persons who do not have a driver's license or access to their own vehicle are most likely to take transit or walk/bike to work. Females were estimated to be more likely to choose the DA-SR mode for commute. The presence of kids in the household significantly increases the chances of choosing DA-SR as the work to home commute mode. Perhaps the worker picks up the children from school or day care on the way back home. Also, an individual is more likely to choose the DA-SR mode when there is another household adult making work trips on the same day. Probably one worker picks up another from work on the way back home. Expected travel times were used as explanatory variables for both auto and transit modes, but were not found to be statistically significant.

Table 6.15 Work-to-home commute mode choice model

	Coefficient	t-statistic
Constants		
Shared-ride	-1.7004	-2.11
Transit	-0.6280	-1.13
Walk	-0.3587	-0.65
DA-SR	-2.7073	-6.58
Specific to shared-ride		
Age	-0.0167	-1.85
Personal vehicle availability	-2.2415	-4.58
Is it a multi-adult HH	1.3224	1.92
Is there another person going to work	1.3405	3.52
Specific to transit		
Personal vehicle availability	-3.1297	-4.91
Specific to Walk		
Personal vehicle availability	-3.4515	-5.31
Specific to drive-alone and shared-ride		
Female	0.7838	2.47
Number of kids in the HH between ages 0 and 4	1.5577	4.23
Number of children in the HH between ages 5 and 15	0.6062	3.95
Is it a multiadult HH	-0.6205	-1.11
Is there another person going to work	0.9100	2.02
Model fit		
Log-likelihood	-475.08	
Number of cases	1072	

The next commute characteristic modeled is the number of work-to-home commute stops. Almost one-half of the workers did not pursue any other activities during the diary day. For these adults, the number of commute stops is necessarily zero. Hence, the number of commute stops is modeled only for workers who decided to participate in activities other than work. The distribution of the number of work-to-home commute stops is presented in Table 6.16. About 56 percent of the workers (who decided to participate in activities other than work) did not make any commute stops on the way back home. About 31 percent made just one stop and about 12 percent made two or more stops.

Table 6.16 Sample shares for number of work-to-home commute stops

Number of stops	Freq.	%
0	319	56.66
1	174	30.91
2	50	8.88
>=3	20	3.55
Total	563	100

The ordered-response model results are presented in Table 6.17. Individuals from multiple adult households are less likely to make commute stops. Workers are more likely to make commute stops than students. Finally, the presence of young children in the household has a negative influence on work-to-home commute stop making. This is probably because the individual desires to get back home as early as possible to attend to the children's needs. The need to pick up and/or drop off children may motivate stop making during the commute. This is captured through the effect of the mode chosen for commute, in particular the choice of DA-SR mode.

The model indicates that the later the work ends in the day, the less likely the person is to make commute stops. People who choose auto modes are more likely to make commute stops than people who take transit or walk to work. It is to be noted that if a person chooses DA-SR mode, then the person necessarily makes at least one stop (i.e., serve-passenger). The model does not explicitly capture this. Practically, however, the very high positive coefficient on the DA-SR mode will ensure that the model will not predict zero stops for any person who chooses the DA-SR mode.

The individual's decisions to participate in personal-business, shopping, and social/recreational activities all have a positive influence on work-to-home commute stop making. The coefficient on the decision to participate in personal-business activity is the largest among the coefficients on activity participation variables. This suggests that personal-business stops are perhaps made during the commute back home.

Table 6.17 Number of work-to-home commute stops

	Coefficient	t-statistic
Sociodemographics		
Is the person employed	0.6224	2.73
Is this a multi-adult HH	-0.2321	-1.91
Number of children between ages 5 and 15 in the HH	-0.2981	-3.35
Work characteristics		
Work end time (in minutes from 3 a.m.)	-0.0016	-3.61
Work-to-home commute characteristics		
Mode is drive alone	0.9075	1.86
Mode is shared-ride	1.8203	3.5
Mode is DA-SR	3.1131	6.02
Activity participation characteristics		
The person decided to pursue shopping activity	0.7321	6.19
The person decided to pursue social/recreational activity	0.5329	4.22
The person decided to pursue personal-business activity	1.0344	8.74
Threshold parameters demarcating		
0 and 1 stop	1.0531	1.84
1 and 2 stops	2.4323	4.18
2 and 3 stops	3.3847	5.69
Model Fit		
Log-likelihood	-444.83	
# Cases	563	

The work-to-home commute duration is modeled next, using linear regression to complete characterizing the worker's commute from work to home. The mean commute duration from the sample is 46.38 minutes with a standard deviation of 60.25 minutes. The regression model developed is presented in Table 6.18. The natural logarithm of the commute duration is taken as the dependent variable. The model indicates that the person tends to have shorter commute duration if the person leaves work late. The greater the number of commute stops, the longer is the estimated commute duration. The mode chosen for commute was also found to have a significant impact on the commute duration. Choice of transit and walk modes results in longer commute times when compared to auto modes, perhaps reflecting that the former are naturally slower modes. Finally, the expected travel time by the chosen mode (auto or transit) also has a positive impact on the total commute duration. This captures the impact of the distance between the home and work zones and the prevailing level-of-service conditions at the time of departure from work.

Table 6.18 Work-to-home commute duration

	Coefficient	t-statistic
Constant	2.885	22.62
Work characteristics		
Work end time (in minutes from 3 AM)	-0.0004	-2.88
Work-to-home commute characteristics		
One stop	1.1897	21.55
Two stops	1.6232	17.31
Three stops	2.1055	14.38
Mode is shared-ride	-0.1352	-1.97
Mode is transit	0.9151	3.02
Mode is walk/bike	0.3537	2.51
Mode is DA-DR	-0.3962	-4.2
Level of service		
Expected auto travel time between work and home (in minutes, if mode is auto)	0.025	17.91
Expected transit travel time between work and home (in minutes, if mode is transit)	0.0145	2.23
Model fit		
Number of Cases	1074	
Sum of Squares (regression)	462.57	
Sum of Squares (residual)	402.75	
Sum of Squares (total)	865.32	
R^2	0.53	
$R^2_{adj.}$	0.53	

6.2.2 Home-to-work commute characteristics

Similar to the work-to-home commute, the home-to-work commute characteristics modeled are the mode, number of stops, and duration. Table 6.19 presents the home-to-work commute mode (in the rows) cross-tabulated against the work-to-home commute mode (in the columns).

