The Day Activity Schedule Approach to Travel Demand Analysis

by

John L. Bowman

Submitted to the Department of Civil and Environmental Engineering
in Partial Fulfillment of the Requirements for the Degree of

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Abstract

This study develops a model of a person's day activity schedule that can be used to forecast urban travel demand. It is motivated by the notion that travel outcomes are part of an activity scheduling decision, and uses discrete choice models to address the basic modeling problem—capturing decision interactions among the many choice dimensions of the immense activity schedule choice set.

An integrated system of choice models represents a person's day activity schedule as an activity pattern and a set of tours. A pattern model identifies purposes, priorities and structure of the day's activities and travel. Conditional tour models describe timing, location and access mode of on-tour activities. The system captures trade-offs people consider, when faced with space and time constraints, among patterns that can include at-home and on-tour activities, multiple tours and trip chaining. It captures sensitivity of pattern choice to activity and travel conditions through a measure of expected tour utility arising from the tour models. When travel and activity conditions change, the relative attractiveness of patterns changes because expected tour utility changes differently for different patterns.

An empirical implementation of the model system for Portland, Oregon, establishes the feasibility of specifying, estimating and using it for forecasting. Estimation results match *a priori* expectations of lifestyle effects on activity selection, including those of (a) household structure and role, such as for females with children, (b) capabilities, such as income, and (c) activity commitments, such as usual work levels. They also confirm the significance of activity and travel accessibility in pattern choice. Application of the model with road pricing and other policies demonstrates its lifestyle effects and how it captures pattern shifting—with accompanying travel changes—that goes undetected by more narrowly focused trip-based and tour-based systems.

Although the model has not yet been validated in before-and-after prediction studies, this study gives strong evidence of its behavioral soundness, current practicality, potential to generate cost-effective predictions superior to those of the best existing systems, and potential for enhanced implementations as computing technology advances.

Thesis Supervisor: Dr. Moshe Ben-Akiva

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Biographical Note

John L. Bowman's research interests lie in the development of disaggregate models of individual and household lifestyle, mobility, activity and travel behavior, to inform public land use, transport, environmental and welfare policy. He has taught a graduate demand modeling course at MIT.

Dr. Bowman received the degree of Master of Science in Transportation from MIT in 1995, and the degree of Bachelor of Science in mathematics, summa cum laude, in 1977 from Marietta College, Marietta, Ohio. He is a member of Phi Beta Kappa. Before his study of transportation he worked for 14 years in systems development, product development and management for an insurance and financial services firm.

Publications of which Dr. Bowman is co-author include "Travel Demand Model System for the Information Era", Transportation 23: 241-266, 1996; "Integration of an Activity-based Model System and a Residential Location Model", Urban Studies 35 (7): 1231-1253, 1998; and "Activity based Travel Demand Models", in Proceedings of the Equilibrium and Advanced Transportation Modeling Colloquium, University of Montreal Center for Research on Transport, 1998.

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Introduction and Summary

1.1 Introduction

This thesis presents a model of the individual's activity and travel scheduling decision that can be used like traditional models for urban travel forecasting and analysis. The work is motivated by the well-established notion that travel demand is derived from the demand for activities. It should therefore be modeled as a component of an activity scheduling decision, and models that fail to do this suffer from misspecification that may substantially undermine their ability to forecast. The second motivation is that, although much research has aimed at improving our conceptual understanding of this phenomenon or developing advanced models for capturing certain components of activity scheduling behavior, few have developed models complete and simple enough to be used for general purpose urban travel forecasting. Of these, none has done it with a scheduling decision that at least spans an entire day, perhaps the most important temporal unit for activity scheduling. Our objective is therefore to develop a model of a person's day activity schedule—the schedule of activities and travel spanning a 24 hour day—that can be incorporated into urban forecasting model systems. We may subsequently refer to the day activity schedule as the activity schedule, or schedule, for short.

A hypothetical example provides an intuitive understanding of the need for a model that represents travel as a component of an activity scheduling decision. Figure 1.1(a) depicts a simplified representation of a person's day activity schedule, showing it as a continuous path in time and space. This person spends time at home in the morning, travels by auto to her workplace where she works throughout the day. In the late afternoon she heads for home in her car, but stops en-route at a familiar store to shop, then continues home where she remains for the rest of the evening. Now suppose the state government decides to impose a peak period toll on the highways in this person's commute path, substantially increasing her commute costs. How might she respond? If she is time sensitive she may breathe a sigh of relief and continue her schedule as is, happy to pay the extra cost in exchange for a faster commute. If she is cost sensitive and has good transit connections between home and work she may change modes for her commute (Figure 1.1(b)). However, if the transit line does not stop near her desired shopping location or she is uncomfortable carrying packages on the transit vehicle, she may come straight home on her commute and either walk or drive to a store after arriving home, depending on whether her neighborhood has walk-accessible shops. Alternatively, she may decide it is time to start planning her shopping activity more carefully and include the shopping stop only occasionally in her schedule. If she lacks good transit connections, but has flexible work hours she may continue using her car, but work earlier in the day and do her shopping on a separate tour[1] to avoid the peak period tolls (Figure 1.1(c)). Or, she might decide to start working four ten-hour days, pay the peak period toll in the afternoons, and shop during the day on her extra day off. She may have the freedom to begin working at home some days, and do her shopping in the middle of the day (Figure 1.1(d)).

These are only some of the likely responses a person may make to a single policy initiative. They include changes in destination, timing and mode, which we refer to as the travel components of the schedule. They also include activity participation adjustment, changes in the number of tours, and trade-offs between at-home and on-tour activity locations. These attributes of the schedule we refer to as the activity pattern[2] , since they define the configuration, or pattern, of the day's activities. In each case, changes in the travel components are linked closely with changes in the activity pattern. Persons with different lifestyles and resulting activity objectives, such as the need to get children to and from day care providers, might choose from a substantially different set of schedule alternatives.

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[1] We define a tour as a journey beginning and ending at the same location. This location is the base of the tour. Thus a journey beginning and ending at home is called a home-based tour. We refer to a work-based tour as a subtour, since it occurs in the midst of a home-based tour.

[2] We also refer to the activity pattern as the day activity pattern or as the pattern. The day activity schedule model we subsequently develop explicitly represents the day activity pattern, and formally defines its attributes.

Other changes in activity and travel conditions, such as infrastructure changes, vehicle or fuel taxes, parking fees or regulation, telecommute or transit incentive programs, and traffic management could induce a similar variety of complex schedule adjustments involving travel components and the activity pattern.

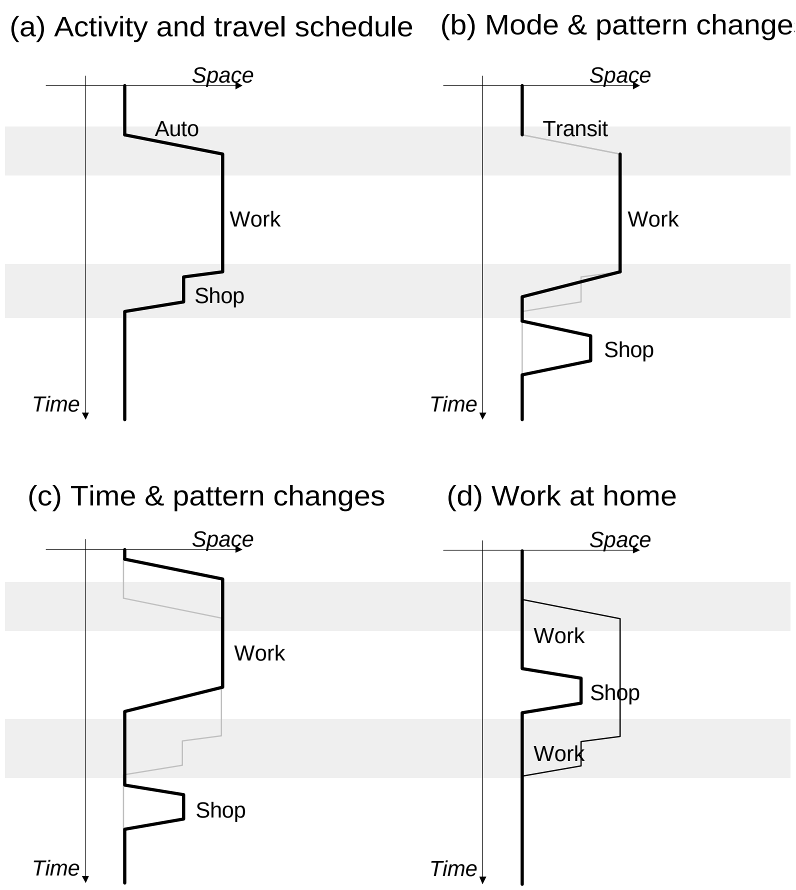

Figure 1.1 Activity schedule adjustments to a peak period toll

(a) The schedule prior to the toll includes travel by auto to work, with a shopping stop on the homebound commute. Possible responses to a peak period toll (shown shaded in gray) include (a) no change, (b) a mode change to avoid the toll, (c) a time shift to avoid the toll, and (d) work at home. In cases (b) through (d), the adjustment also involves a pattern change, either the splitting of the shopping activity into a separate tour, or the shift from on-tour work to at-home work.

1.2 Summary

1.2.1 Theory of activity-based travel demand

The literature establishes our objective of modeling travel demand as part of the activity scheduling decision, of which it is a component. The scheduling decision is motivated by the individual's desire to satisfy personal needs through activity participation, with at least a desire or tendency toward maximizing some objective related to this needs satisfaction (Ben-Akiva and Bowman, 1998). Great heterogeneity of needs exists among people, correlated with observable household and personal characteristics (Jones, Dix, Clarke et al., 1983). People face constraints that limit their activity schedule choice. Notably, activities are sequentially connected in a continuous domain of time and space, and are interrupted on a daily basis for a major period of rest. Travel occurs primarily to achieve activity objectives in the presence of these constraints (Hagerstrand, 1970).

Activity and travel scheduling occurs within a broader framework of interacting household decisions and urban processes (Ben-Akiva, 1973; Ben-Akiva and Lerman, 1985; Ben-Akiva, Bowman and Gopinath, 1996). From the standpoint of our desire to model activity and travel scheduling, four characteristics of the decision framework are most important. First, the scheduling decision is conditioned by the outcomes of longer term processes, including the household's lifestyle and mobility outcomes, as well as the activity opportunity outcomes of the urban development process. Second, and closely related to the first, the scheduling process is not temporally sequential, but is governed by commitments and priorities, within the constraints of a given scheduling time period. Third, a one-day schedule period is natural because of the daily rest period's regulating effect, but scheduling interactions occur over even longer time periods. Fourth, the scheduling process interacts with the performance of the transportation system; the demand resulting from the aggregation of all individuals' scheduling choices determines system performance, and the scheduling decisions are influenced by perceptions of that system performance.

The biggest problem facing the activity schedule modeler is the immense number of schedule alternatives from which the activity scheduler may choose; the scheduling decision involves the selection of activity purpose, sequence, timing, location, mode and route for many inter-related activities. The process can be viewed as comprising two stages: choice set generation—the search for alternatives—and the choice of one alternative from the choice set[3]. Within this basic structure many alternative assumptions can be made about the nature of the process. The most frequently assumed protocol for modeling decisions is that of utility maximization from an exhaustively determined feasible set of alternatives. This is not realistic in the context of such a large set of alternatives, but successful methods of implementing alternative protocols for choice problems approaching this size have not been developed.

The review of activity-based travel behavior theory has sharpened the modeling objective. We aim to model travel demand decisions as components of a day activity schedule, including the interacting dimensions of activity purpose, priority, timing, location, and travel mode. The model should be conditioned on longer-term urban processes, and household lifestyle and mobility outcomes, and interact with processes that determine transportation system performance attributes. Finally, the model needs to be tractable and accurately represent the scheduler's need to simplify a decision that has countless feasible outcomes.

1.2.2 Models of activity and travel scheduling

We supplement the behavior-theoretical requirements to assure the development of a model that is technically sound, has adequate detail to be sensitive to relevant policies, has practical resource requirements for implementation and use, and produces valid forecasts.

Given the modeling requirements, a review of approaches that have been used in attempts to make activity-based travel forecasting practical leads to the modeling approach taken in this research, a nested system of discrete choice models. Markov and semi-Markov approaches represent the scheduling decision as a sequence of transitions, following the temporal sequence of the day, with transitions between states corresponding to trips between activities. Their fundamental weakness is their basis in a decision sequence tied to the temporal activity

[3] For a general discussion of the choice process, including definitions of choice set (the alternatives considered), universal set (the feasible alternatives), choice set generation and other terms, see Section 2.4 .

sequence, rendering them unable to adequately represent a decision process that is governed more by commitments and priorities than by sequence.

Rule-based models, reviewed in Section 3.3 , simulate schedule outcomes, employing a complex search rule accompanied by a simpler choice model, frequently with iteration occurring between search and choice. These systems are based on various decision theories, such as cognitive limitation or the notion of a search that terminates with acceptance of a satisfactory alternative. Existing rule-based simulations face two important challenges. First, they rely on a detailed exogenous activity program or schedule that determines all or much of the activity participation decision, as well as other important attributes such as location and timing. Thus, although the resulting schedules may be fairly complete in scope, important major components of the schedule are not modeled. Second, they rely on unproven search heuristics and their decision protocols can be extremely complex. Extensive data and validation requirements accompany their complexity. Although rule-based simulations are attractive because of the freedom they give to attempt new and potentially improved decision protocols, the accompanying challenges make them unlikely to yield a comprehensive, validated scheduling model in the near future.

In contrast, utility maximization, usually employed in tandem with simple deterministic choice set generation by econometric model systems, is a much simpler protocol for which the schedule scope is a less formidable modeling challenge. The protocol has a solid basis in consumer theory. Although its use of a large choice set pushes it beyond the limits of purely representing rational consumer behavior, the protocol has been successfully used and validated in discrete choice travel demand model systems where the size of the choice set exceeds the number a person can rationally consider.

Econometric models, systems of equations representing probabilities of decision outcomes, can be viewed in two subclasses, discrete and mixed discrete-continuous. Discrete choice models partition the activity schedule outcome space into discrete alternatives. They deal with the big universal set by subdividing decision outcomes and aggregating alternatives. For example, the simplest models subdivide outcomes by modeling trip decisions instead of an entire day’s schedule, and aggregate activity locations into geographic zones.

Mixed discrete-continuous models focus attention on the continuous time dimension of the activity schedule, seeking to improve on its traditionally missing or weak aggregate representation in discrete choice models. They combine continuous duration models with discrete choice models for other dimensions of the schedule. However, they have not yet expanded in scope to include most dimensions of the activity schedule, nor have they incorporated duration sensitivity to time-variant activity and travel conditions. Their use in models satisfying the requirements we have identified awaits further methodological development.

1.2.3 Discrete choice modeling approaches

Over time, discrete choice modelers have tried to improve behavioral realism by including more and more dimensions of choice in an integrated system matching the natural hierarchy of the decision process. Lower dimensions of the scheduling hierarchy are conditioned by the outcomes of the higher dimensions. For example, choice of travel mode for the work commute is conditioned by choice of workplace. At the same time the utility of a higher dimension alternative depends on the expected utility[4] arising from the conditional dimension's alternatives. In our example, the choice of workplace is influenced by the expected utility of travel arising from all the available commute modes.

Nested logit models effectively model multidimensional choice processes where a natural hierarchy exists in the decision process, using conditionality and expected utility as described above. The expected utility of the conditional dimension is commonly referred to as accessibility because it measures how accessible an upper dimension alternative is to opportunities for utility in the lower dimension. It is also often referred to as the "logsum", because in nested logit models it is computed as the logarithm of the sum of the exponentiated utility among the available lower dimension alternatives (Ben-Akiva and Lerman, 1985, Chapter 10).

[4] The utility arising from the conditional dimension's alternatives is the maximum utility among the alternatives. This is a random variable, and its expected value is the expected utility referred to here, sometimes also referred to as expected maximum utility.

The models are disaggregate, representing the behavior of a single decisionmaker. A Monte-Carlo procedure is often used to produce aggregate predictions. In other words, the models make predictions with disaggregate data, requiring the generation of a representative population. The model is applied to each decisionmaker in the population—or a representative sample—yielding either a simulated daily travel itinerary or a set of probabilities for alternatives in the choice set. The trips in the itinerary can then be aggregated and assigned to the transport network, resulting in a prediction of transport system performance. This process may require replications to achieve statistically reliable predictions.

The simplest and oldest subclass of discrete choice model systems divides the activity schedule into trips[5]. One of the earliest of the integrated trip-based systems, developed for the Metropolitan Transportation Commission (MTC) of the San Francisco Bay area is reviewed in Section 3.4.3 (Ruiter and Ben-Akiva, 1978). More recently, models have been developed that combine trips explicitly in tours, including the Stockholm model system reviewed in Section 3.4.4 (Algers, Daly, Kjellman et al., 1995).

The main behavioral criticism of the trip- and tour-based discrete choice model systems is the division of the schedule outcome into separate pieces—trips or tours—and the failure to represent at-home activity participation. Otherwise, they satisfy the identified theoretical and practical requirements. Although their practicality is closely tied to their undesirable division of the schedule into pieces, advances in computing technology make further integration of the schedule representation an attractive possibility. Thus, we choose the discrete choice approach.

1.2.4 The day activity schedule model system

The day activity schedule is viewed as a set of tours and at-home activity episodes tied together by an overarching day activity pattern, or pattern for short (Figure 1.2). Decisions about a specific tour in the schedule are conditioned by the choice of day activity pattern.

[5] A trip is defined as the journey from one activity location to the next. It may involve travel by more than one mode.

This is based on the notion that some decisions about the basic agenda and pattern of the day's activities take precedence over details of the travel decisions. The probability of a particular day activity schedule is therefore expressed in the model as the product of a marginal pattern probability and a conditional tours probability

$$p(schedule) = p(pattern)\,p(tours|\,pattern)$$

where the pattern probability is the probability of a particular day activity pattern and the conditional probability is the probability of a particular set of tours, given the choice of pattern.

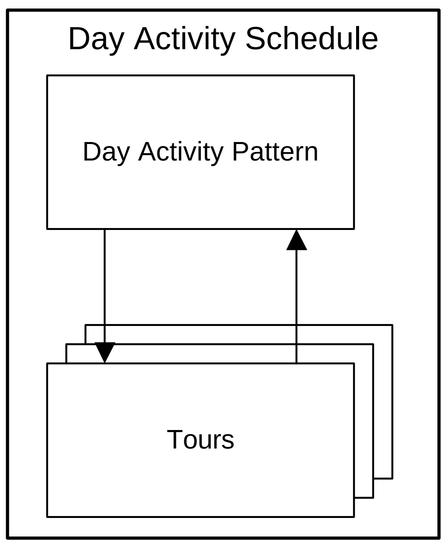

Figure 1.2 The day activity schedule

An individual's multidimensional choice of a day's activities and travel consists of tours interrelated in a day activity pattern.

The day activity pattern represents the basic decisions of activity participation and priorities, and places each activity in a configuration of tours and at-home episodes. Each pattern alternative is defined by (a) the primary activity of the day, (b) whether the primary activity occurs at home or away, (c) the type of tour for the primary activity, including the number, purpose and sequence of activity stops, (d) the number and purpose of secondary tours, and (e) purpose-specific participation in at-home activities. For each tour, details of time of day, destination and mode are represented in the conditional tour models. Within each tour, the choice of timing, mode and primary destination condition the choices of secondary stop locations.

We assume the utility of a pattern includes additively a component for each activity, a component for the overall pattern, and a component for the expected utility of its tours. The activity components can capture basic differences among people in the value of various kinds of activity participation. The pattern component captures the effect of time and space constraints in a 24-hour day. The expected utility component captures the effect of tour conditions on pattern choice. Through it the relative attractiveness—or utility—of each pattern, depends not just directly on attributes of the pattern itself, but also on the maximum utility to be gained from its associated tours. Patterns are attractive if their expected tour utility is high, reflecting, for example, low travel times and costs. This ability to capture sensitivity of pattern choice—including inter-tour and at-home vs on-tour trade-offs—to spatial characteristics and transportation system level of service distinguishes the day activity schedule model from tour models, and is its most important feature.

The day activity schedule model also improves on tour models' ability to represent the time dimension by explicitly modeling the time of each one of the inter-related tours in the pattern. With these features, the day activity schedule model satisfies the identified behavior-theoretical requirements.

1.2.5 The Portland day activity schedule model system

The empirical implementation for Portland, Oregon, tests the feasibility of achieving the requirements for a practical forecasting system without compromising the theoretical requirements. Secondly it tests the importance of the integrated day activity schedule representation; is there evidence that the extra cost and complexity yield improvements in model performance?

We adopt a structure in which tours are assumed to be conditionally independent, given the pattern choice. For home-based tours, tour timing conditions the joint choice of tour mode and destination. Work-based subtours are modeled conditional on the work tour, and these condition any stops occurring before or after the primary activity. At each conditional level, the probability is represented by a multinomial logit model.

Figure 1.3 shows the overall structure of the activity-based model system. Lower level choices are conditioned by decisions modeled at the higher level, and higher level decisions are informed from the lower level through expected maximum utility variables.

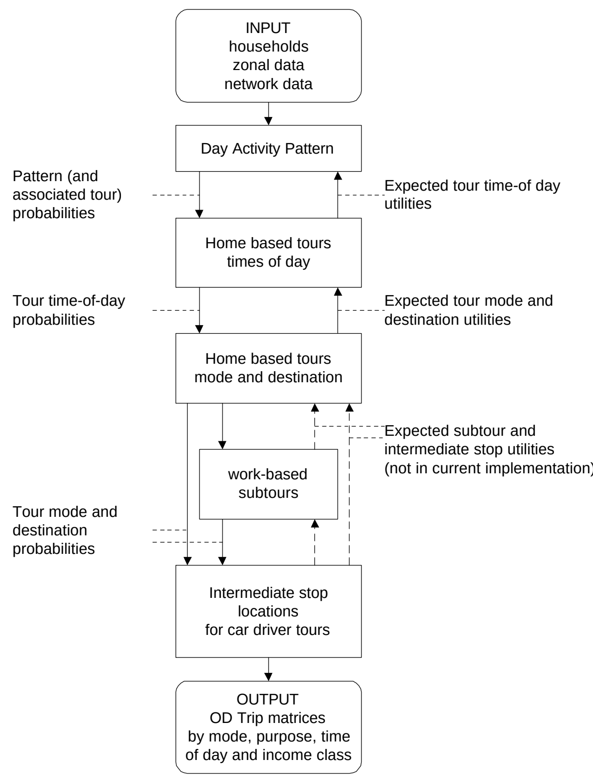

Figure 1.3 Portland day activity schedule model system

Table 1.1 shows the five main types of models included in the system, as well as the types of variables included in each of the model types. The variables include important lifestyle categories and mobility decisions, attributes of the activity and travel environment, and the expected utility variables from the conditional models. The entire system includes 633 estimated parameters, including 297 measuring the importance of lifestyle and mobility variables, 95 measuring the importance of the activity and travel environment—including expected utility, and 241 measuring unexplained preferences and the influence of marginal choice dimensions on conditional dimension utility.

Table 1.1 Model and variable types in the Portland day activity schedule model system

Model / Variable Types	Lifestyle variables (hh structure, role, capabilities, activity commitments)	Mobility variables (residence land use, auto ownership)	Destination activity conditions (land use)	Travel conditions (Network times, costs)	Conditional model expected utility (i.e., accessibility logsums)
Day Activity Pattern	✓	✓			✓
Home-based Tour Times of Day	✓	✓			✓
Home-based Tour Mode and Destination	✓	✓	✓	✓	
Work-based Subtour Mode and Destination	✓*		✓	✓	
Intermediate Stop Location for Car Driver Tours	✓*	✓	✓	✓	

*these are included only as aggregate categories in the current model system

As implemented, the home-based tour predictions are aggregated into zone-to-zone counts of half-tours[6] for each of several income classes. The work-based subtour and intermediate stop[7] models are applied to these counts, using aggregate categorical variables, and do not supply the upper level models with measures of expected maximum utility. This design compromise substantially reduces the time required to apply the model in a production setting, making it feasible to apply the entire model system using 300mhz Pentium-based microcomputers. This compromise should be eliminated in subsequent production implementations of the model system as advances in computing technology allow. As discussed in Chapter 6, it makes the pattern model insensitive to differential effects of travel conditions on patterns with different numbers of secondary stops.

In the day activity pattern model, likelihood ratio tests were conducted to test the collective significance of groups of variables in the pattern model. The tests support the importance of variables in the four lifestyle categories used in the model: household structure, role in household, personal and financial capabilities, and activity commitments. They support the

[6] A half-tour is either portion of a tour between the origin and the primary destination. It includes more than one trip if activities occur between the origin and primary destination.

[7] An intermediate stop is a stop for activity during a half-tour. Each intermediate stop adds a trip to the half-tour.

importance of the secondary at-home maintenance activity parameters in subsistence and leisure patterns, indicating that the identification of secondary at-home maintenance is important in the pattern choice set definition[8]. The tests also indicate that it is important in the choice set definition to distinguish the placement of secondary activities on the pattern in several ways: (a) whether they occur on the primary tour or a separate tour, (b) relative to the primary activity in the primary tour, and (c) specific to pattern purpose and secondary activity purpose. Finally, a test supports the importance of the tour expected maximum utility parameters as a group. This is an important result in light of the major hypothesis of this study that it is important to represent travel demand in the context of the day activity schedule. With these expected maximum utility variables, changes in tour utility, caused by changes in the transport system performance or in spatial activity opportunities, have a significant effect on the choice of pattern. Such effects cannot be captured by tour or trip-based travel demand models. Testing of the pattern model's multinomial logit assumption remains as a future objective. The need probably exists for nesting, and perhaps more complex correlation structures, because of the multidimensional nature of the pattern choice. For example, strong random utility correlation probably exists among patterns that share primary purpose. Nevertheless, the tests conducted provide strong evidence, in addition to the individual parameter tests of the previous sections, in support of the basic model structure, utility function structure and lifestyle variable categories of the day activity schedule model.

1.2.6 Model application and evaluation

The model system demonstrates the benefits of its design in various policy applications, including peak period pricing. There, in response to a toll levied on all travel paths during the morning and evening peak travel periods, the model predicts not only shifts in travel

[8] Pas (1982), adopting the approach of Reichman (1976), places all out-of-home activities in the three broad categories of subsistence, maintenance and leisure. He defines work and school as subsistence, and shopping and personal business as maintenance. We adopt these categories for in-home activities as well, defining subsistence as activity, including education, devoted to the current or future generation of household income, maintenance as non-income-generating activities required to maintain a household, and leisure as optional activities engaged in for enjoyment. We also use the term discretionary interchangeably with leisure.

mode and timing, but also shifts in pattern purpose and structure. As shown in Table 1.2, the net result is an increase in the predicted number of tours for leisure purposes; increases in leisure tours induced by pattern changes more than offset leisure tour decreases caused by the peak period toll.

Table 1.2 Peak period toll--induced leisure travel captured by the day activity schedule model

	Percent change in number of tours, by tour purpose, in response to $.50 per mile peak period toll on all roads		
Time of day	Work	Maintenance	Leisure
A.M. peak period	-7.1%	-8.4%	-6.2%
P.M. peak period	-7.4	-7.7	-1.5
Midday	3.1	3.6	2.8
Outside peaks	6.8	2.3	2.7
Total	-2.5%	-0.3%	+.8%

How does the model capture this induced demand? Increased peak period travel costs reduce expected maximum mode/destination utility (logsums) in the peak period alternatives of the times-of-day choice models, and expected maximum time of day utility in the pattern choice model, where patterns with tours that rely most heavily on peak period auto travel become relatively less attractive. Thus, there is a shift away from patterns with subsistence tours in the pattern model, toward all other pattern types. The net change in maintenance and leisure tours could be positive or negative, because the increase in number of maintenance and leisure patterns, and the introduction of secondary tours on changed patterns, tend to offset the pattern simplification effect for these purposes. In the example, the model actually predicts a net increase in leisure tours.

The above explanation of model response to the peak period tolls excludes the impact on intermediate stop location models and work-based tours. These too are affected by the peak period tolls, through the toll's direct effect on stop utility, as well as pattern changes and tour destination changes. However, by omitting the expected utility connection of intermediate stops to home-based tours, the model system underestimates the toll's tendency to reduce trip chaining during the peak period.

The previous analysis ignores the lifestyle effects in schedule choice and the associated potential heterogeneity of response to the toll policy. Predicted pattern shifts are analyzed in each of four activity pattern dimensions—primary activity purpose, primary tour type, secondary tours, and at-home maintenance activity—for 22 population segments, defined by household structure and role, capabilities, activity commitments and mobility decisions. The model captures much heterogeneity in pattern choice and in response to the toll policy, clearly demonstrating the importance of explicitly modeling heterogeneity in the pattern choice.

Analysis of model response to additional policies, including transit improvements, vehicle ownership restrictions, fuel taxes, auto registration fees, parking regulation, neighborhood walkability improvements, mixed use development, and ITS highway capacity increases, and telecommunications advances indicate that the day activity schedule model structure enables the capture of pattern shifts and associated changes in travel demand in a great variety of situations. However, in some cases, the implemented model's sensitivity to the policy would be limited because of coarse resolution of schedule dimensions or because of missing variables in the specification. For one example, coarse spatial resolution limits the model's ability to capture the effect of walkability improvements. For another example, the model lacks variables such as the possession of a credit card or a home computer with modem, that if included might enable it to capture pattern changes caused by improvements in information technology.

1.2.7 Conclusions

The overall conclusion of this study is that a travel forecasting model system based on a discrete choice model of the day activity schedule is practical and captures anticipated activity pattern shifting, with associated travel changes, that previous models have missed.

The day activity schedule model, specified in Chapter 4, satisfies a rich set of requirements derived from the literature on activity-based travel demand, providing the foundation for the development of behaviorally improved travel demand forecasting models. Its full-day scope; detail of pattern, activity and travel dimensions; and integrated structure give the model design three important realistic performance capabilities. First, it can capture the trade-offs people consider as they face time and space constraints in scheduling their day's activities. These include variations in activity participation, on-tour versus at-home activity location, number of tours, trip chaining, timing, destination and travel mode. Second, it can realistically capture the significant influence of lifestyle-based heterogeneity on schedule choice by identifying lifestyle and mobility factors in each of the model's many scheduling dimensions. Third, it can capture the impact of exogenous factors upon all dimensions of schedule choice, even if the factors only act directly in one dimension. Importantly, this includes the influence of activity accessibility—including travel conditions—on the choice of activity pattern.

The empirical implementation has shown that, though compromises were made in the representation of the activity schedule to enable practical use of the approach, it can handle the scope of the activity schedule at a level of detail matching or exceeding trip or tour-based systems. The model system demonstrates the benefits of its design in various policy applications, such as peak period pricing, capturing pattern shifts and resulting travel demand effects that trip and tour-based models cannot capture.

1.2.8 Research topics

This study creates many opportunities for fruitful research and development, to verify and exploit the benefits of the day activity schedule approach in travel forecasting, to enhance it by addressing unresolved issues, and to integrate it with related models of household choice, urban development and transport systems. It can also be evaluated for theoretical weaknesses, serving as grist for the further development of theory and models of activity and travel behavior. Specific research topics include (a) model validation; (b) development of efficient, consistent application procedures with known confidence levels; (c) testing and enhancement of the day activity schedule model, including the 570 alternative pattern, integration of expected utility from secondary stops and subtours, generalized day activity pattern correlation structures, temporal and spatial resolution, secondary tours conditioned by primary tour outcomes, and conditioning of model on usual workplace and commute mode; (d) procedures to combine data from enhanced surveys; (e) schedule model enhancements that require improved data sets, including improved activity purpose resolution, telecommunications effects, effects of unusual transportation conditions, and heterogeneity; (f) techniques to improve computational efficiency and incorporate alternative decision protocols; (g) integration of activity and mobility models, using expected schedule utility to explain mobility choices; and (h) reconciliation of the day activity schedule model specification with formal theories of transport economics and home production economics.

1.2.9 Outline of the thesis

In Chapter 2, the theory of activity-based travel demand is examined, resulting in a set of behavior-theoretical requirements for an activity-based travel demand model system based on a day activity schedule. Chapter 3 studies previous attempts to model travel demand as part of a larger activity schedule, leading to the selection of the discrete choice modeling approach. Chapter 4 presents the concepts and mathematical form of the day activity schedule model, and identifies important model design issues. Chapters 5 and 6 present the results of an empirical implementation in Portland, Oregon, that (a) demonstrates the practical feasibility a day activity schedule model system satisfying the behavioral requirements of Chapter 2, and (b) tests the importance of the day activity schedule representation. Chapter 7 draws the final conclusions of the thesis and discusses specific ideas for future research to build on those conclusions.

2

Theory of Activity-based Travel Demand

In the first section of this chapter an examination of the literature establishes our objective of modeling travel demand as part of the activity scheduling decision. Given this objective, we place the activity scheduling decision in a broader decision framework, then consider how activity scheduling is affected by longer term lifestyle decisions and outcomes, and face the principal challenge of modeling activity scheduling behavior, namely the immense set of alternatives from which the activity schedule is chosen. This leads to a set of theoretical requirements for the development of an activity-based travel demand model.

2.1 The characteristics of activity and travel demand

One of the most fundamental and well-known principles is that travel demand is derived from activity demand. This principle implies a decision framework in which travel decisions are components of a broader activity scheduling decision, and calls for modeling activity demand. Chapin (1974) theorized that activity demand is motivated by basic human desires, such as survival, social encounters and ego gratification. Activity demand is also moderated by various factors, including, for example, commitments, capabilities and health. Unfortunately, it is difficult to model the factors underlying this demand, and little progress has been made in incorporating the factors in travel demand models. However, a significant amount of research has been conducted on how household characteristics moderate activity demand. This research concludes that (a) households influence activity decisions, (b) the effects differ by household type, size, member relationships, age, gender and employment status and (c) children, in particular, impose significant demands and constraints on others in the household (Chapin, 1974; Jones, Dix, Clarke et al., 1983; Pas, 1984).

Hagerstrand (1970) focused attention on constraints--among them coupling, authority, and capability--which limit the individual's available activity options. Coupling constraints require the presence of another person or some other resource in order to participate in the activity. Examples include participation in joint household activities or in those that require an automobile for access. Authority constraints are institutionally imposed restrictions, such as office or store hours, and regulations such as noise restrictions. Capability constraints are imposed by the limits of nature or technology. One very important example is the nearly universal human need to return daily to a home base for rest and personal maintenance. Another example Hagerstrand called the time-space prism: we live in a time-space continuum and can only function in different locations at different points in time by experiencing the time and cost of movement between the locations.

The concepts of activity-based demand, and time and space constraints, have also been incorporated in the classical model of the budget-constrained utility-maximizing consumer. Becker (1965) made utility a function of the consumption of commodities that require the purchase of goods and the expenditure of time. DeSerpa (1971) explicitly identified the existence of minimum time requirements for consumption of goods. Evans (1972) generalized the model, making utility a function only of activity participation; formulating a budget constraint based on a transformation which relates the time spent on activities, the goods used in those activities and the associated flow of money; and introducing coupling constraints which, among other things, allow the explicit linking of transportation requirements to the participation in activities. Jara-Diaz (1994) extended an Evans type model explicitly to allow the purchase of goods at alternative locations, each associated with its own prices, travel times and travel costs, all of which enter the time and budget constraints. He also included a transformation relating the purchase of goods to required trip-making. In maximizing utility, the consumer chooses how much time to spend on various activities, how many trips to make overall, what goods to buy and where, and the travel mode for each trip. These efforts to incorporate activities, time and space into the formal economic model of the consumer stop short of addressing important aspects of the scheduling problem, such as temporally linking activities or allowing for the chaining of trips between activity locations.

A substantial amount of analysis has been done to refine the notion of activity-based travel demand, test specific behavioral hypotheses, and explore modeling methods. We present here only a few highlights. Pas and Koppelman (1987) examine day-to-day variations in travel patterns, and Pas (1988) and Hirsch, et al (1986) explore the representation of activity and travel choices in weekly activity patterns. Kitamura (1984) identifies the interdependence of destination choices in trip chains. Kitamura, et al (1995) develop a time- and distance-based measure of activity utility that contrasts with the typical travel disutility measure. Hamed and Mannering (1993) and Bhat (1996b) explore methods of modeling activity duration. Bhat and Koppelman (1993) propose a framework of activity agenda generation.

For extensive summaries of other results, and access to reading lists, the interested reader can examine one or more of the published reviews of this literature. Damm (1983) compiles a list of empirical research, categorizes the hypotheses tested, lists the explanatory variables associated with each class of hypothesis, and presents the statistical results of parameter estimates. Golob and Golob (1983) examine the literature by categorizing 361 works by primary and secondary focus, with the five focus categories being activities, attitudes, segmentations, experiments, and choices. Kitamura (1988) updates the review, categorizing works by the topics of activity participation and scheduling, constraints, interaction in travel decisions, household structure and roles, dynamic aspects, policy applications, activity models and methodological developments. Perhaps the best recent review of the theoretical contributions in activity-based travel demand analysis is that of Ettema (1996) who describes contributions from the fields of geography, urban planning, microeconomics and cognitive science.

In summary, the literature establishes our objective of modeling travel demand as part of the activity scheduling decision, of which it is a component. The scheduling decision is motivated by the individual’s desire to satisfy personal needs through activity participation, with at least a desire or tendency toward maximizing some objective related to this needs satisfaction. Great heterogeneity of needs exists among people, correlated with observable household and personal characteristics. People face constraints that limit their activity schedule choice. Notably, activities are sequentially connected in a continuous domain of time and space, and are interrupted on a daily basis for a major period of rest.

We next examine the context of the activity and travel scheduling decision.

