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Activity-based disaggregate travel demand model system with activity schedules

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Abstract

We present an integrated activity-based discrete choice model system of an individual's activity and travel schedule, for forecasting urban passenger travel demand. A prototype demonstrates the system concept using a 1991 Boston travel survey and transportation system level of service data. The model system represents a person's choice of activities and associated travel as an activity pattern overarching a set of tours. A tour is defined as the travel from home to one or more activity locations and back home again. The activity pattern consists of important decisions that provide overall structure for the day's activities and travel. In the prototype the activity pattern includes (a) the primary – most important – activity of the day, with one alternative being to remain at home for all the day's activities; (b) the type of tour for the primary activity, including the number, purpose and sequence of activity stops; and (c) the number and purpose of secondary – additional – tours. Tour models include the choice of time of day, destination and mode of travel, and are conditioned by the choice of activity pattern. The choice of activity pattern is influenced by the expected maximum utility derived from the available tour alternatives.

Keywords: Activity; Schedule; Travel demand model; Disaggregate; Forecast; Choice

1. Background

1.1. Introduction

Significant advances in modeling travel demand have been made over the past 25 years. The methods of disaggregate choice modeling have been widely applied (Ben-Akiva and Lerman,

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1985). Furthermore, the choice processes that the models represent have become better understood through research on the nature of individual activity and travel decisions. Some of the most advanced operational model systems capture the interrelated decisions a person makes regarding the travel from home to one or more activity locations and back home again. (See, for example, Gunn, 1994; Algers et al., 1995.) These tour-based models address some complexities, such as trip chaining, but ignore the constraints and opportunities associated with activity schedules that can include at-home activities and multiple tours.

In this paper we extend the tour-based model concept, explicitly modeling an individual's choice of an entire day's schedule, as proposed by Ben-Akiva et al. (1996) and briefly described by Ben-Akiva and Bowman (1998). The larger scope improves the model's ability to capture important activity-based demand responses, such as the choice between trip chaining on one tour and conducting two separate tours – an inter-tour trade-off – or the choice between conducting an activity at home and conducting it on a tour – an on-tour vs at-home trade-off. It also enhances the model's capability for policy sensitive forecasting.

In the remainder of this section we place the proposed model system in the context of the theory of activity and travel decisions, and other activity-based travel forecasting model development. The second section is devoted to the conceptual design of the proposed model system. The third and largest section presents a prototype, specified and estimated using 1991 Boston data; the system concept is demonstrated, limitations of the prototype are analyzed, and prospects for an operational implementation are discussed. This is followed by a brief concluding section.

1.2. Activity-based travel theory

The most important elements of activity-based travel theory can be summarized in two basic ideas. First, the demand for travel is derived from the demand for activities. (See, for example, the discussion in Jones, 1977.) Travel causes disutility and is only undertaken when the net utility of the activity and travel exceeds the utility available from activities involving no travel. Second, humans face temporal–spatial constraints, functioning in different locations at different points in time by experiencing the time and cost of movement between the locations (Hagerstrand, 1970). They are also generally constrained to return to a home base for rest and personal maintenance.

A substantial amount of analysis has been done to refine the theory, test specific behavioral hypotheses, and explore methods of modeling important aspects of activity-based travel behavior. Damm (1983), Golob and Golob (1983), Kitamura (1988) and Ettema (1996) provide extensive reviews of the literature on activity-based travel theory. We present here only a few highlights. Pas (1984) finds demographic factors such as employment status, gender and presence of children to have significant effects on the choice of the activity and travel pattern. Pas and Koppelman (1987) examine day-to-day variations in travel patterns, and Pas (1988) explores the representation of activity and travel choices in a week long activity pattern. 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 (1996) explore methods of modeling activity duration. Bhat and Koppelman (1993) propose a framework of activity agenda generation.

1.3. Research and development in urban travel forecasting

In the last 25 years researchers have attempted to incorporate the insights gained on activity-based travel theory into urban travel forecasting models. Here we review operational forecasting systems representative of the best current practice worldwide, and prototypes that demonstrate the current frontier in model development. More extensive reviews can be found in Bowman (1995) and Bowman (1998).