Table 6.19 Cross tabulation of home-to-work commute mode against work-to-home commute mode

	Drive-alone	Shared-ride	Transit	Walk/Bike	DA-SR	Total
Drive-alone	842	3			25	870
Shared-ride	9	82	2	4	3	100
Transit		1	18			19
Walk/Bike		2		17		19
DA-SR	35	1			30	66
Total	886	89	20	21	58	1074

The above table indicates that the home-to-work commute mode is, in most cases, the same as the work-to-home mode (see entries along the diagonal). Hence, it is assumed that if the person chose shared-ride, walk, or transit as the work-to-home commute mode, the home-to-work commute mode is also the same. Also, if the commute mode was drive-alone and the person did not choose to make "other" activities for the day, the home-to-work commute mode is assumed to be drive-alone. The home-to-work commute mode could be different from the work-to-home mode only if the person decided to make "other" activities and chose either drive-alone or DA-SR as the work-to-home commute mode. In such cases, the home-to-work mode is determined using one of two binary-logit models (Table 6.20). Model 1 determines whether the home-to-work mode is drive-alone or DA-SR, given that the work-to-home mode is drive-alone. Model 2 determines whether the home-to-work mode is drive-alone or DA-SR, given that the work-to-home mode is DA-SR.

Table 6.20 Home-to-work commute mode choice models

	Model 1		Model 2	
	Coefficient	t-statistic	Coefficient	t-statistic
Constant	2.2155	2.167	0.3476	0.696
Sociodemographics				
Age	0.0398	1.991		
Is this a multi-adult HH	-0.846	-0.961		
Number of kids between ages 0 and 4 in the HH			-0.4632	-0.743
Number of children between ages 5 and 15 in the HH	-0.9106	-4.576	-0.4249	-1.188
Work characteristics				
Is there another adult making work activity	-0.8651	-1.652		
Model Fit				
Log-likelihood	-83.49		-37.07	
Number of cases	274		55	

Given that the work-to-home commute mode is drive-alone and the person has decided to participate in "other" activities for the day, elderly people are more likely to choose drive- alone as their home-to-work mode. Presence of children and another household adult making work trips on the day favor choosing DA-SR over drive-alone.

Given that the work-to-home commute mode is DA-SR and the person has decided to participate in "other" activities for the day, presence of children in the household favors the adult choosing DA-SR as the work-to-home commute mode also. (These parameters are not statistically significant at the 95 percent confidence level, but considering the number of data points in the sample, the most significant variables were retained.)

Next, the number of home-to-work commute stops is modeled for adults who decided to participate in activities other than work. Almost 80 percent of the adults in the sample (the sample comprises all of the adults that decided to make activities other than work) did not make any home-to-work commute stops. About 16 percent make one stop and the rest make two or more. The ordered-response model developed is presented in Table 6.21.

Table 6.21 Number of home-to-work commute stops

	Coefficient	t-statistic
Sociodemographics		
Age	0.0135	2.28
Number of kids between ages 0 and 4 in the HH	0.3248	1.66
Activity participation characteristics		
The person decided to pursue social/recreational activity	0.3727	2.24
The person decided to pursue personal-business activity	0.6259	4.06
Work characteristics		
Work start time (in minutes from 3 a.m.)	0.0024	4.22
Home-to-work commute characteristics		
Mode is DA-SR	2.7598	13.03
Level of Service		
Expected auto travel time between work and home (in minutes, if mode is auto)	0.0205	3.9
Threshold parameters demarcating		
0 and 1 stop	3.519	8.43
1 and 2 stops	5.3058	11.29
Model fit		
Log-likelihood	-208.53	
Number of cases	563	

Elderly people are estimated to be more likely to make commute stops. Similarly, adults from households with very young children are also likely to make commute stops, perhaps to drop kids off at school or daycare. The decisions to make social and personal-business activities are found to positively impact home-to-work commute stop making. Perhaps these are the most common stops made during the commute. The model indicates that the later the worker starts work, the more likely the worker is to make stops in his/her home-to-work commute. The expected auto IVTT between the home and work zone was found to have a positive impact on home-to-work commute stop making. This suggests that people who have to travel longer to work are more likely to make stops on the way. Finally, the coefficient on DA-SR as the mode is large and positive. This ensures that the model always predicts one or more stops for people who chose this mode.

The last model developed for characterizing the home-to-work commute is a linear-regression model for the commute duration. The mean commute duration from the sample is 29.48 minutes with a standard deviation of 25.27 minutes. The mean home-to-work commute duration is found to be much lesser than the mean work-to-home duration of 46.38 minutes. The regression model developed is presented in Table 6.22. The natural logarithm of the commute duration is taken as the dependent variable.

The model indicates that the persons who decide to start work later in the day are more likely to have longer commute durations. The greater the number of commute stops, the longer is the commute duration. The mode chosen for commute was also found to have a significant impact on the commute duration. Choice of transit and shared-ride modes results in longer commute times when compared to drive-alone and DA-SR modes.

The expected travel time by the chosen mode (auto or transit) also has a positive impact on the total commute duration. The model also suggests that people who make longer work-to-home commutes also tend to make longer home-to-work commutes. These variables could all be capturing the impact of the distance between the home and work zones and the prevailing level of service conditions at the time of arrival at work.

Table 6.22 Home-to-work commute duration

	Coefficient	t-statistic
Constant	2.2076	36.73
Work characteristics		
Work start time (in minutes from 3 a.m.)	0.0005	3.61
Home-to-work commute characteristics		
One stop	0.7481	9
Two stops	1.0745	7.67
Mode is shared-ride	0.1326	2.32
Mode is transit	0.7113	2.4
Mode is DA-SR	-0.329	-3.18
Work-to-home commute characteristics		
Commute duration	0.0014	4.91
Level of service		
Expected auto travel time between work and home (in minutes, if mode is auto)	0.0267	22
Expected transit travel time between work and home (in minutes, if mode is transit)	0.0184	2.88
Model Fit		
Number of Cases	1074	
Sum of Squares (regression)	235.33	
Sum of Squares (residual)	310.61	
Sum of Squares (total)	545.94	
R^2	0.43	
$R^2_{adj.}$	0.43	

6.2.3 Worker's decision to make tours

The preceding subsections of the report discussed models developed to determine the commute characteristics of workers. This subsection presents a MNL model developed to model a worker's decision to make a tour during one or more of the before-work, work-based, and after-work periods. The model is estimated only for those workers who decided to participate in activities other than work.

Let U_{bw}, U_{wb}, and U_{aw} be the respective utilities derived by a person in making a tour before work, based at work, and after work. If an adult makes a tour in more than one period, the total utility derived is defined as the sum of the utilities derived by making each tour.

$$U = \delta_{bw} U_{bw} + \delta_{wb} U_{wb} + \delta_{aw} U_{aw}$$

where,

δ_{bw} = 1, if the person makes a tour before work, 0 otherwise

δ_{wb} = 1, if the person makes a work-based tour, 0 otherwise

δ_{aw} = 1, if the person makes a tour after work, 0 otherwise

The worker is assumed to make tours in one or more different periods so as to maximize his/her total utility, *U*. The sample shares are presented below (Table 6.23). About one-third of all workers that decided to participate in activities other than work do not make any tours. Twenty-five percent of workers made only work-based tours and another 25 percent made tours only after work. Only 16 percent made two or more tours.