2.2 Activity and travel decision framework

Figure 2.1 shows how activity and travel scheduling decisions are made in the context of a broader framework. They are part of a set of decisions made by a household and its individual members, and in that context they interact with the urban development process and the performance of the transportation system. (Ben-Akiva, 1973; Ben-Akiva and Lerman, 1985; Ben-Akiva, Bowman and Gopinath, 1996).

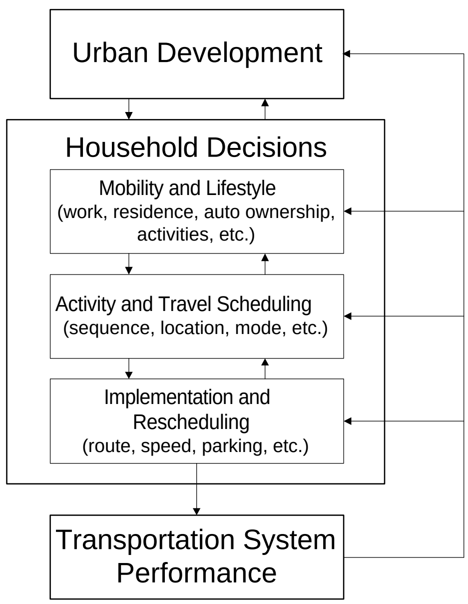

Figure 2.1 Activity and travel decision framework

Many household decisions, occurring over a broad range of timeframes, interact with each other and with the urban development process and transportation system performance.

In the figure, the urban development box represents decisions of governments, real estate developers and other businesses. Governments may invest in infrastructure, provide services, and tax and regulate the behavior of individuals and businesses. Real estate developers provide the locations for residential housing and businesses. Where a firm chooses to locate, and its production decisions, affect job opportunities in that area. This conditioning of individual behavior by urban development outcomes is represented in the figure by the downward pointing arrow joining the urban development and household decision boxes. The corresponding upward pointing arrow represents the fact that household decisions, such as residential choice, also influence urban development decisions. Taken together, the two arrows represent the interplay of household and urban development decisions in markets, such as real estate and employment, that establish conditions under which individual households and developers must operate.

Urban development and household decisions affect performance of the transportation system, such as travel volume, speed, congestion and environmental impact. At the same time, transportation system performance affects urban development and individual decisions.

Household and individual choices, including (a) lifestyle and mobility decisions, (b) activity and travel scheduling, and (c) implementation and rescheduling, fall into distinct time frames of decision making. Lifestyle and mobility decisions occur at irregular and infrequent intervals, in a time frame of years. Activity and travel scheduling occurs at more frequent and regular intervals. Unplanned implementation and rescheduling decisions occur within the day. Outcomes of the longer term processes condition the shorter term decisions, and are influenced by expected benefits associated with anticipated short term decisions.

We define lifestyle broadly, as a set of individual and household attributes, established as outcomes of major life decisions and events, and the gradual accumulation of minor changes, habits and preferences, that determines needs and preferences for activities, and the resources available for their satisfaction. The lifestyle formation processes are strongly influenced by the accumulation of mobility, activity and travel outcomes. Lifestyle includes household structure (such as single adult, married couple with pre-school children or non-family adult group); individual role in the household (such as principal income earner or childcare giver); activity priorities, commitments and habits (such as absolute and relative devotion to job, property maintenance, hobbies, recreation and participation in civic, religious or social organizations); and financial and personal capabilities and limitations (such as wealth, income, vocational skills and physical disabilities).

Mobility outcomes are attributes, established by lifestyle-constrained decisions and events, that determine the availability and cost of access to activities. They are dominated by clearly defined choices occurring on an irregular and infrequent basis, but can also involve unchosen events such as a job transfer and emergent phenomena such as the gradual selection of a favorite shopping location. Although mobility decisions occur within a given lifestyle context, some of these decisions may be so major as to cause significant lifestyle changes. A mobility decision cannot be conditioned by the more frequent activity and travel decisions, but is influenced by expectations about the benefits to be gained from the activity and travel opportunities made possible by the choice, given the current lifestyle. Mobility decisions include location choices for work, residence, school and other repetitive activities determined by lifestyle; auto acquisition and other transportation arrangements; and arrangements for repetitive conduct of other activities by electronic or other non-travel means.

The activity and travel schedule is a set of activities conducted by a person over a continuous period of time, each activity characterized by purpose, priority, location, timing, and means of access. It is natural to view the schedule as spanning a one day time period because of the regulating effect of the overnight rest period. However, day-to-day interactions occur in scheduling decisions, so the schedule can also be viewed as having a longer time period. The schedule, although carried out by an individual, may be partly determined or influenced by the household. Alternatively, it can be viewed as a household schedule, including a set of activities for each member, and identifying activities in which members participate jointly.

The schedule is the outcome of two processes depicted by separate boxes in Figure 2.1, activity and travel scheduling , and implementation and rescheduling. Activity and travel scheduling yields a planned schedule. It is conditioned by the longer-term lifestyle and mobility outcomes. Given these constraints, and a scheduling period, the decisionmaker may freely arrange activities in various ways to best achieve activity objectives according to his or her priorities. Although the resulting schedule has a temporal sequence, the scheduling process is not temporally sequential. Instead, it is governed by commitments and activity priorities. Each component of the schedule is determined with basic knowledge of the other components of the schedule, and its placement is strongly conditioned by the placement of higher priority components of the schedule

Implementation and rescheduling yield an implemented schedule; during the scheduling period decisions are made to fill previously unscheduled time with unplanned activities, and rescheduling occurs in response to unexpected events. It can be viewed as the reiteration of the scheduling process, employing schedule adjustments at each step rather than replanning the entire schedule. The schedule adjustment decision is based on revised objectives and constraints, informed by the most recent events.

The framework presented here is consistent with the notions of Chapin, Hagerstrand and the activity-based consumer demand economists. Urban development and transportation system outcomes determine many of Hagerstrand's constraints. Lifestyle and mobility decisions are conditioned by the same underlying factors that Chapin identified as motivating activity selection. They, along with urban development and transportation system outcomes determine many of Chapin's moderating factors that also influence activity choice. Likewise, they determine many of the time and space constraints incorporated in the activity-based consumer economists' models of consumer behavior.

From the standpoint of our desire to model activity and travel scheduling, four characteristics of the decision framework are most important. First, the scheduling decision is conditioned by the outcomes of longer-term processes, including the household's lifestyle and mobility outcomes, as well as the activity opportunity outcomes of the urban development process. Second, and closely related to the first, the scheduling process is not temporally sequential, but is governed by commitments and priorities, within the constraints of a given scheduling time period. Third, a one-day schedule period is natural because of the daily rest period's regulating effect, but scheduling interactions occur over even longer time periods. Fourth, the scheduling process interacts with the performance of the transportation system; the demand resulting from the aggregation of all individuals' scheduling choices determines system performance, and the scheduling decisions are influenced by perceptions of that system performance.

2.3 Lifestyle basis of activity decisions

Activity theory and the activity scheduling decision framework suggest that accurately modeling activity and travel behavior might depend upon a careful representation of the lifestyle and mobility outcomes. We hypothesize that lifestyle factors are very important in explaining the activity and travel scheduling decision. The lifestyle attributes of household structure; individual role in the household; activity priorities, commitments and habits; and financial and personal capabilities may all be important factors in the activity and travel scheduling decision. The first three determine needs and preferences, whereas financial and personal capabilities determine the resources available for their satisfaction. We next describe how each of these attributes may affect activity scheduling, noting observable variables that might be used in empirical studies to capture the effects.

Household structure. Household structure is defined by the number, personal capabilities and relations among household members. Household structure affects the activity selection of its members, namely the balance of time given to subsistence, maintenance and leisure activity. The household time required for each of subsistence and maintenance activities naturally grows with household size, but at a slower rate because of scale economies. These economies may be greater for families[9] than for nonfamilies because of greater role specialization. On the other hand, the subsistence and maintenance activity requirements placed on adults in the household are greater in families when children and disabled members are present, and may vary substantially with the number and age of children.

Household structure may also affect the tendency to conduct activity at home or away. Larger households, especially families, may more easily satisfy social needs in at-home leisure activities. On the other hand, families often have more chauffeur's tasks, to provide activity access for non-driving children.

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[9] We define a household as one or more persons living together. We define families as household subsets in which the members are related by blood, marriage or long term cohabitation commitment.

In light of this discussion, potentially important household structure categories include household size, family vs nonfamily, number of children in various age groups, and the presence of disabled members.

Role specialization. Role specialization allocates household activities by type to particular members of the household. For example, one member may be responsible for subsistence and another for maintenance. The benefit of scale economies should be a natural force toward role specialization in households, especially in families where it is aided by the stability of the cohabitation arrangement. Some role specialization, such as relative workload commitment, is directly observable. Other specialization, such as responsibility for certain maintenance tasks and childcare, is harder to observe. Nevertheless, good proxies may exist, arising from prevailing social mores or natural selection. Of particular importance are gender and age, with pronounced gender effects likely in families with children, and age effects likely in multigenerational families. Observable variables that may capture significant role specialization in activity scheduling behavior include relative workload (defined as individual's usual weekly work hours minus the average hours per working age adult), gender interacted with household structure, and categories for adult children and senior adults in families with other adults.

Activity commitments, priorities and habits. The lifestyle formation process establishes commitments, priorities and habits for activity participation. Some of these outcomes may be schedule-specific, determining the periodic participation in a particular activity at prescribed times. Examples include the office worker's lifestyle defined in part by regular work activity from nine to five, five days per week, or the church member's lifestyle that includes attendance at religious services at the same times every week. Other outcomes may be less schedule-specific, but still determine the allocation of time to various types of activity, such as the homeowner's time commitment for maintaining the residence, or the sports fan's priority for watching athletic events on television. These lifestyle outcomes include individual attributes such as usual work hours, as well as household attributes such as the number of working adults. Although work commitments and home ownership are usually collected in surveys from which activity and travel models are developed, many important lifestyle decisions in this category are not.

Financial and personal capabilities. We adopt the view taken in the activity-based transportation economics and home production economics literature (see for instance, Gronau, 1986) that recognizes the trade-offs in the use of time and money for satisfaction of activity objectives, treating income as an endogenous variable in the process because of the household's ability to choose the level of work participation. In our modeling framework, income is endogenous to the lifestyle formation process, where it is determined and treated as exogenous in the activity and travel scheduling process. There, higher income carries with it more activity options as well as a higher value of time. Wealth is also an important lifestyle outcome that partially determines income, but may also have a profound impact on mobility, activity and travel decisions because of the activity opportunities and security it provides the household. Personal capabilities, determined by the mixing of natural endowment, personal development and special events in the lifestyle formation process, vary substantially. They also significantly influence activity and travel scheduling choices, by shaping the choice set and affecting the costs and benefits of various activity alternatives.

Household, and sometimes personal, income information is often available in surveys as a direct measure of financial resources. We usually lack a direct measure of wealth, although auto ownership is a mobility outcome that probably correlates with wealth and might serve as a proxy. Occupation and the presence of a mobility impairing disability are measures of personal capability.

2.4 The choice process and the complexity of the activity scheduling decision

The decision framework, and the lifestyle factors influencing activity and travel demand, give some picture of the nature of activity and travel decisions. However, we still need a model of the decision that characterizes the schedule outcome and approximates the scheduler's decision process. In this section we discuss this process, and in that context face its most challenging characteristic, the immense set of scheduling alternatives.

Every choice has three important elements, including (a) a set of alternatives, (b) a decisionmaker, and (c) a decision protocol, or set of rules. The set of all feasible alternatives is often referred to as the universal set, whereas the set of alternatives the decisionmaker actually considers is called the choice set. The alternatives in the choice set are defined to be mutually exclusive and collectively exhaustive, so that the decisionmaker must choose one and only one alternative from the choice set.

The alternatives. The biggest problem facing the activity schedule modeler is the size of the universal set. The scheduling decision involves the selection of activity purpose, timing, location, mode and route for many inter-related activities. From the standpoint of travel forecasting it is important to model timing, location, mode and route for all activities because these determine the transport network demand. It is important to include purpose, because of its strong interaction with the other dimensions. It is also important to include these dimensions for all activities in the schedule because of the interdependency caused by time and space constraints.

The challenge is to represent adequately a decision process having infinite feasible outcomes in all these dimensions. Table 2.1 lists dimensions of the activity and travel scheduling decision, and provides a crude estimate of the number of alternatives faced in each dimension by the individual. This indicates the size of the problem for a one-day scheduling period, the minimum required to capture the desired within-day scheduling interactions. Some of the dimensions—notably timing and location—are continuous. However, if for illustration purposes we simplify by transforming these dimensions into discrete categories, ignoring purpose and assuming a person participates in 10 activities during a day, we get a conservative estimate of 10^{16} schedule alternatives. The universal set size would further multiply if the schedule was viewed as a household outcome, including the necessary schedule dimensions for all household members, or as a weekly outcome, including the dimensions for each day of the week.

Table 2.1 An estimate of the number of day activity schedule alternatives faced by an individual

The large number turns the challenge of adequately representing the process into a combinatorial problem.

Number of activities per day	10	
Sequence		10!
Timing	10 per activity	100
Location	1000 per activity	10,000
Mode	5 per activity	50
Route	10 per activity	100
Total		10^{16}

The decisionmaker. Furthermore, the decisionmaker possesses limited resources and capabilities for making this complex decision. Information processing limitations prevent us from being aware of all available alternatives, fully understanding the alternatives we are aware of, and distinguishing similar alternatives. Gathering the information takes time, energy and, often, money that are all in limited supply. The result is that decisionmakers act on incomplete information, especially when the choice involves a large, complex alternative set. Like the decisionmaker, the modeler must simplify. Unlike the decisionmaker, who can simplify any way he or she pleases, the modeler must simplify in a manner matching the behavior of the decisionmakers.

The decision protocol. A variety of decision protocols may be employed to make decisions, but all of them can be described in terms of a two-stage process of (a) choice set generation, in which the choice set is selected from the universal set, and (b) choice, in which one alternative is chosen from the choice set. The process can be deliberative or reactive (Rich and Knight, 1991; as cited in Ettema, Borgers and Timmermans, 1995). In a deliberative process all the alternatives are identified before any are evaluated, and the two stages are conducted sequentially. In a reactive process the evaluation of some alternatives can lead to the identification of additional alternatives, and the two stages are partially completed in an iterative fashion until the choice is finally made.

In models of decisions one of the most commonly assumed decision protocols is a deliberative process in which an exhaustive search is followed by a utility maximization choice among all feasible alternatives. The utility function serves as a composite criterion, a scalar transformation of multiple criteria. The use of this decision protocol in choices with large universal sets can be criticized, as we have just done. The large set makes it unrealistic to assume an exhaustive search followed by the rational evaluation of a utility function for every feasible alternative (Thill, 1992).

Several alternative decision protocols have been hypothesized to represent how individuals cope with complex alternative sets. These include (a)non-exhaustive search, (b) selection based on habit, (c) adaptive decisions, which adjust prior decisions in response to changing conditions, (d) satisfaction rules that stop the search when a satisfying alternative is found, and (e) bounded rational decisions (Simon, 1957), in which a non-exhaustive search generates a manageable choice set, to which a utility-based decision rule is applied. However, none is accompanied by a proven modeling method that has been used successfully in a practical model of a decision as complex as the activity schedule.

In summary, this examination of the scheduling choice identifies the immense multidimensional universal set as the most challenging aspect of the activity schedule modeling problem. In choosing a modeling approach it is important to (a) retain the dimensions of the set, representing inter-dimensional decision interactions, (b) retain activities spanning at least a one-day timeframe, representing inter-activity decision interactions, and (c) use a decision protocol that can represent without distortion the behavior of decisionmakers who can’t rationally consider all feasible schedule alternatives.

2.5 Behavior-theoretical modeling requirements

Our study of the theory of activity-based travel demand leads to several summary statements, gathered together as Table 2.2, that serve as a set of theoretical requirements for incorporating activity-based travel theory in a travel forecasting system.

Table 2.2 Behavior-theoretical requirements of the activity-based travel demand forecasting model

1. Model travel demand decisions as components of an activity schedule outcome.
2. Represent as a single schedule outcome all activity spanning a time period of at least one day, preserving space and time constraints and associated decision interactions across all activities.
3. Include purpose, priority, timing, location and mode for all activities and associated travel, retaining decision interactions among all dimensions and activities.
4. Condition activity schedule choice on outcomes of longer term processes, including
    a) activity opportunities;
    b) lifestyle outcomes of household structure, role within household, capabilities, and activity commitments and priorities; and
    c) household mobility decisions.
5. Represent the scheduling decision as a process governed by commitments and priorities, rather than temporal sequence, within the constraints of the scheduling time period.
6. Interact schedule choice with transportation system performance attributes.
7. Use a decision protocol that can represent without distortion the behavior of decisionmakers who cannot rationally consider all feasible schedule alternatives.

3

Models of Activity and Travel Schedules

The previous chapter supplies a set of requirements for incorporating activity-based travel theory into a travel demand forecasting model. This chapter leads us to a specific modeling approach. Since behavior-theoretical requirements are not the only consideration in developing a sound practical model, Section 3.1 augments the list of requirements. The remainder of the chapter is devoted to examining alternative approaches that have been used in attempts to bring activity-based travel theory into practical forecasting models. In the end, it leads directly to the modeling approach taken in this research, a nested system of discrete choice models.

We focus on the model of activity and travel scheduling, considering lifestyle and mobility primarily as they affect activity and travel scheduling decisions. We do not consider models of implementation and rescheduling behavior (see, for example, Cascetta and Cantarella, 1993; Mahmassani, Hu, Peeta et al., 1994; Antoniou, Ben-Akiva, Bierlaire et al., 1997) or land use (see, for example, Webster, Bailey and Paulley, 1988; Anas, 1994; Owers, Echenique, Williams et al., 1994; Putman, 1995; Wegener, 1995).

3.1 Model system requirements

An activity-based travel demand model system should first be theoretically sound, both behaviorally and mathematically; lacking this assurance, we cannot rely on the results. Second, sufficient resolution is required to capture behavior that affects the aggregate phenomena of interest. This includes resolution of the universal set as well as resolution of the factors explaining choice. As an example of the universal set resolution, the resolution of the time dimension must be fine enough to capture time-of-day shifts in response to congestion pricing and the effects of such shifts on traffic congestion. As an example of explanatory factor resolution, the characterization of residential neighborhood walkability must be accurate enough to capture effects that influence decisions to walk instead of drive for secondary activities in the schedule. Third, the resource requirements of the model must allow it to be implemented. Data is needed for estimating model parameters, and a different set of data is needed to validate the model. To use the model for prediction we must be able to generate its input variables. The model must also be technically and financially feasible to develop, maintain and operate. This includes the need for maintainable software, reasonable computational requirements, and usable procedures. Finally, it must produce valid results; not only must the data be available for validation, but the model must also prove itself in validation. These requirements, listed in Table 3.1, combined with the detailed behavioral requirements of Table 2.2, establish a basic set of requirements for the development of an activity-based travel demand forecasting model.

Table 3.1 Requirements of the activity-based travel demand forecasting model

1. Theoretically sound for accurate results
    a) behaviorally
    b) mathematically
2. Activity schedule resolution for policy sensitive information
    a) universal alternative set
    b) explanatory factors
3. Practical resource requirements for implementation
    a) data for estimation, validation and model inputs
    b) maintainable logic (software)
    c) affordable computation (hardware)
    d) usable operator procedures
4. Valid results

3.2 Overview of modeling approaches

No previously existing model system satisfies all the requirements of an activity-based travel demand forecasting model. As we shall see in the models reviewed below, none provides a full day's scope and a complete representation of all schedule dimensions. Nevertheless, they provide insight into the nature of the modeling problem, and the techniques employed may provide the foundation for an extended or enhanced model that satisfies the requirements. In fact, the day activity schedule model presented in Chapter 4 is a direct descendent of the discrete choice model systems presented in this chapter.

The following presentation of modeling approaches is two-tiered. This section provides an overview of three distinct model classes—Markov, rule-based and econometric. Examples of rule-based simulations and econometric models are reviewed in more detail in subsequent sections.

Markov modeling approaches for trip chaining were explored extensively in the 1970's. They represent the scheduling decision as a sequence of transitions, following the temporal sequence of the day, with transitions between states corresponding to trips between activities. The schedule is defined by a matrix of transition probabilities. Each matrix element is the probability of transition from one state to another. Each activity state is characterized by its important attributes, such as location and travel mode. Early implementations of the model estimated transition probabilities from observed data with no behavioral model of the transition probability. Subsequent semi-Markovian models employed discrete choice or joint discrete-continuous choice models for the transition probabilities, thus enabling the models to be used for forecasting (see, for example, Lerman, 1979). However, no models expanded the scope of the state definition to accommodate all the required dimensions of a full day's activity schedule. Other weaknesses of the approach include the difficulty of accommodating history dependence and time-variance of the transition probabilities. These reflect the fundamental weakness of the approach—its basis in a decision sequence tied to the temporal activity sequence. This renders it unable to represent adequately a decision process that is governed more by commitments and priorities than by sequence. For more detailed reviews of Markov models, see Jones (1976), Horowitz (1980), and Timmermans and Golledge (1990).

The rule-based simulation approach has been popular for modeling the activity schedule since the 1970's. Rule-based models focus most of their attention on choice set generation, employing a complex search rule that yields a very small choice set. A simple choice model is used to represent the choice from this set, frequently with iteration occurring between choice set generation and choice. These models simulate schedule outcomes rather than calculating schedule probabilities. All rule-based simulations developed to date deal with the big universal set by limiting the decision scope and omitting important dimensions of the activity and travel scheduling decision.

Econometric models, perhaps the most popular models of travel demand, have gradually evolved toward an activity schedule representation of demand. They usually employ simple deterministic choice set generation rules and focus attention on the complex representation of a utility-based multi-dimensional choice. No iteration occurs between search and choice. These models are systems of equations representing probabilities of decision outcomes. To get aggregate forecasts the probabilities can be aggregated directly or used to simulate schedule outcomes before aggregation. Econometric models can be viewed in two subclasses, discrete and mixed continuous-discrete.

Discrete choice models partition the activity schedule outcome space into discrete alternatives. They deal with the big universal set by subdividing decision outcomes and aggregating alternatives. For example, the simplest models subdivide outcomes by modeling trip decisions instead of an entire day's schedule, and aggregate activity locations into geographic zones. Over time, discrete choice modelers have tried to improve behavioral realism by including more and more dimensions of choice in an integrated model system. Our review of discrete choice models will emphasize their evolutionary development, leading to the currently presented day activity schedule model.

Research on mixed continuous-discrete models has become active in the 1990s (see for example, Hamed and Mannering, 1993; Bhat, 1996a). Developers of mixed discrete-continuous models have focused their attention on the continuous time dimension of the activity schedule, seeking to improve on its traditionally missing or weak aggregate discrete representation in discrete choice models. Duration models are employed jointly with discrete models of other choice dimensions. Continuous-discrete models have not yet expanded in scope to include most dimensions of the activity schedule, nor have they yet incorporated sensitivity to time-variant activity and travel conditions. Their use in models satisfying the requirements we have identified awaits further methodological development, and we provide no subsequent in-depth reviews.

3.3 Rule-based simulations

We have already described rule-based simulations as sequential decision rules predicting decision process outcomes, and noted their focus of attention on choice set generation. These systems are based on various decision theories, such as cognitive limitation or the notion of a search that terminates with acceptance of a satisfying alternative. A simple utility-based decision rule is often used in the choice stage of the decision protocol. Rule-based simulations achieve simplification by subdividing the decision process into separate sequential steps. Additionally, all rule-based simulations developed to date achieve simplification by limiting the decision scope, omitting important dimensions of the activity and travel scheduling decision.

A great variety of rule-based simulations is possible, and they are harder to subclassify than the econometric systems. We review three particular model systems which, although they do not characterize the entire class of rule-based simulations, are important examples and demonstrate some of its variety. The STARCHILD system (Recker, McNally and Root, 1986b; Recker, McNally and Root, 1986a) is the earliest example reviewed in this class, modeling the activity and travel scheduling decision as a classification and choice process. AMOS (RDC Inc., 1995) is a recent example that has been partially implemented in the Washington, D.C. area, representing the decision as a search for a satisfactory adjustment. SMASH (Ettema, Borgers and Timmermans, 1993; Ettema, Borgers and Timmermans, 1995) was developed in the Netherlands, and represents the scheduling decision as a sequence of schedule building decisions.

3.3.1 STARCHILD: classification and choice

STARCHILD (Figure 3.1) starts with a detailed activity program that must be supplied from outside the model. The activity program identifies many details of the schedule, including activity purpose, participation, duration and location, as well as constraints on sequence, timing and coupling of activities. It then models the scheduling decision as a four-step process which yields the timing and sequence of the activities in the program. Choice set generation occurs in the first two steps. Feasible alternatives are exhaustively enumerated with careful attention to constraints. They are then classified, using a statistical similarity measure, and one alternative is chosen to represent each of approximately 3-10 classes. The remaining two steps comprise the choice process. A decision rule is used to eliminate some alternatives. In the prototype which was developed, all inferior alternatives are eliminated, according to an intuitive objective criterion. A multinomial logit model then represents a utility maximizing choice among the remaining non-inferior alternatives. The developers of STARCHILD conceived the activity schedule as a plan, which is followed by implementation and rescheduling, but did not develop the latter model.

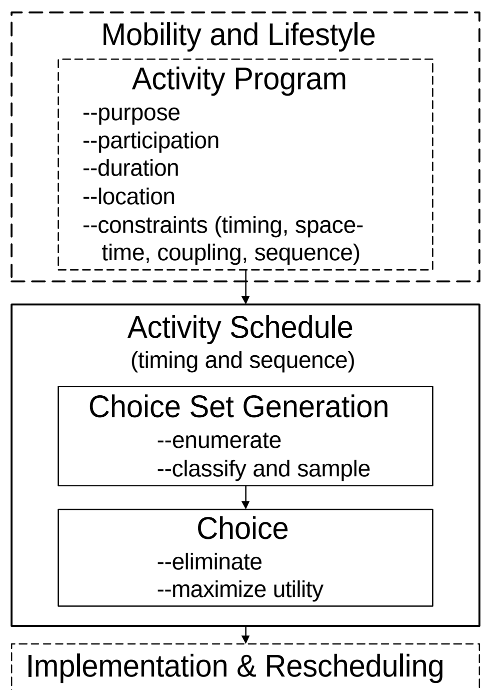

Figure 3.1 STARCHILD model system

STARCHILD takes an externally supplied activity program and simulates the scheduling decision. Choice set generation involves enumerating, classifying and sampling the schedule alternatives. This is followed by a simple utility maximization choice.

STARCHILD's key features are its detailed representation of constraints in the identification of feasible alternatives, and the use of a classification method to generate the choice set. As a model intended for use in forecasting travel, it has two key weaknesses. First, it relies on external sources to predict important dimensions of the activity and travel schedule, including activity participation, purpose, location and travel mode. Second, the classification and sampling rule may inadequately represent the true choice set. The rule generates a very small choice set with only one alternative of each distinctively different class, whereas people may frequently choose from a small choice set of similar competing alternatives.

3.3.2 AMOS: search for a satisfactory adjustment

AMOS (Figure 3.2) requires as input an even more detailed activity schedule than STARCHILD. This, however, is because AMOS is designed as a switching model. Given a baseline schedule and a policy change, it chooses a basic response, such as a mode change, which limits the domain of search for a feasible adjustment. A structured search rule then completes the choice set generation stage, yielding one feasible adjustment. A simple choice model accepts or rejects the adjustment. If the adjustment is rejected then the structured search is repeated until an acceptable adjustment has been found. If no acceptable alternative is found for the desired basic response, then the process can loop back to the choice of another basic response.

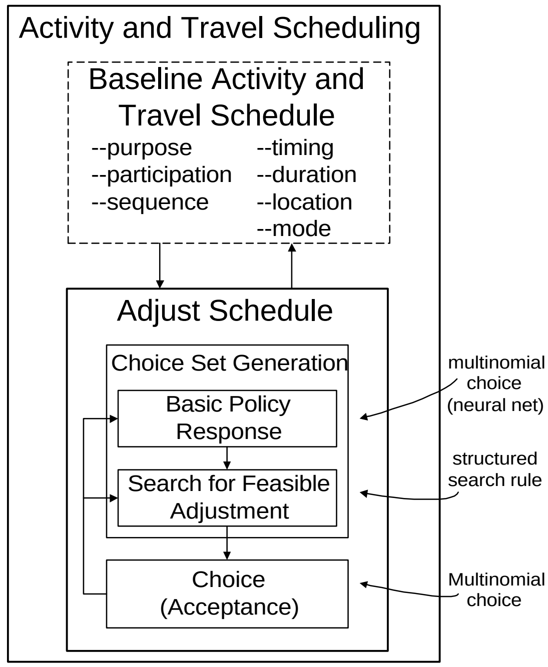

Figure 3.2 AMOS model system

AMOS takes a detailed schedule and searches for an acceptable adjustment to a specific policy change. The process involves the selection of a basic policy response which narrows the domain of search. This is followed by the search for one feasible adjustment and the decision to accept the adjustment or continue the search.

The basic response model is policy specific. Six policies are included in the prototype for Washington, D.C.:

1. Workplace parking surcharge
2. Improved bicycle and pedestrian facilities
3. combination of 1 and 2
4. Workplace parking surcharge with employer-supplied commuter voucher
5. Peak period driver charge
6. combination of 4 and 5

The basic response is modeled as a multinomial choice from a set of eight alternatives:

1. No change
2. Change departure time to work
3. Switch to transit
4. Switch to car/vanpool
5. Switch to bicycle
6. Switch to walk
7. Work at home
8. Other

The prototype implements the multinomial choice model via the combination of a neural network and a multinomial logit model (MNL). The neural network predicts an output signal for each alternative, which is a scalar function of 36 decisionmaker characteristics under the policy change. The MNL converts the output signals to probabilities by using the output signal as the only explanatory variable in the utility function. The parameters of the basic response model are estimated from data supplied by a policy-specific stated preference survey.

Given a basic response, a context specific search rule is used to find a feasible schedule adjustment. Figure 3.3 shows a portion of the prototype's search rule for a basic response of mode change from single occupant vehicle to transit. The rule checks first for the presence in the baseline schedule of stops on the way to work. If it finds some, it assumes they cannot be chained in the new transit commute, and switches them into a home-based tour before work. Then it checks to see if the revised schedule allows for timely arrival at work. The rule continues like this to make schedule adjustments and feasibility checks, eventually arriving at a feasible alternative. Each time a schedule adjustment is needed, the adjustment is made via an intuitive decision rule or a simple choice model. The entire rule allows, in order of priority, changes to sequence and at-home stops, mode, and timing.

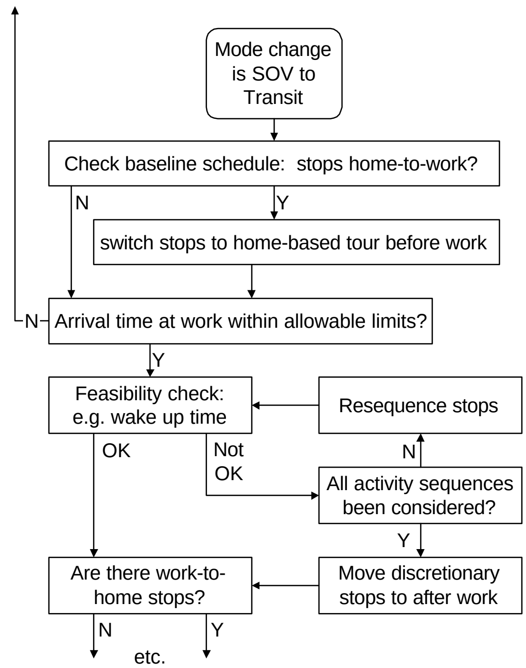

Figure 3.3 A portion of the AMOS context specific search

AMOS search for a feasible schedule adjustment, given the basic policy response of a mode change from single occupant vehicle to transit. (source: RDC Inc., 1995)

In summary, AMOS has two key features. First, it is a policy-specific switching model. Because it is anchored in a baseline schedule and predicts switches based on policy-specific survey data, it has great potential to be very informative in predicting short-term responses to specific policy changes. The second key feature is the three-step decision protocol of basic response, structured search and satisfaction-based decision.

AMOS has a few weaknesses linked to its design. First, it requires custom development for each policy. Second, validation is needed for each specific policy response model, and the availability of revealed preference data for this validation is very unlikely. Third, it does not forecast long run effects. Fourth, it requires the exogenous forecast of a baseline schedule for each application of the model. Fifth, the basic response and search models may inadequately represent the search process; the structured search sequence may not match the way some people search, and may systematically bias the predicted outcomes. Beyond these five design-related weaknesses, the prototype implementation of AMOS suffers from an incomplete scope; it is unable to predict changes in non-work schedules, or changes in activity participation, purpose, duration or location.

3.3.3 SMASH: sequential schedule building

SMASH (Figure 3.4) starts with a detailed activity program similar to that required by STARCHILD. Through an iterative process it gradually builds a schedule using activities from the program. In each iteration it starts with a schedule (a blank schedule in the first iteration) and conducts a generic non-exhaustive search, enumerating all schedule adjustments which would insert, delete or substitute one activity from the agenda. It then chooses one of the potential adjustments from the choice set and continues the search, or accepts the previous schedule and ends the search. Conceptually, the model could be used as a rescheduler, being rerun after the conduct of each activity, but the prototype was not implemented in this way.

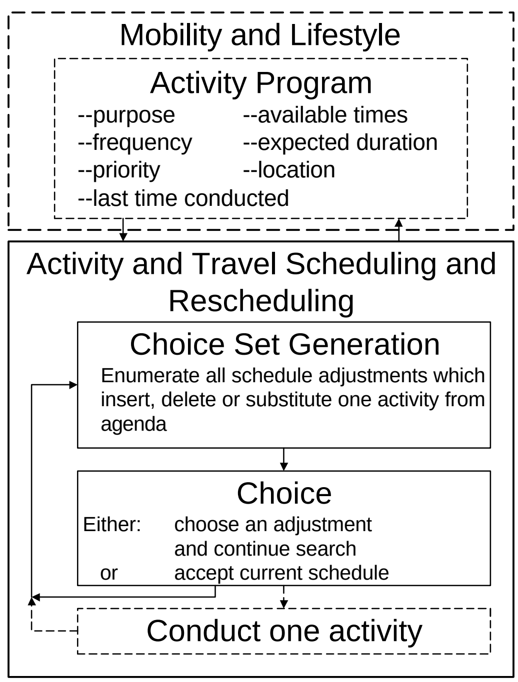

Figure 3.4 SMASH model system

SMASH starts with a detailed activity program and an empty schedule. Then it builds the schedule by adding, deleting or substituting one program activity at a time. A decision is made each time whether or not to accept the current schedule and stop the building process.

The choice between schedule adjustment and schedule acceptance is implemented as a nested logit model. Schedule acceptance occurs when the utility of the schedule acceptance alternative is greater than that of all the schedule adjustments under consideration in the iteration. A schedule is more likely to be accepted if it has a lot of scheduled activity time, little travel time, includes the high priority activities from the program and lacks schedule conflicts.

The key feature of SMASH is the schedule construction process with a cost-benefit based stopping criterion. SMASH has three major weaknesses. First, it relies on an externally supplied detailed activity program which includes several important dimensions of the activity schedule, including desired participation, purpose, duration, location and mode of travel. Second, it requires a very complex survey for model estimation. Respondents must step through the entire schedule building process. Finally, the non-exhaustive search heuristic may be inadequate, and needs to be validated. Its method of restricting the search domain may systematically exclude alternatives which people frequently choose.

3.3.4 Summary evaluation of rule-based simulations

Recalling the purpose of this examination, to identify promising approaches for development of an activity-based travel demand forecasting model satisfying the requirements in Table 2.2 and Table 3.1, we evaluate the rule-based simulations in terms of their potential in the short term to satisfy the requirements. All three examples face two important challenges. First, they rely on a detailed exogenous activity program or schedule that determines all or much of the activity participation decision, as well as other important attributes such as location and timing. Thus, although the resulting schedules may be fairly complete in scope, important major components of the schedule are not modeled. That is, they are not conditioned by the long term urban and lifestyle processes, nor do they interact with the transportation system attributes.

Secondly, all three examples rely on unproven search heuristics. STARCHILD relies on an arbitrary similarity criterion to sample the universal set, while AMOS relies on a complex arbitrary decision tree for finding schedule adjustments. SMASH’s carefully reasoned heuristic is nevertheless unvalidated. For two of the three, AMOS and SMASH, the decision protocol is also extremely complex, which may partly explain why the scope of the scheduling model is so narrow in the prototype models. Extensive data and validation requirements accompany their complexity.

The attractiveness of rule-based simulations is the freedom they give to attempt new decision protocol models that may better represent human behavior in the activity scheduling decision. However, the above challenges this presents make it unlikely that such an approach can yield a comprehensive, validated scheduling model in the near future.

In contrast, utility maximization is a much simpler protocol for which the schedule scope is a less formidable modeling challenge. The protocol has a solid basis in consumer theory. Although the large universal alternative set pushes it beyond the limits of purely representing rational consumer behavior, the protocol has been successfully used and validated in discrete choice travel demand model systems where the universal set far exceeds such limits. In the next section we examine such systems.

3.4 Discrete choice models

3.4.1 Discrete choice methods

As mentioned in the introductory review, discrete choice travel demand model systems deal with the big universal set by subdividing decision outcomes and aggregating alternatives. They attempt to retain behavioral realism by linking the component models of the system in a hierarchy that matches the natural hierarchy of the decision process. Lower dimensions of the scheduling hierarchy are conditioned by the outcomes of the higher dimensions. For example, choice of travel mode for the work commute is conditioned by choice of workplace. At the same time the utility of a higher dimension alternative depends on the expected utility arising from the conditional dimension's alternatives. In our example, the choice of workplace is influenced by the expected utility of travel arising from all the available commute modes.