Table 6.23 Sample shares: Worker's decision to make tours

	Freq.	%
No tours	170	32.08
Only after work	138	26.04
Only work based	136	25.66
Only before work	23	4.34
After work and work based	54	10.19
After work and before work	6	1.13
Work based and before work	2	0.38
Before work, after work, and work based	1	0.19
Total	530	100

The MNL model estimated is presented in Table 6.24. An alternative-specific constant is estimated for the choice of making a tour in each one of the three periods. A single constant is estimated for the choices of making tours in two or more periods, as the number of cases in which a person makes multiple tours is few. This approach helps preserve degrees of freedom and makes interpretation of results easier.

Students are estimated to be more likely to make a tour after school than employed adults are to make a tour after work. The number of work-to-home commute stops has a negative influence on the propensity to make a tour after work. This suggests a possible substitution in stop making between the work-to-home commute and the post-home arrival period. Also, the later the person gets home from work, the less likely is the person to make a tour after work. The model suggests that the individual's decision to participate in different types of activities has a positive influence on making a tour after work. The coefficient on the activity-participation variable specific to personal business is least positive among all the activity-participation-related variables.

The model suggests that elderly people and females are less likely to make work-based tours. Students are less likely to make school-based tours than workers are to make work-based tours. The presence of kids in the household negatively influences making any work-based tours. Possibly, these persons prefer to get back early to attend to the children. The total work-based duration of the person has a positive influence on making a work-based tour. The longer the person spends at work, the more likely he/she is to make a work-based tour. The decision to make social, personal-business, and "other" activities each has a positive influence on the propensity to make a work-based tour. Decision to participate in "other" activities has the most positive influence (and perhaps this "other" activity is work-related or eat-out).

Elderly people and students are less likely to make a tour before work. The presence of children positively influences making tours before work; these could possibly be to drop off children at school or day care. The model also suggests that persons who do not have access to their own vehicle (as indicated by the coefficient on the personal vehicle availability variable) are more likely to make tours before work. This could be a consequence of having to share the household auto. The number of home-to-work commute stops is found to negatively influence making a tour before work. Finally, the later the person departs for work in the day, the more likely he/she is to make a tour before work.

Table 6.24 Decision of workers to make tours

	Coefficient	t-statistic
Constants		
Tour after work	0.3645	0.8
Work-based tour	-2.7229	-4.28
Tour before work	-0.196	-0.41
Two or more tours	-3.3902	-4.15
Specific to tours after work		
Is the person a student	0.7703	1.84
Number of stops in work-to-home commute	-1.7154	-8.12
Arrival time home from work (in minutes from 3 AM)	-0.1898	-5.4
The person decided to pursue shopping activity	2.6428	7.91
The person decided to pursue social/recreational activity	2.6155	7.86
The person decided to pursue “other” activity	2.1394	6.93
The person decided to pursue personal-business activity	1.3486	4.79
Specific to work-based tours		
Age	-0.015	-1.69
Female	-0.527	-2.66
Is the person a student	-0.8703	-1.67
Number of kids between age 0 and 4 in the HH	-0.8361	-2.53
Work based time (in minutes)	0.2411	4.59
The person decided to pursue social/recreational activity	0.6361	2.46
The person decided to pursue “other” activity	1.5344	6.49
The person decided to pursue personal-business activity	0.7292	3.29
Specific to tours before work		
Age	-0.0708	-4.28
Is the person a student	-2.4754	-2.85
Number of children between ages 5 and 15 in the HH	0.6683	2.23
Personal vehicle available	-3.8185	-5.34
Number of home-to-work commute stops	-1.8078	-2.6
Departure time for work (in minutes from 3 a.m.)	0.777	7.5
Model fit		
Log-likelihood	-617.72	
Number of cases	530	

6.2.4 Number of tours for nonworker

This subsection focuses on the pattern-level model for nonworkers. The only pattern-level attribute to be modeled for nonworkers is the total number of tours. For adults who decided to not participate in any out-of-home activity for the day, the number of tours is necessarily zero. Thus, an ordered-response model was developed to determine the number of tours only for adults who decided to participate in one or more activities. About 60 percent made just one tour, 28 percent made two tours, and the rest made three or more tours. The model results are presented in Table 6.25.

Table 6.25 Number of tours made by nonworkers

	Coefficient	t-statistic
Sociodemographics		
The person has driver's license	0.830	2
Number of children between ages 5 and 15 in the HH	0.374	3.97
Household income (1000 $$)	0.001	1.66
Activity participation characteristics		
The person decided to pursue shopping activity	0.619	5.27
The person decided to pursue social/recreational activity	0.883	7.11
The person decided to pursue “other” activity	1.084	8.81
The person decided to pursue personal-business activity	0.854	7.26
Threshold parameter demarcating		
1 and 2 tours	2.741	6.36
2 and 3 tours	3.982	8.89
Model fit		
Log-likelihood	-373.92	
Number of cases	520	

Individuals with a driver’s license are estimated to make more tours than others. Persons without a driver’s license are more mobility restrained and, therefore, may be expected to make fewer tours in the day. The presence of children in the household increases the nonworker’s propensity to make tours, possibly to pick-up and/or drop off children at their school. Persons from higher income households are likely to make more tours than persons from lower income households. The decision of the person to participate in different activities has a positive impact on the propensity to make tours.

6.3 The Tour-Level Model System

The results of models developed to determine the tour-level attributes are presented in this section. The tour-level attributes are the mode, number of stops, tour duration, and the home-stay duration before any tour. In the case of workers, it would be ideal to estimate models separately for tours made during before-work, work-based, and after-work periods. Similarly, in the case of nonworkers it would be ideal to estimate separate models for each of the first, second, and third tours in the day. However, data limitations prohibit such an approach and a single model was developed to model all tours of workers and another model was estimated for tours of nonworkers. Indicators are appropriately used to identify the position of the tour in the overall activity sequence of the person. These models are discussed in detail in the subsequent subsections.

6.3.1 Mode choice for a tour

The mode choice for a tour is modeled as a MNL model. The data set does not provide any instances where transit was chosen as a tour mode. Hence, one or more of *four* different modes are available for each adult. These are drive-alone, shared-ride, walk/bike and DA-SR. Drive-alone is available for all adults who have a driver's license (98.09 percent in the worker sample and 97.26 percent in the nonworker sample). Shared-ride and non-motorized modes (walk/bike) are assumed to be available for all. DA-SR is assumed to be available to all persons who have a driver's license and decided to make "other" activity in the day (72.97 percent in the worker sample and 54.72 percent in the nonworker sample). The sample shares for both workers ands nonworkers are presented in Table 6.26. The table indicates that the shares of drive-alone and shared-ride are almost the same for workers and nonworkers. The workers are found to use the non-motorized modes more than nonworkers, whereas the nonworkers are found to be more likely to choose DA-SR as the tour mode than the workers.

Table 6.26 Sample shares for tour mode: workers and nonworkers

	Workers		Nonworkers	
Tour mode	Freq.	%	Freq.	%
Drive-alone	224	53.59	390	54.17
Shared-ride	141	33.73	246	34.17
Walk/Bike	28	6.70	17	2.36
DA-SR	25	5.98	67	9.31
Total	418	100.00	720	100

Table 6.27 presents the tour mode choice model for workers. The alternative-specific constants are all negative indicating a generic dispreference for all modes when compared to drive-alone. The presence of multiple adults and children in the household increases the propensity for share-ride as a mode for any tour. However, when another household adult also makes work trips, the propensity for shared-ride as a mode for any tour decreases, possibly because differences in work schedules may not favor joint trip making. Adults who have decided to make personal-business activities for the day are less likely to choose shared-ride as a tour

mode; perhaps, these are activities that are done independently. Shared-ride is more likely to be a mode for tours after work than a mode for tours before work or based at work.

Walk/bike is estimated to be more likely a mode for work-based tours than for home-based tours. Further, the non availability of auto also favors walk as a tour mode. The presence of multiple adults and children in the household increases the propensity of any tour to have DA-SR as the mode. A household with several persons are more likely to generate serve-passenger activities to facilitate activity participation by its members. Tours made before work have the highest propensity to have DA-SR as the tour mode. Work-based tours are least likely to have DA-SR as the tour mode.

Table 6.27 *Tour mode choice model for workers*

	Coefficient	t-statistic
Constants		
Shared-ride	-3.0943	-6.001
Walk/bike	-1.6494	-2.528
DA-SR	-3.4678	-4.326
Specific to shared-ride		
Number of children between ages 5 and 15 in the HH	0.4444	2.457
Multi-adult HH	3.1637	6.421
The person decided to pursue "other" activity	1.438	4.369
The person decided to pursue personal-business activity	-0.5935	-2.124
Another HH adult goes to work on the day	-0.8769	-3.141
Tour before work	-1.2131	-1.906
Work-based tour	-1.2092	-4.328
Specific to walk/bike		
Personal vehicle availability	-0.9719	-1.536
Work-based tour	0.8568	1.927
Specific to DA-SR		
Number of kids between ages 0 and 4 in the HH	1.16	2.22
Number of children between ages 5 and 15 in the HH	0.7381	2.978
Multiadult HH	1.8663	2.343
Tour before work	1.3555	2.036
Work-based tour	-1.1098	-2.032
Model fit		
Log-likelihood	-338.46	
Number of cases	418	

Table 6.28 presents the mode choice model for nonworkers. The alternative-specific constants are all negative indicating a generic dispreference for all modes when compared to drive-alone. Females are estimated to be more likely to choose shared-ride as a tour mode. The non-availability of auto also favors shared-ride as a tour mode. Presence of multiple adults and children in the household increases the propensity of shared-ride as a mode for any tour. However, when another adult in the household makes work trips, the propensity for shared-ride, as a mode for any tour, drops as the worker's work schedule may not favor joint trip making. For persons who make multiple tours in a day, shared-ride is more likely to be a mode for their second tour.

Non availability of auto was estimated to be the primary factor influencing walk/bike as a tour mode. The presence of multiple adults and children in the household increases the propensity of any tour having DA-SR as the mode. A person who makes multiple tours is more likely to make a tour where the mode is DA-SR.

Table 6.28 Tour mode choice for nonworkers

	Coefficient	t-statistic
Constants		
Shared-ride	-3.478	-6.13
Walk/bike	-0.894	-1.73
DA-SR	-3.870	-4.9
Specific to shared-ride		
Female	0.775	4.15
Multiadult HH	3.402	7.1
Number of kids between ages 0 and 4 in the HH	1.196	4.46
Number of children between ages 5 and 15 in the HH	0.481	3.01
Personal vehicle available	-0.721	-2.36
Person make multiple tours	-0.683	-2.77
Tour 2	0.575	2.23
Tour 3	0.031	0.08
The person decided to pursue "other" activity	0.694	3.42
Another HH adult goes to work	-0.618	-3.16
Specific to walk/bike		
Personal vehicle available	-2.855	-4.43
Specific to DA-SR		
Multiadult HH	2.144	2.86
Number of kids between ages 0 and 4 in the HH	1.472	4.03
Number of children between ages 5 and 15 in the HH	0.502	2.65
Person makes multiple tours	0.782	1.73
Tour 2	0.050	0.15
Tour 3	-0.869	-1.39
Model fit		
Log-likelihood	-552.86	
Number of cases	720	

6.3.2 Number of stops in a tour

This section of the report presents ordered probit models estimated to determine the number of stops in any tour. The sample shares for both workers and nonworkers are presented in Table

6.29. The sample indicates that nonworkers make more tours with multiple stops than workers. Most of the tours made by workers are found to have a single stop.

Table 6.29 Sample shares: number of stops in a tour for workers and nonworkers

	Worker		Nonworkers	
Number of stops	Freq.	%	Freq.	%
1	315	75.36	455	63.19
2	68	16.27	133	18.47
>=3	35	8.37	132	18.33
Total	418	10.00	720	100.00

The model estimated for workers (Table 6.30) indicates that the decision of the worker to participate in the different activities positively impacts the number of stops in any tour. Tours made after work are likely to have more stops than before-work or work-based tours. In the after-work period, after the work activity for the day has been completed, the workers are less constrained by time and can make tours with more stops. Tours made before work are likely to have fewer number of stops. This is because the worker is constrained by the need to be at the work place by a certain time. In addition, the number of stops in a before-work tour is positively influenced by the start-time of commute (later the departure for work, the greater is the time available for the before-work tour and hence the greater the probability of making several stops) and the number of home-to-work commute stops (suggesting that people who make stops on the way to work are more likely to make more stops in a before-work tour, should they decide to make one). The total work-based time positively influences the number of stops in a work-based tour. The decision of DA-SR as the tour mode has a large positive effect on the number of stops. Tours with DA-SR as the mode necessarily have a serve-passenger stop. The large positive coefficient is perhaps indicative of the fact that people typically decide to pursue some other activities along with serve-passenger and do not undertake a tour for only pickup or dropoff.