Nested logit models effectively model multidimensional choice processes where a natural hierarchy exists in the decision process, using conditionality and expected utility as described above. The expected utility of the conditional dimension is commonly referred to as accessibility because it measures how accessible an upper dimension alternative is to opportunities for utility in the lower dimension. It is also often referred to as the "logsum", because in nested logit models it is computed as the logarithm of the sum of the exponentiated utility among the available lower dimension alternatives. For more detail, see Ben-Akiva and Lerman (1985, Chapter 10).

The models are disaggregate, representing the behavior of a single decisionmaker. A Monte-Carlo procedure is often used to produce aggregate predictions. In other words, the models make predictions with disaggregate data, requiring the generation of a representative population. The model is applied to each decisionmaker in the population—or a representative sample—yielding either a simulated daily travel itinerary or a set of probabilities for alternatives in the choice set. The trips in the itinerary can then be aggregated and assigned to the transport network, resulting in a prediction of transport system performance. This process may require replications to achieve statistically reliable predictions.

3.4.2 Trips and tours

Within the class of discrete choice model systems we identify two subclasses, based on how each divides the decision outcomes. The simplest and oldest subclass divides the activity schedule into trips. Some more recent models combine trips explicitly in tours.

Figure 3.5 compares the two subclasses according to their representation of a hypothetical day activity schedule: the person departed for work at 7:30 A.M., traveling by transit. At noon she walked out for personal business, returning to work at 12:50 P.M. At 4:40 P.M. she returned home from work, again by transit. That evening at 7:00 P.M. she drove to another location to shop, returning home at 10:00 P.M. The trip-based model represents the schedule as six one-way trips. The "direction" of the trips is usually portrayed in terms of trip production and attraction rather than direction of movement. In the tour-based model the trips are explicitly connected in tours, introducing spatial constraints and direction of movement. We will look at an example of both modeling approaches.

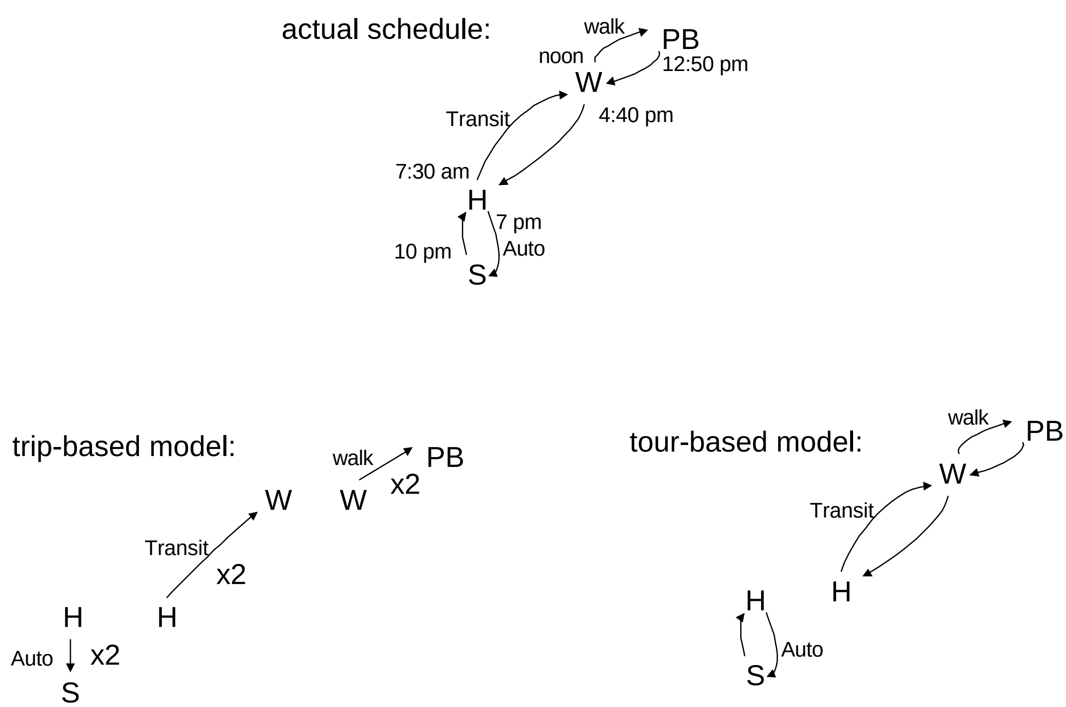

Figure 3.5 Trip and tour-based model subdivision of the day activity schedule

Trip-based models subdivide the schedule into one-way trips. Tour-based models separate the schedule into tours.

3.4.3 Trip-based system

The first integrated trip-based disaggregate model systems were developed during the mid 1970's for Washington D.C. (Ben-Akiva, Adler, Jacobsen et al., 1977) and for the Metropolitan Transportation Commission (MTC) of the San Francisco Bay area (Ruiter and Ben-Akiva, 1978). We review here the demand model portion of the MTC system. It consists of three major components, as shown in Figure 3.6(a). The mobility and lifestyle component represents long-term decisions related to auto ownership and home-based work trips. Short term activity and travel decisions deal with other home-based trips and non-home-based trips. Each model component is conditioned by choices at the higher level, and the activity and travel models influence the mobility and lifestyle models via measures of expected utility. Figure 3.6(b) shows detail of the mobility and lifestyle component of the model system. The system explicitly models work travel decisions for the primary and secondary workers in the household. Arrows in the figure show how the models are integrated: solid arrows indicate conditionality; dashed arrows indicate expected utility. For example, the number of autos chosen in the auto ownership model is conditioned by the choice of workplace; the model assumes the workplace is known when it models the auto ownership decision. The auto ownership decision itself conditions the mode choice model. The model also accounts for the influence on auto ownership of ease of travel to shopping and work, by including variables of expected utility generated by the shopping destination and mode choice and work mode choice models.

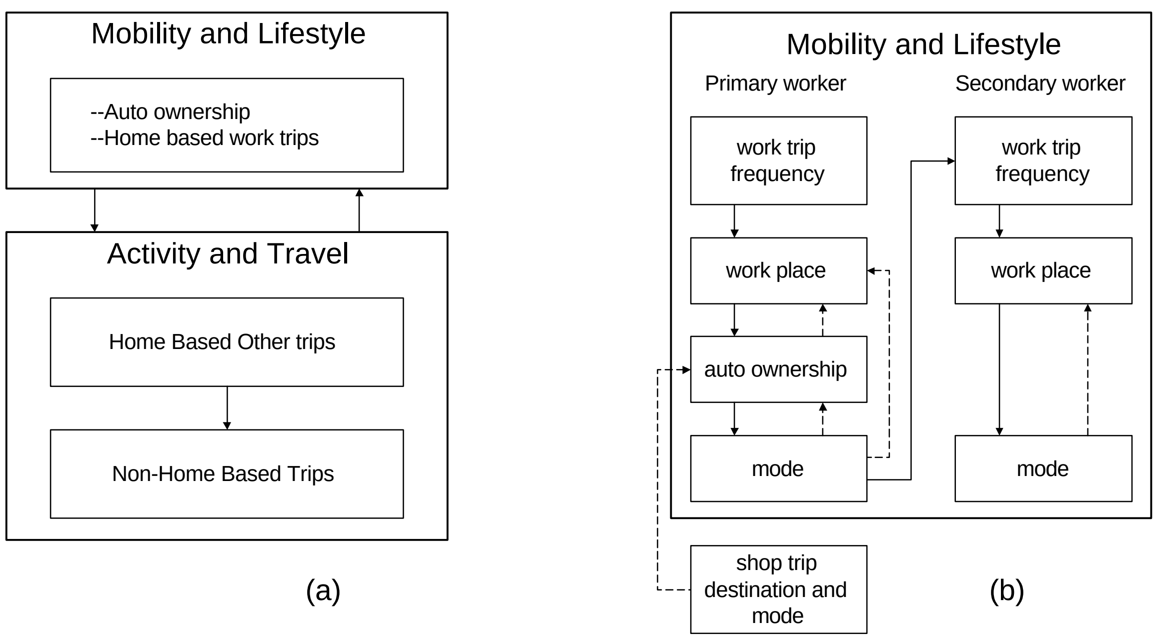

Figure 3.6 The MTC trip-based model system

(a) Three major components of the MTC model system, and (b) details of the mobility and lifestyle component, showing integration of the models via conditionality (solid arrows) and expected utility (dashed arrows). (Source: Ruiter and Ben-Akiva, 1978)

In summary, key features of the trip-based model systems, exemplified by the MTC system, are the composition of disaggregate choice models and the integration via conditionality and measures of expected utility according to the decision framework. The model's weaknesses come from its subdivision of the day schedule. The key weakness is the sequential modeling of home-based and non-home-based-trips as opposed to the explicit representation of tours. This hurts its ability to predict correctly scheduling changes, such as trip chaining, that can occur in response to changing conditions. The trip frequency models are not sensitive to changes affecting other dimensions of the schedule.

The MTC model system has been continuously updated since its development in the mid-70's, and is being used as the transportation planning model for the San Francisco Bay area (Kollo and Purvis, 1989; Metropolitan Transportation Commission Planning Section, 1997).

3.4.4 Tour-based system

Tour-based systems were first developed in the late 1970's and 80's in the Netherlands (Daly, van Zwam and van der Valk, 1983; Gunn, van der Hoorn and Daly, 1987; Hague Consulting Group, 1992), and are being used extensively there and elsewhere in Europe, with the most recent systems being developed in Stockholm, Sweden (Algers, Daly, Kjellman et al., 1995) and Salerno, Italy (Cascetta, Nuzzolo and Velardi, 1993). We review here the Stockholm system as an example of this class. Figure 3.7 shows how the tours for various purposes are explicitly modeled. Work tour decisions are conditioned by the mobility and lifestyle decisions, and condition all other activity and travel decisions. The model system heavily uses expected utility measures, strengthening the connections across dimensions of the activity and travel scheduling decision.

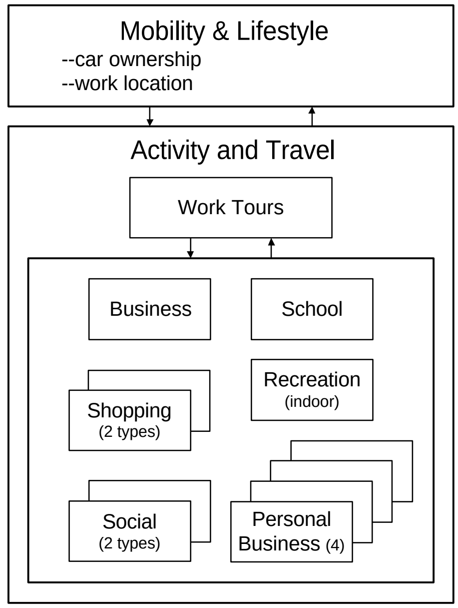

Figure 3.7 The Stockholm tour-based model system

Work tour decisions are conditioned by the mobility and lifestyle decisions, and condition all other activity and travel decisions.

The work tour decision, Figure 3.8 , includes the household's decision of who will work today, how the household's autos will be allocated among the workers, and the travel mode for workers who do not use a household auto.

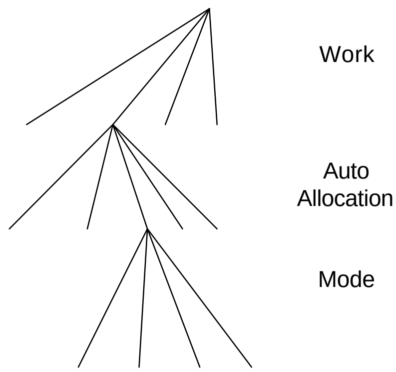

Figure 3.8 The Stockholm nested logit work tour model

The work tour model represents household work participation, auto allocation among workers, and commute mode in a conditional hierarchy

The model of household shopping tours, Figure 3.9 , conditioned by the work decision, determines how many shopping activities the household will undertake, who will perform them, on what type of tour they will be performed, and the tour mode and destination. A shopping activity can be assigned to one or more household members. If it is assigned to a worker, the existing options are to conduct the activity on a home-based or work-based tour, or chained to the work tour en route between work and home.

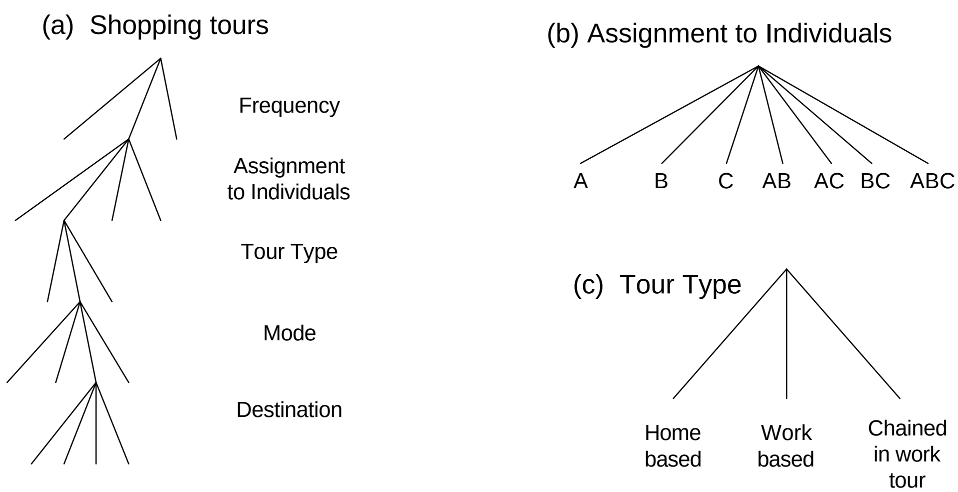

Figure 3.9 The Stockholm shopping tours model

(a) The Stockholm shopping tours model. (b) Each shopping activity is assigned to one or more household members. (c) If a shopping activity is assigned to a worker, the tour type model determines whether the activity occurs on a home-based tour, a work-based tour, or chained in the work tour.

To summarize the tour-based approach, the key features are the explicit representation of tours and trip chaining within tours. The Stockholm example also explicitly models household decisions. The key weaknesses are the lack of an overarching pattern connecting the day's tours, and the failure to integrate the time dimension into the model structure. These may prevent the model from accurately predicting some inter-tour schedule adjustments, such as splitting a chained tour into two tours, and time-of-day adjustments.

Tour-based systems represent the most advanced state of the practice of disaggregate travel demand modeling. These systems have been carefully validated and are being widely applied.

3.4.5 Summary evaluation of trip and tour-based discrete choice model systems

The main behavioral criticism of the trip and tour-based discrete choice model systems is the division of the schedule outcome into separate pieces, trips and tours, respectively. Otherwise, they satisfy the behavioral requirements laid out in Table 2.2. They are able to retain many interactions among the dimensions of the schedule through the conditionality and expected utility mechanisms. They fit in the broader decision hierarchy; that is, they are conditioned by longer-term outcomes and interact with the transportation system performance. As already mentioned, they have been extensively validated, demonstrating their ability to perform reasonably well in forecasting despite their utility maximization assumption in the presence of very large universal sets.

The models also satisfy most of the requirements of Table 3.1. They employ well-accepted econometric techniques for statistically estimating and testing the model specification. As already mentioned, they have been used and validated extensively in practice. On the other hand, their practicality is closely tied to their undesirable division of the schedule into pieces.

In conclusion, discrete choice models provide a mechanism for integrating the dimensions of the day activity schedule. Indeed, they have successfully evolved over the years toward such an integrated representation. Furthermore, a principal barrier to further integration has been the level of resources required for implementation, and advances in computing technology are causing that barrier to recede. Thus, we choose this approach.

4

The Day Activity Schedule Model System

4.1 Introduction and overview of the model system

In the last two chapters we presented theoretical background and a review of past modeling approaches for a practical activity-based travel demand model system. This provided us with a set of requirements and the selection of discrete choice analysis as the preferred approach. In this chapter we present a model of the activity and travel scheduling choice. It takes an evolutionary step within the category of discrete choice models, beyond trip-based and tour-based models, to represent the choice of a full day's schedule. We refer to this as the day activity schedule or, more simply, the activity schedule or schedule. Thus we call the model a day activity schedule model.

Demand for activity and travel is viewed as a utility maximizing individual's choice of one day activity schedule from a discrete set of all possible schedules. The choice is modeled using an integrated system of logit and nested logit models that can calculate the probability of each schedule alternative.

We use a one day time period because of the day's primary importance in regulating activity and travel behavior. People organize their activities in day-sized packages, allowing substantial interactions among within-day scheduling decisions as they cope with time and space constraints while attempting to achieve their activity objectives.

As noted in Chapter 2, a time period longer than one day would enable the model to capture inter-day scheduling interactions. Discrete choice methods have been developed for these interactions, and demonstrated for shopping activity (Hirsh, Prashker and Ben-Akiva, 1986). However, we model a one-day schedule because computational costs for model operation grow exponentially with the number of days in the schedule, and seven-day activity and travel surveys are not currently available for model estimation. The model presented in this chapter can capture important day-of-the-week variation by customizing the empirical specification of schedule utility for different days of the week.

As also noted in Chapter 2 and implemented in the tour-based model reviewed in Section 3.4.4, the schedule can be defined as a household schedule, explicitly capturing interactions among household members. Since this also multiplies the size of the problem, we instead capture household interactions implicitly by differentiating the empirical specification of schedule utility according to household structure and the individual's role in it.

The day activity schedule is viewed as a set of tours and at-home activity episodes tied together by an overarching day activity pattern (Figure 4.1). Decisions about a specific tour in the schedule are conditioned, or constrained, by the choice of day activity pattern. This is based on the notion that some decisions about the basic agenda and pattern of the day's activities take precedence over details of the travel decisions. The probability of a particular day activity schedule is therefore expressed in the model as the product of a marginal pattern probability and a conditional tours probability

$$prob(schedule) = prob(pattern)\,prob(tour\ attributes|\ pattern)$$

where the pattern probability is the probability of a particular day activity pattern and the conditional probability is the probability of the pattern's tour attributes.

The day activity pattern represents the basic decisions of activity participation and priorities, and places each activity in a configuration of tours and at-home episodes. Each pattern alternative is defined by (a) the primary activity of the day, (b) whether the primary activity occurs at home or away, (c) the type of tour for the primary activity, including the number, purpose and sequence of activity stops, (d) the number and purpose of secondary tours, and (e) purpose-specific participation in at-home activities. Table 4.1 gives a hypothetical example of an activity and travel diary, and Table 4.2 shows the attributes explicitly modeled for the day activity pattern.

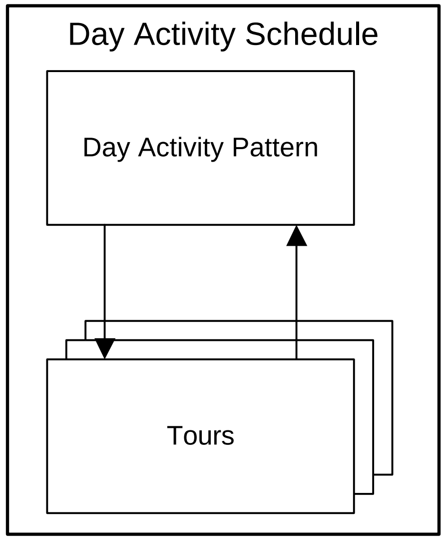

Figure 4.1 The day activity schedule

An individual's multidimensional choice of a day's activities and travel consists of tours interrelated in a day activity pattern.

For each tour, details of time-of-day, destination and mode are represented in the conditional tour models. Within each tour, the choice of timing, mode and primary destination condition the choices of secondary stop locations. Table 4.3 shows the tour attributes explicitly modeled by the conditional tour models for the example.

The choice of pattern is not independent of the conditional tour decisions. The relative attractiveness—or utility—of each pattern, depends not just directly on attributes of the pattern itself, but also on the maximum utility to be gained from its associated tours. Patterns are attractive if their expected tour utility is high, reflecting, for example, low travel times and costs. The model system captures this effect by using measures of expected utility from the conditional tour models to explain pattern choice, an example of the use of expected utility in nested systems of discrete choice models described in Chapter 3. This ability to capture sensitivity of pattern choice—including inter-tour and at-home vs on-tour trade-offs—to spatial characteristics and transportation system level of service distinguishes the day activity schedule model from tour models, and is its most important feature. The day activity schedule model also improves on tour models' ability to represent the time dimension by explicitly modeling the time of each one of the inter-related tours in the

Table 4.1 Hypothetical example--activity and travel diary

Begin	End	Activity or travel
6:00 a.m.	7:15	get ready for work
7:15	7:45	drive alone to work at 872 4th Ave
7:45	12:00	Work
12:00	12:10	walk to lunch at 905 4th Ave
12:10	12:35	Lunch
12:35	12:45	walk back from lunch
12:45	4:30	Work
4:30	5:00	drive alone to pick up daughter at school, 1325 Lakeview Blvd.
5:00	5:10	drive home with daughter
5:10	6:00	fix supper
6:00	6:30	eat supper
6:30	7:20	read paper and relax
7:20	7:30	drive to school for PTO meeting
7:30	9:00	PTO meeting
9:00	9:10	drive home
9:10	10:30	watch TV
10:30	6:00	Sleep

Table 4.2 Hypothetical example—day activity pattern attributes

The model explicitly translates the diary example in Table 4.1 into these day activity pattern attributes.

Pattern attribute	Example value
Primary activity	work on tour
primary tour type	no stop before work-based subtour maintenance stop after
Secondary tours	1 leisure tour
at-home maintenance activity	yes

Table 4.3 Hypothetical example—tour attributes

The model explicitly translates the diary example in Table 4.1 into these tour attributes

Tour	Tour attribute	Example value
Primary tour	departure time to primary destination mode departure time from stop after location	a.m. peak period zone 12 auto drive alone p.m. peak period zone 329
Work-based subtour	departure time to destination mode departure time from	midday zone 12 walk midday
Secondary tour	departure time to mode destination departure time from	after p.m. peak auto drive alone zone 329 after p.m. peak

pattern. With these features, the day activity schedule model satisfies the behavior-theoretical requirements of Table 2.2.

4.2 Mathematical form of the model system

Having described the day activity schedule model with words, figures and an example in the last section, we now present its mathematical form.

4.2.1 Day activity schedule probability

The day activity schedule s is characterized by an activity pattern and the characteristics of the pattern's tours:

$$s = (p, \{c_t, \forall t \in T_p\}), \qquad s \in S,$$

where p is a pattern, chosen from the set P of available patterns; T_p is the set of tours in p, with index t; c_t is the vector of characteristics of tour t, chosen from set C_t; and S is the set of available activity schedules.

The characterization of p identifies the purpose of each activity a in its set of activities, A_p, and locates each activity, either at home or on a particular tour t in T_p. It also identifies the most important activity, $a^1 \in A_p$. If a^1 occurs on a tour we call this the primary tour, denoted $t^1 \in T_p$, and refer to the other tours as secondary. Thus we have

$$p = (A_p, T_p, a^1, t^1), \quad p \in P$$

The probability of s is expressed as

$$prob(s) = prob(p)\, prob(c_{t^1} | p) \prod_{\substack{t \in T_p \\ t \neq t^1}} prob(c_t | c_{t^1}, p), \quad s \in S, \tag{1}$$

where we have assumed conditional independence of the secondary tours, given the primary tour. We may adopt the stronger assumption that all tours are conditionally independent, given the pattern, and express the schedule probability as

$$prob(s) = prob(p)\prod_{t\in T_p} prob(c_t | p), \quad s \in S. \tag{2}$$

4.2.2 Pattern model

Assume a choice of pattern *p* from choice set *P* can be represented by a random utility model, where

$$U_p = V_p + e_p, \qquad p \in P, \tag{3}$$

is *p*'s utility with systematic component V_p and random component e_p. In the MNL model e_p is Gumbel distributed, independently and identically (IID) across patterns, and the probability that *p* will be chosen is

$$prob(p) = \frac{\exp(m^P V_p)}{\sum_{p'\in P}\exp(m^P V_{p'})}, \quad p \in P, \tag{4}$$

where m^P is the scale parameter. We assume the utility of a pattern includes additively a component V_a for each activity, a component $\tilde{V}_p$ for the overall pattern, representing the effect of time and energy limitations and activity synergy, and a component V_t for the expected utility of each tour *t*, given pattern *p*. This yields

$$V_p = \tilde{V}_p + \sum_{a\in A_p} V_a + \sum_{t\in T_p} V_t, \qquad p \in P, \tag{5}$$

where V_t is the utility of tour $t \in T_p$.

4.2.3 Tour model

The schedule model, (1) or (2), requires a conditional probability for each tour t in the pattern. Assume a choice of alternative c_t from choice set C_t can also be represented by a random utility model, where

$$U_{c_t} = V_{c_t} + e_{c_t}, \qquad c_t \in C_t,\ t \in T_p,\ p \in P \qquad (6)$$

is c_t's utility with systematic component V_{c_t} and random component e_{c_t}. In the MNL model the conditional probability that c_t will be chosen, given pattern p, is

$$prob(c_t | p) = \frac{\exp(m^t V_{c_t})}{\sum_{c'_t \in C_t} \exp(m^t V_{c'_t})}, \qquad c_t \in C_t, t \in T_p, p \in P, \qquad (7)$$

where m^t is the scale parameter.

The log of the denominator is the expected value of the maximum utility among available alternatives for this tour, given p. That is, it is the expected utility measure for this tour required in the pattern utility function, (5). Specifically,

$$V_t = \frac{1}{m^t} \ln \sum_{c_t \in C_t} \exp(m^t V_{c_t}) + g \,/\, m^t = E(\max_{c_t \in C_t} U_{c_t}), \qquad t \in T_p, p \in P, \ (8)$$

where γ is Euler's constant (~ 0.577). The constant term $g \,/\, m^t$ can be ignored.

4.2.4 Tour model details

The choice of a tour is itself multidimensional. We assume that decisions related to the overall tour and its primary activity condition the decisions about secondary stops. Tour level decisions include departure times h from home and from the primary activity, primary destination d and tour mode m. Conditional secondary stop decisions include attributes of any secondary stops, including subtours, d_s, and stops before, d_b, or after, d_a, the primary destination. We thus express the tour probability as

$$prob(c_t|p) = prob(h,m,d|p)\,prob(d_s,d_b,d_a|h,m,d,p), \quad c_t \in C_t, t \in T_p, p \in P. \tag{9}$$

4.3 Model design issues

Several model system design issues arise at those points where the demands of the modeling problem push the limits of the chosen modeling methods, given the available data and computational power. They point to areas where additional research and development are needed. Nearly all the issues relate to the biggest modeling challenge of the day activity schedule, the immense universal set of alternatives.

4.3.1 Conditional independence

The day activity schedule model must address the fact that a schedule can include any number of conditional tours. In theory, it could handle this through a conditional hierarchy among tours, and implement a pure nested logit model with a nesting level for each tour. However, in practice such a structure would be cumbersome, intractable, and perhaps insufficiently supported by the data for parameter estimation. Alternatively, the model assumes conditional independence among tours, given the pattern, using (1), with conditional independence among secondary tours, or (2), with conditional independence among all tours. Similarly, the tour model system assumes conditional independence of intermediate stop locations, given attributes of the tour and primary stop. In such cases, it is important to include in the marginal choice dimension the attributes of the joint decision that would be correlated in the conditional dimension. For instance, suppose that tours are assumed to be conditionally independent, as in (2). If secondary tour mode choice depends on primary tour mode choice, then either primary tour mode choice should be modeled as an attribute of the pattern in the marginal pattern choice model, or else the more complex model form of (1) should be adopted, with the secondary tour modeled conditional on primary tour outcome.

4.3.2 Additive expected maximum utility

In the two cases just noted where conditional choices are conditionally independent, the model needs to accommodate the effect of multiple conditional choices on the marginal choice. It handles this via multiple expected utility measures combined additively in the marginal choice utility functions. In most cases this requires estimating a separate parameter for each expected utility measure. This serves two purposes. First, it accommodates the possibility of importance differences among the conditional model expected utilities. Secondly, it accommodates the possibility of scale differences that may exist between two expected utility measures that are used together but come from different conditional model specifications. For instance, the importance of expected tour utility may be different for a secondary leisure tour than for a primary subsistence tour, and the scale of these two measures may also be different since they come from two different tour model specifications. It may be difficult to specify desirable interactive effects among these measures, because it requires identifying the difference in scale of the two measures.

4.3.3 Utility correlation assumptions

Choice models with multidimensional choice sets are prone to correlation among subsets of alternatives. It is very likely that, although the day activity schedule specification in Section 0addresses the issue via the nesting of correlated subsets, some substantial correlations remain that may distort the model's predictions.

First, the day activity schedule includes many dimensions and only some of them are nested. Of particular importance for further investigation is the form of the day activity pattern model. For example, it is likely that the subsistence pattern alternatives share unobserved attributes related to the subsistence purpose.

Second, even within one dimension it is sometimes difficult to eliminate shared unobserved attributes among subsets of alternatives. In particular, in spatial choice dimensions, alternatives physically near each other are likely to share unobserved attributes affecting utility.

Third, in some cases simple nesting may not adequately represent the utility correlation. Even in a simple two-dimensional model, the nested logit form requires the assumption of no correlation among alternatives sharing the same conditional dimension outcome. For example, for a mode and destination choice modeled by nested logit with marginal mode choice and conditional destination choice, the assumptions allow alternatives to share unobserved mode attributes but do not allow them to share unobserved destination attributes. In reality it is impossible to specify fully the attributes in either dimension, so the assumption is always violated. At issue is whether they can be fully enough specified in one of the dimensions so that distortions caused by the violation are inconsequential. If not, a more general model form is required, such as multinomial probit that allows shared unobserved attributes in both dimensions via a more generally specified error correlation structure. The issue may arise in the pattern choice , where correlations by purpose, location (home or away) and tour structure may all be significant.

This creates a dilemma because the complexity of the decision also makes the more general model forms intractable. We are forced to either model simpler outcomes, such as trips, without a behavioral basis, or to seek a nesting structure that adequately represents the correlation among utilities. It is theoretically possible, sometimes practically feasible, and certainly desirable, to test the correlation conditions required by the nested logit model (Ben-Akiva and Lerman, 1985, Chapters 7 and 10; McFadden, 1987), seeking a specification that best satisfies them. As computing technology continues to advance it may also become possible to specify models that allow more general correlation structures in cases where the nested logit assumptions are most severely violated. Important future research agenda include identifying these violations and developing more general models to accommodate them.

4.3.4 Choice set generation

A weakness of all discrete choice models is their dependence on availability information that is difficult to determine. This is important with the day activity schedule because of the effect of time and space constraints on alternative availability, and the difficulty of accurately judging availability for such a complex outcome. If availability is incorrectly judged when model parameters are estimated, then their estimates may be biased. If availability is judged the same way when the model is applied, then the parameter bias may have little effect, provided the relation of the flawed availability judgment and the true availability process has not significantly changed. However, it is not desirable to rely on hope for such favorable cancellation of error.

The problem of choice set generation is sometimes handled by probabilistic models of alternative availability, but such models are too cumbersome for the large multidimensional day activity schedule choice set. Instead, it relies on deterministic availability rules. Time and space constraints—important elements of activity-based travel theory—can be incorporated in the model system by explicitly evaluating alternative availability at each conditional level of the model, taking into consideration schedule attributes determined in marginal models that restrict conditional opportunities. They might also be incorporated for a particular dimension of the schedule decision by observing the distribution of outcomes in the data sample and considering unobserved outcomes as unavailable. The first method suffers from imprecision because of coarse time and space resolution of the day activity schedule. The second method suffers from imprecision because it infers availability from a sample. Its policy sensitivity is limited for the same reason. Nevertheless, careful use of these methods can provide reasonable approximations of important constraints.

4.3.5 Lifestyle outcomes versus day activity schedule choices

Activity schedule decisions such as destination and mode often closely reflect long-term decisions or habits. The day activity schedule model fits within the larger decision framework in which lifestyle and mobility outcomes can be modeled. The question arises whether to model these closely related long-term outcomes or to rely only on the day activity schedule decision. Usual workplace, usual work travel mode, usual weekly work hours, and usual amounts of time spent in other activity purposes (i.e., activity program) are all prime candidates for modeling the lifestyle outcome, and then using it to condition the daily scheduling decision.

An important benefit of modeling the long term outcomes is that the expected utility measures used in conditional models carry this information, which is likely to substantially influence intermediate conditional choice. For example, activity pattern choice, which occurs between the usual workplace choice and the daily work destination choice in the choice hierarchy, is probably influenced by usual work location. If usual workplace is not modeled and work destination is only modeled in the day activity pattern, then the expected work tour utility used to explain pattern choice treats all possible work locations equally, in the sense that it doesn't weigh more heavily those that match the usual work location. One result is that the pattern model cannot capture any tendency of people who live far from their usual work location to more frequently work at home. If, on the other hand, the usual workplace is modeled, then the day activity schedule work destination choice model can include a dummy variable for the usual work location, with a large positive parameter because people tend to go to their usual work location. In this case the expected tour utility will be naturally weighted to favor patterns for which it is easy to get to the usual work location. Through this variable, the model can capture the tendency to work at home associated with distance from the usual workplace.

The disadvantage of modeling closely correlated lifestyle and daily outcomes is the increased model complexity. This increases the cost of model development and substantially increases operation, because each additional dimension in a fully connected nested hierarchy multiplies operational cost by the number of alternatives in the dimension.

A compromise approach is to condition the calculation of expected utility on the conditional choices that closely reflect longer-term decisions. For instance, the work tour expected utility measure used to explain pattern choice could be conditioned by work mode and destination choice. In this way, an approximation of the lifestyle-conditioned expected utility would be available without the extra cost.

5

The Portland Day Activity Schedule Model System

5.1 Introduction

This chapter is the first of two describing an empirical implementation for Portland, Oregon, of the day activity schedule model presented in Chapter 4. The empirical study has three purposes. First, it tests the feasibility of achieving the Table 3.1 requirements for a practical forecasting system, without compromising the theoretical requirements. Second, it tests the importance of lifestyle, mobility outcomes, and activity accessibility on pattern choice. In so doing, it examines closely specific lifestyle and mobility effects. Third, it tests the importance of the integrated day activity schedule representation for travel forecasting; does the design improve the ability to predict travel response to relevant exogenous changes?

This chapter presents model specification details, parameter estimation results and statistical tests. Special attention is given to the specification of the day activity pattern, including its choice set, utility function structure and the effects of lifestyle differences on pattern preferences. The chapter closes with a summary of model and survey design issues related to the empirical implementation. It supports the empirical study's first purpose by demonstrating a successfully estimated model system, identifying points where the demands of the modeling problem push the limits of the chosen modeling methods, and pointing to areas where additional research and development are needed. Clear statistical evidence of the significance of lifestyle, mobility and accessibility strongly support the study's second purpose.

Chapter 6 provides model application results for two policy scenarios, and analyses how the model would handle several other exogenous changes. It supports the first purpose by demonstrating the system's ability to forecast, and identifying how design compromises impact the results. It supports the second and third purposes by showing lifestyle variation in pattern choice, as well as pattern and travel adjustments that trip-based and tour-based models could not produce.

5.2 Development history

This research has been facilitated by, and interspersed with, a parallel effort to implement an operational pilot of the model for Metro, the metropolitan planning organization serving Portland, Oregon, and surrounding counties. Some of the model design presented in Chapter 4 occurred in 1996 as the first phase of the pilot implementation. The model system was then developed for the pilot implementation during 1996 and 1997. Subsequently, further research effort went into the design of the upper levels of the model system, namely the day activity pattern. This work was expedited by the availability of tour models that had been developed for the pilot implementation according to the earlier design work. The model system reported here is thus a hybrid. The conditional tour models are components of a production pilot system, whereas the day activity pattern is a non-production model incorporating additional research activity. In some cases, which we subsequently note, the implementation of the tour models sacrifices design features for the sake of computational performance required by the initial production implementation. When it is important to distinguish the model system presented in this thesis from the initial production version implemented for Portland, we refer to the former as the demonstration system, and to the latter as the production system.[10]

[10] The model parameter estimates and application software for the production system were developed by Mark Bradley, using the system design specified by the author. This includes the estimation results presented in Section 5.5 and Appendix B, and the software that generated the production system application results presented in Chapter 6.

5.3 The Portland sample data

In 1994, a household survey was carried out in Portland and surrounding counties. Background data was collected about the household and its members, and each member of the household completed a two-day diary listing all on-tour activities, major at-home activities, and all travel. Figure 5.1 shows the form used by respondents for each activity reported. The survey contained roughly 5,000 households, giving more than 10,000 persons and 20,000 person-days of travel and activities, and is the primary source of choice information for model development. We subsequently refer to these data as the RP data.

Stated preference (SP) experiments were also carried out in conjunction with the household survey. One experiment looked at mode choice, time of day choice, route choice and travel frequency in response to changes in travel times, fuel costs, transit fares and hypothetical tolls introduced on major roads. It provided supplemental information for the estimation of traveler values of time used in the analysis of the RP data.

In order to use the survey data in model estimation, it was necessary to perform the following steps:

1. merge corresponding household, person, activity, and location data,
2. translate the activity and travel sequences into tours and day activity patterns, as defined for the model system,
3. draw samples of alternative locations for all destination choice dimensions and the residential choice dimension of the model system,
4. attach zonal land use data to tour origins and alternative destinations,
5. attach zone-to-zone car and transit times, costs and distances to all possible tour origin/destination pairs.