Table 6.30 Number of stops in a tour for workers

	Coefficient	t-statistic
Activity participation characteristics		
The person decided to pursue shopping activity	0.9727	6.16
The person decided to pursue social/recreational activity	0.5295	3.3
The person decided to pursue “other” activity	0.418	2.48
The person decided to pursue personal-business activity	0.9415	6.29
Tour characteristics		
Tour before work	-5.0246	-3.09
Work based tour	-2.2784	-3.13
Mode is DA-SR	1.7143	5.72
Work and commute characteristics		
Number of stops in home-to-work commute (for tours before work)	1.8143	1.77
Start time of home-to-work commute (for tours before work)	0.0068	3.18
Work-based time (for work-based tours)	0.0037	3
Threshold parameter demarcating		
1 and 2 stops	1.8453	9.11
2 and 3 stops	2.7582	12.09
Model fit		
Log-likelihood	-240.01	
Number of cases	418	

The corresponding model for nonworkers is presented in Table 6.31. The decision of a nonworker to participate in different activities is estimated to have a positive impact on the number of stops in any tour. The model suggests that persons who make multiple tours in the day are likely to make fewer stops in each tour. In such a case, the total number of stops gets distributed over several tours resulting in fewer stops per tour. The model also indicates that the number of stops in the second and third tours is fewer than the number of stops in the first tour. As in the model for workers, the tours with DA-SR as the mode are estimated to have more stops than tours with other modes. Such a tour necessarily has a serve-passenger stop. Perhaps, people tend to chain a serve-passenger stop with other activity stops leading to multiple stops in such tours.

Table 6.31 Number of stops in a tour for nonworkers

	Coefficient	t-statistic
Activity participation characteristics		
The person decided to pursue shopping activity	1.1013	10.14
The person decided to pursue social/recreational activity	0.7617	6.63
The person decided to pursue “other” activity	0.9891	8.43
The person decided to pursue personal-business activity	1.0349	9.55
Pattern-level characteristics		
Person makes multiple tours in the day	-0.9554	-6.75
Tour-level characteristics		
Second tour	-0.3937	-2.82
Third tour	-0.5332	-2.4
Mode is DA-SR	0.7912	4.48
Threshold parameter demarcating		
1 and 2 stops	1.6559	12.96
2 and 3 stops	2.3958	17.08
Model fit		
Log-likelihood	-538.85	
Number of cases	720	

6.3.3 Tour duration

The next tour-level attribute modeled is the tour duration. For the workers, the mean sample tour duration is 100.63 minutes with a standard deviation of 85.23 minutes. The mean sample tour duration for the nonworkers is 163.81 minutes with a standard deviation of 158.23 minutes. The average tour duration for nonworkers being higher than that of workers is consistent with our expectations, as the workers have much less time during the day to invest in tours when compared to nonworkers. The natural logarithm of the tour duration is taken as the dependent variable. The linear-regression models estimated for workers and nonworkers is presented here.

Table 6.32 presents the regression model developed to determine the tour duration for workers. Elderly workers are estimated to make home-based tours of shorter duration when compared to younger workers. However, older workers make longer work-based tours than younger workers (see both the effects of demographics and the interaction effects in Table 6.32). One possible reason for this could be that elderly people take more time off during the day for lunch. Workers with very young children in the household make tours of shorter duration. Females are estimated to make shorter work-based tours.

The model for workers indicates that the tour duration is positively influenced by the available time (for the tour and home stay before the tour). The available time is computed as the time between 3 a.m. and the time of departure to work, for tours before work, as the work-based time for work-based tours, and as the time between home arrival and 3 a.m. of the next day for tours made after work. Work-based tours are estimated to have a shorter duration than tours made before or after work. This is probably because the person is required to be at work for most of the work-based time and, hence, cannot afford to make long tours. Tours with a greater number of stops are found to be longer than tours with fewer stops. Shared-ride tours are estimated to be longer than drive-alone tours. This could be because people tend to spend more time when they are traveling together than when they are traveling alone. Walk/bike tours are estimated to be of shorter duration. Similarly, the DA-SR tours are also estimated to be of shorter duration than tours made using any other mode. One of the activities of any DA-SR tour is the serve-passenger activity, which typically tends to be very short. This could contribute to DA-SR tours being of shorter duration.

Table 6.32 Tour duration for workers

	Coefficient	t-statistic
Constant	3.7546	14.37
Sociodemographics		
Age	-0.0076	-2.16
Female	0.1318	1.49
Number of kids between ages 0 and 4 in the household	-0.2265	-2
Tour-level characteristics		
Total time available for tour and home stay before tour	0.0013	4.15
Tour before work	0.0783	0.59
Work-based tour	-0.621	-2.57
Two stops in the tour	0.2707	3.04
Three stops in the tour	0.9148	7.48
Mode is shared-ride	0.2015	2.78
Mode is walk/bike	-0.2396	-1.79
Mode is DA-SR	-0.6696	-4.46
Interaction effects		
Female and work based tour	-0.2639	-2.01
Age and work-based tour	0.0132	2.43
Model Fit		
Number of cases	418	
Sums of squares (regression)	74.07	
Sums of squares (residual)	172.39	
Sums of squares (total)	246.47	
R^2	0.3	
$R^2_{adj.}$	0.28	

The corresponding model for non-workers is presented in Table 6.33. This model indicates that elderly people make longer tours. Perhaps they travel slower and participate in activities for a longer duration. Students and employed persons who do not make school or work trips on the day are likely to make longer tours than unemployed adults. The duration of any tour is typically shorter for persons who make multiple tours in the day. Tours with multiple stops are estimated to be longer than tours with a single stop. Again, as in the case of workers, the tours made with shared-ride as the mode are found to be longer than tours made with drive-alone. Also, walk tours and DA-SR tours are shorter than drive-alone tours. The total time available for any tour (defined as the entire day for the first tour, the time from the end of tour 1 to the end of day for the second tour, and the time from the end of the second tour to the end of the day for the third tour) was also introduced as an explanatory variable, but did not turn out to be significant.

Table 6.33 Tour duration for nonworkers

	Coefficient	t-statistic
Constant	4.4741	33.74
Sociodemographics		
Age	0.0064	2.85
Person is not employed	-0.2642	-3.3
Pattern-level characteristics		
Person makes multiple tours	-0.3427	-4.15
Tour-level characteristics		
Second tour	-0.0775	-0.84
Third tour	-0.0743	-0.5
Two stops in the tour	0.3683	4.23
Three stops in the tour	0.9322	10.54
Mode is shared-ride	0.134	1.83
Mode is walk/bike	-0.3464	-1.57
Mode is DA-SR	-0.3718	-3.08
Model Fit		
Number of cases	720	
Sums of squares (regression)	161.02	
Sums of squares (residual)	537.11	
Sums of squares (total)	698.12	
R^2	0.23	
$R^2_{adj.}$	0.22	

6.3.4 Home-stay duration before the tour

The final tour-level attribute modeled is the home-stay duration before any tour. The mean home-stay duration before any tour for the workers is 178.53 minutes and the standard deviation is 120.22 minutes. In the case of nonworkers, the mean home-stay duration before any tour is 535.52 minutes with a standard deviation of 282.78 minutes. Linear-regression models were developed separately for workers and nonworkers, and the results are presented in this subsection. The natural logarithm of home-stay duration is taken as the dependent variable.

The regression model for workers (Table 6.34) indicates that females spend more time at home (or work, in the case of work-based tours) before any tour than males. The total time available for home stay (defined as the difference between available time for the tour and the tour duration) has a positive influence on the home-stay duration. Home-stay duration before a post-home-arrival tour is estimated to be much less than the home-stay duration before a before-work tour, or the work-stay duration before a work-based tour.

Table 6.34 Home-stay duration before a tour (for workers)

	Coefficient	t-statistic
Constant	2.5127	4.37
Sociodemographics		
Female	0.5321	2.16
Tour-level characteristics		
Time available for home stay before tour	0.0021	1.92
Tour before work	2.0056	4.12
Work-based tour	1.6617	6.52
Model Fit		
Number of cases	418	
Sums of squares (regression)	339.57	
Sums of squares (residual)	2571.09	
Sums of squares (total)	2910.67	
R^2	0.12	
$R^2_{adj.}$	0.11	

The regression model for nonworkers (Table 6.35) indicates that persons making multiple tours are likely to have shorter home-stay duration before any tour than persons making a single tour. This is reflective of the time constraints involved in making several tours in the day. The total time available for home stay (defined as the difference between available time for the tour and the tour duration) has a positive influence on the home-stay duration. Home-stay duration before a second tour is estimated to be much less than the home-stay duration before a first or third tour. Finally, home-stay duration before a shared-ride tour is found to be longer than the duration before a tour of any other mode. Perhaps the departure time in such a case depends on the convenience of all people traveling together and, hence, it may take longer for the party to depart than it would take a single person to depart for a tour.

Table 6.35 Home-stay duration before a tour for nonworkers

	Coefficient	t-statistic
Constant	4.9492	32.59
Pattern-level characteristics		
Person makes multiple tours	-0.2699	-5.05
Tour-level characteristics		
Time available for home stay before tour	0.0013	10.57
Second tour	-0.6627	-6.37
Third tour	0.2312	1.88
Mode is shared-ride	0.1217	2.73
Model Fit		
Number of cases	720	
Sums of squares (regression)	414.47	
Sums of squares (residual)	228.23	
Sums of squares (total)	642.7	
R^2	0.64	
$R^2_{adj.}$	0.64	

6.4 The Stop-Level Model System

This section of the report presents the models developed to determine the stop-level attributes, namely, the activity type, activity duration, travel time to activity, and the activity location. It would be ideal to determine these characteristics jointly for all the stops that an individual decides to make. However, practical modeling considerations and data limitations do not allow us to adopt such an approach. It is assumed here that decisions about stops in any tour are made independently of decisions about stops in any other tour. Within a tour (and the commute, in the case of workers), the characteristics of the stops are determined sequentially from the first stop to the last stop. Consequently, it is assumed that while determining the characteristics of any stop, characteristics of all prior stops in the tour are known. For each attribute, separate models are developed for workers and nonworkers. These are presented in the following subsections.

6.4.1 Activity type of the stop

The first stop-level characteristic modeled is the activity type at the stop. The generation-allocation model identified a person's desire to participate in shopping, social/recreational, personal business, and "other" activities for the day. In the activity-type choice models, the "other" activity is further classified into serve-passenger, eat-out, and miscellaneous activities.

The inclusion of an activity type in the choice set of an individual for any stop is determined by the person's decision to participate in that activity type. For example, shopping is a candidate in the choice set of an adult only if the adult has decided to participate in shopping activity for the day (and this decision is modeled by the generation-allocation model system). If the person has decided to participate in the “other” activity, both eat-out and miscellaneous activity types are assumed to be available in the choice set. Serve-passenger is an available activity type in the choice set only for stops in tours with the DA-SR mode. These assumptions imply that individuals decide upon the different activities to participate in prior to scheduling and actually participate in only these types of activities during the course of the day. In other words, individuals do not make decisions “on the fly” about the type of activity to participate in.

The availability of the different activity types in the choice sets is presented in Table 6.36 and the sample shares are presented in Table 6.37. Only those persons that had at least two different activity types in their choice set are included in the counts in the tables below. These are also the persons that were used in the model estimation. Eat-out and personal business are the most common activity types for workers, whereas shopping and personal-business are the most common activity types for nonworkers.

Table 6.36 Availability of activity type alternatives

	Workers		Nonworkers	
Activity Type	Freq.	%	Freq.	%
Shopping	202	32.9	365	57.57
Social/recreational	168	27.36	224	35.33
Personal business	275	44.79	353	55.68
Eat out (part of "other")	552	89.9	456	71.92
Serve-passenger (part of "other")	72	11.73	226	35.65
Miscellaneous (part of "other")	552	89.9	456	71.92

Table 6.37 Sample shares

	Workers		Nonworkers	
Activity Type	Freq.	%	Freq.	%
Shopping	80	13.03	154	24.29
Social/recreational	59	9.61	84	13.25
Personal business	116	18.89	149	23.5
Eat out (part of "other")	215	35.02	99	15.62
Serve-passenger (part of "other")	39	6.35	52	8.2
Miscellaneous (part of "other")	105	17.1	96	15.14
Total	614	100	634	100

The model for workers is presented in Table 6.38. Shopping is used as the base in the model. This model indicates that social/recreational activities are less likely to be pursued in the home-to-work commute. In a tour with multiple stops, the third stop is more likely to be a social/recreational stop. Personal-business stops are more likely to be in the work-based tour than in the commute or other home-based tours. In a tour with multiple stops, the second stop is less likely to be a personal-business stop. Tours made with shared-ride or walk/bike as the modes are less likely to have a personal-business stop. Work-based tours are more likely to have an eat-out stop. This could be the tour taken to have lunch. Any tour made with the shared-ride mode is more likely to have an eat-out stop. The home-to-work commute is more likely to have a serve-passenger stop. (As defined, any tour or commute made with the DA-SR mode will contain a serve-passenger stop. The sample used in this model estimation only has cases with multiple stops in the DA-SR tour.) Work-based tours are more likely to contain stops of the "miscellaneous" type; these are probably work-related activities. The home-to-work commute is less likely to have a miscellaneous activity stop. As these are the least important of all activity types, it can be expected that a person would not participate in such an activity during the commute to work. Females are estimated to be less likely to participate in any miscellaneous activity either during the work-based tour or during the commute home.