Of these five items, translation of the activity and travel sequences into day activity patterns and tours is the most different from data preparation activities usually done for trip or tour-based systems. Respondents did not report activity priorities, upon which the model structure depends. Therefore, rules based on activity purpose, location and duration were used to assign priorities to activities. Rules were also used to translate a large number of reported activity purposes into the three categories of subsistence (work or school), maintenance and leisure (also referred to as discretionary), and to translate a large number of

Day One: Activity Eight

1 What was your activity?

2 Where did your activity take place?

Name of place: ____________

Address: ____________

City: ____________

3 What time did your activity start?

____________ am / pm

4 What time did your activity end?

____________ am / pm

5 Did you have to travel to get to this activity?

❑ Yes → **Continue with Question 6**

❑ No → **Go to Next Activity**

6 What time did your travel start?

____________ am / pm

7 What time did your travel end?

____________ am / pm

8 How did you travel to the activity? **(Circle one and follow instructions)**

Private Vehicle → Answer Questions 9-16

Public: Bus, Max → Answer Questions 17-28

Walk, Bicycle, School Bus, Other → Answer Questions 29-32

If you traveled by private vehicle, answer Questions 9-16, then 33-34

9 Which vehicle did you use? (Make/Model)

Household: ____________

Other: ____________

10 Were you the . . .

❑ Driver ❑ Passenger

11 How many people were in the vehicle? (including driver)

12 Where did you park? ❑ Did not park

❑ Street ❑ Drive-through ❑ Driveway

❑ Parking lot/garage ❑ Other

13 How did you pay for parking?

❑ Did not pay

❑ Hourly ❑ Weekly ❑ Semesterly

❑ Daily ❑ Monthly ❑ Other

14 How much did you pay for parking?

$ ____________

15 Who subsidized your parking?

❑ No one ❑ Employer

❑ Business/store ❑ Other

16 What was the full unsubsidized price to park? $ ____________

Figure 5.1(a) Portland activity and travel diary form, page 1

If you traveled by public bus or Max, answer Questions 17-28, then 33-34

17 Did you have a vehicle available?
❑ Yes ❑ No

18 How would you have paid for parking if you went by car?
❑ Would not pay
❑ Hourly ❑ Weekly ❑ Semesterly
❑ Daily ❑ Monthly ❑ Other

19 How much would you have had to pay for parking if you went by car?
$ ________

20 What was the first transit route taken?

21 Where did you board?
Address/place: ________
Cross streets: ________
City: ________

22 How did you get to the stop?
❑ Drove & parked ❑ Dropped off
❑ Carpooled ❑ Walked ❑ Other

23 How did you get from the stop to your destination?
❑ Drove & parked ❑ Picked up
❑ Carpooled ❑ Walked ❑ Other

24 How did you pay for the trip?
❑ Cash ❑ Fareless square
❑ Ticket ❑ Transfer
❑ Pass ❑ Other

25 Who subsidized your transit fare?
❑ No one ❑ Employer
❑ Business/store ❑ Other

26 Did you transfer to another bus or Max?
❑ Yes ❑ No

27 To what line did you transfer?

28 How many people were in your party?

If you traveled by walking, biking, school bus or other non-private vehicle, answer Questions 29-22, then 33-34

29 Did you have a vehicle available?
❑ Yes ❑ No

30 How would you have paid for parking if you went by car?
❑ Would not pay
❑ Hourly ❑ Weekly ❑ Semesterly
❑ Daily ❑ Monthly ❑ Other

31 How much would you have had to pay for parking if you went by car?
$ ________

32 How many people were in your party?

If your travel mode changed during this trip (even to walking), answer Questions 33-34

33 To what did you change?
❑ Walk ❑ Public bus
❑ Max ❑ Private vehicle
❑ Bicycle ❑ School bus
❑ Other

34 Where did you change travel modes?
Address/place: ________
Cross streets: ________
City: ________

Figure 5.1(b) Portland activity and travel diary form, page 2 inter-modal trip sequences into a smaller set of inter-modal tour mode choice alternatives. Appendix A provides details of how the data translation occurred.

Although over 5,000 households reported over 20,000 person days in the survey, many responses were incomplete or otherwise not usable. Only 17,000 home-based tours were usable for estimation of the tour models. The loss due to incomplete reporting was much more severe for day activity patterns because of greater data needs in these models. Day activity patterns were screened from the original data set of 21,508 schedules if they occurred on a weekend (4778); lacked information on residence zone (1884); lacked any data required to translate the day activity schedule into the model's schedule definition (72); lacked usual weekly work hours if worker (6550), income (3109), or home ownership (59); or reported work activity but no employed status (741). The resulting pattern estimation data set includes only 6475 patterns. The poor screening survival rate yields a high probability of undetected sampling bias, and deserves attention to improve the collection of key data items in future surveys. The greatest data losses came from the failure of households to report income and failure of workers to report usual work hours. The former is a well-known problem, but the latter is new because usual work hours, which has been seldom used in the past, is a valuable lifestyle variable in the activity pattern model[11].

5.4 Day activity schedule model system

We adopt the basic structure of (2), repeated here,

$$prob(s) = prob(p)\prod_{t \in T_p} prob(c_t \mid p), \qquad s \in S \tag{2}$$

in which tours, *t*, are conditioned by the choice of pattern, *p*, and all tours except work-based subtours are assumed to be conditionally independent, given the pattern choice. For home-based tours, tour timing, *h*, conditions the joint choice of tour mode, *m*, and primary

[11] The production version of the model uses full-time and part-time work status instead of usual work hours. These provide less information in each observation, but in the Portland sample a far higher percentage of respondents supplied this information.

destination, d. Work-based subtours, d_s, are modeled conditional on the work tour, and these condition any stops occurring before, d_b, or after, d_a, the primary activity. d_b and d_a are generically referred to as intermediate stops, and treated as conditionally independent. This generalizes the tour probability of (9) to

$$\begin{aligned} prob(c_t \mid p) = {} & prob(h \mid p)\, prob(m,d \mid h,p)\, prob(d_s \mid m,d,h,p) \\ & \cdot prob(d_b \mid d_s,m,d,h,p)\, prob(d_a \mid d_s,m,d,h,p), \qquad c_t \in C_t, t \in T_p, p \in P. \end{aligned} \tag{10}$$

Figure 5.2 shows the overall structure of the activity-based model system. Lower level choices are conditioned by decisions modeled at the higher level, and higher level decisions are informed from the lower level through expected maximum utility variables.

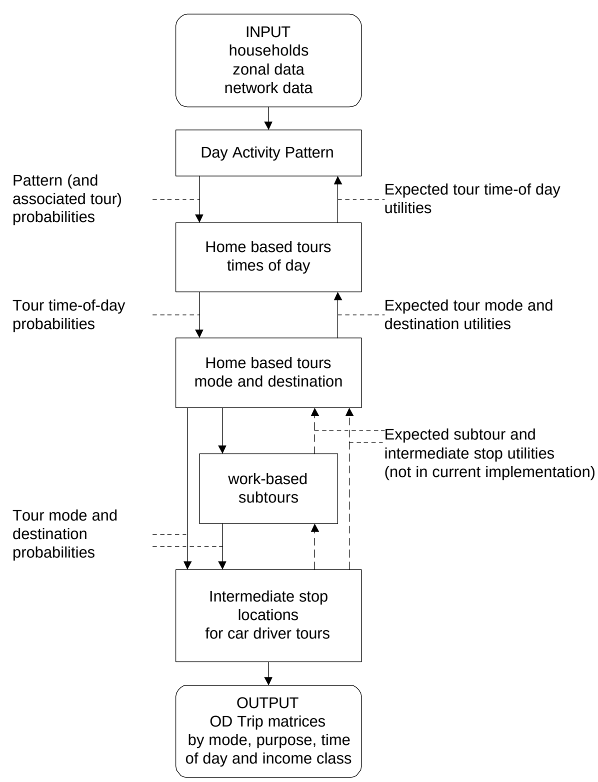

Figure 5.2 Portland day activity schedule model system

Table 5.1 shows the five main types of models included in the system, as well as the types of variables included in each of the model types. The variables include the lifestyle categories discussed in Chapter 2; mobility decisions of residence location, work location and auto ownership; attributes of the activity and travel environment including zonal attributes and travel times and costs; and the expected utility variables from the conditional models. Residence area land use is included in the models at the traffic zone (TAZ) level. Destination land use variables and network times and costs for car and transit are used in the mode and destination models and the intermediate stop location models. These variables are not used directly in the times of day or activity pattern models, but their influence is captured through the "accessibility logsum" variables, which are the expected maximum utility arising from conditional models, as already discussed.

Table 5.1 Model and variable types in the Portland day activity schedule model system

Model / Variable Types	Lifestyle variables (hh structure, role, capabilities, activity commitments)	Mobility variables (residence land use, auto ownership)	Destination activity conditions (land use)	Travel conditions (Network times, costs)	Conditional model expected utility (i.e., accessibility logsums)
Day Activity Pattern	✓	✓			✓
Home-based Tour Times of Day	✓	✓			✓
Home-based Tour Mode and Destination	✓	✓	✓	✓	
Work-based Subtour Mode and Destination	✓*		✓	✓	
Intermediate Stop Location for Car Driver Tours	✓*	✓	✓	✓	

* these are included only as aggregate categories in the current model system

As implemented in the pilot, the home-based tour predictions are aggregated into zone-to-zone counts of half-tours for each of several income classes. The work-based subtour and intermediate stop models are applied to these counts, using aggregate categorical variables, and do not supply the upper level models with measures of expected maximum utility. This design compromise substantially reduces the time required to apply the model in a production setting, making it feasible to apply the entire model system using 300mhz Pentium-based microcomputers. This compromise should be eliminated in subsequent production implementations of the model system as advances in computing technology allow. As discussed in Chapter 6, it makes the pattern model insensitive to differential effects of travel conditions on patterns with different numbers of secondary stops.

5.5 Tour models

The tour decisions are modeled conditional on the activity pattern outcome, in the conditional sequence identified in (10). We present the design and estimation results, level by level, starting with the tour time of day models and proceeding through the intermediate stop models.

5.5.1 Home-based tour time-of-day models

Once the day activity pattern is determined in terms of the number, purpose and trip chain type of all tours during the day, the time of day models determine the sequencing and duration of these tours and the out-of-home activities that comprise them. We distinguish five different time periods:

1. Early 3:00 AM to 6:59 AM
2. AM Peak 7:00 AM to 9:29 AM
3. Midday 9:30 AM to 3:59 PM
4. PM Peak 4:00 PM to 6:59 PM
5. Late 7:00 PM to 2:59 AM

For each tour, the time of day model predicts the combination of departure time from home and departure time from the primary activity. There are twenty-five combinations of start and end periods. However, all pairs extending overnight were eliminated in application because the number of overnight tours is insignificant, leaving the fifteen combinations shown below. All intermediate activities occurring within a half-tour are assigned to the same time period.

(1) Early—Early	(2) Early—AM Peak	(3) Early—Midday	(4) Early—PM Peak	(5) Early—Late
	(6) AM Peak—AM Peak	(7) AM Peak—Midday	(8) AM Peak—PM Peak	(9) AM Peak—Late
		(10) Midday—Midday	(11) Midday—PM Peak	(12) Midday—Late
			(13) PM Peak—PM Peak	(14) PM Peak—Late
				(15) Late—Late

We have estimated three separate tour time of day models, one for work/school tours, a second for maintenance tours, and a third for discretionary tours. Various person and household variables are used as independent variables, as well as logsums from the lower level mode/destination choice models. Tour purpose and tour type are also used as variables, meaning that the time-of-day models are applied conditionally on the results of the day activity pattern model. These models take into account whether or not there are intermediate activities on the half-tours, whether it is a primary tour or a secondary tour, and whether or not a work/school tour is also made during the day. The estimation results are shown in Table 5.2 and Table 5.3, with parameters again grouped by subset of alternatives.

Note that it was only possible to get a significant mode/destination logsum coefficient for the work/school model. This coefficient could be estimated only on the peak period logsums, but in the final model this parameter was constrained to apply to all three time periods. For the non-work tour purposes, no significant logsum coefficients could be estimated, although there was an indication of a result in the range 0.05 to 0.20. Lacking stronger evidence, we have constrained the maintenance and discretionary models to have the same logsum coefficient as the work/school model.

Time of day is one of the most difficult aspects to include in full detail in the model system. This is partially due to the lack of variation in network time and cost data across times of day, but is mainly due to the fact that the number of possible combinations of activity sequences and start and end times for all activities across the day is immense, particularly if we wish to use short time periods such as fifteen minutes or one hour. We have chosen an

Table 5.2 Home-based work/school tour times of day choice model

Observations	7443	
Final log(L)	-12736	
Rho-squared (0)	0.368	
Rho-squared (c)	0.075	

Alternative / variable	Coeff.	T-Stat.
Logsum variables		
Mode / destination choice logsum	0.175	3.3
1- Early combinations		
Constant- Early-Early	-3.074	-17.0
Constant- Early-AM peak	-3.17	-16.7
Constant- AM peak-AM peak	-5.076	-11.2
2- Early—Midday		
Constant	-1.496	-8.1
No intermediate stops[12]	-0.2794	-3.1
Full time worker	1.407	9.2
Age is under 35	-0.3322	-3.4
Male, no children in hhld	0.6681	6.5
Children over age 12 are in hhld	0.7253	5.5
Children under age 5 are in hhld	0.5195	3.8
3- Early—PM Peak or Late		
Constant- Early – PM peak	-3.026	-11.5
Constant- Early – Late	-5.456	-18.1
Intermed. stop on way back home	0.6805	4.9
Full time worker	2.275	9.0
Male	0.612	5.6
4- AM Peak—Midday		
Constant	0.0543	0.6
Intermed. stop on way from home	0.8926	13.3
Age under 20	1.334	11.8
Male, children over 12 are in hhld	0.4845	4.2
Female, children are in household	0.4864	6.2
5- AM Peak—PM Peak		
Intermed. stop on way back home	0.6956	8.4
Full time worker	1.357	17.0
Household income is over 60K	0.2442	4.2
Female	0.1455	2.5
6- AM Peak—Late		
Constant	-2.057	-9.2
No intermediate stops	0.4983	2.2
Intermed. stop on way back home	1.746	7.0
Male, single worker	0.6793	3.1
7- Midday—Midday		
Constant	-1.04	-7.4
No intermediate stops	-0.8178	-6.6
Part time worker	1.104	8.3
1+ non-working adult in hhld	0.694	5.5
8- Midday—PM Peak		
Constant	-1.55	-10.9
Intermed. stop on way back home	1.045	7.6
Part time worker	0.6398	5.2
Male, no children are in hhld	0.8838	6.7
Female, no children are in hhld	0.4365	3.2
Household income is under 30K	0.4485	3.8
9 – Midday—Late		
Constant	-1.823	-9.5
No intermediate stops	0.7554	4.4
Intermed. stop on way back home	1.522	7.5
Age is under 25	1.244	10.5
Male, no children are in hhld	0.4102	3.7
Household income is under 30K	0.4679	4.0
Household income is over 60K	-0.593	-3.7
10 – Late combinations		
Constant – PM peak – PM peak	-4.686	-16.1
Constant – PM peak – Late	-2.886	-13.7
Constant – Late – Late	-3.674	-15.9
No intermediate stops	0.6219	3.4
Part time worker	0.628	3.8
Age is under 25	0.7022	3.9
Male, no children are in hhld	0.5364	3.4
Female, children under 5 are in hhld	1.202	5.0

approach that distinguishes the major time periods in the day. There is still a great deal of room for improving this aspect of the model.

[12] This variable is a dummy variable; it takes the value 1 if the tour has no intermediate stops, and 0 otherwise. Throughout this document, dummy variables are not explicitly denoted as such. Instead, the variable description is worded to avoid confusion as to whether the variable is a dummy or can take on values other than 0 or 1. That is, the description of a dummy variable describes the conditions under which it takes the value 1, and the description of a regular variable describes the variable itself.

Table 5.3 Home-based non-work tour times of day choice models

		Maintenance		Discretionary	
	Observations	5876		3513	
	Final log(L)	-9228.7		-5787.4	
	Rho-squared (0)	0.42		0.392	
	Rho-squared (c)	0.126		0.117	
Alternative group	**Alternative / variable**	**Coeff.**	**T-Stat.**	**Coeff.**	**T-Stat.**
Logsum variables	Mode / destination choice logsum	0.175	constr.	0.175	constr.
1- Early combinations	Constant- Early-Early	-6.026	-19.7	-4.7	-11.9
	Constant- Early-AM peak	-6.373	-19.8	-3.321	-13.3
	Constant- AM peak-AM peak	-3.851	-14.3	-2.971	-12.6
	Secondary tour	1.459	10.1		
	No intermediate stops	1.31	5.2		
	Intermediate stop on way from home	1.183	4.1		
	Subsistence tour made during the day	-2.115	-10.3	-1.115	-2.8
	Full time worker	0.5257	4.4	0.5396	1.8
	Age is over 65			0.7721	2.9
2- Early or AM peak—Midday	Constant- Early-Midday	-5.319	-14.4	-3.046	-9.5
	Constant- AM peak-Midday	-1.268	-11.0	0.004247	0.0
	Secondary tour	-0.8329	-6.6		
	No intermediate stops	-0.4637	-3.7	-1.079	-6.1
	Intermediate stops, both directions	1.314	8.3	0.8681	3.3
	Household income is under 15K	0.5662	3.4		
	Age is over 65	0.7228	5.4	0.2733	1.8
	Subsistence tour made during the day			-2.354	-6.3
3- Early or AM Peak— PM Peak or Late	Constant - Early-PM peak	-4.527	-14.0	-4.078	-6.5
	Constant- Early-Late	-5.49	-10.9	-3.294	-7.4
	Constant- AM peak-PM peak	-3.544	-16.5	-1.29	-4.6
	Constant- AM peak-Late	-4.811	-12.5	-2.627	-7.0
	Secondary tour	-3.11	-5.2	-3.031	-5.8
	No intermediate stops			-0.867	-2.8
	Intermediate stops, both directions			1.129	2.6
4- Midday—Midday	Secondary tour			0.3142	2.6
	Intermediate stop on way from home	0.7611	8.7	0.7641	5.2
	Age is over 65	0.5536	6.2	0.3545	3.3
	No children are in household	0.358	5.4		
	Subsistence tour made during the day	-1.38	-11.1	-1.681	-9.2
5- Midday—PM peak	Constant	-0.5367	-5.2	-0.483	-2.6
	No intermediate stops	-0.4483	-4.3	-0.6384	-3.5
	Secondary tour	-0.4893	-4.6		
	Children under age 12 are in hhld	-0.4783	-4.6		
	Intermediate stops, both directions	0.7021	4.5	0.8306	2.8
	Age is under 20			0.8789	3.9
6- Midday—Late	Constant	-3.174	-15.6	-0.8297	-3.7
	No intermediate stops	-1.332	-4.1	-1.393	-5.5
	Secondary tour			-0.8405	-3.2
	Age is under 20			1.312	3.6

5.5.2 Home-based tour primary destination and mode choice models

Once the day activity pattern is determined in terms of number, purpose, hierarchy, trip chain type, and times of day of each tour, the model system predicts the primary mode and

Table 5.3 Home-based non-work tour times of day choice models (continued)

		Maintenance		Discretionary	
Alternative group	**Alternative / variable**	**Coeff.**	**T-Stat.**	**Coeff.**	**T-Stat.**
7- PM peak—PM peak	Constant	-2.597	-15.3	-2.057	-10.9
	Secondary tour	1.041	8.6	1.404	6.7
	No intermediate stops	0.6305	4.2		
	Full time worker	0.4076	4.3		
	Subsistence tour made during the day	0.2062	1.6		
	Intermediate stop on way from home	0.7849	4.5		
8- PM peak—Late	Constant	-2.641	-24.4	-0.8091	-7.0
	Intermediate stop on way back home	0.583	5.0	0.862	5.8
	Full time worker	0.6669	5.9	0.3426	3.5
	Subsistence tour made during the day	1.644	11.4	0.483	3.8
	Secondary tour			1.215	9.2
9- Late—Late	Constant	-2.839	-19.7	-2.664	-10.6
	Secondary tour	0.8704	5.5	2.034	9.5
	Full time worker	0.732	6.6	0.3746	3.0
	Age is under 35	0.3291	3.3	0.4955	4.9
	Subsistence tour made during the day	0.7225	4.9	0.5486	3.8
	No intermediate stops			0.397	2.3
	Children under age 12 are in hhld			-0.5221	-4.1
	2+ adults, 1+ non-worker in hhld			0.3132	2.6

destination for each tour. It predicts the probability that each zone will be the primary tour destination, and that each of nine possible modes will be the main mode of the tour. The nine possible main modes are:

1. Auto drive alone
2. Auto drive with passenger
3. Auto passenger
4. MAX (light rail) with auto access
5. MAX (light rail) with walk access
6. Bus with auto access
7. Bus with walk access
8. Bicycle
9. Walk only

In reality, separate trips on the same tour can use different modes. This occurs in about 3% of cases in the Portland survey data, with the most common combination being auto drive alone in one direction and drive with passenger in the other direction. To include these cases in model estimation, a set of rules was used to translate all possible mode combinations into the nine modeled modes. Although it has not been done here, the most important mode combinations could be explicitly modeled in the mode choice alternatives.

For destination choice, alternative sampling procedures are used in parameter estimation and model application, using a sample of 21 alternatives from the full set of 1244 zones. Sampled alternatives are weighted according to their sampling probability to achieve consistent estimates, while keeping the number of choice alternatives manageable for model estimation and application (see Ben-Akiva and Lerman, 1985).

The mode/destination models use household and person data as well as network distance, time and cost data. In the course of testing, it was found that the RP data would not support estimation of reasonable coefficients for both the time and cost variables for any of the tour purposes. This is probably due to the fact that both parking costs and traffic congestion are fairly low in Portland (at least at the level of definition in the data), meaning that both car costs and car travel times are strongly related to distance and thus highly correlated with each other. Another possible explanation is that transit usage is very low in Portland, and those who do use transit may be basing their choice on factors other than travel time and cost.

For these reasons, the values of travel time are constrained to be equal to those estimated from the concurrent stated preference survey. Another attractive feature of the SP data is that it looked directly at reactions to congestion pricing--an important policy measure to be analyzed with the model and that does not exist in Portland presently. The SP-based values of time were estimated separately for home-work trips and home-other trips, and were estimated for three different income classes. The values are shown in Table 5.4. The variation is greater between income classes than it is between purposes, particularly for the work trips.

The SP-based values of time were used to calculate "generalized time" for the car and transit modes (the total time and cost utility divided by the car drive alone time coefficient), which is used as a variable in the mode/destination choice models shown below in Table 5.5. In other words, the values of time are used to translate all time and cost data into equivalent

drive alone minutes. In each of the mode/destination models, a utility function was estimated that contains linear, quadratic and cubic terms for this generalized time. The results are highly significant, with the same general shape in all the models. The function is slightly S-shaped, with disutility rising sharply at first, then leveling off a bit, and then rising more sharply again at very high travel times (Figure 5.3). When the model is applied to the estimation data set, this function gives a reasonable match to the actual distribution of tour distances in the data for all modes.

Table 5.4 Values of time estimated from stated preference data

	Home to Work Travel			Home to Other Travel		
	Annual Household Income			Annual Household Income		
Type of travel time	Less than $30,000	$30,000-60,000	More than $60,000	Less than $30,000	$30,000-60,000	More than $60,000
Drive alone In-vehicle	8.9	12.3	17.7	12.2	12.2	23.7
Drive w/pass. In-vehicle	9.4	13.1	18.8	7.9	7.9	15.3
Transit In-vehicle	5.8	8.1	11.6	1.6	1.6	3.1
Transit Walk	21.5	29.7	42.8	29.4	29.4	56.9
Transit Headway*	4.9	6.8	9.8	9.8	9.8	19.0
Transit Boardings**	39.0	53.9	77.8	75.0	75.0	145.2

All values are in cents per minute, except for Transit Boardings, which is cents per boarding.
*Used to estimate wait time: estimated wait time equals headway/2.
**Equivalent to number of transfers plus one.

The other mode-specific variables in the models are mostly related to age, gender and household type. The car availability variables are very strong, particularly for the car driver and transit alternatives.

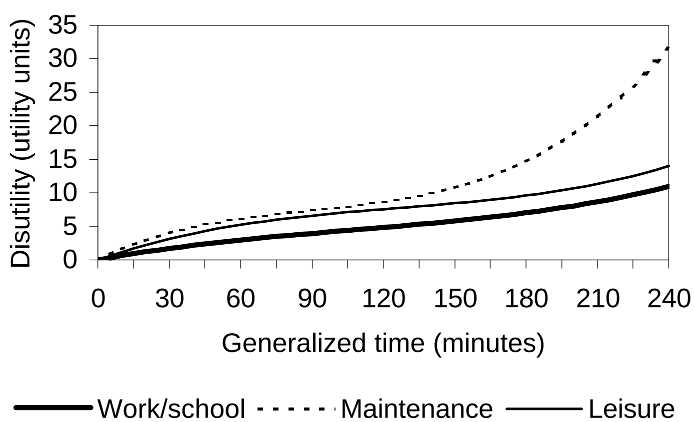

Figure 5.3 Estimated disutility of generalized time in the tour models

Table 5.5 Home-based tour mode/destination choice models

	Work/School		Maintenance		Discretionary	
Observations	7353		5852		3488	
Final log(L)	-23455.8		-20186		-13660.5	
Rho-squared (0)	0.335		0.284		0.188	
Alternative / variable	**Coefficient**	**T-st.**	**Coefficient**	**T-st.**	**Coefficient**	**T-st.**
Car and transit modes						
SP-based generalized time (min)	-0.06668	-23.2	-0.1763	-36.7	-0.1262	-21.2
SP-based generalized time squared	3.52E-04	8.3	0.001514	14.7	7.70E-04	6.9
SP-based generalized time cubed	-1.10E-06	-6.3	-5.59E-06	-9.3	-2.03E-06	-3.6
Drive alone						
Car competition in hhld*	-1.981	-19.5	-0.8392	-9.5	-1.163	-7.5
Age is under 20	-1.292	-9.7	-0.4316	-2.1	-0.5352	-3.1
Age is over 45	0.2951	3.9	0.2722	3.6		
Age is over 65			-0.3434	-3.7		
Income is over 45K			0.2389	3.8		
Children under age 5 are in hhld	0.2937	2.7	-0.357	-3.0		
Female in 2+ adult HH with 1+ non-worker	-0.4483	-3.6				
2+ adults in household, all workers	0.1852	2.3			-0.2505	-2.6
No intermediate stops	-0.6925	-9.3	0.1852	2.3		
Secondary tour			0.3176	4.0	-0.3256	-3.1
Leave home before AM peak	-0.265	-2.1	1.115	3.5	0.8652	2.5
Leave home during AM peak	-0.1664	-1.9	0.5792	6.2	0.5061	3.8
Drive with passenger						
Constant	-3.334	-16.4	-1.593	-11.6	-1.512	-9.4
Log of distance (miles)	-0.4338	-10.6	-0.3063	-10.8	-0.4475	-12.1
Car competition in hhld*	-0.9051	-5.1	-0.5058	-5.1	-0.9564	-5.9
Age is under 25	-0.3338	-1.8	-0.7288	-4.0	-1.204	-7.2
Male	0.651	4.6			0.4878	4.0
Children are in household			0.406	4.3		
Female, children under 5 are in hhld	1.317	6.1	1.388	10.2	1.391	8.5
Female, children 5 to 11 are in hhld			0.6648	5.7	0.8226	5.3
Male in 2+ adult HH with 1+ non-worker	-1.026	-4.3	0.5894	6.6	0.3886	2.9
Single adult, no children in hhld	-1.814	-4.9	-1.596	-8.4	-1.591	-8.7
Intermediate stop on way from home	1.014	7.5	0.1306	1.5	0.3891	3.1
Intermediate stop on way back home	0.8121	5.6	0.2859	3.2	0.2749	2.0
Leave home in PM peak or later			0.6638	8.2	0.7675	7.6
Car passenger						
Constant	-2.671	-15.5	-2.41	-16.3	-2.017	-11.2
Car competition in hhld*					-0.5533	-3.4
Age is under 25	0.6181	4.7	0.744	4.6		
Female	0.3747	3.5	0.7871	8.4	1.142	11.2
2+ adults, 1+ non-worker, no children			0.553	5.4	0.3525	3.2
Single adult	-0.9054	-4.9	-1.197	-7.5	-1.113	-7.3
Secondary tour			-0.5366	-4.9	-0.7501	-5.8
Leave home before AM peak	-0.558	-3.0	0.8411	2.0	1.201	2.8
Return home after PM peak	-0.6223	-3.4	0.6168	4.6	0.6849	4.5
Leave home in PM peak or later			0.6518	4.9	0.669	3.9
Transit with walk access						
Constant	-4.536	-7.3	-4.541	-3.8	-2.416	-1.7
MAX LRT constant	-0.319	-2.1	-1.712	-2.3	-0.5283	-1.2
No car in household	1.045	5.9	2.178	6.5	1.917	4.8
Car competition in hhld*			0.8529	2.3	0.8264	2.2
Secondary tour			-0.5801	-2.0	-1.611	-5.1
Hhld within 1/4 mi. of transit, origin zone	1.73	6.4	4.561	3.8	0.5758	0.9
Empl. within 1/4 mi. of transit, dest. zone	1.875	3.2			1.62	1.2

Table 5.5 Home-based tour mode/destination choice models (continued)

	Work/School		Maintenance		Discretionary	
Alternative / variable	**Coefficient**	**T-st.**	**Coefficient**	**T-st.**	**Coefficient**	**T-st.**
Park and ride						
Constant	-4.553	-3.8	-1.169	-2.9	-1.418	-2.7
MAX LRT constant	-0.319	-2.1	-1.712	-2.3	-0.5283	-1.2
Car competition in hhld*	-0.8869	-3.5				
Secondary tour			-1.979	-1.8	-2.069	-3.4
Return home after PM peak	-2.353	-3.3				
Mixed use within half mile of dest. zone	3.14E-04	4.8			4.19E-04	1.9
Empl. within 1/4 mi. of transit, dest. zone	2.223	1.8				
Bicycle						
Constant	-3.24	-10.2	-3.772	-10.0	-3.184	-9.3
Travel time (min)	-0.09731	-6.2	-0.1107	-8.0	-0.0925	-7.6
Travel time squared	4.88E-04	2.2				
Travel time cubed	-9.95E-07	-1.3				
Female	-0.9397	-4.0	-0.5491	-1.7	-0.7731	-2.1
Mixed use within half mile of origin zone			5.19E-04	3.4		
Mixed use within half mile of dest. zone	2.12E-04	2.7				
Walk only						
Constant	-1.496	-7.0	-2.828	-11.2	-1.94	-7.0
Travel time (min)	-0.0422	-19.9	-0.04804	-18.1	-0.03695	-18.0
Age is under 20	0.7079	3.3				
Age is under 35	0.4211	2.8				
Female, children under 5 are in hhld			1.224	5.5	0.614	2.3
Female, children 5 to 11 are in hhld			1.177	6.2		
No intermediate stops			1.502	8.0	1.239	5.5
Secondary tour			0.3535	2.2		
Mixed use within half mile of origin zone			6.06E-04	8.0		
Mixed use within half mile of dest zone	2.78E-04	5.0				
Destination is in origin zone	0.4912	2.5	1.128	7.1	1.714	10.0
Destination land use						
Destination is in origin zone	0.3622	3.4	0.2781	3.9	0.3104	3.0
Number households within half-mile radius			3.34E-04	11.4	3.33E-04	8.5
Mixed use within half-mile radius			-0.00102	-14.1	-7.60E-04	-8.1
Employment within half-mile radius	3.55E-05	18.0			3.78E-05	9.2
Retail employment within half-mile radius	-1.91E-04	-10.0	1.63E-04	8.0	-1.97E-04	-5.7
Fraction of land used for recreation	1.161	7.6			2.026	9.1
Log of relevant size variable**	1.0	constr	1.0	constr	1.0	constr

* Car competition means <1 vehicle per worker for work/school, <1 vehicle per adult for other purposes.
** Size variables are total employment for work/school tours, retail + service employment for maintenance tours and retail + service employment + households for discretionary tours.

5.5.3 Work-based subtour and intermediate stop models

We did not estimate models to predict work-based subtour time of day, but instead apply fixed fractions based on the shares observed in the survey data. As one would expect, the time of day fractions are strongly correlated with the times of day the work tour begins and ends.

This still leaves us to predict the mode and destination of the work-based subtours. The mode-destination choice model is very similar to the models for home-based tours described above, except now the choices are strongly dependent on the mode used to go between home and work. In particular, the mode to work determines whether or not a car is available for any work-based tours made during the day, and each mode alternative includes a dummy variable with an estimated coefficient that increases its utility if the mode was used to get from home to work. Estimation results are shown in Table 5.6.

Table 5.6 Work-based tour mode/destination choice model

	Work-Based Tours	
Observations	1331	
Final log(L)	-4270.1	
Rho-squared (0)	0.328	
Alternative / variable	**Coeff.**	**T-stat.**
Car and transit modes		
SP-based generalized time (min)	-0.1234	-18.7
SP-based generalized time squared	6.23E-04	5.9
SP-based generalized time cubed	-1.01E-06	-2.7
Drive alone		
Household income is over 60K	-0.4665	-3.1
Leave work in AM peak	1.005	2.6
Leave work in PM peak or later	0.7945	1.8
Drive with passenger		
Constant	-2.062	-11.1
Drive with passenger to work	1.089	3.1
Log of distance (miles)	-0.2479	-3.1
Car passenger		
Constant	-2.539	-13.2
Car passenger to work	1.861	4.6
Transit		
Constant -walk access	-1.565	-4.0
Constant- park and ride	-3.583	-3.4
Constant - MAX LRT	0.4805	0.6
Transit to work	0.5864	1.1
Bicycle		
Constant	-5.461	-6.6
Bicycle to work	3.426	4.8
Travel time (min)	-0.1015	-3.1
Mixed use in half-mile radius	4.83E-04	1.8
Walk only		
Constant	0.6105	2.0
Walk only to work	1.227	2.4
Travel time (min)	-0.1064	-7.9
Travel time squared	4.50E-04	2.8
Travel time cubed	-4.93E-07	-1.0
Mixed use in half-mile radius	4.73E-04	6.5
Destination is origin zone	0.4369	2.9
Destination land use		
Households in half-mile radius	3.12E-04	5.1
Mixed use in half-mile radius	-0.001042	-7.6
Employment in half-mile radius	1.84E-05	4.9
Log of retail + service employment	1.0	constr

The final models in the tour model subsystem determine the locations for intermediate activities. The structure, sampling procedure and model specification are analogous to those of the mode/destination models described above, with a few important differences. First, the model is conditioned by all other tour and work subtour decisions, and takes the tour mode as given for the intermediate stop. Second, the travel costs, times and distances used in the utility functions and for sampling of alternatives include only the extra amount required to make the stop relative to making no intermediate stop.

This model was estimated only for auto driver tours, and uses only mode (drive alone vs. drive with passenger), time of day, income class, tour origin and tour destination as variables, the only variables available in application because of the aggregate application procedure. Estimation results are presented in Table 5.7. Graphs of the disutility of generalized travel time for work-based subtours and intermediate stops are shown in Figure 5.4.

Table 5.7 Intermediate activity location choice models for car driver tours

	Work/Sch. Tours		**Other Tours**	
Observations	3016		2630	
Final log(L)	-8602.6		-6966.1	
Rho-squared (0)	0.077		0.143	
Alternative / Variable	**Coeff.**	**T-stat.**	**Coeff.**	**T-stat.**
Car driver modes				
SP-based generalized time (min)	-0.1387	-16.8	-0.2405	-24.8
SP-based generalized time squared	6.03E-04	4.0	0.002298	9.8
SP-based generalized time cubed	-8.38E-07	-1.0	-9.21E-06	-5.8
Specific locations				
tour origin zone	1.084	7.0	0.6321	4.3
tour origin zone * drive w/pass			1.051	4.8
tour origin zone * AM peak	1.196	5.0		
tour origin zone * PM peak	0.4804	2.1	-0.4251	-1.5
tour destination zone	0.329	2.3	-0.05166	-0.4
tour dest zone * drive w/pass			0.4438	2.2
tour dest zone * midday	0.678	3.9		
tour dest zone * from home	0.784	4.5		
Location land use				
Mixed use in half-mile radius	-2.19E-04	-7.3	-2.52E-04	-6.5
Log of retail + service employment	1.0	constr.	1.0	constr.

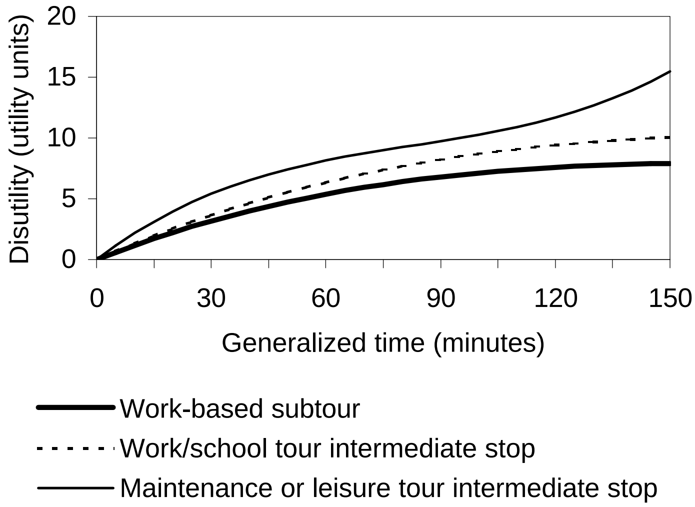

Figure 5.4 Estimated disutility of generalized time in subtours and intermediate stops

5.6 Day activity pattern model

In this section we examine the details of the day activity pattern model specification. We start by defining the pattern choice set and the structure of the pattern utility function. Then, taking the pattern utility function, component by component, we discuss expectations and results of parameter estimation. Finally, we present a summary of the specification and the results of specification tests.

5.6.1 Pattern model choice set

As mentioned in the model system overview, the day activity pattern represents the basic decisions of activity participation and priorities, and places each activity in a configuration of tours and at-home episodes. The definition of the pattern alternatives determines the choice set, and significantly affects how well the model satisfies the stated requirements of adequate scope and detail. We first present the pattern definition, and then evaluate it in terms of scope and detail.