Table 6.38 Activity-type choice model for workers

	Coefficient	t-statistic
Constant		
Social/recreational	0.2598	0.803
Personal business	0.0156	0.056
Eat-out	-1.4832	-6.645
Serve-passenger	-0.1109	-0.339
Miscellaneous	-0.9473	-3.38
Specific to social/recreational		
Stop in home-to-work commute	-1.7734	-1.615
Multiple stops in the tour	-0.7572	-1.896
Third stop	3.517	3.704
Specific to personal business		
Stop in work-based tour	1.4496	3.032
Multiple stops in the tour	0.1749	0.539
Second stop	-0.8317	-2.394
Third stop	1.2109	1.789
Mode is shared-ride	-0.7097	-1.837
Mode is walk	-1.6605	-1.569
Specific to eat-out		
Stop in work-based tour	2.9551	6.786
Mode is shared-ride	0.9692	3.861
Specific to serve passenger		
Stop in home-to-work commute	1.6357	2.27
Specific to miscellaneous		
Stop in work-based tour	1.1444	2.141
Stop in home-to-work commute	-0.869	-1.734
Stop in work-to-home commute	-0.234	-0.604
Female	0.1356	0.415
Female and stop in work based tour	-2.3852	-2.175
Female and stop in work-to-home commute	-0.9402	-1.649
Model fit		
Log-likelihood	-507.28	
Number of cases	614	

The model for nonworkers is presented in Table 6.39. Shopping activity is taken as the base for this model. In tours with multiple stops, the second and third stops are more likely to be shopping than any other activity type (see the negative coefficients on the indicator variables corresponding to the second and/or third stops specific to most of the activity types). For persons who make multiple tours, the third tour is more likely to have a social/recreational or a serve-passenger stop. The second tour is less likely to have a personal-business or miscellaneous-activity stop when compared to shopping. Tours made with the shared-ride mode are more likely to have an eat-out stop. As discussed in the case of workers, any tour with DA-SR as the mode will contain a serve-passenger stop. The sample used in this model estimation only has cases where there were multiple stops in the DA-SR tour. Wherever possible, the impact of socio demographics on activity-type choice was examined, but was not found to be statistically significant.

Table 6.39 Activity-type choice model for nonworkers

	Coefficient	t-statistic
Constant		
Social/recreational	0.2169	0.78
Personal business	0.4008	1.35
Eat-out	-1.4897	-4.73
Serve-passenger	-0.6613	-1.85
Miscellaneous	-0.3464	-1.2
Specific to social/recreational		
Tour 3	1.9447	3.64
Second stop	-1.9567	-4.05
Third stop	-1.1109	-1.93
Multiple stops in the tour	0.0441	0.11
Specific to personal business		
Tour 2	-0.7633	-2.74
Second stop	-1.2129	-3.87
Third stop	-2.0548	-4.01
Multiple stops in the tour	0.5408	1.49
Specific to eat-out		
Third stop	-1.3038	-2.17
Mode is shared-ride	1.6006	6.26
Multiple stops in the tour	0.0273	0.08
Specific to serve passenger		
Tour 3	0.947	1.73
Second stop	-1.0845	-2.43
Multiple stops in the tour	0.6842	1.52
Specific to miscellaneous		
Tour 2	-0.6849	-2.15
Second stop	-1.0795	-2.67
Third stop	-1.3012	-2.3
Multiple stops in the tour	-0.059	-0.15
Model fit		
Log-likelihood	-623.29	
Number of cases	634	

6.4.2 Activity duration

The next stop-level attribute modeled is the activity duration at the stop. For the workers, the mean activity-duration time is 46.4 minutes, with a standard deviation of 65.75 minutes. For the nonworkers, the mean activity duration is 77.51 minutes with a standard deviation of 108.53 minutes. The logarithm of the activity duration is modeled using linear regression.

Table 6.40 presents the model for workers. The total available time for the stop and travel to the stop is found to positively influence the activity duration of any stop. Available time is defined as the entire tour duration for the first stop, duration from the end of activity at the first stop to the end of the tour for the second stop, and the duration from the end of the activity at the second stop to the end of the tour for the third stop. This positive influence is, however, less for tours with three stops. The type of activity at the stop is found to significantly influence the duration of the activity. Social/recreational, eat-out, and miscellaneous activities are estimated to be of longer duration than shopping activities. Personal-business and serve-passenger activities are shorter, with serve-passenger activity taking the least time.

The duration of an activity stop also depends on the tour or commute that the stop is a part of. Stops in the home-to-work commute are estimated to have very short durations, reflecting the need to be at work at a certain time after participating in the activity. Stops in work-based tours and work-to-home commute are estimated to be longer than stops in the home-to-work commute, but shorter than stops made in the tours after work. The activity duration at any stop decreases with increase in the number of stops in the tour. However, the later stops in a multiple stop tour are estimated to be of longer duration than the first stop. Finally, stops in tours with the shared-ride mode are estimated to be longer than stops made in tours with other mode. Perhaps, people spend longer in activity participation when they are traveling together.

Table 6.40 Activity-duration model for workers

	Coefficient	t-statistic
Constant	2.7348	32.26
Stop-level characteristics		
Available time for activity and travel to activity (in minutes)	0.0077	19.83
Social/recreational activity	0.6932	6.77
Personal-business activity	-0.3631	-4.2
Eat-out activity	0.3862	4.32
Serve-passenger activity	-0.8653	-7.87
Miscellaneous activity	0.4597	4.42
Stop in tour before work	0.1867	1.29
Stop in work based tour	-0.1693	-2.06
Stop in home-to-work commute	-0.6513	-6.08
Stop in work-to-home commute	-0.1944	-2.72
Second stop in a tour or commute	0.3808	4.13
Third stop in a tour or commute	0.753	4.07
Tour-level characteristics		
Mode is shared-ride	0.1398	2.12
Two stops in the tour	-0.5527	-7.11
Three stops in the tour	-0.8626	-4.97
Interaction effects		
Available time and three stops in the tour	-0.002	-2.31
Model fit		
Number of Cases	870	
Sum of Squares (regression)	784.63	
Sum of Squares (residual)	424.33	
Sum of Squares (total)	1208.96	
R^2	0.65	
$R^2_{adj.}$	0.64	

Table 6.41 presents the corresponding model for nonworkers. The available time for activity participation and travel to activity (definition same as that for workers) is estimated to positively influence the activity duration at any stop. The activity type is found to significantly influence activity duration. As in the case of workers, personal business and serve-passenger are estimated to have shorter durations than shopping activities, whereas social/recreational and miscellaneous activity types have longer durations than shopping. The second and third stops in a multiple stop tour are estimated to have longer durations than the first stop.

Stops in multiple stop tours are estimated to be of shorter duration than stops in single stop tours. Finally, stops in shared-ride tours are longer than stops in tours made with any other mode.

Table 6.41 Activity-duration model for nonworkers

	Coefficient	t-statistic
Constant	2.6465	22.12
Sociodemographics		
Age	0.0055	3.45
Female	0.1535	2.91
Stop-level characteristics		
Available time for activity and travel to activity (in minutes)	0.006	27.69
Social/recreational activity	0.537	6.53
Personal-business activity	-0.2294	-3.52
Serve-passenger activity	-1.1936	-10.06
Miscellaneous activity	0.312	3.39
Stop in tour 2	0.081	1.3
Stop in tour 3	-0.0917	-0.83
Second stop	0.2188	2.78
Third Stop	0.5909	4.82
Tour-level characteristics		
Mode is shared-ride	0.2112	3.87
Two stops in the tour	-0.5517	-7.65
Three stops in the tour	-0.8208	-9.5
Model fit		
Number of Cases	902	
Sum of Squares (regression)	841.64	
Sum of Squares (residual)	456.77	
Sum of Squares (total)	1298.41	
R^2	0.65	
$R^2_{adj.}$	0.64	

6.4.3 Travel time to activity

This section presents the linear-regression models developed to determine the travel time to any activity stop. The mean travel time for workers is 15.18 minutes with a standard deviation of 12.07 minutes. The mean travel time for nonworkers is 16.89 minutes with a standard deviation of 17.25 minutes.

Table 6.42 presents the model for workers. The available time for travel to a stop (defined as the difference between the available time for activity participation and travel for any stop and the activity duration of that stop) is found to positively influence the travel time to any activity. However, this positive influence decreases with the increasing number of stops in the tour. The activity duration is also estimated to positively influence travel time to the activity. Thus, if a person decides to participate in an activity for long durations, he is also willing to travel longer. The activity type at the destination was not found to critically influence the travel time. Travel to miscellaneous activities is found to be longer than travel to any other activity type. Travel duration to a stop in a work-based tour is found to be shorter, whereas the travel duration to a stop in the work-to-home commute is estimated to be longer when compared to travel to a stop in any other tour or commute. In tours with multiple stops, the travel time to the second stop is estimated to be shorter than travel time to any other stop. Finally, travel duration by non-motorized modes is found to be shorter than travel duration by any other mode.

Table 6.42 *Travel time to activity: model for workers*

	Coefficient	t-statistic
Constant	1.9822	32.06
Stop-level characteristics		
Available time for travel	0.0099	9.8
Duration of activity at destination (in minutes)	0.0014	3.32
Miscellaneous activity type	0.1974	2.49
Stop in tour before work	-0.0491	-0.41
Stop in work-based tour	-0.1165	-1.69
Stop in home-to-work commute	0.1112	1.35
Stop in work-to-home commute	0.4053	6.65
Second stop in a tour or commute	-0.2986	-3.28
Third stop in a tour or commute	-0.1474	-0.79
Tour-level characteristics		
Mode is walk	-0.5536	-4.3
Two stops in the tour	0.1112	1.07
Three stops in the tour	0.0578	0.36
Interaction effects		
Available travel time and two stops in the tour	-0.0067	-4.74
Available travel time and three stops in the tour	-0.0075	-5.48
Model fit		
Number of Cases	870	
Sum of Squares (regression)	174.54	
Sum of Squares (residual)	404.91	
Sum of Squares (total)	579.45	
R^2	0.3	
$R^2_{adj.}$	0.29	

Table 6.43 presents the corresponding model for nonworkers. The available time for travel to a stop (defined as in the case of workers) is found to positively influence the travel time to any activity. However, this positive influence decreases with the increasing number of stops in the tour. The activity duration is also estimated to positively influence travel time to the activity. Again, the activity type was not found to influence the travel time, except that travel time to eat-out activities is significantly shorter than travel to any other activity. Unlike in the case of workers, the travel time to second and third stops in tours with multiple stops is estimated to be longer for nonworkers than the travel time to the first stop. Finally, the travel mode was also found to influence travel durations. Travel by shared-ride mode is estimated to be longer than travel by any other mode. Travel by walk/bike is estimated to be shorter than travel by any other mode.

Table 6.43 Travel time to activity: model for nonworkers

	Coefficient	t-statistic
Constant	1.6851	30.16
Stop-level characteristics		
Duration of activity at destination (in minutes)	0.001	4.71
Available time for travel (in minutes)	0.0197	20.29
Eat-out activity	-0.1333	-1.88
Stop in tour 2	-0.0479	-0.91
Stop in tour 3	-0.0216	-0.23
Second stop in a tour	0.2095	2.99
Third stop in a tour	0.3417	2.87
Tour-level characteristics		
Mode is shared-ride	0.1798	3.81
Mode is walk	-0.2984	-1.81
Two stops in the tour	0.3499	4.15
Three stops in the tour	0.0169	0.15
Interaction effects		
Available travel time and two stops in the tour	-0.0154	-14.15
Available travel time and three stops in the tour	-0.0157	-14.03
Model fit		
Number of Cases	902	
Sum of Squares (regression)	278.76	
Sum of Squares (residual)	366.8	
Sum of Squares (total)	645.56	
R^2	0.43	
$R^2_{adj.}$	0.42	

6.4.4 Activity location

The activity location models are in the process of estimation.

7. Summary

There has been an increasing realization in the travel-demand modeling field that the conventional trip-based approach needs to be replaced with an activity-based approach that is behaviorally oriented. Several comprehensive activity-based systems have been developed. The current research aims at advancing state-of-the-art in activity-based modeling by addressing the activity patterns of both workers and non-workers within a household.

In this report, detailed conceptual frameworks were presented for the modeling of medium-term household choices (such as residential location and auto ownership) as well as short-term individual level activity-travel choices. The framework developed for the medium-term decisions identifies the different medium-term decisions that households typically make and capture the interrelationships among these different choices. The framework presented for the modeling of short-term activity-travel choices recognizes the spatial and temporal relationships among the activity-travel patterns of all adults in a household.

Data from various sources such as the Public Use Microdata Samples (PUMS) and the Dallas-Fort Worth (DFW) activity-travel survey of 1996 were used for estimating the different models. Chapter 3 presents details of the data sources and the sample formation procedure.

Analysis frameworks were developed for the modeling of both medium-term household decisions and short-term activity-travel decisions for the Dallas-Fort Worth area. The frameworks draw from the overall conceptual frameworks developed but were suitably modified to accommodate data availability and limitations. These frameworks were discussed in detail in Chapter 4.

Chapters 5 and 6 present the empirical models developed for the DFW area. Chapter 5 presents the different medium-term household choice models developed and Chapter 6 discusses the short-term activity-travel modeling system in detail.

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