5.6.1.1 Pattern definition

The pattern choice set includes 570 alternatives, each defined by (a) the primary activity of the day, (b) whether the primary activity occurs at home or away, (c) the type of tour for the primary activity, including the participation and purpose of any intermediate stops before or after the primary stop and, for subsistence patterns, the participation and purpose of a work-based subtour, (d) the number and purpose of secondary tours, and (e) whether at-home maintenance activities are conducted.

Table 5.8 lists these dimensions of the choice set and, for each dimension, how the space is partitioned into alternatives.

Table 5.8 Day activity pattern choice dimensions and choice set for each dimension

Day activity pattern dimension	**Choice set within dimension**
Primary activity	
purpose	subsistence, maintenance, leisure
location	at-home, on-tour
Primary tour structure	
intermediate stop(s) before primary destination	none, maintenance, leisure
subtour (subsistence patterns only)	none, maintenance, leisure
intermediate stop(s) after primary destination	none, maintenance, leisure
Secondary tours, number and purpose	none, 1 maintenance, 1 leisure, 2+ maintenance, 2+ leisure, 2+ mixed (1+ maintenance & 1+ leisure)
At-home maintenance activity participation	yes, no

To provide a sense of the distribution of pattern choice among the members of the sample used for parameter estimation, Table 5.9 through Table 5.11 provide distributions among certain dimensions and combinations of dimensions.

5.6.1.2 Scope

To satisfy the scope requirement, every possible pattern of activity spanning a 24-hour day must fit into exactly one pattern alternative in the choice set. Stated this way, the scope requirement is easy to satisfy by defining alternatives in aggregate categories that span the space of the choice set. For purposes of model estimation, the attributes used to define the categories must be present in the data set, or else adequate rules must exist for translating reported attributes into modeled attributes. As noted in Section 5.3 , the choice set requires

Table 5.9 Sample pattern distribution by primary activity, at-home vs on-tour and primary tour type

Pattern description	Percent in sample
Subsistence at home	2.6
Maintenance at home	7.7
Leisure at home	5.3
Subsistence on tour	
without a work-based subtour	
no extra stops	29.0
stop before	3.9
stop after	9.3
stop before and after	3.0
with a work-based subtour	
no extra stops	5.0
stop before	.6
stop after	2.2
stop before and after	0.7
Maintenance on tour	
no extra stops	10.6
stop before	3.7
stop after	4.4
stop before and after	2.4
Leisure on tour	
no extra stops	6.8
stop before	1.0
stop after	1.2
stop before and after	0.6

Table 5.10 Sample pattern distribution by primary activity and at-home maintenance participation

Pattern description	Percent in sample
Subsistence at home	
without at-home maintenance	1.7
with at-home maintenance	.9
Maintenance at home	7.7
Leisure at home	
without at-home maintenance	3.8
with at-home maintenance	1.5
Subsistence on tour	
without at-home maintenance	39.2
with at-home maintenance	14.4
Maintenance on tour	
without at-home maintenance	6.8
with at-home maintenance	14.4
Leisure on tour	
without at-home maintenance	4.0
with at-home maintenance	5.7
All primary activity types	
without at-home maintenance	55.5
with at-home maintenance	44.5

Table 5.11 Sample pattern distribution by primary activity and number & purpose of secondary tours

Pattern description	Percent in sample
Subsistence at home	
0 secondary tours	0.6
1 secondary maintenance tour	0.7
1 secondary leisure tour	0.4
2+ secondary maintenance tours	0.3
2+ secondary leisure tours	0.1
1+ secondary maintenance and 1+ secondary leisure tours	0.6
Maintenance at home	
0 secondary tours	6.2
1 secondary maintenance tour	0.9
1 secondary leisure tour	0.4
2+ secondary maintenance tours	0.1
2+ secondary leisure tours	0.0
1+ secondary maintenance and 1+ secondary leisure tours	0.0
Leisure at home	
0 secondary tours	4.8
1 secondary maintenance tour	0.4
1 secondary leisure tour	0.1
2+ secondary maintenance tours	0.0
2+ secondary leisure tours	0.0
1+ secondary maintenance and 1+ secondary leisure tours	0.0
Subsistence on tour	
0 secondary tours	37.3
1 secondary maintenance tour	7.8
1 secondary leisure tour	0.8
2+ secondary maintenance tours	6.8
2+ secondary leisure tours	0.2
1+ secondary maintenance and 1+ secondary leisure tours	0.7
Maintenance on tour	
0 secondary tours	10.4
1 secondary maintenance tour	3.4
1 secondary leisure tour	1.2
2+ secondary maintenance tours	3.7
2+ secondary leisure tours	0.7
1+ secondary maintenance and 1+ secondary leisure tours	1.8
Leisure on tour	
0 secondary tours	6.5
1 secondary maintenance tour	1.0
1 secondary leisure tour	0.2
2+ secondary maintenance tours	1.4
2+ secondary leisure tours	0.2
1+ secondary maintenance and 1+ secondary leisure tours	0.3
All primary activity types	
0 secondary tours	65.7
1 secondary maintenance tour	14.2
1 secondary leisure tour	3.0
2+ secondary maintenance tours	12.3
2+ secondary leisure tours	1.2
1+ secondary maintenance and 1+ secondary leisure tours	3.5

identification of activity priorities, which were inferred because Portland survey respondents did not identify priorities explicitly.

5.6.1.3 Detail

Activity participation. To satisfy the detail requirement, each pattern in the choice set should account for all activity participation in the day. If the model doesn't account for all activity participation, then it will be unable to capture changes induced by conditions that affect unmodeled activity utility, and unable to distinguish changes in overall activity participation from shifts between modeled and unmodeled activity participation. For instance, suppose the activity pattern model does not explicitly identify participation in at-home activities. Suppose also that technology and policy changes make it easier to work at home, and therefore at-home work participation replaces some on-tour work activities, and the overall participation in work increases. If the cause comes only from the ease of at-home work participation, then the model will completely miss the effect. If, on the other hand, it becomes more difficult to work on-tour, the model will confound shifts to at-home participation with (a) drops in work participation and (b) shifts toward on-tour work patterns that gain advantage as a result of the change.

In the Portland survey, although data was collected on at-home activity participation, it excluded at-home activities requiring less than a half-hour. The resulting data set had a great amount of variation in the total amount of reported activity time, and no information on how the unreported time was spent. The variation was so great that we suspect serious under-reporting of at-home activity. Although our aim in specifying an activity pattern is to include all activities in the day, this lack of full data requires a compromise and some assumptions in interpreting the data. We have assumed that if an at-home leisure activity was indeed primary, then it was explicitly reported. We have also assumed that if an at-home maintenance activity exceeding 30 minutes was conducted, then it was accurately reported. The model explicitly represents primary subsistence, maintenance and leisure activity on-tour and at-home; secondary maintenance (including subsistence) and leisure activities occurring on tour; and the presence or absence of at least one at-home maintenance activity of 30 or more minutes in duration. The utility of all primary activities is measured against the base case of the explicitly modeled at-home leisure primary activity. The utility of all explicitly modeled secondary activities is measured against the implicit alternative of spending more time at home in leisure and short duration maintenance or subsistence activities. In the sample this implicit at-home alternative includes all unreported time in the day.

In summary, the model explicitly represents all on-tour and at-home activity participation in each of the three purpose categories, except for at-home leisure activity, which is accounted for implicitly as the base case in utility comparisons.

Tour sequences. To satisfy the detail requirement, the pattern should locate each on-tour activity in sequence on a particular tour. This is needed to capture inter-tour trade-offs people make in their schedules; that is, whether to combine activities in chains on one tour, or conduct separate tours. On this count, the Portland pattern definition has three weaknesses. First, it accommodates trip chaining explicitly only on the primary tour. Second, on the primary tour it identifies three principal positions for secondary stops on the tour relative to the primary activity—before, after, or on a subtour—but does not explicitly account for multiple secondary stops at any one of the positions, which occurs on nearly 14 per cent of the patterns. Third, the pattern model only explicitly models up to 2 secondary tours, but over 1 per cent of the patterns have 3 or more secondary tours. The model preserves its complete scope by aggregating alternatives, but this prevents it from capturing trade-offs between pattern types within an aggregate category. Despite these weaknesses, the model is still able to represent explicitly most inter-tour trade-offs. In all cases unmodeled pattern detail can be accounted for in application—without policy sensitivity—through the use of proportions observed in the estimation sample among patterns that have been aggregated into a single pattern alternative.

Activity purpose. Purpose is important because accessibility and its importance to the person both depend on purpose. If purpose is defined coarsely, then important purpose-specific accessibility information is lost; the model will be insensitive to policy or external changes that affect accessibility differently for different purposes. The distinction between work and other purposes is extremely important. The distinction between leisure and maintenance is also important because of differences in accessibility and its importance.

Within these two categories, more detail would also be valuable. Purposes with distinctly different accessibility profiles—that is, a different temporal-spatial distribution of activity opportunities—include shopping, acquiring services, serving the household at home, eating, social or recreational activity at a residence, and social or recreational activity at a non-residential location. Thus, the pattern choice set definition includes essentials of purpose detail, but lacks additional detail that might substantially improve the information in the model.

Other tour conditioning. An additional requirement for detail depends on the structure assumed for the conditional tour models. If, as in this case, the equation (2) form of the schedule model is used, with primary and secondary tours assumed to be conditionally independent, then some correlated attributes of the tours should be considered as part of the pattern. An important example is tour timing, which is interdependent among tours since it is impossible to conduct two tours at the same time. The timing of secondary tours relative to the primary tour may be of most importance. Therefore, either primary tour timing should be included as a pattern attribute or else the equation (1) form of the schedule model should be adopted, with secondary tours conditioned by primary tour outcomes, including timing. Additional correlations may occur in mode and destination choice between primary and secondary tours, making the equation (1) model form preferable unless primary tour mode and destination are modeled as attributes of the pattern. In summary, given the conditional independence assumption of the Portland model, the pattern definition lacks important primary tour attributes. However, it is probably preferable to revise the structure, modeling secondary tours conditional on primary tour outcomes, as in (1).

5.6.2 Pattern model utility functions—components and variables

We turn attention to the pattern utility function, which must be specified for each alternative in the pattern choice set. We specified its form in (5), identifying a component V_a for each activity a, a component $\tilde{V}_p$ for the overall pattern p, representing the effect of time and energy limitations and activity synergy, and a component V_t for the expected utility of each tour t, given pattern p. Since V_t depends entirely on the tour utility function definitions, we deal here only with the activity and pattern components.

The V_a components have estimated parameters distinguished by activity priority, purpose and whether the activity occurs at home or on tour. Thus, for example, a set of distinct parameters exists for primary work activities occurring on tour, included in the utility function of each pattern alternative for which work on tour is the primary activity. As another example, a set of parameters for secondary maintenance activities on tour is included once per on-tour secondary maintenance activity present in each pattern alternative.

The utility functions include parameters for three main types of pattern components $\tilde{V}_p$. One type identifies utility associated with the placement of secondary activities in the pattern, differentiating utility of secondary activities that share a common purpose but occur at different places in the pattern or in different pattern types. The second type identifies utility of particular combinations of two or more secondary activities on primary tours. The third type identifies utility (or more accurately, disutility) associated with particular pattern-wide combinations of activities, taking into consideration multiple primary tour activities, multiple tours and at-home maintenance participation.

V_a and $\tilde{V}_p$ depend on attributes of p that vary with the person. They also depend on lifestyle and mobility characteristics, including vectors for household structure; role in household; financial and personal capabilities; activity commitments, priorities and habits; and a mobility vector for characteristics such as residential location, workplace, and auto ownership. The lifestyle vectors match the lifestyle categories and variables defined and defended in Chapter 2 as being important in the scheduling decision.

For each lifestyle category, we examined the data available in the Portland data set and identified available variables that might capture important lifestyle effects. Using these variables we conducted exploratory analysis with the Portland pattern choice data set, using simple logit models for single dimensions of the pattern choice, to identify which variables might have the most important effects, and in which dimensions. Based on this analysis we selected a set of lifestyle variables, shown in Table 5.12, for the pattern utility function specification.

Table 5.12 Lifestyle and mobility variables in the Portland day activity pattern utility functions

Lifestyle Category	Variable Category	Variable Definition
Household structure	family vs nonfamily	family: At least one member of the household is related to the household's responding representative by blood or marriage
	2+ adults	the household has 2 or more members 18 or older
		nonfamily with 2+ adults
	Disabled members	the number or presence of persons in the household with a disability that makes it difficult to travel outside the home without assistance.
Role in household	adult child	a person 18 years or older who is the child of the household's responding representative
	gender	female (or male)
	gender (with household interactions)	female (or male) with children 0-4
		female (or male) with children 0-12
		female (or male) in family with children 0-12 or disabled household members
		number of children 0-17 plus # disabled, for female (or male)
		male or female in family with 2+ adults
	relative workload	person's usual work hours minus (household's total usual weekly work hours)/(number of household members 18 through 64)
Capabilities	per capita income	household annual income divided by household size
		per capita income, for full-time worker (or other)
	disabled	person has a disability that makes it difficult to travel outside the home without assistance.
	occupation	professional (or nonprofessional)
	age	
Activity commitments and priorities	household workforce participation rate	proportion of household's adults 18-64 who are employed or students
	employment status	full-time worker
	student status	full-time student
	usual weekly work hours	the number of hours per week the person reports or is exogenously predicted to usually work
	housing tenure	principal residence is owned (or rented)
Mobility	1+ vehicles in household	household has 1 or more vehicles
	1+ vehicles per adult	household has 1 or more vehicles per person 18 or older

Table 5.13 provides summary statistics identifying the distribution of these variable values among the activity patterns in the estimation data set.

Table 5.13 Distribution of the sample patterns, classified by variables in the model

Category	Variable name and description	Percent of patterns
household structure	family with 1 adult	3.0
	family with 2+ adults	73.4
	nonfamily with 1 adult	19.4
	nonfamily with 2 adults	4.2
	household with disabled members	8.1
role in household	male	47.6
	adult child	6.2
	male with children 0-4	4.7
	female with children 0-4	5.6
	male with children 0-12	10.2
	female with children 0-12	11.5
	male with children 0-17	14.9
	female with children 0-17	16.7
	male in family with 2+ adults	36.0
	female in family with 2+ adults	37.4
	relative workload (usual weekly work hours minus household avg.)	
	less than –40	2.5
	between –40 and –20	8.8
	between –20 and 0	14.5
	0	53.5
	between 0 and 10	8.0
	between 10 an 20	6.1
	over 20	6.6
capabilities	per capita income	
	under $10,000	21.6
	10,000 to 20,000	34.8
	20,000 to 30,000	25.4
	over 30,000	18.3
	disabled	4.6
	professional	31.5
activity commitments and priorities	workforce participation (# workers divided by # working age adults)	
	0	24.4
	over 0 and under 1	14.4
	1	61.2
	full-time worker	52.1
	full-time student	6.7
	usual weekly work hours	
	0	37.4
	1 to 19	3.1
	20 to 34	8.9
	35 to 44	34.1
	45 to 54	11.1
	55 and over	5.4
	homeowner	75.2
Mobility	household has 1+ vehicles	94.3
	1+ vehicles per adult	76.9

5.6.3 Summary of pattern model estimation results

This section provides a summary of the results of parameter estimation, before the detailed estimation results appearing in subsequent sections.

Table 5.14 shows the basic summary statistics of model estimation. The estimation sample includes 6475 pattern observations, prepared as described in Section 5.3 . The total number of cases, equal to the sum of the available alternatives minus the number of observations, is 2,983,715, reflecting availability of all 570 patterns to workers and students, and 234 nonwork patterns to other people. The model includes 276 parameters, estimated by maximum likelihood for the multinomial logit specification, yielding a rho squared fit statistic of .3876.

Table 5.14 Summary statistics from day activity pattern model estimation

Number of observations	6475
Number of cases	2,983,715
Number of parameters	276
LL(0)	-39241
LL(final)	-24033
rho squared	.3876

Table 5.15 identifies the number of parameters estimated, categorized by activity pattern utility function component and variable type. A substantial number of constants, usually gender-specific, are estimated for all component types except the tour expected utility component. Lifestyle and mobility variables, on the other hand, appear most frequently in the activity components, less frequently in the placement of secondary activities in the pattern, and seldom for primary tour and inter-tour combination effects. The number of lifestyle variables in each category gives a rough measure of the model's lifestyle sensitivity in the category.

Table 5.15 Day activity pattern model—number of parameters by utility component and variable type

Variable type / Utility component	Constants and gender	Household structure	Role in household	Financial and personal capabilities	Activity commit-ments	Mobility decisions	Tour expected utility
Primary activity	8	3	18	10	13	4	
Secondary activity	18	9	42	21	11	12	
Secondary activity placement	20	2	4	3	5	10	
Primary tour combinations	7		2	1		1	
Inter-tour combinations	34		4	3	1		
Tour expected utility							10
Total	87	14	70	38	30	27	10

Since the magnitudes of model coefficient utility effects are relative, identifying the effects of a few benchmark model variables can aid in interpreting the magnitude of other estimated coefficients presented in the next section. Table 5.16 identifies the utility effect of four variables on certain patterns for certain people. Full-time student status increases the utility of all subsistence on tour patterns by 1.86 units. Each additional 10 usual work hours increases the utility of work on tour patterns by .44 units. Each child in the household increases the utility of on-tour secondary maintenance activities (once per activity) by .26 for females on work patterns. Each $10,000 of per capita income increases the utility of leisure on tour patterns by .17 for people who are not full-time workers.

Table 5.16 Benchmark variable values for evaluating scale of utility function

Variable and its value	**Magnitude of utility effect**	**Persons affected**	**Activity or Pattern(s) affected**
full-time student status	1.86	students	subsistence on tour patterns
each 10 usual work hours (under 40)	.44	workers	work on tour patterns
each child 0-18 in HH	.26	females	on-tour secondary maintenance activity on work patterns
each $10,000 per capita income	.17	not full-time workers	leisure on tour patterns

Detailed parameter estimates appear in the next several sections. We identified in advance those variables expected to be important. Many are retained in the presented specification, even if they are not statistically significant at typical 95% confidence levels, and occasionally when they are not significant at all or even take the unexpected sign. In cases where the standard error is approximately as large as the estimate and the sign matches our reasoning we would retain the parameter permanently. In cases where the parameters are insignificant and perhaps also take the wrong sign, we would remove the parameters in a production version of the model. They are retained here to provide awareness of the model specification process and results. In cases where the estimate takes the wrong sign and is significant, we have sometimes also retained the parameter, admitting an imperfect specification or faulty reasoning, or both.

5.6.4 Primary activity components

The analysis of pattern utility begins by considering its components directly associated with participation in a particular activity, differentiating activities by priority in the pattern (primary vs secondary), purpose and whether it is conducted on-tour or at home.

For workers and students there are three possible choices of the primary activity's purpose—subsistence, maintenance and leisure—and it may be conducted either at home or on tour. For other people, subsistence activity is considered unavailable. Leisure at home is the base case, so the utility of the remaining five components is relative to leisure at home.

5.6.4.1 Primary subsistence activity

Work participation follows a long-term commitment made by some household members to satisfy household income needs. In the absence of activity commitment data (observed and modeled) household structure and role variables might serve as proxies. However, activity commitment data is available in the form of part or full-time worker (and student) status, and usual weekly work hours. These serve as the principal explanatory variables for subsistence at home and subsistence on tour. We specify them separately for at-home and on-tour components, anticipating that usual workload can affect the choice between working at home vs on tour.

Table 5.17 shows that people who work few hours are more inclined than others to work at home. As the usual weekly work hours increase, the likelihood of working on tour increases more rapidly than working at home, but as work hours increase beyond 40, people again shift toward working at home.

Table 5.17 Primary subsistence activity lifestyle variables

	Subsistence on tour		Subsistence at home	
	Coeff.	Std. Err.	Coeff.	Std. Err.
constant(Leisure at home is primary activity base)	-.2297E+1	.68E+0	-.1965E+1	.44E+0
female w children 0-4	-.6920E+0	.18E+0	-.3113E-1	.39E+0
professional	.3062E+0	.10E+0	.4049E+0	.19E+0
usual weekly work hours up to 40 (40 if work hours exceed 40)	.4407E-1	.66E-2	.1363E-1	.11E-1
usual work hours 41 to 50 (10 if work hours exceed 50)	.1283E-1	.14E-1	.7377E-1	.25E-1
full time student	.1855E+1	.25E+0	.1038E+1	.40E+0

The choice between working at home and on-tour is influenced by coupling constraints operating at either or both places. The coupling constraints for some workers may be atypical, so we include variables for them in both work components. These include professionals, expected to have more flexibility to work at home, and working mothers with young children, expected to have strong home-based coupling constraints.

5.6.4.2 Primary maintenance activity

Every person in a household requires a certain amount of maintenance activity. This may vary across individuals based on lifestyle, and we anticipate a gender difference based on activity priorities, with females more inclined to conduct maintenance activity. Household structure causes variation in maintenance need, interacting with gender-based role specialization. In particular, maintenance needs may increase with the number of children and disabled in the household, with females picking up more of the load. The presence of additional adults in the household may decrease the maintenance work due to scale economies of role specialization, with greater effects in families, and females in families taking more of the maintenance load. There may be additional role specialization effects, with adult children and those with larger relative workloads picking up less of the maintenance load. The commitment of homeowners to maintain their residence should increase the load. Persons with disabilities may have less ability to meet maintenance needs. Persons in higher income households have more material possessions to buy and maintain, but a greater ability to pay for maintenance services. We expect to see most of these effects, with some important variation, in the demand for primary and secondary maintenance activity, on-tour and at-home.

Considering maintenance as the primary activity, females may be more likely to take maintenance activity at home as their primary task of the day, especially in the presence of children or other adults in the household. When the household has two or more adults, specialization may increase the likelihood of men and women to choose maintenance as the primary activity. On their days off work, persons with higher relative workloads in the household may be more inclined to conduct maintenance activity on-tour and less inclined to conduct it at home. Homeowners, on the other hand, may be more inclined than others to devote their primary activity to at-home maintenance rather than maintenance on tour. As per capita income—and the relative value of time—increases, people may be less likely to choose maintenance as a primary activity, choosing instead to purchase services that reduce the need to spend large amounts of maintenance time. Finally, the availability of vehicles, especially one or more vehicles per adult, should increase the likelihood of choosing primary maintenance on tour.

Table 5.18 lists the parameter estimates for on tour and at home maintenance patterns. For the most part the parameter estimates are consistent with the stated expectations. In many cases the standard errors are approximately as large as the parameter estimates.

5.6.4.3 Primary leisure activity

Since leisure naturally ranks behind subsistence and maintenance in activity priority, variation in leisure participation may depend as much on lifestyle outcomes for subsistence and maintenance activity as it does for direct leisure outcomes. In this sense, leisure demand

Table 5.18 Primary maintenance activity lifestyle variables

	Maint on tour		Maint at home	
	Coeff.	Std. Err.	Coeff.	Std. Err.
constant, male	-.8030E+0	.56E+0	-.9697E-2	.29E+0
constant, female	-.1094E+1	.56E+0	.7154E+0	.22E+0
female w children 0-4			-.2004E+0	.22E+0
# children 0-17 plus # disabled, male	-.1151E+0	.14E+0	-.2060E-1	.12E+0
# children 0-17 plus # disabled, female	-.1809E+0	.12E+0	.3721E+0	.88E-1
nonfamily with 2+ adults	.3059E+0	.34E+0	.4254E+0	.36E+0
family with 2+ adults, male	-.2834E+0	.25E+0	.4744E+0	.28E+0
family with 2+ adults, female	.2460E+0	.23E+0	.1561E+0	.20E+0
adult child	.1722E+0	.32E+0	-.1025E+1	.36E+0
relative workload	.1707E-2	.65E-2	-.1051E-1	.54E-2
disabled	-.4731E+0	.25E+0	-.1533E+1	.23E+0
per capita income	.5757E-1	.61E-1	-.6401E-1	.60E-1
workforce participation rate	-.2860E+0	.16E+0		
full-time worker or student	.6863E-1	.17E+0	-.2878E+0	.18E+0
homeowner	-.1723E-1	.16E+0	.2292E+0	.15E+0
1+ cars in HH	-.4983E-2	.22E+0		
1+ cars per adult	.1596E+0	.14E+0		

is a derived demand, taking up the time that subsistence and maintenance activity do not require. However, leisure demand also depends on lifestyle outcomes directly related to leisure, such as ownership of recreational real estate and personal property, club memberships or avocational commitments. Unfortunately, this information is not generally collected in activity and travel surveys, and is not available for including in demand models, making it necessary to seek proxies.

We consider primary leisure activity at home as the base case for specifying primary activity utility, and identify factors that affect the likelihood of choosing primary leisure activity on tour. The presence of children may decrease the probability of choosing leisure activity on tour. Members of non-family households and adult children may have greater demand for leisure on-tour, to satisfy social needs that family members satisfy at home. Persons with disabilities may be more constrained to home than other people. Income for non-full-time workers and availability of at least one car per adult should both increase the probability of choosing leisure activity on tour. The greater schedule flexibility of professionals may enable them to more frequently choose leisure on tour as the primary activity of the day. Full-time workers may be accustomed to leaving home for the day, and on their days off be more inclined to travel for leisure activities than to remain at home.

Table 5.19 lists the parameter estimates for on-tour primary leisure activities. The results for nonfamily members, adult children and professionals are not as expected, and these along with several other parameters have large standard errors relative to the magnitude of the estimates. This component of the utility function is specified with greater lifestyle variation than the data and the coarse resolution of the activity schedule categories can support. It is also possible that important factors have been missed and correlation with included variables is confounding the reported results.

Table 5.19 Primary leisure activity lifestyle variables

	Leisure on tour	
	Coeff.	Std. Err.
constant, male	-.1392E+1	.76E+0
constant, female	-.1548E+0	.15E+0
children 0-12 are in HH, male	-.2214E+0	.32E+0
children 0-12 are in HH, female	-.1711E+0	.23E+0
nonfamily	-.2152E+0	.18E+0
adult child	-.3055E+0	.37E+0
disabled	-.9632E+0	.25E+0
per capita income ($10K), full time worker	-.8319E-1	.10E+0
per capita income ($10K), not full time worker	.1743E+0	.65E-1
professional	-.3056E+0	.20E+0
workforce participation rate	-.2552E+0	.18E+0
full-time worker or student	.4679E+0	.25E+0
1+ cars are in HH	-.5252E-1	.27E+0
1+ cars per adult	.3786E+0	.16E+0

5.6.5 Secondary activity components

We define only two possible choices of secondary activity purpose—maintenance and leisure—including any secondary work and work related activity as maintenance. As with the primary activities, these may be conducted on tour or at home. On-tour activity utility is associated with a particular episode of activity. In contrast, at-home maintenance utility is associated with all at-home maintenance of the day, and secondary at-home maintenance is not distinguished from the primary activity if it is maintenance at home. We separately specify secondary activity utility components for subsistence, maintenance and leisure patterns. In each case the utility is measured against a base of "no participation", which implicitly allows more time for at-home leisure activity.

5.6.5.1 Secondary maintenance activity

The general maintenance activity demand effects described in Section 5.6.4.2 probably apply to secondary activities, but with some differences because here maintenance is a secondary activity. Households with greater workforce participation may have more adults out and about, thereby spreading the on-tour maintenance load. Households with at least one auto may generate more on-tour maintenance demand because car availability reduces the marginal cost of additional trips. Availability of one auto per adult may increase this effect.

Secondary on-tour maintenance activity coefficients are listed in Table 5.20. As expected, children induce additional secondary on-tour maintenance activities, except for males with subsistence patterns. The presence of more than one adult in the household has the most effect on females and males in families, where we see a reduction in secondary on-tour maintenance on leisure days. Adult children, those with higher relative workloads and disabled persons are all less likely to conduct secondary on-tour maintenance. Homeowners are more likely to attach maintenance stops to subsistence patterns, and less likely to attach them to maintenance patterns. Overall, the parameter estimates for secondary on-tour maintenance activity match expectations very closely and are statistically significant.

Table 5.20 Secondary on-tour maintenance activity lifestyle variables

	Subsistence patterns		**Maint. patterns**		**Leisure patterns**	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
constant, male	-.3156E+1	.35E+0	-.1611E+1	.61E+0	-.2220E+1	.14E+1
constant, female	-.3012E+1	.34E+0	-.1737E+1	.61E+0	-.1333E+0	.21E+0
# children 0-17 plus # disabled, male	.5584E-1	.34E-1	.1094E+0	.76E-1	.1969E+0	.10E+0
# children 0-17 plus # disabled, female	.2566E+0	.37E-1	.1927E+0	.37E-1	.3146E+0	.63E-1
nonfamily with 2+ adults	.4443E-2	.13E+0	-.2539E-1	.19E+0	.1291E+0	.32E+0
family with 2+ adults, male	.8699E-1	.10E+0	-.7628E-1	.13E+0	-.3077E+0	.21E+0
family with 2+ adults, female	-.1133E+0	.84E-1	.1319E+0	.98E-1	-.2619E+0	.18E+0
adult child	-.5246E+0	.11E+0	-.3006E+0	.20E+0	-.2817E+0	.39E+0
relative workload	-.4719E-2	.30E-2	-.5125E-2	.25E-2	-.4349E-2	.48E-2
disabled	-.7440E+0	.28E+0	-.3855E+0	.14E+0	-.8603E+0	.31E+0
per capita income ($10K)	.7212E-1	.25E-1	.1334E-1	.30E-1	-.2649E-1	.54E-1
homeowner	.1734E+0	.64E-1	-.1236E+0	.79E-1	-.4031E-1	.15E+0
workforce participation rate	-.1688E+0	.14E+0				
1+ cars are in HH	.6411E+0	.29E+0	.4143E+0	.17E+0	.8059E+0	.42E+0
1+ cars per adult	.1666E+0	.97E-1	-.3509E-1	.88E-1	.2272E+0	.17E+0

Table 5.21 shows the parameter estimates for secondary at-home maintenance. A very strong tendency is present among females to attach at-home activities to an on-tour maintenance pattern, and an even greater tendency among men on leisure patterns to avoid at-home maintenance activity. Children increase at-home maintenance activity of working parents, but only for mothers if the pattern is maintenance or leisure. Additional household adults have a small but clear effect to reduce at-home maintenance on subsistence patterns, but the effects are less consistent and significant on other patterns. Persons with high relative workloads are relieved of at-home maintenance tasks in all pattern types. High per capita income reduces at-home maintenance on subsistence patterns, and home ownership increases at-home maintenance on all pattern types. In summary, most of the estimates for secondary at-home maintenance activity are as expected and statistically significant.

Table 5.21 Secondary at-home maintenance activity lifestyle variables

	Subsistence patterns		**Maint. patterns**		**Leisure patterns**	
	Coeff.	Std Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
constant, male	-.3439E-1	.41E+0	-.1101E+0	.25E+0	-.1251E+1	.28E+0
constant, female	.1302E+0	.40E+0	.8582E+0	.22E+0	.3135E+0	.24E+0
# children 0-17 plus # disabled, male	.1738E+0	.54E-1	-.5966E-1	.13E+0	-.2397E+0	.15E+0
# children 0-17 plus # disabled, female	.3857E+0	.61E-1	.4185E+0	.10E+0	.1718E+0	.98E-1
nonfamily with 2+ adults	-.2944E+0	.12E+0	-.5180E-1	.34E+0	.3641E+0	.34E+0
family with 2+ adults, male	-.2436E+0	.84E-1	.3065E+0	.23E+0	-.7424E-1	.24E+0
family with 2+ adults, female	-.1423E+0	.76E-1	-.4783E+0	.19E+0	.3450E-1	.20E+0
adult child	-.7575E+0	.17E+0	-.1037E+1	.36E+0	-.7022E+0	.43E+0
relative workload	-.6702E-2	.36E-2	-.8577E-2	.55E-2	-.9475E-2	.55E-2
disabled	-.1202E+1	.44E+0	-.1003E+1	.23E+0	-.4730E+0	.24E+0
per capita income	-.1011E+0	.37E-1	-.3026E-1	.51E-1	-.3407E-1	.58E-1
homeowner	.2111E+0	.99E-1	.4054E+0	.16E+0	.2389E+0	.16E+0

5.6.5.2 Secondary leisure activity

The secondary leisure constant represents a baseline level of demand for on-tour leisure activity relative to remaining at home. We expect to see gender differences in this baseline, perhaps with males being more leisure oriented, even after controlling for level of work participation, which probably dampens leisure participation, especially when work hours exceed 40 hours per week. Members of non-family households may conduct more leisure activities on-tour, satisfying social needs that family members satisfy at home. People with young children and/or disabled family members probably have lower demand for on-tour leisure, due to greater costs and less opportunities for on-tour participation. Higher income may induce greater demand for on-tour leisure, especially among those who have available time because they are not full-time workers. Persons with travel related disabilities may have lower demand for on-tour leisure. Finally, the availability of a car for every adult in the household may increase demand for on-tour secondary leisure activity.

The estimation results for secondary on-tour leisure activity, listed in Table 5.22, differ somewhat from our expectations, but are plausible. Working over 40 hours per week does not significantly alter demand for secondary on-tour leisure activity. The effect of children is in most cases small and insignificant, and the most important effects are the tendency to reduce on-tour leisure for working females and increase it for females already on leisure patterns, with the latter effect potentially representing mothers at play with their children. The effect of income is to increase secondary on-tour leisure activity, and not surprisingly it occurs on subsistence patterns for full-time workers and on maintenance patterns for others. Disability increases the likelihood of secondary on-tour leisure activity attached to subsistence patterns, probably because disabled people on subsistence patterns have made their transportation arrangements and the marginal cost of an extra stop for leisure is much lower than on at-home patterns; associating a disability parameter for secondary on-tour activities on on-tour patterns may be more appropriate. Finally, the effect of the first car in the household is more important than the effect of additional cars, enabling persons to attach leisure stops to maintenance and leisure patterns.

Table 5.22 Secondary on-tour leisure activity lifestyle variables

	Subsistence patterns		**Maint. patterns**		**Leisure patterns**	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
constant, male	-.3070E+1	.33E+0	-.2566E+1	.62E+0	-.1852E+1	.14E+1
constant, female	-.3104E+1	.34E+0	-.2571E+1	.62E+0	-.2094E+1	.13E+0
children 0-12 are in HH, male	-.3373E-1	.12E+0	.1316E+0	.24E+0	-.2103E+0	.43E+0
children 0-12 are in HH, female	-.2476E+0	.15E+0	.1107E+0	.13E+0	.2927E+0	.23E+0
nonfamily	.1588E+0	.78E-1	.2198E+0	.90E-1	.3965E+0	.14E+0
disabled	.8747E+0	.23E+0	-.2960E+0	.17E+0	-.3844E+0	.30E+0
per capita income, full time worker	.8586E-1	.53E-1	-.6387E-1	.61E-1	-.1196E-1	.11E+0
per capita income, not full-time worker	.1478E-1	.24E+0	.5138E-1	.35E-1	-.1532E-1	.53E-1
usual weekly work hours	-.1131E-1	.40E-2	-.2326E-2	.37E-2	-.5950E-2	.66E-2
# work hours over 40	.8876E-2	.61E-2				
1+ cars are in HH	-.2569E+0	.18E+0	.3156E+0	.19E+0	.6609E+0	.37E+0
1+ cars per adult	.6443E-1	.33E-1	.4051E-1	.11E+0	.6516E-1	.18E+0

5.6.6 Pattern components

Now turn attention to the pattern utility components associated with the pattern in which the activities are conducted. The utility in these components is not inherent in the activity itself, but rather comes from scheduling cost, synergy, fatigue or opportunity cost of the pattern—in particular, lost opportunity for at-home leisure activity. These components implicitly capture the effect of the 24-hour time constraint restricting the number of activities in the schedule. The model includes three categories of pattern component—placement, primary tour activity combinations and inter-tour combinations—all of which are directly observed in the pattern and together comprise the component $\tilde{V}_p$ in (5).

5.6.6.1 Secondary activity placement components

Secondary activity placement components differentiate utility of secondary activities that share a common purpose but occur at different places in the pattern or in different pattern types. The utility comes from the activity's placement relative to the primary activity. On-tour secondary maintenance activities differ in utility, depending on whether they occur on an at-home subsistence pattern, on the primary subsistence tour—either before, as a subtour or after the primary stop—or on a separate secondary tour. The same is true for on-tour secondary maintenance activities on maintenance and leisure patterns, as well as for on-tour secondary leisure activities. In the model, one placement must serve as a base for each purpose, with utility of other placements measured relative to the base. We arbitrarily identify a secondary stop after the primary stop as the base case.

Secondary maintenance on on-tour subsistence patterns. For secondary maintenance activities on on-tour subsistence patterns, usual workload probably affects placement utility; as the workday gets longer separate maintenance tours should decrease relative to stops after, while subtours and stops before might increase. For family members, especially those with children, family ties may make work-based subtours less appealing because they preclude coupling with other family members. Higher income may alter the utility of chained primary tours relative to separate secondary tours, inducing convenience shopping activity attached to the subsistence tour, and also to allowing unplanned secondary tours with less concern for travel costs. The availability of cars will tend to increase freedom to attach maintenance stops to primary tours, reducing the relative attractiveness of separate maintenance tours. Apart from the lifestyle and mobility effects on placement, stops after work may be the most attractive of the placement options because of the convenience of chaining stops with the primary stop, and the greater schedule flexibility of stops after work. This is in contrast to stops before work and on subtours where a timely arrival at work may be important. Since stop after work is the base case for placement utility, we expect negative constants on all other alternatives.

The parameter estimates for secondary stop placement on subsistence tours, in Table 5.23, show a few differences from our expectations. Although having children does tend to eliminate the work-based subtour for women, other family connections do not. Also, when usual work hours are very small, the model indicates a preference for separate maintenance tours, with maintenance stops after subsistence surpassing a separate tour only when usual work hours exceed about 30 hours.

When the primary subsistence activity is conducted at home, higher work hours probably reduces utility of secondary maintenance tours, relative to the utility of maintenance stops after work on on-tour patterns, because of the inconvenience of leaving home. Presence of children and disabled may keep home-based workers from making maintenance tours, and the availability of cars may not hurt the attractiveness of secondary tours for at-home workers as much as for on-tour workers. Overall, however, we expect the schedule flexibility of working at home, and the associated unavailability of chaining opportunities, to make the utility of secondary tours higher for subsistence at home patterns than for subsistence on tour patterns. We see all these effects in the Table 5.23 estimation results.

Secondary leisure on on-tour subsistence patterns. For secondary leisure on-tour activities, placement lifestyle effects related to usual workload and presence of children are probably different than for maintenance activities. People with heavy workloads may find increased utility in a leisure subtour, providing a recuperative break in a long workday. People with children or disabled in the household may be inclined to avoid a second tour for leisure, instead chaining leisure activities with their subsistence tour. Car availability and income may have effects similar to those with maintenance patterns. On subsistence-at-home patterns, nonfamily persons may take secondary leisure tours more often than family members, satisfying social needs.

Estimation results for secondary leisure activity placement in subsistence patterns are also shown in Table 5.23. Unexpected results include a rather strong effect of car availability to decrease work-based leisure subtours relative to stops after work, and of nonfamily status to decrease secondary leisure tours on at-home subsistence patterns. Otherwise, the results are as expected.

Table 5.23 Placement of secondary maintenance and leisure activities in subsistence patterns

Component	Variable	Coeff.	Std. Err.
Secondary maintenance stop after	Base case for secondary on-tour maintenance activity		
Secondary maintenance stop before	constant	-.6762E+0	.20E+0
	usual weekly work hours	.5109E-2	.47E-2
Secondary maintenance subtour	constant	-.9690E+0	.30E+0
	Family	-.2999E-1	.16E+0
	children 0-12 are in HH, female	-.8172E+0	.30E+0
	usual weekly work hours	.1248E-1	.62E-2
Secondary maintenance tour on on-tour subsistence patterns	Constant	.1885E+1	.54E+0
	usual weekly work hours	-.6237E-2	.37E-2
	per capita income	-.8682E-1	.39E-1
	1+ cars in HH	-.4123E+0	.37E+0
	1+ cars per adult	-.4115E+0	.14E+0
Secondary maintenance tour on at-home subsistence patterns	Constant	.3001E+1	.71E+0
	# children 0-17 plus # disabled, female	-.3019E+0	.12E+0
	usual weekly work hours	-.5627E-2	.57E-2
	1+ cars in HH	-.4422E+0	.52E+0
	1+ cars per adult	-.7181E-1	.22E+0
Secondary leisure stop after	Base case for secondary on-tour leisure activity		
Secondary leisure stop before	Constant	-.4185E+0	.36E+0
	1+ cars per adult	-.6591E+0	.38E+0
Secondary leisure subtour	Constant	.4321E+0	.34E+0
	usual weekly work hours	.1944E-1	.49E-2
	1+ cars per adult	-.6085E+0	.28E+0
Secondary leisure tour on on-tour subsistence patterns	Constant	.2981E+0	.78E+0
	family w children 0-12 or disabled	-.1074E+0	.17E+0
	female in family w children 0-12 or disabled	.1029E+0	.20E+0
	per capita income	-.1596E+0	.50E-1
	1+ cars per adult	-.3819E+0	.26E+0
Secondary leisure tour on at-home subsistence patterns	Constant	.1815E+1	.80E+0
	Nonfamily	-.6694E+0	.29E+0
	per capita income	.2116E+0	.77E-1
	1+ cars per adult	-.1467E+1	.32E+0

Maintenance and leisure patterns. On maintenance and leisure patterns, the distinction between primary and secondary activities is not as clear as on subsistence patterns, and these patterns lack lifestyle information to indicate the usual duration of the primary activity. Thus it is more difficult to establish a rich set of expectations and estimated parameters explaining secondary stop placement. We expect to see a preference for combining secondary maintenance stops with primary maintenance tours, but otherwise to conduct secondary activities on separate tours. In contrast to subsistence patterns, if the primary activity is at home there is probably less tendency to conduct secondary activities on-tour, for the same reasons that keep the primary activity at home, with the effect softened by the presence of one or more cars per adult.

Estimation results for secondary activity placement in maintenance patterns are in Table 5.24, and for leisure patterns are in Table 5.25. In maintenance patterns with secondary on-tour leisure activity there is an unexpected but plausible strong tendency to attach the leisure activity to the maintenance tour. There is also an extremely strong tendency to avoid secondary on-tour activities when the primary activity is at home, especially for secondary leisure activities. People on leisure patterns have a strong tendency to avoid a second leisure tour, preferring to attach the second leisure stop to the primary. There is an even stronger tendency to avoid a leisure tour altogether when the primary leisure activity is at home.

Table 5.24 Placement of secondary maintenance and leisure activities in maintenance patterns

Component	Variable	Coeff.	Std. Err.
Secondary maintenance stop after	Base case for secondary on-tour maintenance activity		
Secondary maintenance stop before	constant	-.2992E+0	.14E+0
Secondary maintenance tour on maintenance tour patterns	constant	-.2145E+0	.67E+0
Secondary maintenance tour on maintenance at home patterns	constant	-.1718E+1	.71E+0
	1+ cars per adult	.6167E+0	.23E+0
Secondary leisure stop after	Base case for secondary on-tour leisure activity		
Secondary leisure stop before	constant	.4151E-3	.17E+0
Secondary leisure tour on maintenance tour patterns	constant	-.2180E+1	.90E+0
Secondary leisure tour on maintenance at home patterns	constant	-.5505E+1	.11E+1
	1+ cars per adult	.5187E+0	.76E+0

Table 5.25 Placement of secondary maintenance and leisure activities in leisure patterns

Component	Variable	Coeff.	Std. Err.
Secondary maintenance stop after	Base case for secondary on-tour maintenance activity		
Secondary maintenance stop before	constant	.1352E+0	.23E+0
Secondary maintenance tour on leisure tour patterns	constant	-.6385E+0	.14E+1
Secondary maintenance tour on leisure at home patterns	constant	-.1598E+1	.14E+1
Secondary leisure stop after	Base case for secondary on-tour leisure activity		
Secondary leisure stop before	constant	-.2832E+0	.22E+0
Secondary leisure tour on leisure tour patterns	constant	-.3435E+1	.15E+1
Secondary leisure tour on leisure at home patterns	constant	-.6419E+1	.16E+1

5.6.6.2 Primary tour combinations

These components capture the utility effects of having multiple secondary stop placements on primary tours. Certain combinations may bring synergy or inconvenience, apart from the implicit time constraint, fatigue and opportunity costs captured by the inter-tour parameters of the next section. For instance, it may be necessary for many people with pre-school children to drop off and pick up their children at daycare locations, increasing the need for maintenance stops before and after work.

5.6.6.3 Estimation results are shown in Inter-tour effects

These components capture the effects on pattern utility of activity combinations beyond the primary tour, capturing trade-offs among secondary at-home maintenance, extra stops on the primary tour, and secondary tour participation. Primarily they capture disutility arising from time constraints, fatigue and lost opportunity for at-home leisure. This disutility would increase with number of activities and tours, with leisure activity combinations causing greater disutility than maintenance combinations because of synergy in combining

Table 5.26 for all subsistence, maintenance and leisure patterns. We find the anticipated effect of pre-school children, which is marginally stronger for mothers than fathers. We also see a general tendency to combine before and after stops to the subsistence pattern, but almost none whatsoever for maintenance and leisure patterns.

5.6.6.4 Inter-tour effects

These components capture the effects on pattern utility of activity combinations beyond the primary tour, capturing trade-offs among secondary at-home maintenance, extra stops on the primary tour, and secondary tour participation. Primarily they capture disutility arising from time constraints, fatigue and lost opportunity for at-home leisure. This disutility would increase with number of activities and tours, with leisure activity combinations causing greater disutility than maintenance combinations because of synergy in combining

Table 5.26 Secondary activity combinations on primary tour

Component	Variable	Coeff.	Std. Err.
Primary subsistence tours			
Maintenance stops before & after	constant	.1144E+1	.17E+0
	children 0-4 are in household	.5700E+0	.31E+0
	female w children 0-4 in household	.3934E+0	.39E+0
other before and after stop combinations	constant	.3012E+0	.20E+0
stops before & after with subtour	constant	.3667E+0	.21E+0
Primary maintenance tours			
stops before and after	constant	.6154E-1	.61E+0
	per capita income	-.8293E-2	.84E-1
	1+ cars per adult	.3018E+0	.26E+0
leisure stops before & after	constant	.6803E-1	.35E+0
maint & leisure stops, before & after	constant	.1731E-1	.21E+0
Primary leisure tours			
stops before and after	constant	.2247E-1	.12E+1

maintenance activities. As with the other pattern categories, inter-tour combination utility must be identified relative to base cases. We choose the simplest combinations as base cases, resulting in the expectation of negative values for all constants. The only lifestyle effects we identify for work patterns are for workload and occupation. Those who regularly work longer hours may prefer simple patterns, that is, patterns with no on-tour secondary stops or tours. Nonprofessionals may have less interests and commitments that take them places other than work on their workdays. Lifestyle effects on maintenance patterns are included for parents of children, who may be more likely to conduct multiple tours, and people over 65, who may be less likely to conduct multiple tours.

The estimation results for inter-tour effects are listed in Table 5.27 through Table 5.29. We see the anticipated effects, although the specification does not distinguish secondary activity purpose. A specification that makes this distinction may significantly improve the model fit. Disutility of multiple tours increases nonlinearly; the addition of a third tour hurts utility much more than the addition of a second tour. In most cases adding at-home maintenance to a pattern also reduces its attractiveness; the effect is that people trade at-home maintenance for extra tours.

Table 5.27 Subsistence pattern inter-tour combinations

	Coeff.	Std. Err.
Constants for patterns with no secondary at-home maintenance:		
subsistence at home with 0 secondary tours—base for subsistence at home patterns		
subsistence at home with 1 secondary tour—base for subsistence at home w secondary tour(s)		
subsistence at home with 2+ secondary tours	-.1365E+1	.47E+0
simple subsistence tour with 0 secondary tours—base for subsistence on tour patterns		
simple subsistence tour w 1 secondary tour—base for simple subsistence tours w sec. tour(s)		
simple subsistence tour with 2+ secondary tours	-.1679E+1	.26E+0
complex subsistence tour with 0 secondary tours	.8683E+0	.59E+0
complex subsistence tour with 1 secondary tour	.2707E+0	.60E+0
complex subsistence tour with 2+ secondary tours	-.1457E+1	.70E+0
Constants for patterns with secondary at-home maintenance:		
subsistence at home w 0 secondary tours—base for subsistence patterns w at-home maint.		
subsistence at home with 1 secondary tour	-.4825E+0	.44E+0
subsistence at home with 2+ secondary tours	-.1611E+1	.71E+0
simple subsistence tour w 0 secondary tours	-.7428E+0	.36E+0
simple subsistence tour with 1 secondary tour	-.7386E+0	.36E+0
simple subsistence tour with 2+ secondary tours	-.1147E+1	.43E+0
complex subsistence tour with 0 secondary tours	.1343E+0	.69E+0
complex subsistence tour with 1 secondary tour	-.4990E+0	.71E+0
complex subsistence tour with 2+ secondary tours	-.1826E+1	.81E+0
Lifestyle effects		
usual weekly work hours: simple subsistence tour w no secondary tours	.4077E-2	.37E-2
nonprofessional: simple subsistence tour w no secondary tours	.2676E+0	.73E-1

Table 5.28 Maintenance pattern inter-tour combinations

	Coeff.	Std.Err.
Constants for patterns with no secondary at-home maintenance:		
maintenance at home with 0 secondary tours—base for maint at home patterns		
maint at home w 1 secondary tour—base for maint at home w secondary tour(s)		
maintenance at home with 2+ secondary tours	.1413E+1	.35E+0
simple maint tour w 0 secondary tours—base for maintenance on tour patterns		
simple maintenance tour with 1 sec. tour—base for simple maint. tours w secondary tour(s)		
simple maintenance tour with 2+ secondary tours	-.2057E+0	.34E+0
complex maint. tour w 0 sec. tours—base for maint-on-tour patterns w complex primary tour		
complex maintenance tour with 1 secondary tour	-.9401E-2	.23E+0
complex maintenance tour with 2+ secondary tours	.8617E-1	.40E+0
Constants for patterns with secondary at-home maintenance:		
simple maint. tour w 0 sec. tours—base for maint-on-tour patterns w at-home sec. maint.		
simple maintenance tour with 1 secondary tour	-.1803E-2	.17E+0
simple maintenance tour with 2+ secondary tours	.3643E+0	.35E+0
complex maintenance tour with 0 secondary tours	.5771E-2	.17E+0
complex maintenance tour with 1 secondary tour	.8976E-1	.27E+0
complex maintenance tour with 2+ secondary tours	-.5358E-1	.44E+0
Lifestyle effects		
simple maint tour with 1+ sec tours, male w kids 0-17 in hh	.4846E+0	.27E+0
simple maint tour with 1+ sec tours, female with kids 0-17 in hh	.1317E+0	.18E+0
simple maint tour with 1+ sec tours, age is over 65	-.4517E+0	.14E+0
complex maint tour with 1+ sec tours, male w kids 0-17 in hh	-.1432E+0	.39E+0
complex maint tour with 1+ sec tours, female with kids 0-17 in hh	.1038E+0	.21E+0
complex maint tour with 1+ sec tours, age is over 65	-.4539E+0	.16E+0

Table 5.29 Leisure pattern inter-tour combinations

	Coeff.	Std. Err.
Constants for patterns with no secondary at-home maintenance:		
leisure at home with 0 secondary tours—base for leisure at home patterns		
leisure at home with 1 secondary tour—base for leisure at home w secondary tour(s)		
leisure at home with 2+ secondary tours	.1922E+1	.71E+0
simple leisure tour with 0 secondary tours—base for leisure on tour patterns		
simple leisure tour with 1 secondary tour—base for simple leisure tours with secondary tour(s)		
simple leisure tour with 2+ secondary tours	.1741E+0	.43E+0
complex leisure tour w 0 secondary tours—base for complex leis. tour patterns		
complex leisure tour with 1 secondary tour	-.3387E+0	.31E+0
complex leisure tour with 2+ secondary tours	-.1055E+1	.70E+0
Constants for patterns with secondary at-home maintenance:		
leisure at home with 0 secondary tours—base for leisure patterns with at-home maintenance		
leisure at home with 1 secondary tour	.1096E+0	.44E+0
leisure at home with 2+ secondary tours	.2507E+1	.77E+0
simple leisure tour with 0 secondary tour	.1514E+1	.18E+0
simple leisure tour with 1 secondary tour	.9532E+0	.24E+0
simple leisure tour with 2+ secondary tours	.1681E+1	.41E+0
complex leisure tour with 0 secondary tours	.9243E+0	.23E+0
complex leisure tour with 1 secondary tour	.1168E+1	.31E+0
complex leisure tour with 2+ secondary tours	.5163E+0	.60E+0

5.6.7 Tours accessibility

The final component in the pattern utility function is the composite measure of expected utility arising from the tours in the pattern, comprising the terms $\sum_{t \in T_p} V_t$ in (5).

This component of the utility is a pattern attribute that can only be measured as a composite of tour and activity attributes among the conditional tour alternatives available for the given pattern. In a standard nested logit model it is the expected utility among the available conditional alternatives, as measured by the conditional logit choice model. Its value only has meaning relative to the alternatives and other expected utility measures derived from the same conditional model. Standard nested logit models have been proven generally to be consistent with random utility theory when the parameter values are in the range zero to one. If the parameters exceed the value 1, then consistency with random utility theory depends on the values of the data.

In the day activity schedule model a pure nested logit form is compromised for the sake of tractability by making conditional independence assumptions among tours. This precludes use of the standard single valued logsum expected utility measure of the nested logit form. Instead, a composite measure is used, derived from the logsums of the tours in the pattern. In the composition, it is important to account for (a) the difference in scale of the component logsums and (b) the different importance to the pattern choice of expected utility for different tour priorities and purposes. This is handled by estimating separate coefficients for each type of logsum in the composite measure. It is difficult to anticipate the relative size of these parameters, because the scale and importance effects cannot be separately identified. Negative values will certainly produce counterintuitive results, predicting an increase in utility of a pattern if the expected utility of a component tour drops.

The tour accessibility parameter estimates are listed in Table 5.30. Each pattern purpose has its own set of parameters because of expected purpose-specific differences of accessibility importance in pattern choice. Primary and secondary tours have separate parameters for the same reason, and also to accommodate potential scale differences between primary and secondary tour utilities. Primary tours with secondary stops have different parameters than those without, for two reasons. First, people may place different weight on expected primary tour utility if it includes multiple activity stops. Second, due to the simplifying compromises made in the Portland tour models, in which expected secondary stop utility is not used to explain tour choices, the measure used for expected tour utility of tours with secondary stops provides only an estimate of the desired expected tour utility measure. As it turns out, the parameter estimates for primary tours with and without extra stops are not significantly different from each other and could be constrained to be equal.

In all cases the estimated parameters are less than one. In only one case is the estimate less than zero, and then with almost no significance. For subsistence patterns, primary tour accessibility carries more weight relative to the secondary tours than it does in maintenance and leisure patterns. Primary tour accessibility is also less significantly different from zero for maintenance and leisure patterns, although three of the four estimates exceed zero by approximately one standard error and should be retained in the model. For all pattern purposes, accessibility is more important for secondary leisure tours than it is for secondary maintenance tours.

Table 5.30 Tour accessibility logsums

	Subsistence patterns		**Maint. patterns**		**Leisure patterns**	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
primary tour with no extra stops	.8103E+0	.18E+0	.1709E+0	.19E+0	.2260E+0	.26E+0
primary tour with extra stops	.6539E+0	.19E+0	.1349E+0	.19E+0	-.6022E-1	.38E+0
secondary maintenance tour*	.1223E+0	.16E+0	.2187E+0	.13E+0	.2187E+0	.13E+0
secondary leisure tour*	.5173E+0	.20E+0	.9845E+0	.20E+0	.9845E+0	.20E+0

*estimated jointly for maintenance and leisure patterns

5.6.8 Pattern model specification tests

We conduct a number of statistical tests on groups of parameters to test various aspects of the model specification. In each test the collective significance of a group of variables is tested by first estimating a model in which their values are restricted to zero, and then conducting a likelihood ratio test. Table 5.31 reports the number of restrictions, restricted loglikelihood, likelihood ratio statistic and p-values for each test. The p-value represents the probability under the null hypothesis—insignificance of the parameter group—of observing data at least as adverse to the hypothesis as is actually observed. Thus, a value near zero, coupled with well-reasoned *a priori* belief that the group belongs, gives a strong indication of the importance of the group in the specification.

Table 5.31 Statistical tests of pattern model restrictions

Test number	Variables removed (parameters restricted to 0)	number of restrictions (n)	restricted loglikelihood LL(R)	Likelihood ratio statistic*	p-value**
	Lifestyle variables				
1	all lifestyle, except gender	152	-24512	958	0+
2	HH structure	14	-24049	32	0.004
3	role	70	-24227	388	0+
4	capabilities	38	-24160	254	0+
5	activity commitments	30	-24125	184	0+
6	**Mobility commitments**	27	-24087	108	0+
	Activity components				
7	subsistence pattern at-home maintenance	12	-24129	192.8	0+
8	leisure pattern at-home maintenance	11	-24054	42.8	0+
	Secondary activity placement components				
9	maintenance in subsistence patterns	16	-24094	122.8	0+
10	leisure in subsistence patterns	14	-24152	238.8	0+
11	maintenance in maintenance patterns	3	-24054	42.8	0+
12	leisure in maintenance patterns	3	-24095	124.8	0+
13	maintenance in leisure patterns	3	-24038.2	11.2	.01
14	leisure in leisure patterns	3	-24067	72.2	0+
	Primary tour combinations				
15	in subsistence patterns	5	-24075	84.8	0+
16	in maintenance patterns	5	-24034	2.8	.7
17	in leisure patterns	1	-24032.6	0	1-
18	**Expected tour utility**	10	-24060	54.8	0+

*-2(LL(R)-LL(U)), where U is full model and R is restricted model of current column, testing significance of removed parameters. Unrestricted loglikelihood, LL(U), equals –24032.6.
** given the true restricted model, under which the likelihood ratio statistic is asymptotically distributed chi squared with n degrees of freedom, the probability of a statistic at least as adverse to the model as the observed statistic

Tests 1 through 5 support the importance of the four lifestyle categories collectively, and individually, and test 6 achieves the same result for the mobility commitments category.

Tests 7 and 8 support the importance of the secondary at-home maintenance activity parameters in subsistence and leisure patterns. In this case, the test result lends support not only to the parameters as a group, but also to the hypothesis that the identification of secondary at-home maintenance is important in the pattern choice set definition.

Tests 9 through 14 test the importance of the parameters that differentiate attractiveness of alternative places within the pattern for secondary activity participation. In the parameters, and in the tests, the placement of secondary activities is distinguished by pattern purpose—that is, purpose of the pattern's primary activity—and secondary activity purpose. In all cases, the parameters are significant as a group. Formal tests were not conducted to test whether the placement parameters are significantly different by pattern purpose or secondary activity purpose, but examination of the individual parameters reveals differences that indicate the importance of these distinctions. These results lend support for a pattern choice set definition that distinguishes pattern placement for secondary activities, specific to pattern and secondary activity purpose.

Tests 15 through 17 examine the importance of primary tour combinations for subsistence, maintenance and leisure patterns. Of the few parameters in this category, we see that they are supported as a group only for subsistence patterns. That is, only for subsistence patterns have we found evidence of utility associated with particular combinations of two or more secondary activities on the primary tour, distinct from any utility or disutility the combination may cause in the pattern as a whole.

Test 18 supports the importance of the tour expected maximum utility parameters as a group. This is an important result in light of the major hypothesis of this study that it is important to represent travel demand in the context of the day activity schedule. With these expected maximum utility variables, changes in tour utility, caused by changes in the transport system performance or in spatial activity opportunities, have a significant effect on the choice of pattern. Such effects cannot be captured by tour or trip-based travel demand models.

It would be possible to conduct more tests that might lead to refinement of the model structure, utility function structure or model variables. Testing of the pattern model's multinomial logit assumption, with the likely introduction of nesting structure to accommodate correlation among subsets of pattern alternatives, remains as a high priority research objective. The need probably exists for nesting, and perhaps more complex correlation structures, because of the multidimensional nature of the pattern choice. For example, strong random utility correlation probably exists among patterns that share primary purpose.

Nevertheless, the tests described in this section provide strong evidence, in addition to the individual parameter tests of the previous sections, in support of the basic model structure, utility function structure and lifestyle variable categories of the day activity schedule model.

5.7 Empirical issues

This section addresses issues of model and survey design that arose in the implementation of the Portland model.

5.7.1 Conditional independence

The Portland empirical implementation assumes conditional independence among all tours. The reason is that this reduces, by a factor equal to the number of primary tour alternatives, the computations required to calculate expected maximum tour utility needed in the pattern model utility function. However, it does not include primary tour timing, mode or destination in the pattern. The consequence is the failure to capture time of day constraints between tours and the dependence of secondary tour choices on primary tour timing, mode and destination.

5.7.2 Resolution of choice dimensions

Detailed resolution of the choice set yields a model with much information, but this exacerbates the combinatorial problem associated with the large choice set, as discussed in Section 2.4 . Therefore, choice set resolution will probably be a perpetual issue, for which the appropriate answers change as technology evolves. Here we discuss some of the model dimensions for which resolution is an issue in the Portland model.

5.7.2.1 Day activity pattern

Activity pattern resolution is discussed in detail in Section 0, where we cite data-induced weaknesses in the distinction of at-home maintenance and leisure activities, and weakness of having only three purpose categories when accessibility and its importance vary at a more detailed level. We note the desirability of including more tour sequence detail, but on the other hand the model is currently able to distinguish most observed patterns in this dimension. The 570 alternative day activity pattern definition is thus quite rich, but would benefit from additional detail, perhaps most in the area of activity purpose.

5.7.2.2 Times of day and destinations

Fine resolution is especially desirable for destination and time of day choices. Fine spatial resolution is desirable because zonal aggregation masks important spatial variability in activity opportunities and point-to-point travel conditions. Attractiveness of nonmotorized modes for secondary activity access is particularly sensitive to this variability, and this can affect pattern choice. Temporal resolution is desirable because small timing differences can make substantial differences in transport level of service and in estimates of air quality impacts associated with auto engine starting temperatures.

Refining temporal and spatial resolution in the choice set presents many challenges because it can substantially increase model size and the need for detailed spatial and time-specific location and travel characteristics. The standard method of handling large choice sets, alternative sampling, is used in the Portland model for destination choices, and might be employed to handle extremely fine resolution of destination and time of day dimensions. The use of geographical information systems is enabling the development and maintenance of detailed spatial databases. The availability of temporally specific transport level of service data is more problematic, although advances in network modeling may make such data available in the future. The prospects for improving temporal and spatial resolution in the near future appear very good, and may lead to substantial improvements in the day activity schedule model.

Even if temporal resolution was substantially improved, the model would retain weakness in this area because time of day is not explicitly modeled for subtours or intermediate stops. With the current temporal resolution, explicit modeling of these decisions provides little information, because they are usually of short duration, occurring within a single time period. However, if temporal resolution was improved, the benefit of explicitly modeling timing of secondary stops would increase.

5.7.3 Integration across the conditional hierarchy

We have already discussed at length the importance of using expected maximum utility from conditional models to explain choices in marginal models, thereby capturing sensitivity of the marginal choice to attributes of alternatives on the conditional level. Unfortunately, the computation required to compute expected maximum utility grows with the number of alternatives, and this grows exponentially with the number of conditional levels in the model. This is why the Portland model system does not use expected utility from conditional subtour and intermediate stop models to explain choice in the upper levels of the model.

5.7.4 Survey data

Development of the day activity schedule for Portland depended upon the availability of data from one of the most advanced activity and travel surveys. This survey, described briefly in Section 5.3 , provides information about a sample of households and its members, including detailed two-day activity and travel diaries and stated preference exercises. The information collected in the survey proved adequate for implementing the day activity schedule model. However, the experience gained in this research yields suggestions for future survey improvements. They address issues of nonresponse, missing items, ambiguous items and unneeded detail. The suggestions involve the collection of additional household and personal information, but may actually ease the respondent's reporting burden in the diary portion of the survey. Of course, these suggestions must be weighed against other needs that such a survey must serve.

5.7.4.1 Household, family and personal information

Suggestions are grouped by the lifestyle and mobility categories used in the specification of the day activity pattern model.

Household structure. Household structure is important in identifying the decision unit for residential choice and for explaining activity schedule decisions. Therefore, a clear identification of this structure is important. Unfortunately, the terms household and family are difficult to define precisely. Define as a household all persons who are living together, and as a family all persons within a household who are related by blood, marriage or long term cohabitation commitment. In the survey, clearly define family and household membership of each person. For each family, identify the principal worker if there is one. This information makes it possible to use family units and non-family individuals as the decision units for residential choice, and to explain activity schedule decisions with well-defined household and family attributes.

Capabilities. Although financial information is difficult to collect, we suggest collecting somewhat more and making concerted efforts to collect it. First, it would be valuable to have earned income for each person in the household. Income differentials within the family may associate with role specialization in pattern choice (for example, higher income individuals may have less maintenance responsibility and/or leisure activity), and differential weighting of schedule accessibility in residential choice. Second, family net worth (assets minus liabilities) can significantly affect value of time, pattern choice and residential choice. Third, educational level attained by each person may be used to explain schedule and residential choice. In particular, persons with high education levels may (a)use telecommunications activity alternatives heavily, (b)exhibit complexity and variety in pattern choice, (c)choose different leisure activities than others, and (d) choose residential locations with above average school quality and cultural amenities.

Activity commitments, priorities and habits. A person’s usual time allocation among types of activities constitutes an activity program that significantly influences daily scheduling decisions. One component of this program, usual weekly work hours was collected in the Portland survey and used to explain pattern choice. Unfortunately, nonresponse to this item was high among workers, and its use in the model reduced the sample size considerably. Collect from each household member a usual weekly time allocation among 7 activity types, including work at home, work away, maintenance at home, maintenance away, leisure at home, leisure away and transportation. These would be used to explain pattern choice, and it would therefore be necessary to model time allocation as a lifestyle decision.

People in work arrangements that require many work related stops probably have distinctive activity patterns, complex work tours and reliance upon auto-drive-alone mode. Collection from each worker of usual number of work-related stops per week at locations other than the usual workplace would enable use of this item to explain activity schedule.

Mobility choices. Non-travel activity alternatives. Two characteristics may significantly affect participation in at-home activities that have traditionally been done away from home. First, collect for each person in the household the possession of a credit card, which is almost a pre-requisite for telephone purchases. Second, for the household collect the number of computers at home with electronic mail and world wide web access capabilities. In households with one or more such computers, ask each person if they are the principal user of one of the machines, and if they have convenient access to use one of the machines.

Automobile and bicycle holdings. Ask the same three questions for motorized private vehicles (autos, vans, trucks, motorcycles, etc.): (a) how many are available in the household, and for each person, (b) are you the principal driver of one of them, and (c) do you have convenient access to drive one of them. Ask the same three questions about bicycles, and additionally ask of each person, (d) have you ridden a bicycle for transportation (as opposed to recreation) in the last 6 months. These questions enable the modeling of mobility outcomes that may prove to be important in explaining activity schedule choice.

Work location and transportation arrangements. For each worker or student, information about location and work transport arrangements can enable modeling of mobility outcomes that condition activity schedule choices. Specifically, ask (a) usual work location, (b) when did you start there, (c) usual mode to and from work (giving the same list of alternatives as is used in the diary survey), (d) what was your previous usual work location, (e) cost to you and payment method of parking, (f) walk time from vehicle to work space for each mode, (g) amount of employer subsidy for not driving and the qualifying alternate modes, and (h) type of bicycle parking facility (indoors, locker, sheltered rack, open rack, none).

Residence. Except for location and housing type, ask residence questions of each family unit and each non-family member of a household, so they can be used as the decision unit in the residential choice model. These questions include ownership category, date moved in, and previous location.

5.7.4.2 Diary information

Reporting period. Substantial variety exists in when people's day activity schedules begin. Rather than arbitrarily starting the reporting period at 3 a.m., have each person start their reporting with their longest episode in bed, and continue reporting for at least 24 hours, until they are again in a long bedtime episode. This enables collecting true day activity schedule information.

Activity categories. A large number of activity purposes is not necessary. However, the procedure for recording activities should satisfy several criteria. (a) Every activity must fit in a category found in a list. (b) Each category should have a clear measure of size for aggregate destination alternatives (including block face and traffic analysis zone). (c) At-home activity categories should be distinguished by the nature of the at-home vs on-tour trade-off; activities that can only be conducted at home should be kept separate from those for which on-tour substitution is possible. (d) For work related activity the actual activity purpose should be noted from the list, and the activity can be noted as work related. Likewise, for chauffeur (pick-up or drop-off) and tagalong activities, the activity purpose of the principal actor rather than the chauffeur or tagalong should be marked in the list, and the activity can be noted as chauffeur or tagalong. In this way, these activities have useful information to explain the destination choice.

Categories satisfying these criteria can be successfully used to refine the three-purpose categorization of the Portland model when technological progress makes more categories feasible. Table 5.32 lists nine suggested activity categories, along with each category's destination size measure. Except for number 8, activity in any category can be conducted at home. Number 5 is the only activity that can only occur at home.

Table 5.32 Suggested activity categories for the activity diary

	Activity Purpose	Destination Size Measure
1	work	total employment
2	school or schoolwork	school enrollment
3	shopping, convenience banking	retail employment
4	acquiring services	medical, professional, government and other non-food service employment
5	serve household at home (meal prep, cleaning, property maintenance, childcare)	
6	eating	food service employment
7	social or recreational at a residence (including own residence)	residential population
8	social, recreational, religious, civic, cultural, spectator, fitness (at a non-residence location)	public facilities annual attendance (charities, civic centers, schools, libraries, social service organizations, theaters, stadiums, amusement parks, pools, parks, playgrounds, athletic facilities, recreational facilities
9	personal hygiene and sleep	

At-home activities. It is important to achieve a full accounting of all time in the day activity schedule, but also to avoid unnecessary detail in the reporting of at-home activities. To achieve this collect information for at-home activity episodes. Each activity episode consists of all activity beginning when arising from bed for the day or when arriving home, and ending when departing from home or returning to bed at the end of the day. For each at-home activity episode, ask the person to report the amount of time spent in each of the relevant activity categories on the list in Table 5.32.

On-tour activities. For on-tour activities, also employ the concept of activity episode. An on-tour activity episode begins with travel, continues with at least one activity from the list (or principal's activity, if this is a chauffeur or tagalong trip), and ends when the next travel begins. Ask when the travel began and when it ended. Rather than using a branching list of questions about travel arrangements, use a table of modes, with several blank columns representing legs of an intermodal journey to the next activity location, as in Figure 5.5. Ask the person to check the mode for each leg, and mark the leg with a 'P' if they parked a car. Ask no additional questions about route, money, party size or other items, none of which are used in developing the model. Ask them to mark on the activity category list the most important activity at the new location. Reporting travel and activity this way should be compact, easy to understand, quick, accurate and easy to interpret.

	Leg of journey					
Mode used	1st	2nd	3rd	4th	5th	6th
walk						
car, drive alone						
car, drive with passenger(s)						
car, passenger						
MAX						
public bus						
other transit service						
bicycle						

Figure 5.5 Suggested table format for collecting transportation information in the diary

Activity Priorities. Since the day activity schedule model structures the day according to activity priorities, it would be better to collect priority information directly rather than inferring it from other attributes. Rather than asking the respondent to give a complete set of priorities, do the following: (a) For each at-home activity episode ask them to mark on the activity category list the activity purpose that was most important. (b) Upon each return home, ask them to look back over all on-tour activity episodes since they last left home and mark the most important. (c) At the end of the day ask them to look back over the day's activity episodes—at-home and on-tour—marking the three most important episodes as first, second and third most important.

6

Model Application and Evaluation

This chapter demonstrates how the day activity schedule model captures behavior that trip and tour-based models miss, by examining how it handles various changes in activity and travel conditions. At the same time it also considers weaknesses of the implemented day activity schedule model, and how they might be overcome. Section 6.1 describes how the day activity schedule is designed to work for prediction with traffic network models, as well as the production system being implemented for Portland and the simplified procedures used here for demonstration purposes. Next we analyze, with application results, the model system's response to a hypothetical peak period toll (Section 6.2) and to improvements in transit accessibility (Section 6.3). Section 6.4 adds less detailed analysis, without application results, of response to other exogenous changes. In all analyses, the focus of attention is on how the day activity schedule model captures activity pattern adjustments, and the resulting impact on travel. The empirical results do not constitute full model validation, which would require a full implementation of the application procedures with network models, and subsequent empirical validation of predicted versus actual results for observed exogenous changes.

6.1 Model system application procedures

6.1.1 Basic procedures and variations

To make predictions, the day activity schedule model is applied to each decision maker in the population—alternatively, a simulated population or representative sample—by calculating a set of probabilities for alternatives in the choice set, and possibly using the probabilities to simulate a day activity schedule. Calculation of the probabilities requires the analyst to supply the model with the characteristics of each decisionmaker and attributes of his or her activity and travel environment explicitly included in the model's utility functions. The probabilities or simulated schedules are translated into a form that can be used by traffic network models to predict route choices and aggregate network conditions. Since the network model relies on demand predictions of the day activity schedule, and the day activity schedule model relies on network conditions predicted by the network model, iterative procedures must be used to assure that assumptions and outputs are consistent between the models. This relation is shown simplistically in Figure 6.1.

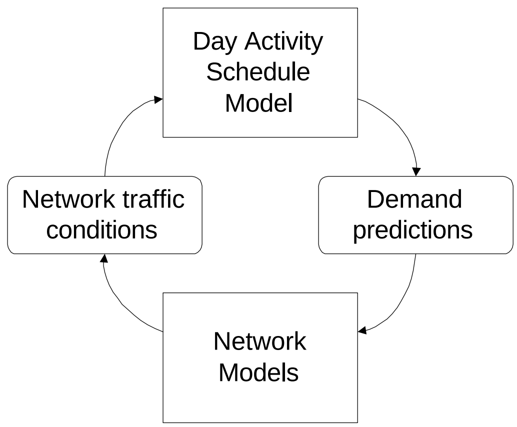

Figure 6.1 Model application

Reiteration of the day activity schedule model and network models is required to achieve consistency of input assumptions and outputs between the two models.

The day activity schedule model can be used in this way with traditional traffic equilibrium models. Schedule probabilities or simulated schedules are translated into a set of trip probabilities or simulated trips, using sequence, timing, mode and destination information from the schedule. These are aggregated in time- and mode-specific trip matrices and assigned to the transport network. The process is reiterated to achieve consistency between models, resulting in a prediction of demand and associated transport system level of service. The process may require replications to achieve statistically reliable predictions.

Recently, attention has been devoted to the development of traffic simulation models. Some simulations being developed require demand predictions in the form of day activity schedules instead of trips, to improve estimation of environmental effects (Barrett, Berkbigler, Smith et al., 1995). The day activity schedule model output satisfies this requirement. Such a combination of the day activity schedule model and a traffic simulation must still achieve consistency between demand and network predictions.

Since the day activity schedule model does not explicitly predict every attribute of the schedule, such as more than one stop on the way home from the primary destination, adjustment procedures are required to include trips not explicitly modeled. This may involve trip matrix adjustment, using factors for each origin-destination pair derived by comparing modeled and actual trips in the estimation data set. Alternatively, the adjustment for unmodeled attributes may occur before the schedule is translated into trips. This can be done by sampling a detailed schedule from a set of observed schedules that match the modeled attributes of the schedule, or using estimation sample proportions to simulate unmodeled attributes. Regardless of the method used, successful implementation of the model system requires a sufficiently detailed representation of the day activity schedule so that the important policy-sensitive travel responses are modeled explicitly rather than relying on a policy-insensitive adjustment procedure.

6.1.2 Portland production system application procedures

The Portland production version of the model is used in conjunction with a multi-class equilibrium assignment model. Figure 6.2 illustrates how the activity-based model system fits within the Portland forecasting system. Using (a) exogenous data for both the base case and policy cases, (b) a synthetic disaggregate population for each scenario generated from the data, and (c) a set of assumed network performance characteristics, the activity-based demand model generates a set of trip matrices. The demand model consists of an auto ownership model plus the day activity schedule model. The demand and network models reiterate to achieve consistency as described above.

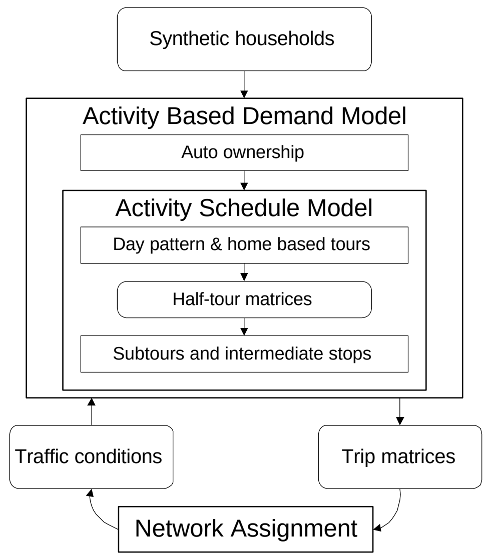

Figure 6.2 Portland forecasting system

The production system version of the day activity schedule model uses a simpler version of the day activity pattern than was presented in Chapter 5. Work subtours and intermediate stops are not identified by purpose, and at-home maintenance activity is not identified. These simplifications reduce the number of pattern alternatives from 570 to 114. In addition, although most of the same variables are included in the specification, the model does not use the utility function structure presented in Chapter 5. The parameters of the production version of the day activity pattern model are presented in Appendix B.

Within the day activity schedule model, aggregate application methods are used for the conditional work-based subtour and intermediate stop components to reduce computer run time. This prevents the use of logsums in the home-based tour models that would otherwise capture the influence on tour choice of expected utility from extra stops on the tour mode and primary destination choices.

The disaggregate component, including the day activity pattern model and the home-based tour models, predicts activity schedule probabilities for each person in the synthetic population. It then aggregates them into a set of half-tour matrices that provide a count of time-period and mode-specific half-tours between all pairs of zones. Since these models do not explicitly identify tour type for secondary tours, tour type fractions for secondary tours in the survey data are applied to each secondary tour predicted by the pattern model. In addition, some of the secondary tour alternatives do not exactly describe the number of secondary tours, so we make them exact during application by using average values from the survey sample.

The aggregate component of the activity schedule model adds work subtours to the half-tour matrices using the predictions of the work subtour model and translates each half-tour into chained or unchained trips using the predictions of the intermediate stop model. To do this, the work-based subtour models are applied to the predicted zonal totals of work stops for each of several market segments. Likewise, the intermediate stop models are applied to the zone-to-zone totals of half-tours for each of the market segments.

6.1.3 Simplified procedure for model demonstration

To test how the day activity schedule model performs in application the disaggregate portion of the Portland application system is adapted in the following ways. First, the model is applied to the estimation sample rather than a synthetic population. Second, network assignment and reiteration procedures are omitted, so the model predictions do not take into account secondary demand adjustments resulting from changed traffic conditions. Third, the 570-alternative pattern model presented in Chapter 5 predicts pattern shifts using expected utility from the tour models. Finally, since the Portland application system cannot yet base travel predictions on the 570-alternative pattern model predictions, the 114-alternative production version shown in Appendix B supplies pattern and half-tour predictions.

6.2 Peak period toll policy

6.2.1 Policy and expected behavioral response

Consider the imposition of a $.50 per mile toll on all auto travel occurring during a 2.5 hour morning peak period and a 3 hour afternoon and early evening peak period.

Many different responses are expected that together reduce peak period auto demand and increase demand for other modes and times. Some people simply change mode or timing to avoid the toll. Some pay the toll and continue as before. Others, with a high value of time, who previously made a short trip to avoid the congestion, take advantage of reduced congestion and happily pay the toll in order to get to a more desirable distant destination. Trip and tour-based models capture these responses. Others make more complex pattern changes, such as eliminating a stop on the way home from work to enable a mode or timing change. These would be missed or modeled separately by a trip-based model, but perhaps captured by a tour-based model. Others may eliminate a stop on the way home from work, but replace it with a separate auto or walk tour in the evening to achieve their activity objective. This kind of change is missed by the trip and tour-based models, but captured by the day activity schedule. The fundamental difference in predictions between the day activity schedule model and trip or tour-based systems is that the day activity schedule predicts travel for an activity pattern that has adapted to the exogenous change.

6.2.2 Activity pattern effects

We apply the day activity schedule model to the estimation sample under the estimation conditions and under the toll policy. In reality, the demand response to a toll would improve travel times on congested facilities, inducing a secondary demand adjustment. The initial and secondary demand adjustments could both be analyzed; both would involve adjustments in activity patterns. However, for simplicity of analysis we limit analysis to the initial peak period toll response. Thus, the model is applied without network equilibration. That is, the model predictions assume a toll without corresponding changes in travel times associated with the demand shifts. Aggregate results are shown in Table 6.1 for the 570 alternative demonstration model as well as the 114 alternative production model. The results are similar, but not the same, for the two model versions. Subtotals by primary purpose show that the 114 alternative production model is more elastic. The following analysis explains how the model captures activity pattern shifts.

Table 6.1 Day activity pattern adjustments for $.50 per mile peak period toll

Pattern type	Demonstration Model* (570 alternatives)			Production Model* (114 alternatives)		
	Pattern's predicted percent in sample without toll	Pattern's predicted percent in sample with toll	Percent change in predicted number of patterns, with toll	Pattern's predicted percent in sample without toll	Pattern's predicted percent in sample with toll	Percent change in predicted number of patterns, with toll
Subsistence Patterns						
Home, 0 sec tours	0.5	0.5	8.6	0.8	0.8	10.8
Home, 1+ sec tours	2.1	2.2	6.5	2.3	2.5	5.9
Simple Tour, 0 sec tours	21.9	21.5	-1.8	17.5	17.3	-1.2
Simple Tour, 1+ sec tours	10.9	10.6	-2.6	9.6	9.3	-3.6
Complex Tour, 0 sec tours	15.3	15.2	-0.8	19.0	18.6	-2.3
Complex Tour, 1+ sec tours	5.5	5.4	-1.7	8.3	7.9	-4.6
Maintenance Patterns						
Home, 0 sec tours	6.2	6.4	2.8	5.6	5.8	4.4
Home, 1+ sec tours	1.5	1.5	1.4	1.5	1.5	0.4
Simple Tour, 0 sec tours	5.6	5.7	2.1	4.5	4.7	3.9
Simple Tour, 1+ sec tours	5.8	5.8	0.2	5.4	5.5	1.3
Complex Tour, 0 sec tours	4.7	4.8	2.3	5.4	5.6	4.2
Complex Tour, 1+ sec tours	5.1	5.1	0.1	5.4	5.5	1.2
Leisure Patterns						
Home, 0 sec tours	4.8	4.9	2.8	4.4	4.7	4.7
Home, 1+ sec tours	0.5	0.6	1.7	0.7	0.7	0.7
Simple Tour, 0 sec tours	4.7	4.8	1.9	4.3	4.4	2.4
Simple Tour, 1+ sec tours	2.2	2.2	-0.5	2.3	2.3	0.5
Complex Tour, 0 sec tours	1.7	1.8	3.3	2.0	2.1	2.3
Complex Tour, 1+ sec tours	1.0	1.0	1.1	0.9	0.9	0.3
Subtotals by home maintenance						
no at-home maintenance	55.5	55.2	-0.5			
at-home maintenance	44.5	44.8	0.6			
Subtotals by secondary tours						
0 sec tours	65.4	65.6	0.3	63.5	63.9	0.7
1+ sec tours	34.6	34.4	-0.6	36.5	36.1	-1.2
Subtotals by Primary tour complexity						
at home	15.6	16.1	3.3	15.3	16.0	4.5
simple	51.1	50.6	-0.9	43.6	43.4	-0.5
complex	33.3	33.3	-0.1	41.1	40.6	-1.2
Subtotals by primary purpose						
subsistence	56.1	55.4	-1.3	57.5	56.4	-2.0
maintenance	28.9	29.3	1.5	27.8	28.6	2.8
leisure	15.0	15.3	1.9	14.6	15.0	2.6
Total all patterns	100.0	100.0		100.0	100.0	

*Both models are applied here with the 6475 observation sample used to estimate the 570 alternative model.

Increased peak period travel costs increase the SP-based generalized time variables for peak period auto tours in the home-based tour mode/destination choice models (Table 5.5), reducing utility of these tours. This reduces expected maximum mode/destination utility (logsums) in the peak period alternatives of the times-of-day choice models (Table 5.2 and Table 5.3.) It also reduces expected maximum time of day utility (estimated by time-of-day weighted mode-destination utility in the production model), which is the expected maximum tour utility used in the pattern choice model (Table 5.30 and Table B.1), where patterns with tours that rely most heavily on peak period auto travel become relatively less attractive. The times-of-day models show that subsistence tours, especially those with stops on the way to or from work (included in 'Complex Tours' in Table 6.1), rely heavily on peak period travel, as do secondary tours on subsistence patterns. Thus, there is a shift away from patterns with subsistence tours in the pattern model, although only in the 114 alternative model is the shift stronger for patterns with complex tours and secondary tours. This is accompanied by a shift toward all other pattern types, especially to at-home patterns and those with no secondary tours. While the pattern shift should definitely reduce the number of subsistence tours and the total number of tours, the net change in maintenance and leisure tours could be positive or negative, because the increase in number of maintenance and leisure patterns offsets the pattern simplification effect for these purposes. This shift in patterns is the response that trip and tour-based models are unable to capture.

6.2.3 Travel effects

Now consider how pattern shifts combine with time and mode change effects to yield travel predictions in the tour models. This analysis is supported by predictions from the production system using the 114-alternative pattern model. Recall that patterns shift from subsistence to maintenance and leisure, and they simplify in terms of number and possibly also complexity of tours, yielding an uncertain net effect on number of maintenance and leisure tours.

In the times-of-day model, a major shift away from the peak periods occurs for all tours predicted by the pattern model. Then in the mode and destination models, a shift occurs away from auto mode for all remaining peak period tours. Combining this with the conclusions from the pattern model, the expected changes in the tour models include (a) shifts away from travel by auto during the peak period, (b) substantial increases in travel for all other combinations of timing and mode, (c) a decrease in the total number of tours, (d) a decrease in subsistence tours, and (e) offsetting changes that may yield small increases or decreases in the number of maintenance and leisure tours.

Table 6.2 shows changes in predicted half-tours. A half-tour constitutes the travel from home to primary destination, or from primary destination back home, always predicted to occur in a single time period with a particular mode.

Table 6.2 Half-tour predictions under the $.50 per mile peak period toll

Results are for the 114 alternative production model.

Tour category	Predicted percent of half-tours in sample without toll	Predicted percent of half-tours in sample with toll	Percent change in predicted number of half-tours, with toll
Subsistence tours			
Auto drive alone peak	18.9	13.4	-29.4
Auto drive alone off-peak	12.2	12.2	-1.3
Auto shared peak	2.5	3.1	21.7
Auto shared off-peak	1.6	1.8	13.8
Other peak	3.6	6.9	90.0
Other off-peak	2.3	3.0	27.7
Maintenance tours			
Auto drive alone peak	6.1	4.9	-20.4
Auto drive alone off-peak	13.4	13.7	1.2
Auto shared peak	3.9	3.8	-2.0
Auto shared off-peak	8.7	9.1	4.2
Other peak	1.1	1.5	45.3
Other off-peak	2.4	2.7	8.5
Leisure tours			
Auto drive alone peak	3.1	2.5	-17.5
Auto drive alone off-peak	6.2	6.2	-0.6
Auto shared peak	3.8	3.8	-0.6
Auto shared off-peak	7.1	7.4	3.1
Other peak	1.0	1.4	34.6
Other off-peak	2.1	2.4	9.5
Subtotals by mode			
Auto drive alone	59.9	53.0	-12.3
Auto shared	27.5	29.1	4.6
Other	12.6	17.9	40.8
Subtotals by time period			
Peak	43.9	41.5	-6.4
Off-peak	56.1	58.5	3.3
Subtotals by purpose			
Subsistence	41.1	40.5	-2.5
Maintenance	35.6	35.8	-0.3
Leisure	23.3	23.7	0.8
Subtotals by priority and purpose			
primary subsistence	41.2	40.5	-2.5
primary maintenance	15.7	16.2	2.5
primary leisure	7.2	7.4	1.7
secondary maintenance	19.9	19.6	-2.5
secondary leisure	16.1	16.3	0.4
Total	100.0	100.0	-1.0

As expected, the mode and time of day effects are very strong. Among subsistence tours, the shift is primarily from auto drive alone to other peak period modes, with smaller time of day effects. For nonwork tours, the mode and time of day effects are more balanced. The total number of tours goes down and the subtotals by tour purpose predict a reduction in number of subsistence tours, as expected. The purpose subtotals also show that the policy's effect to reduce tourmaking in maintenance patterns is nearly offset by the shift from subsistence to maintenance patterns, netting almost no change in number of maintenance tours. Finally, the offsetting effect is even stronger for the leisure purpose where we see a net increase in primary and secondary leisure tours. This indicates that shifts to leisure patterns and secondary leisure tours on subsistence and maintenance patterns more than offset the toll's curtailment of tourmaking on leisure patterns. This is a very important capture of induced demand made possible by the day activity schedule model.

The above explanation of model response to the peak period tolls excludes the impact on intermediate stop location models and work-based tours. These too are affected by the peak period tolls, through the toll's direct effect on stop utility, as well as pattern changes and tour destination changes. However, the reductions in peak period intermediate stop utility for auto do not influence the model's pattern predictions, because the home-based tour models do not include expected intermediate stop utility as an explanatory variable. Thus, the model system fails to capture pattern changes induced by the policy's effect on subtours and intermediate stops.

Consider the effect in the model system if it included this omitted variable in the tour models. Increased peak period travel costs increase the SP-based generalized time variables for intermediate stops in peak period auto tours in the intermediate stop model, reducing utility of these stops. This reduces expected maximum stop location utility (logsums) in the peak period auto tours with intermediate stops in the home-based tour mode/destination choice models (Table 5.5), reinforcing the reduced utility already caused by the increased generalized time. Thus, including the missing variable would strengthen the effects seen in the current implementation. In other words, by omitting the expected utility connection of intermediate stops to home-based tours, the model system underestimates the toll's tendency to reduce trip chaining during the peak period.

6.2.4 Heterogeneity of activity patterns and pattern effects

The previous analysis ignored the lifestyle effects in schedule choice and the associated potential heterogeneity of response to the toll policy. Consider these effects now, by observing predicted shifts in each of four dimensions of the activity pattern for 22 population segments, defined by household structure and role, capabilities, activity commitments and mobility decisions. Predictions come from the 570 alternative demonstration model, applied to the 6475 observation estimation sample. In this discussion, results attributed to population segments are the model's predictions for the sample.

Table 6.3 shows for each population segment (a) its percentage in the sample; (b) the distribution of primary activity purpose among subsistence, maintenance and leisure; and (c) the percentage change induced by the toll for each purpose. Role specialization occurs by gender in families, with a greater tendency of parents to work, and a stronger policy effectcurtailing work among women. Income, usual work hours and auto ownership correlate strongly with probability of working. The policy's work curtailment effect is relatively weak for disabled persons, people with long work hours and people who do not have cars.

For the same 22 population segments, Table 6.4 examines whether the primary activity occurs at home or on tour, and whether that tour is simple or includes extra stops. Again the effect of children is very strong, with fathers much less likely to stay home, mothers more likely to make extra stops on the primary tour, and parents' travel is curtailed. Primary tour complexity and income have strong positive correlation that is not curtailed by the toll policy; this is consistent with the expectation of high willingness to pay for convenient auto-based schedule complexity among people with high value of time. Disabled people choose simpler patterns and are less affected by the policy than nondisabled counterparts. Work hours and primary tour complexity are positively correlated. The policy curtails primary activity travel less among nonworkers and students than it does among others, probably reflecting lower need to travel during the peak period. People with one vehicle per adult are far less likely to stay home for the primary activity, and the policy curtails this tendency, probably because of auto dependency.

Table 6.3 Predicted toll response of 22 population segments—primary activity purpose

		Subsistence Patterns		Maintenance Patterns		Leisure Patterns	
Population segment	Segment's percent of sample	Pattern's predicted percent in segment without toll	Percent change with toll	Pattern's predicted percent in segment without toll	Percent change with toll	Pattern's predicted percent in segment without toll	Percent change with toll
Household structure and role							
Nonfamilies	23.5	53.4	-1.1	29.6	1.1	17.0	1.4
Families with no children, males	22.0	53.1	-1.0	27.4	1.1	19.6	1.3
Families with no children females	23.1	44.0	-1.7	38.4	1.2	17.6	1.7
Families with children, males	14.8	85.1	-1.0	9.4	5.2	5.5	6.4
Families with children, females	16.5	55.1	-1.9	34.2	2.1	10.7	3.1
Household annual income ($1000s)							
under 15	10.5	31.8	-1.2	43.9	0.4	24.4	0.8
15 to 29	22.3	43.0	-1.3	37.3	0.8	19.7	1.3
30 to 44	25.4	58.2	-1.4	27.5	1.7	14.3	2.2
45 to 59	18.2	64.9	-1.4	23.5	2.4	11.6	3.0
over 60	23.6	70.4	-1.2	20.0	2.7	9.6	2.9
Disability limits travel							
no	95.4	58.1	-1.4	28.1	1.7	13.8	2.1
yes	4.6	16.6	-0.8	45.5	-0.1	37.9	0.4
Usual weekly work hours							
nonworker	32.2			65.1	-0.2	34.9	0.3
1 to 19	3.1	62.2	-2.2	27.2	3.7	10.6	3.7
20 to 34	8.9	71.8	-1.7	19.9	4.2	8.2	5.1
35 to 44	34.1	86.2	-1.3	9.4	8.0	4.5	8.9
45 to 54	11.1	89.0	-1.0	7.4	7.6	3.6	8.6
55 or more	5.4	90.3	-0.9	6.5	7.6	3.3	8.8
students without other employment	5.2	70.9	-1.0	18.4	2.3	10.7	3.1
Vehicles per adult							
0	5.7	37.1	-0.1	39.4	0.1	23.5	0.1
under 1	17.4	47.6	-0.9	35.2	0.6	17.3	1.2
1 or more	76.9	59.5	-1.5	26.7	2.0	13.8	2.4
Total	100.0	56.1	-1.3	28.9	1.6	15.0	1.9

Table 6.5 examines two dimensions of the activity pattern, secondary tour participation and participation in at-home maintenance activity. Mothers are much more likely to conduct extra tours, and the toll appears to curtail extra tours less among fathers than among others. Income has little effect on secondary tour participation, but here again the toll policy has greater tendency to simplify the patterns of lower income persons. Persons with disabilities make less secondary tours, whereas students, part-time workers and those with more car availability are more likely to conduct extra tours, and the toll reduces secondary tours more among nonworkers and people with cars.

Table 6.4 Predicted toll response of 22 population segments—primary tour type

	Primary activity at home		Simple primary tour		Complex primary tour	
Population segment	Pattern's predicted percent in segment without toll	Percent change with toll	Pattern's predicted percent in segment without toll	Percent change with toll	Pattern's predicted percent in segment without toll	Percent change with toll
Household structure and role						
Nonfamilies	14.5	2.5	51.6	-0.6	33.8	-0.1
families with no children, males	16.8	2.8	51.9	-0.8	31.4	-0.1
families with no children females	19.6	2.8	49.4	-0.9	31.0	-0.3
families with children, males	8.3	7.6	57.0	-1.1	34.8	0.1
families with children, females	16.5	3.8	46.2	-1.1	37.3	-0.3
Household annual income ($1000s)						
under 15	25.0	1.4	48.7	-0.6	26.3	-0.1
15 to 29	19.1	2.3	50.3	-0.8	30.6	-0.2
30 to 44	14.4	3.8	51.8	-0.9	33.7	-0.2
45 to 59	13.0	4.7	52.0	-1.1	35.1	-0.2
over 60	11.4	4.8	51.4	-1.0	37.3	-0.1
Disability limits independent travel						
No	14.5	3.8	51.5	-0.8	34.0	-0.4
Yes	39.0	0.7	41.6	-0.5	19.3	-0.2
Usual weekly work hours						
Nonworkers	30.0	0.9	41.6	-0.5	28.3	-0.2
1 to 19	17.4	4.0	48.6	-1.1	34.1	-0.6
20 to 34	13.2	5.3	52.7	-1.1	34.2	-0.4
35 to 44	6.7	9.2	57.5	-1.0	35.8	-0.1
45 to 54	7.6	8.7	55.1	-1.1	37.3	-0.1
55 or more	7.3	9.0	53.9	-1.2	38.8	-0.1
students without other employment	13.6	3.3	54.5	-0.6	31.9	-0.3
Vehicles per adult						
0	27.3	0.2	52.9	-0.2	19.8	0.0
under 1	21.1	2.0	51.9	-0.7	27.0	-0.3
1 or more	13.5	4.3	50.8	-0.9	35.8	-0.3
Total	15.6	3.4	51.1	-0.8	33.3	-0.3

Turning finally to participation in at-home maintenance activity, we see a strong gender-based role specialization that is heightened in the presence of children. Income and usual work hours are negatively correlated with at-home maintenance. The toll policy has very little effect on at-home maintenance.

In summary, the model captures much heterogeneity in both pattern choice and response to the toll policy captured by the model. The results, none of which is surprising, clearly demonstrate the importance of explicitly modeling heterogeneity in the pattern choice.

Table 6.5 Predicted toll response of 22 population segments—secondary tours and at-home maintenance

	with secondary tours		with at-home maintenance	
Population segment	Pattern's predicted percent in segment without toll	Percent change with toll	Pattern's predicted percent in segment without toll	Percent change with toll
Household structure and role				
nonfamilies	34.1	-0.5	36.0	0.3
families with no children, males	31.7	-0.7	31.6	0.2
families with no children females	33.3	-0.7	41.8	0.2
families with children, males	32.8	-0.2	29.0	0.4
families with children, females	42.6	-0.7	53.8	0.1
Household annual income ($1000s)				
under 15	32.0	-1.0	42.0	-0.1
15 to 29	34.3	-0.9	41.1	0.1
30 to 44	35.1	-0.7	38.7	0.2
45 to 59	35.2	-0.5	37.1	0.4
over 60	35.0	-0.2	34.5	0.5
Disability limits independent travel				
no	35.2	-0.8	38.6	0.2
yes	22.7	-0.7	31.1	-0.1
Usual weekly work hours				
nonworkers	35.3	-1.5	52.2	-0.3
1 to 19	41.5	-0.4	43.1	0.3
20 to 34	37.3	-0.6	37.3	0.5
35 to 44	33.0	-0.1	30.5	0.8
45 to 54	32.2	0.2	27.9	0.7
55 or more	30.1	0.2	27.1	0.7
students without other employment	41.5	-0.6	35.8	0.2
Vehicles per adult				
0	24.7	-0.1	35.5	-0.1
under 1	32.3	-0.7	36.5	0.0
1 or more	35.8	-0.8	38.9	0.3
Total	34.6	-0.7	38.3	0.2

6.3 Improved transit access

This section examines two related scenarios. In the first scenario, transit is improved so that there is a transit stop within a quarter mile of all households and all job locations. All transit walk and wait times are reduced by 50%. In the second scenario, transit is improved in the same way, but now we also exogenously restrict auto ownership to no more than one vehicle per household. We examine the scenarios in order, and draw comparisons. The predicted pattern effects under both policies are shown in Table 6.6 for the 570-alternative demonstration model and the 114-alternative production model. Tour effects predicted by the production model are shown in Table 6.7 for both policies.

Table 6.6 Pattern adjustments for transit access improvement and auto ownership restriction

	Demonstration Model* (570 alternatives)			Production Model* (114 alternatives)		
		Percent change with improved transit access			Percent change with improved transit access	
Pattern type	Percent without policy changes	without restricted auto ownership	with restricted auto ownership	Percent without policy changes	without restricted auto ownership	with restricted auto ownership
Subsistence Patterns						
Home, 0 sec tours	0.5	-1.2	16.6	0.8	-1.6	22.6
Home, 1+ sec tours	2.1	-1.0	35.5	2.3	-0.8	13.6
Simple Tour, 0 sec tours	21.9	0.4	7.2	17.5	0.5	11.4
Simple Tour, 1+ sec tours	10.9	0.6	4.0	9.6	0.8	2.7
Complex Tour, 0 sec tours	15.3	-0.2	-12.6	19.0	0.0	-7.4
Complex Tour, 1+ sec tours	5.5	-0.1	-15.0	8.3	0.2	-14.4
Maintenance Patterns						
Home, 0 sec tours	6.2	-0.6	14.6	5.6	-1.0	16.6
Home, 1+ sec tours	1.5	-0.2	-29.2	1.5	-0.1	15.9
Simple Tour, 0 sec tours	5.6	-0.3	3.9	4.5	-0.6	8.8
Simple Tour, 1+ sec tours	5.8	0.2	0.1	5.4	0.0	1.2
Complex Tour, 0 sec tours	4.7	-0.3	1.9	5.4	-0.4	-5.8
Complex Tour, 1+ sec tours	5.1	0.2	-2.4	5.4	-0.1	-13.6
Leisure Patterns						
Home, 0 sec tours	4.8	-0.7	11.7	4.4	-1.2	14.3
Home, 1+ sec tours	0.5	-0.3	-3.7	0.7	-0.2	13.2
Simple Tour, 0 sec tours	4.7	-0.1	-7.7	4.3	0.1	-8.7
Simple Tour, 1+ sec tours	2.2	0.3	-19.4	2.3	0.4	-17.7
Complex Tour, 0 sec tours	1.7	-0.6	-14.3	2.0	0.1	-20.0
Complex Tour, 1+ sec tours	1.0	-0.2	-23.1	0.9	0.3	-27.9
Subtotals by home maintenance						
no at-home maintenance	55.5	0.1	0.1			
at-home maintenance	44.5	-0.1	-0.1			
Subtotals by secondary tours						
0 sec tours	65.4	-0.1	1.3	63.5	-0.1	2.6
1+ sec tours	34.6	0.2	-2.5	36.5	0.2	-4.4
Subtotals by Primary tour complexity						
at home	15.6	-0.7	11.7	15.3	-0.9	15.5
simple	51.1	0.3	2.8	43.6	0.4	4.4
complex	33.3	-0.1	-9.8	41.1	0.0	-10.5
Subtotals by primary purpose						
subsistence	56.1	0.2	0.1	57.5	0.2	0.3
maintenance	28.9	-0.2	2.3	27.8	-0.4	2.1
leisure	15.0	-0.3	-4.9	14.6	-0.3	-4.9
Total all patterns	100.0			100.0		

*Both models are applied here with the 6475 observation sample used to estimate the 570 alternative model.

6.3.1 Transit access improvement without restricted auto ownership

As expected, patterns with travel increase, as does the number of tours on patterns, induced by increased transit accessibility. This is accompanied by some shift from auto to transit usage, especially for primary tours. An expected simplification of the subsistence tour and

Table 6.7 Half-tour predictions for transit access improvement and auto ownership restriction

		without auto restrictions		with auto restrictions	
Pattern type	Percent of all patterns without policy	Percent of all patterns with policy	Percent change	Percent of all patterns with policy	Percent change
Subsistence tours					
Simple auto	16.9	15.5	-8.3	14.6	-16.5
Simple nonauto	3.6	5.1	42.6	8.4	125.8
Complex auto	18.3	17.2	-5.8	14.0	-26.0
Complex nonauto	2.4	3.4	45.5	5.3	118.6
Maintenance tours					
Primary simple auto	6.4	6.1	-5.6	6.3	-6.0
Primary simple nonauto	1.1	1.4	31.6	1.9	68.8
Primary complex auto	7.6	7.2	-5.4	6.4	-18.8
Primary complex nonauto	0.6	0.9	70.3	1.2	116.1
Secondary simple auto	12.9	12.6	-1.8	12.6	-5.3
Secondary simple nonauto	1.6	1.9	18.2	2.6	57.8
Secondary complex auto	5.1	5.0	-2.1	5.1	-4.3
Secondary complex nonauto	0.3	0.4	42.1	0.6	96.2
Leisure tours					
Primary simple auto	4.2	3.9	-6.1	3.1	-28.4
Primary simple nonauto	0.8	1.1	31.5	1.5	71.0
Primary complex auto	2.1	1.9	-5.6	1.4	-34.6
Primary complex nonauto	0.2	0.3	60.8	0.4	110.1
Secondary simple auto	11.7	11.5	-1.6	9.5	-21.6
Secondary simple nonauto	2.0	2.2	9.6	2.9	41.7
Secondary complex auto	2.2	2.1	-1.8	1.8	-18.6
Secondary complex nonauto	0.2	0.2	29.6	0.3	71.8
Subtotals by mode					
auto	87.4	83.1	-4.8	74.9	-17.3
nonauto	12.6	16.9	34.5	25.1	92.2
Subtotals by complexity					
simple	61.1	61.2	0.3	63.3	0.0
complex	38.9	38.8	0.0	36.7	-9.0
Subtotals by priority					
primary	64.1	64.0	0.2	64.5	-2.8
secondary	35.9	36.0	0.3	35.5	-4.7
Subtotals by mode and priority					
auto primary	55.5	51.8	-6.5	45.8	-20.3
auto secondary	31.9	31.3	-1.8	29.1	-12.1
nonauto primary	8.6	12.3	43.1	18.7	110.5
nonauto secondary	4.0	4.7	16.3	6.4	53.4
Subtotals by purpose and priority					
primary subsistence	41.2	41.2	0.3	42.4	-0.6
primary maintenance	15.7	15.6	-0.3	15.8	-2.8
primary leisure	7.2	7.2	0.1	6.3	-15.2
secondary maintenance	19.9	19.9	0.4	20.9	1.5
secondary leisure	16.1	16.1	0.1	14.6	-12.4
Total	100.0	100.0	0.2	100.0	-3.5

accompanying increase in secondary tours, to accommodate the transit mode, are barely perceptible in the predictions. Thus, although the anticipated mode shift occurs, the pattern shifts and their impact on travel outputs are minimal because the mode shift is mild and the original transit mode share is so low. Nevertheless, consider how the integrated model captures the small effect.

In the tour models, household transit proximity increases utility of transit with walk access for all tour purposes; employment transit proximity increases utility of transit with walk access for subsistence and leisure purposes. These effects increase expected tour utility of all pattern types, but especially patterns that favor transit, namely those with no chained tours. In the pattern model, an increase in expected tour utility increases the number of tours on patterns, and decreases the relative proportion of chained tours. Back down in the tour models, we expect to see a mode shift toward transit because of the increased transit utility, but auto will be used for some of the induced tours, softening the effect of the mode shift. The net effect in the model is an increase in patterns with one or more tours, a decrease in the proportion of chained tours, an increase in transit tours, and a small increase or decrease in auto tours, depending on whether the mode change or the uncoupling of secondary stops from primary tours has a stronger effect. All these effects occur differently than they would in a trip or tour-based model, taking place in the context of the activity schedule. However, the effect the day activity schedule captures that the other models would miss is the offsetting increase in auto tours caused by the pattern shift.

6.3.2 Transit access improvement with auto ownership restriction

Recall that in this scenario transit improvements match those of the previous scenario, but now we also exogenously restrict auto ownership to no more than one vehicle per household.

In light of the small effects of the transit policy, its tendency to increase mobility should be overpowered by the loss of mobility caused by auto ownership restriction. The pattern model outputs show strong shifts toward simpler tours, less tours in patterns, and curtailment of lower priority on-tour leisure activity in the presence of intra-household competition for the only car. The tour model outputs reflect these shifts, and show the expected reinforcement of the mode shift from auto to transit. Again, consider how the models capture these effects.

In the tour models, transit proximity still increases utility of transit with walk access for all tour purposes, slightly increasing expected tour utility. However, competition for a car within the household decreases the utility of auto modes, thereby reducing expected tour utility, and this overpowers the transit effect. In the pattern model, a reduction in expected tour utility decreases the number of tours on patterns. Competition for a car also has direct effects in the pattern choice, eliminating and simplifying primary and secondary tours, especially for leisure tours and leisure patterns.

Unlike the previous examples, auto ownership does not have a significant effect on subtour and intermediate stop choices, given the primary tour mode choice. Therefore, the lack of expected secondary stop utility explaining tour choice does not distort predictions.

6.4 Other policy applications

This section provides a qualitative discussion of model system performance for additional exogenous changes in four categories, including demand management policies, spatial accessibility improvements, highway service level changes, and changes in telecommunications.

6.4.1 Demand management

Fuel tax, or other uniform increase in auto variable costs. This type of policy is like the peak period toll, but affects all time periods. Expect to see a tendency toward pattern simplification, which the day activity schedule could capture in the same way as described above, without the time-of-day shifting. The lack of expected utility from subtour and intermediate stop alternatives would have a similar effect.

Auto registration fees. The expected principal effect of auto registration fees would be a reduction of auto ownership levels. Individuals in households with reduced vehicle holdings would then adjust their activity schedules, along the lines of the auto ownership restriction example, to achieve a revised set of activity objectives.

Parking regulation. The effects of parking regulation depend on the policy. A ban on overnight on-street parking would reduce auto ownership, inducing the effects described for the auto ownership restriction example. Policies restricting parking at activity destinations would induce mode and destination changes, and probably related pattern changes. A regulation that varied throughout the day would also affect time-of-day choices, again with related pattern changes.

There are no variables in the model system that capture the effect of parking availability on schedule choice. To achieve sensitivity to this kind of regulation would require variables characterizing the regulation in the mode-destination choice models. If these were included, then the model would capture pattern effects as it does for policies affecting travel costs.

6.4.2 Spatial accessibility improvements

Walkable residential locations, with many shops and restaurants located near residences. Urban development that increases walkable access to commercial activity might cause substantial shifts in activity patterns. An overall increase in tours would be likely, with secondary walk tours replacing secondary auto tours and intermediate stops on primary auto tours. The day activity schedule model's structure makes it very well suited for this kind of policy analysis, because it places all activity decisions together, including secondary activities for which walkable neighborhoods are well suited.

The model's ability to capture these effects depends on the inclusion of appropriate variables in the tour mode and destination choice models, characterizing activity attraction and walkability, accompanied by sufficient spatial resolution to enable accurate measurement of the variables. In such a case, under the policy, the mode and destination choice models would predict greater probability of walking for each predicted tour. However, the improvement in walk tour utility would increase the expected maximum tour utility, increasing the predicted share of patterns with more tours. Many of these tours would be by non-walk modes. Thus, the model would appropriately catch pattern shifts that might dampen the desirable effects of the policy.

The current model includes origin and destination mixed use variables and travel time variables in the walk and bicycle modes, providing some of the needed sensitivity. However, it is hindered by limited spatial resolution and would also benefit greatly from improved measures of walkability.

Walkable mixed use areas, with close proximity of employment and population. This kind of development might bring a decrease in auto subsistence tours, both simple and chained. This would be accompanied by an increase in subsistence and nonwork walk tours to walkable locations, as well as an increase in nonwork auto tours to nonwalkable locations for activities formerly attached to the subsistence tour, plus those to which a nonworking family member now has access because of an available car. These changes correspond with an increase in multi-tour patterns and a decrease in non-travel patterns. Since the car is being replaced for commute trips, auto ownership might decline among households with two or more cars.

All of these changes depend on residential and workplace choices that put the workplace and home close together. The day activity schedule model does not include residential and workplace choice, although it does model the work destination choice, essentially a proxy for workplace choice. Destination attraction and travel cost variables in the tour mode and destination choice model would increase the relative utility of walk mode on subsistence patterns to the nearby work destinations. Expected subsistence tour utility would increase, especially for patterns without chained subsistence tours because of intermediate stop variables in the mode choice model, resulting in a predicted increase in subsistence patterns of all types. The increase might be overpredicted because of the uniform cross-elasticities of the MNL pattern choice model. Shifts toward simpler patterns would be induced by reductions in auto availability. The mode and destination choice models would predict a shift toward nearby walk commutes. In summary, the model would capture the anticipated kinds of pattern shifting.

Walkable workplace locations, with many shops located near employers. Work-based secondary activity might increase because of good accessibility from the workplace, some of which would be new, while some would be replacing other less convenient activity participation. The additional work-based activity would probably include a substantial amount of walk subtours, but if parking is convenient we might also see an increase in intermediate auto stops on the way to or from work.

The work-based subtour mode-destination model and intermediate stop location model include destination attraction variables, and the subtour model includes walk-specific variables that would increase the utility of the affected secondary stops. As with the other walkability policies, the model's spatial aggregation and lack of good walkability measures would hinder its performance in capturing mode and pattern shifts. In addition, in this case the expected utility improvements occur in secondary stops for which the tour and pattern models omit the expected utility variable. Thus, the model as implemented might roughly approximate the mode shifts because of its limited walkability measures, and fail to capture offsetting pattern shifts. The model's design, however, is quite suitable for this kind of policy analysis.

6.4.3 Highway service level changes

Increased capacity of congested urban highways from ITS deployment. The capacity increase of congested urban highways would be used most during the peak periods. The effect would be almost the opposite of a peak period toll, already discussed in detail, with two differences. First, increased capacity affects travel time, rather than cost, inducing pattern shifts among people with higher values of time. Second, as described and applied, the peak period toll affected all auto travel rather than only major highways. Limiting the change to major highways would complicate the response and analysis.

6.4.4 Telecommunications

Advance in telecommunications technology increases the availability of virtual workplaces and commercial centers, or employer incentive program increases the attractiveness of telecommuting. These changes constitute an increase in available activity opportunities that require no travel. Activity patterns may shift, with increases in at-home subsistence patterns and with at-home secondary maintenance replacing some on-tour activities. This may be accompanied by the addition of new related on-tour activities.

The day activity schedule model includes at-home subsistence and maintenance alternatives. It can capture changes in at-home activity participation induced by changes in travel conditions and on-tour activity opportunities, and differences in relative attractiveness of at-home alternatives based on lifestyle characteristics. However, the model does not depend on characteristics of the at-home alternatives themselves, or upon activity commitments or mobility decisions that directly affect the availability and attractiveness of telecommunications alternatives. For example, the utility of at-home work is not explained by the availability at home of a computer with electronic mail and Internet access, or the participation in an employer's telecommute incentive program.

In summary, the model structure and choice set accommodate at-home activities, and can capture changes in at-home participation. Variables are present to capture sensitivity to on-tour activity and travel conditions, but not to capture sensitivity to exogenous changes in telecommunications technology or practice that change the availability or attractiveness of at-home activities.

6.5 Conclusions

This chapter's discussion of model application procedures and the analysis of the day activity schedule model's treatment of various situations yield three important summary conclusions. First, the model is practcal. It can be integrated with traditional network equilibrium models to generate aggregate travel predictions based on disaggregate predictions of the activity schedule model. It also has potential to be used with full-day traffic simulators that rely on disaggregate predictions of activity schedules. Second, the model captures much heterogeneity in both pattern choice and policy response, clearly demonstrating the importance of explicitly modeling heterogeneity in the day activity schedule model. The heterogeneity effects are governed by a comprehensive model specification that is independent of specific policies, but yields heterogeneity effects that depend on the nature of specific policies. Third, and perhaps most importantly, the day activity schedule model can capture pattern adjustments and associated travel changes, arising from a variety of exogenous changes in activity and travel conditions, that trip and tour-based models would miss. A notable example is the predicted response to a peak period toll, in which pattern shifts cause a net increase in leisure tours despite a $.50 per mile peak period toll.

The analysis of model operation also identifies weaknesses of the Portland model, indicating the need for further improvements. First, omission of expected maximum utility from conditional subtour and intermediate stop alternatives hinders the model from capturing effects of their attractiveness on pattern choice. Second, some variables, not in the current model, might enable it to capture additional policy effects, especially for walk and electronic access to activity opportunities. Third, assumption of MNL for the pattern choice, and resulting uniform cross elasticities, probably distorts predicted response to policies. These weaknesses are not inherent in the design, and can be alleviated in subsequent implementations, especially in light of continually advancing technology that makes collection of disaggregate data and use of computationally intensive specifications increasingly feasible.

As indicated at the beginning of this chapter, the above analysis has been primarily qualitative. The reliability of model predictions depends on accuracy of specification that can ultimately only be evaluated through empirical validation of aggregate outcomes predicted by the model.

7

Conclusions and Recommendations

7.1 Conclusions

This study, motivated by the notion that travel decisions are components of a larger activity scheduling decision, developed a model of a person's day activity schedule that can be incorporated into urban forecasting model systems. Discrete choice methods were chosen because of their potential to capture practically the interactions among the many dimensions of the scheduling decision, because they rely on random utility theory, for which validated models with large choice sets abound, and because well-established statistical methods can be used for model estimation and validation. Other modeling approaches, including Markov chains, rule-based simulations and joint discrete-continuous econometric methods, were rejected either because of a fundamental mismatch between the method and the hypothesized activity scheduling behavior, or because they have not yet overcome major roadblocks preventing implementation of a behaviorally sound and practical system.

7.1.1 Theoretical model

The day activity schedule model, specified in Chapter 4, satisfies a rich set of requirements derived from the literature on activity-based travel demand, providing the foundation for the development of behaviorally improved travel demand forecasting models. The schedule outcome is an integrated composition of the important scheduling dimensions spanning a 24 hour day, including the travel dimensions needed for forecasting travel demand. Its integrated hierarchical structure reflects a priority- and commitment-based scheduling decision in which overall pattern and high priority activities condition the decisions related to lower priority activities and travel details, but are also influenced by the expected utility of the conditional decisions. Its full-day scope; detail of pattern, activity and travel dimensions; and integrated structure give the model design three important realistic performance capabilities. First, it can capture the full spectrum of trade-offs people consider as they face time and space constraints in scheduling their day's activities. These trade-offs include variations in activity participation, on-tour versus at-home activity location, number of tours, trip chaining, timing, destination and travel mode. Second, it can realistically capture the significant influence of lifestyle-based heterogeneity on schedule choice by identifying lifestyle and mobility factors in each of the model's many scheduling dimensions. Thus, for example, one set of lifestyle factors can explain activity selection, and another set can help explain mode and destination choices. Third, it can capture the impact of exogenous factors upon all dimensions of schedule choice, even if the factors only act directly in one dimension. Importantly, this includes the influence of activity accessibility—including travel conditions—on the choice of activity pattern. For example, the model's design would allow it to capture the impact on activity and pattern choice of a policy that only impacts travel costs between one origin and destination, at one time of day, by one travel mode. If these coincide with a worker's commute corridor, the impact can be substantial.

The choice of day activity schedule is complex, with so many potential outcomes that it is necessary to make many simplifying assumptions to achieve a tractable model. However, the design of the model is complete and flexible enough to allow well-reasoned simplifications without undermining its basic satisfaction of the important behavior-theoretical requirements. The principal techniques for simplification are the aggregation of outcomes and the elimination of marginal choice dependence on expected conditional choice utility in dimensions. Satisfaction of behavior theory is retained by preserving the model's scope and structure, and by choosing simplifications that substantially improve computational performance without removing the most important behavioral realism.

The model design is also robust enough to allow ongoing refinement of empirical implementations as improvements come in data, knowledge of details of the decision process, and computational capabilities. In particular, the basic structure can accommodate improved resolution of the schedule choice set and associated data, notably in the dimensions of time, space and activity purpose; enhancements in representation of inter-dimensional utility correlations, such as the relaxation of conditional independence assumptions among tours and correlations among activity pattern dimensions; and addition of important new explanatory factors, such as the availability of electronic telecommunications capabilities.

7.1.2 Empirical model

We successfully specified and estimated the parameters of an empirical implementation of the day activity schedule model. The estimation results match reasoned expectations, derived from activity-based travel demand theory, of the factors explaining pattern choice, providing a degree of confidence in the model specification. The pattern representation includes all on-tour activities, as well as all primary at-home activities and secondary at-home maintenance activity, enabling the model to capture at-home versus on-tour activity participation trade-offs. The model also includes enough detail about on-tour activity purpose, priority, sequence, location and access modes to capture inter-tour and trip chaining behavior. Statistical tests confirm the importance of at-home activities and activity sequence in pattern choice.

The model captures the influence of lifestyle and mobility characteristics on activity schedule choice primarily through the selection of activities (purpose and priorities) and through travel preferences (timing, mode and destination). It includes lifestyle parameters in four major categories, including household structure, role in household, personal and financial capabilities, and activity commitments. Parameters in all categories were found to be important in both the pattern and travel dimensions. Important household structure and role variables, included separately and with various interactions, are family versus nonfamily, number of adults, children, gender and relative workload. Of these, the most noticeable effect is gender specialization in families, especially in the presence of children, where we see males taking traditional work responsibilities and females taking maintenance and child-care responsibilities. Important capability variables include income, travel-impairing disabilities and occupation. The influence of activity commitments on schedule choice is captured primarily through individual and household work commitment variables. Mobility effects are captured through the residential location and auto ownership levels.

The model includes accessibility parameters measuring the impact of expected tour utility—for primary and secondary tours of all purposes—on pattern choice. Accessibility is relatively more important for the primary tour on subsistence patterns and for secondary tours on maintenance and leisure patterns. Statistical tests support the importance of these parameters. This is an important result because it confirms the value of a model that represents travel demand in the context of the day activity schedule. Changes in tour utility—caused by changes in the transport system performance or in spatial activity opportunities—have a significant effect on the choice of pattern because of these expected maximum utility variables,. Such effects cannot be captured by tour- or trip-based travel demand models.

Tractability of the empirical model was achieved through two major simplifications. First, all tours are modeled as conditionally independent, given the pattern outcome. This prevents the explicit modeling of destination, mode and timing correlation among tours. Second, expected utility of secondary stops on tours and work-based subtours is not used to explain other dimensions of schedule choice. This prevents the model from accurately capturing the effect of changes in secondary stop utility on pattern choice. While both of these simplifications reduce the model's behavioral realism, it nevertheless retains most of its ability to capture interactions among activity schedule dimensions. In both cases, the data is available to remove the simplifications, when available computational power substantially exceeds that of the 300mhz Pentium processor used for the initial model application.

7.1.3 Model application results

The day activity schedule model system can and is being applied in a number of ways for travel prediction. A production version of this study's empirical model has been implemented in conjunction with traffic network models to predict aggregate travel response to exogenous changes. Taking the place of trip generation, distribution and mode split models used in traditional trip-based systems, it generates trip matrices by aggregating schedule probabilities calculated for each member of a representative population. Alternatively, simulated schedules can be used to generate aggregate trip matrices, or the model can provide simulated 24-hour schedules directly to traffic microsimulators.

The model system demonstrates the benefits of its design in various policy applications, simplified to exclude network equilibration. In response to a toll levied on all travel paths during the morning and evening peak travel periods, the model predicts not only shifts in travel mode and timing, but also shifts in pattern purpose and structure. The toll reduces the travel utility of peak-period auto tours. Through the expected tour utility measure, this reduces the utility of all patterns, with greatest effects on patterns that rely most heavily on peak period auto travel, namely, work patterns and multi-tour patterns with secondary maintenance tours. The result is a shift from work patterns and patterns with secondary maintenance tours, causing a net increase in the predicted number of tours for leisure purposes. This induced leisure travel demand is an important manifestation of activity scheduling behavior that trip- and tour-based models cannot capture.

In the same application, the model exhibits lifestyle and mobility heterogeneity in pattern choice and in policy response, demonstrating the importance of lifestyle in the specification. Persons in households with more cars experience a greater percentage decrease in subsistence patterns, increase in at-home primary activity participation, and decrease in secondary tour participation than their counterparts with less cars, reflecting a greater dependence on auto travel. Working females in families, especially females with children, are more likely than others to shift to a nonwork primary activity. The percentage increase in at-home primary activity participation is greater for full-time workers than others, reflecting the group’s dependence on peak-period travel. Cost sensitivity makes the percentage decrease in secondary tour participation greater for low income persons than for those with high income. Participation in at-home maintenance activity decreases for nonworkers and increases for workers, as more workers are predicted to choose nonwork primary activities, making them more available for at-home maintenance.

The model’s ability to capture policy responsive pattern shifting and heterogeneity is not limited to the toll policy. Application of the model with transit improvements and auto ownership restrictions demonstrate the same adjustment mechanisms, yielding different net results. Analysis, without model application, indicates that the model would capture expected pattern changes in response to other demand management, land use and highway service level changes. In some cases, the implemented model would fail to capture an expected effect because of missing model variables or limited resolution of a choice dimension. As an example of a missing variable, the model lacks information about at-home telecommunications capabilities. Therefore, it cannot capture any tendency of at-home Internet access to increase at-home work activity or induce any other pattern changes, some of which probably affect travel. The model's limited spatial resolution probably renders it insensitive to changes in neighborhood characteristics that can substantially influence reliance on secondary walking tours for maintenance and leisure activities.

7.2 Recommendations

This study has not yet proven that the day activity schedule approach is ready for immediate widespread adoption as a principal tool for travel forecasting. Such a conclusion should be made only after the model has demonstrated quantitatively its cost effectiveness in providing travel predictions superior to existing forecasting models.

On the other hand, the conclusions of this study give very strong evidence of the behavioral advantages of the model design, its current practicality, its potential for providing cost effective predictions superior to those of the best existing systems, and its potential for supporting continued improvements in implementation as advancing computing technology enables it to tap the benefits of disaggregate data and model integration.

We recommend continued efforts to implement the day activity schedule approach in a small but growing number of pilots, where the model can be validated and its cost effectiveness can be demonstrated. At the same time, ongoing research can be conducted to enhance the model and to integrate it with related models of household choice, urban development and transport systems. It can also be evaluated for theoretical weaknesses, serving as grist for the further development of theory and models of activity and travel behavior. We conclude with a list of specific research and development opportunities.

7.2.1 Model validation

The complexity of the scheduling process and of the resulting models makes validation via model application very important. An established production environment provides the best opportunity to conduct research projects specifically aimed at model testing and validation, in parallel with model application for policy analysis, and the implementation of the policies themselves. Data sets of policy conditions and corresponding travel outcomes could be established and repeatedly used for validation testing of enhanced models, as part of a research and development laboratory.

7.2.2 Application procedures

The day activity schedule works in conjunction with network traffic models to generate predictions, as described in Section 6.1 . Procedures have been developed that integrate the model with Portland's traffic equilibrium model, and are currently under development to integrate it with a traffic simulation model that requires simulated day activity schedules. Several issues are important in the implementation of application procedures that may require research. These include computational efficiency, consistency between demand and network models, and prediction confidence levels.

Optimizing the reiteration procedures for demand and network model equilibration might make improved, computationally intensive model enhancements feasible. Possibilities may exist for reiteration techniques that allow streamlined demand model procedures at each iteration.

The issue of consistency between demand and network models may be more important than the efficiency issue, because inconsistency can bias predictions. Each model relies on assumptions about its inputs to achieve its theoretical support. Achieving consistency with simple equilibrium assignment models may be straightforward. Achieving consistency with multiclass assignment models and simulation models may require careful study.

In model application the model system relies on estimated parameters, sampling of alternatives, and in some cases Monte Carlo simulation of outcomes, all of which introduce statistical variance in the predictions. Research that empirically evaluates the variance of important aggregate prediction outputs could improve the value of model forecasts, and establish application procedural requirements, such averaging of repeated applications, for achieving desired forecast confidence levels.

7.2.3 Day activity schedule model improvements

The existing Portland model provides a natural setting to address weaknesses identified in the model system evaluation, where costs and benefits of the enhanced system could be evaluated in side by side comparisons with the existing system, ideally in the validation test environment described above. Some of the most clearly defined and potentially beneficial efforts follow.

1. Incorporate the 570 alternative pattern choice set, to improve the model's ability to capture purpose-specific inter-tour trade-offs and at-home vs on-tour activity trade-offs.
2. Incorporate expected maximum utility from secondary stops and subtours, to improve the model's ability to capture the influence of secondary stop accessibility on pattern choice.
3. Test more general utility correlation structures of the activity pattern model, to reduce bias caused by unrealistic independence assumptions. Conduct specification tests with the existing structure, specify alternate nested logit structures, compare one or more alternate structures with the existing model, and consider more general correlation structures.
4. Develop and test methods for improving the temporal and spatial resolution of the model system, to refine the model's ability to capture the impact of temporal and spatial variations in activity and travel conditions. Methods include (a) disaggregating the choice set in the day activity schedule model and explicitly modeling the time dimension for secondary stops, and (b) adding detail of predicted schedule outcomes by subsampling observed detailed schedules from samples that match modeled attributes of predicted day activity schedules.
5. Develop a model with the choice set resolution equivalent to the Portland model, but using the model structure of (1), conditioning secondary tours on the outcome of the primary tour decision. This would incorporate more inter-tour temporal constraints and utility interactions related to destination, mode and timing, potentially improving prediction accuracy.

6. Adjust the model to condition it on usual workplace and work commute mode, to improve the accuracy of pattern sensitivity to work accessibility.

7.2.4 Model enhancement using merged data from evolving surveys.

Some of the weaknesses and potential improvements of the Portland implementation of the day activity schedule model require data that is not available in the estimation data set. This is not uncommon; invariably the model development process points to unmet data needs. On the other hand, activity surveys are expensive; the data assembled and the models built from them represent a major investment. It may be feasible to implement methods of combining data sets so that one or more subsequent activity surveys, aimed at incrementally improving the original survey, and targeted to satisfy specific unmet information needs, could be used to augment existing data sets. This would leverage survey data investment, accelerating research, development and implementation.

In the Portland case, this approach might successfully enable (a) enhanced schedule definition via improved reporting of activity purposes and at-home participation; (b) improved model sensitivity to telecommunications and non-auto modes via the collection of new variables for these alternatives; (c) estimation of important parameters for unusual activity and travel conditions, or market segments, through the use of sample enrichment techniques; and (d) improved sensitivity to lifestyle via improved reporting of household characteristics.

7.2.5 Survey design and data collection methods.

The previous research topic involves survey design, and provides a context for evolutionary improvement of survey methods. Section 5.7.4 identifies specific survey improvement suggestions emerging from this study's empirical work. Here we focus on the need to invest in research targeted at improving survey method, to provide data that enables improved activity-based model development. The objectives include streamlining to eliminate unnecessary complexity, enhancing techniques for reducing nonresponse on key items, and capturing important information missing on existing surveys.

7.2.6 Computational efficiency, application methods and alternative decision protocols

Computational costs associated with the large universal set are a barrier to the improvement of the day activity schedule model. It may be possible to devise methods that improve computational efficiency substantially via techniques that only minimally reduce model realism, or perhaps even improve it, thereby enabling the implementation of model features that substantially improve model performance. For example, alternative sampling techniques might be employed to reduce the number of alternatives used for prediction, while still providing a good approximation of the scheduler's behavior. It may even be possible to discover methods that achieve the objective of improving computational efficiency while simultaneously improving behavioral realism by matching the simplifying behavior of real decisionmakers. Techniques to simulate boundedly rational behavior, in which the consumer chooses rationally from a heuristically chosen subset of feasible alternatives, may be possible. Such a development would constitute the merger of discrete choice methods and rule-based simulations contrasted in Chapter 3.

7.2.7 Integrated activity and mobility models

Research with the day activity schedule model has already indicated the potential value of integrating it with models of household mobility choices (Ben-Akiva and Bowman, 1998). Expected maximum utility of the day activity schedule provides a more complete measure of accessibility than is currently used in mobility choice models, and may improve the explanation of such choices. By improving the measurement of accessibility's influence in residential and work related choices, it may be possible to substantially improve the analysis of transportation policies and other policies that affect or depend on accessibility, including their welfare impacts. Further integration of the mobility choice models in land use forecasting model systems may substantially improve the ability to forecast the impacts of policies that affect land use through changes to transportation and activity conditions.

7.2.8 Theoretical research

The day activity schedule model represents behavior that is addressed by formal theories of transport economics and home production, but the complexity of the day activity schedule has not been formally incorporated in these theories. An evaluation of the model in light of these theories might lead to important improvements in the model, advances in transport economics and home production theory, and formalization of the theory of activity-based travel behavior.

Appendix A

Translation of survey data into day activity patterns

This appendix presents Sections 3 through 5 of an August, 1996, design specification developed by the author, which was used in the development of the Portland production system.

3	Interpreting the Survey Data	Provides rules for translating observed daily schedules into the model hierarchy, providing additional definition of the dimensions of the daily schedule.
4	Definitions of Activity Purposes	Translates the survey activity codes into the three activity purpose categories of work, maintenance and discretionary.
5	Assigning Mode	Provides logic for assigning the principal mode of any tour in the daily activity schedule.

Section 3: Interpreting the Survey Data

These rules explain how to interpret the survey data set in terms of the model system design, assigning all the attributes which together define the daily schedule.

1. Assign each reported activity to one daily schedule.
2. Assign a purpose of W[13], M or D to every activity, using the attached definition of activity purposes.
3. Determine if the daily activity pattern is work on tour, work at home or non-work.
   a) **Calculate the total reported duration of work activities conducted away from home, and call this total the work on tour duration.**
   b) Add the total reported duration of work activities conducted at home to the work on tour duration. Call this the work duration.
   c) Using the results of a) and b) for the entire sample, generate histograms of work duration and work on tour duration. For the work (alternatively, work on tour) histogram choose a threshold which is as large as possible without interpreting as nonwork (alternatively, work at home) very many patterns which include work activity (alternatively, work on tour). **A threshold of 60 minutes was chosen for work on tour (MAB, actproc3.doc).**
   d) If the work duration exceeds the work threshold, assign the pattern as work; else assign it as non-work. For work patterns, if the work on tour exceeds the work on tour threshold, assign it as work on tour; else assign it as work at home **and assign as the primary activity the at home W activity with the greatest duration.**
4. For work on tour patterns, define the primary tour, and the work-based subtour if applicable.
   a) Assign as the primary work destination the work destination within the daily pattern which is visited the largest number of times. If this number of visits is shared by 2 or more destinations, assign as primary the one with the largest total work duration.
   b) If the primary work destination is visited more than once in the daily activity pattern, assign a pattern which includes WOW.
   c) For patterns with WOW, include in the primary tour workday the 2 work stops with longest duration at the primary work location, and, for patterns with 3 or more stops at the primary location, any additional stops which occur at the primary work location without an intervening trip home. Also include in the workday any stops which occur between these workday work activities.
   d) Assign as the departure time from home the last departure time from home prior to the arrival at the first of the workday's stops at the primary work location. Use as the departure time from work the departure time from the last of the workday's stops at the primary workplace. Assign the tour mode using the attached rule for assigning modes, using the half-tour which begins at the assigned departure time from home, and the half-tour which begins at the assigned departure time from work.
   e) For WOW patterns use, as the explicitly modeled subtour, the subtour which includes the destination which is farthest from the work location. Use the departure time from work on the subtour and the departure time from the destination as the departure times of the subtour. Assign the mode using the attached rule for assigning modes, using the tour defined by the assigned departure times.
   f) If destinations are visited after the workday, before the return home, then assign a pattern which includes WOH. If more than 1 destination is visited on the way home, assign as the destination the location which has the longest distance on the WOH path. Assign as the departure time from the after work stop, the departure time from this location.
   g) If destinations are visited before the workday, after the departure from home on the work tour, then assign a pattern which includes HOW. If more than 1 destination is visited on the way to work, assign as the destination the location which has the longest distance on the HOW path. **Assign as the departure time from the before work stop, the departure time from this location.**

[13] The code 'W' corresponds to the subsistence purpose defined in the body of the thesis. It is left as 'W' here to retain the original text of the memo.

5. Determine the purpose of all tours other than primary work tours. Sum together the activity duration of W and M activities, and sum separately the duration of D activities. Use the following priority table to assign each of the sums to a priority category. **(Analysis of the sample data may lead to the adjustment of the thresholds in the table.)** Assign the purpose of the tour as M if the W/M sum is higher priority than the D sum; else assign a purpose of D.

Priority	Purpose	Duration
1	W/M	over 2
2	D	over 4
3	W/M	1-2
4	D	2-4
5	W/M	under 1
6	D	under 2

6. For non-work patterns, determine whether the pattern is maintenance on tour (MT), discretionary on tour (DT), maintenance at home (MH) or discretionary at home (DH).
   a) Examine nonwork patterns to establish thresholds for MT, DT and MH patterns.
      i) Generate a histogram of the M tour of longest duration in each nonwork pattern, and select an M on tour threshold which excludes tours of the shorter durations. Use as duration the elapsed time between departure from home and arrival at home.
      ii) Generate a histogram of the D tour of longest duration among nonwork patterns lacking an M tour which exceeds the M threshold. Select a D on tour threshold which excludes tours of the shorter durations.
      iii) Generate a histogram of the total at-home W/M duration among nonwork patterns lacking an M or D tour which exceeds the M, or D respectively, threshold. Select an M at home threshold which excludes patterns with shorter W/M durations.
   b) Using the thresholds, assign each nonwork pattern a pattern of MT, DT MH or DH, as follows:
      If there is an M tour that exceeds the M on tour duration threshold, then call the pattern MT, and assign the M tour with longest W+M duration as the primary tour.
      Else, if there is a D tour which exceeds the D on tour duration threshold, then call the pattern DT, and assign the D tour with longest D duration as the primary tour.
      Else, if the total W+M time at home exceeds the M at home threshold, then call the pattern MH, and assign as the primary activity the W or M activity with the greatest duration.
      Else, call the pattern DH, and assign as the primary activity the D activity with the greatest duration.
7. For primary non-work tours, define the tour.
   a) Assign the primary tour type using the number of stops which occur on the tour.
   b) Assign as the primary destination the highest duration activity of the tour's purpose. Assign as departure times the departure time from home and the departure time from the primary destination. Assign the tour mode using the attached rule for assigning modes, using the tour defined by the assigned departure times.
   c) Assign as the secondary destination the destination with the longest distance along the path from home to the secondary destination and on to the primary destination. Assign the secondary sequence as before or after the primary stop, and assign the departure time from the secondary stop.
   d) Assign as the tertiary destination the destination with the longest distance along the path from the preceding higher priority stop (or home) to the tertiary destination and on to the following higher priority stop (or home). Assign the tertiary sequence as before, between or after, and assign the departure time from the tertiary stop.
8. For primary at home patterns, define the begin and end times corresponding to the reported begin and end times of the activity of longest duration with purpose (W/M or D) which matches the pattern purpose.
9. For every daily schedule assign the number and purpose of secondary tours by counting the non-primary tours of each purpose.
10. Define each secondary tour. Assign the primary destination as the **stop with the longest duration of activities** which match the tour purpose (W/M or D). Assign the departure time from home and the departure time from the primary destination. Assign the tour mode using the attached rule for assigning mode.

Section 4: Definition of Activity Purposes

W Work, work related and school
M Maintenance (business of HH or individual. could be called business)
D Discretionary (activities engaged in for pleasure, recreation, or refreshment. Could be called recreation)

Where the survey responses are interpreted as follows:

Survey Description	Survey Code	Model Purpose	Model Code
Meals	11	D	3
Work	12	W	1
Work-related	13	W	1
Shopping (general)	14	M	2
Shopping (major)	15	M	2
Personal services	16	M	2
Medical care	17	M	2
Professional services	18	M	2
Household or personal business	19	M	2
Household maintenance	20	M	2
Household obligations	21	M	2
Pick-Up/Drop-Off passengers	22	M	2
Visiting	31	D	3
Casual entertaining	32	D	3
Formal entertaining	33	D	3
School	41	W	1
Culture	42	D	3
Religion/Civil Services	43	D	3
Civic	44	D	3
Volunteer work	45	D	3
Amusements (at-home)	51	D	3
Amusements (out-of-home)	52	D	3
Hobbies	53	D	3
Exercise/Athletics	54	D	3
Rest and relaxation	55	D	3
Spectator athletic events	56	D	3
Incidental trip	90	D	3
Tag along trip	91	D	3

Section 5: Assigning Mode

Introduction

In the model system we are explicitly modeling the mode for tours. The tour mode is based on the mode used for each of the two half-tours (journey to destination and journey from destination), excluding from consideration modes used for subtours (of the tour or subtour being considered), but including modes used for detours on the journey to or from the destination.

We are modeling tour mode for primary work tours, work-based subtours, primary non-work tours and secondary tours.

Terminology

Trip Mode (M)	The mode used for the travel from one activity location to the next activity location
Half-tour mode (HTM)	The principal mode used among all trips on the journey from the tour origin to its primary destination, or on the return journey from the primary destination to the tour origin.
Half-tour mode set (HTMS)	The list of trip modes used on a half-tour
Tour mode set (TMS)	The two half-tour modes associated with a tour
Tour mode (TM)	The principal mode of the tour

Mode alternatives

DA	Auto drive alone
DP	Auto drive with passenger
PA	Auto passenger
MA	MAX with auto access
MW	MAX with walk access
BA	Bus with auto access
BW	Bus with walk access
WA	Walk
BI	Bicycle
OT	Other

Assignment Rules

Trip mode (M)

```
CASE (Got to activity by...)
    Private vehicle (7)
        IF driver
        THEN    IF 1 person in vehicle                          M =  DA
                ELSE                                                 DP
        ELSE                                                         PA
    MAX (6)
        IF trip ends at home
        THEN    IF got from stop to destination by walk              MW
                ELSE                                                 MA
        ELSE    IF got to stop by walk                               MW
                ELSE                                                 MA
    Public bus (5)
        IF trip ends at home
        THEN    IF got from stop to destination by walk              BW
                ELSE                                                 BA
        ELSE    IF got to stop by walk                               BW
                ELSE                                                 BA
    Bicycle (3)                                                      BI
    Walk (2)                                                         WA
    Anything else                                                    OT
```

Half-tour mode (HTM)

```
IF HTMS includes MA                                        HTM =     MA
ELSE    IF HTMS includes BA                                          BA
    ELSE    IF HTMS includes MW
        THEN    IF HTMS includes DA, DP or PA                        MA
                ELSE                                                 MW
        ELSE    IF HTMS includes BW
            THEN    IF HTMS includes DA, DP or PA                    BA
                    ELSE                                             BW
            ELSE    IF more than 60% of half-tour distance is DP and PA
                THEN    IF HTMS includes DP                          DP
                        ELSE                                         PA
                ELSE    IF HTMS includes DA                          DA
                    ELSE    IF HTMS includes BI                      BI
                        ELSE    IF HTMS includes only WA             WA
                            ELSE                                     OT
```

Tour mode

```
IF TMS includes DA                                         TM =      DA
ELSE    IF TMS includes DP                                           DP
    ELSE    IF TMS includes BI                                       BI
        ELSE    IF TMS includes WA                                   WA
            ELSE    IF TMS includes MA                               MA
                ELSE    IF TMS includes BA                           BA
                    ELSE    IF   TMS includes MW                     MW
                        ELSE    IF TMS includes BW                   BW
                            ELSE    IF TMS includes PA               PA
                                ELSE                                 OT
```

Appendix B

The Portland 114 alternative day activity pattern model

Table B.1 lists the parameters of the production version of the Portland day activity pattern model.

Table B.1 Production system 114 alternative day activity pattern model

Observations	14774
Final log(L)	-47622
Rho-squared (0)	0.319
Rho-squared (c)	0.089

Alternative / variable	**Coeff.**	**T-stat**
Mode / destination logsums		
Work/school primary tour	0.1815	6.5
Maintenance primary tour	0.04447	1.9
Discretionary primary tour	0.1039	3.3
Maintenance secondary tours	0.1472	8.8
Discretionary secondary tours	0.0468	4.3
WT-Work on tour variables		
Constant	-1.958	-6.5
Full time worker	3.125	39.6
Part time worker	2.674	27.9
Age under 20	2.109	15.2
Age 20-24	0.8328	7.5
Age 25-34	0.2458	4.0
Age 55-64	-0.398	-5.5
Age over 65	-1.676	-16.0
Female, 2+ adults in hh	-0.2473	-4.3
Kids under 5 in hh	-0.4059	-5.7
WH-Work at home variables		
Constant	-2.799	-16.1
Full time worker	2.302	14.8
Part time worker	2.282	12.6
Age over 65	-0.73	-3.6
Male, only adult in hh, worker	0.7659	4.5
Male, 2+ adults in hh	0.2364	2.2
MT-Maintenance on tour vars		
Constant	-0.1193	-0.5
Part time worker	0.229	2.3
Age under 20	-0.7626	-4.4
Male, 2+ adults in hh	-0.371	-6.1
Female, kids under 12 in hh	0.3196	4.1
No cars in hh	-0.0082	-0.1
Fewer cars then adults in hh	-0.1113	-1.4
MH-Maintenance at home vars		
Constant	0.2151	2.6
Full time worker	-0.5532	-5.1
Age under 20	-1.379	-4.1
Female, kids under 12 in hh	0.3932	3.6
Female, 2+ adults in hh	0.4894	6.0

Alternative / variable	**Coeff.**	**T-stat**
DT-Discretionary on tour vars		
Constant	-0.6862	-2.2
Full time worker	-0.3153	-3.5
No cars in hh	-0.5246	-3.1
Fewer cars then adults in hh	-0.4174	-4.2
DH-Discretionary at home vars		
Income under $30,000	0.3247	3.6
Income over $60,000	-0.2256	-1.5
WT-Work on tour constants		
Stop on way to	-1.194	-23.0
Stop on way back	-2.001	-37.6
Stop both ways	-2.502	-30.7
No stops plus subtour	-1.99	-23.3
Stop on way to plus subtour	-3.03	-29.3
Stop on way back plus subtour	-3.904	-32.8
Stop both ways plus subtour	-4.452	-31.8
WI- Work intermed. stop vars		
Income over $60,000	0.2646	7.0
Age under 20	-0.3113	-3.9
Age over 45	-0.0868	-2.3
Female, kids under 12 in hh	0.6242	12.3
Male, 2+ adlts in hh, 1+ non-wrkr	-0.2247	-4.2
Female, single, worker	0.2457	4.3
No cars in hh	-0.2681	-2.4
Fewer cars then adults in hh	-0.2233	-4.4
WS-Work-based subtour vars		
Income over $60,000	0.2721	4.3
Full time worker	0.5434	6.7
Female, kids under 12 in hh	-0.3532	-3.5
Male, single, worker	0.2833	2.9
No cars in hh	-0.2913	-1.6
Fewer cars then adults in hh	-0.1551	-1.9
MT-Maint. tour constants		
Stop on way to	-0.5774	-8.2
Stop on way back	-0.5494	-8.5
Stop both ways	-1.047	-10.8
MI-Maint. intermed. stop vars		
Full time worker	-0.2123	-3.2
Age over 65	-0.2521	-4.4
No cars in hh	-0.6641	-4.6
Fewer cars then adults in hh	-0.2376	-3.2

Table B.1 Production system 114 alternative day activity pattern model (continued)

Alternative / variable	Coeff.	T-stat
DT-Discret. on tour constants		
Stop on way to	-1.408	-14.1
Stop on way back	-1.456	-14.4
Stop both ways	-1.823	-14.0
DI-Discret. intermed. stop vars		
Age over 65	-0.3606	-3.7
Male, 2+ adlts in hh, 1+ non-wrkr	-0.3894	-3.6
No cars in hh	-0.7553	-2.5
Fewer cars then adults in hh	-0.1963	-1.5
All purposes, additional vars		
Stop on way to- No kids in hh	0.1941	4.3
Stop both ways- Kids under 5 in hh	0.5752	6.7
SM-secondary maint. tour vars		
Full time worker	-0.168	-2.5
Part time worker	0.2507	3.1
Female, no kids in hh	-0.1809	-3.2
Age over 65	-0.3541	-4.8
Female, kids in hh	0.4878	7.3
Female, 2+ adults in hh, all workers	-0.0218	-0.3
No cars in hh	-0.604	-4.6
Fewer cars then adults in hh	0.0781	1.4
SD-second. discret. tour variables		
Age under 35	0.1246	2.4
Full time worker	-0.2837	-5.1
Age under 20	0.1819	1.8
Age over 65	-0.2838	-4.0
No cars in hh	-0.4526	-3.7
Fewer cars then adults in hh	-0.232	-3.9
SM-1 second. maint. tour constants		
Primary = work/school on tour	-2.738	-16.0
Primary = work/school at home	-1.153	-5.6
Primary = maintenance on tour	-2.201	-12.9
Primary = maintenance at home	-3.014	-16.0
Primary = discretionary on tour	-3.193	-16.8
Primary = discretionary at home	-3.464	-16.2
Prim. tour has 1 intermed. stop	-0.2244	-3.9
Prima. tour has 2 intermed. stops	-0.1938	-2.0
Prim. tour has work-based subtour	-0.1447	-1.7

Alternative / variable	Coeff.	T-stat
SD-1 second. discret. tour constants		
Primary = work/school on tour	-1.632	-13.6
Primary = work/school at home	-0.7052	-3.8
Primary = maintenance on tour	-1.038	-8.6
Primary = maintenance at home	-4.01	-14.7
Primary = discretionary on tour	-1.47	-11.2
Primary = discretionary at home	-4.697	-11.1
Prim. tour has 1 intermed. stop	-0.2343	-4.2
Prim. tour has 2 intermed. stops	-0.4573	-4.5
Prim. tour has work-based subtour	-0.0708	-0.9
SMM-2+ sec. maint. tours constants		
Primary = work/school on tour	-6.226	-18.6
Primary = work/school at home	-3.218	-9.2
Primary = maintenance on tour	-4.522	-13.8
Primary = maintenance at home	-5.08	-14.9
Primary = discretionary on tour	-6.073	-16.1
Primary = discretionary at home	-6.163	-15.0
Prim. tour has 1 intermed. stop	-0.154	-1.3
Prim. tour has 2 intermed. stops	-0.3307	-1.6
Prim. tour has work-based subtour	-0.6844	-2.5
SDD-2+ sec. discret. tours constants		
Primary = work/school on tour	-5.416	-19.7
Primary = work/school at home	-2.697	-7.9
Primary = maintenance on tour	-3.107	-12.8
Primary = maintenance at home	-5	*
Primary = discretionary on tour	-3.597	-13.6
Primary = discretionary at home	-5	*
Prim. tour has 1 intermed. stop	-0.2219	-1.3
Prim. tour has 2 intermed. stops	-0.7337	-2.3
Prim. tour has work-based subtour	-0.1867	-0.5
SMD-1+ maint & 1+ discr tours		
Primary = work/school on tour	-5.048	-22.4
Primary = work/school at home	-1.829	-7.5
Primary = maintenance on tour	-2.943	-13.9
Primary = maintenance at home	-6.704	-12.5
Primary = discretionary on tour	-4.468	-17.5
Primary = discretionary at home	-6.329	-11.8
Prim. tour has 1 intermed. stop	-0.3399	-3.1
Prim. tour has 2 intermed. stops	-0.3125	-1.9
Prim. tour has work-based subtour	-0.5777	-2.2

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Index of Important Terms