Integrated trip-based models. The MTC system (Ruiter and Ben-Akiva, 1978; Ben-Akiva et al., 1978) was developed for the San Francisco Bay Area, and has been used in forecasting for many years. It is estimated as an integrated disaggregate choice model system. Models include accessibility variables representing expected maximum utility derived from related conditional models. The linkages across models introduce a partial representation of time and space constraints and household interactions. However, the system ignores some natural time and space constraints by modeling trip decisions separately – hence the label trip-based – and excluding the modeling of duration and time of day. Horowitz (1980) presents a trip frequency, destination and mode choice model that incorporates inter-trip dependence and can be implemented in a trip-based model system.

Tour-based models. Tour-based systems were first developed in the late 1970s and 1980s in the Netherlands (Daly et al., 1983; Gunn et al., 1987; Hague Consulting Group, 1992; Gunn, 1994), and are being used extensively there and elsewhere. Recent tour-based model systems have been developed for Stockholm (Algers et al., 1995), Salerno, Italy (Cascetta et al., 1993), the Italian Transportation System (Cascetta and Biggiero, 1997), Boise, Idaho, (Shiftan, 1995) and New-Hampshire (Rossi and Shiftan, 1997). These models group trips into tours based on the fact that all travel can be viewed in terms of round-trip journeys based at the home. A tour is assumed to have a primary activity and destination that is the major motivation for the journey.

The modeling of tour decisions provides an incremental improvement over trip-based model systems, incorporating an explicit representation of temporal–spatial constraints among activity stops within a tour. However, the tour-based approach lacks a connection among multiple tours taken in the same day, thereby failing to capture the effects of inter-tour temporal–spatial constraints.

Day and week models. Significant attempts have been made to broaden the scope of forecasting models to incorporate activity and travel decisions spanning an entire day or more. Some of these rely exclusively on econometric choice models and the theory of the utility maximizing consumer, while others use rule-based decision simulations.

Among the econometric models Ben-Akiva et al. (1980) develop two interrelated models to represent a time budget and activity schedule. Adler and Ben-Akiva (1979) develop a model of a day non-work travel pattern. The choice of travel pattern is modeled as a single complex decision, in which many component decisions together define a day's travel. Hamed and Mannering (1993) use a variety of econometric model forms to represent an individual's temporally sequential construction of an activity and travel schedule, including activity duration. Hirsh et al. (1986) present a dynamic model of an individual's pattern of shopping activity for a week, based on the theory that individuals plan their activity participation on a weekly basis, and update these plans daily throughout the week.

The earliest rule-based simulation model, STARCHILD (Recker et al., 1986a,b), takes a destination-specific household activity agenda – a list of planned activities – and models detailed activity and travel schedules for household members. Recker (1995) formalizes the STARCHILD approach with a mathematical program that also addresses activity and vehicle allocation. Axhausen et al. (1991) propose a simulation model in which a sample of simulated households is used to model the evolution of travel behavior in daily, medium-term and longer time frames. RDC (1995) uses a two stage model that includes a basic policy response and a heuristic search for a detailed schedule adjustment. Ettema et al. (1993, 1995) represent the scheduling decision as a sequence of schedule building decisions.

Broadening the decision scope to include activity decisions spanning a day or more is difficult because the variety of available schedules is immense and, despite the advances in activity-based travel theory, the factors underlying the decisions are still not well understood. Accordingly, all the day or week models were developed only as incomplete prototypes, and rely on exogenous forecasts of important dimensions of the activity and travel scheduling decision, such as activity participation, location, and travel mode.

2. Activity schedule model system design

We present an econometric model system that can represent an individual's choice of a day's activities and travel spanning 24 h (day activity schedule, activity schedule, or schedule for short) with enough scope and detail to enable its use for travel forecasting. It is a disaggregate, discrete choice model system that uses and extends aspects of existing travel demand models, and can be integrated with other existing components of forecasting model systems, including land use, mobility and transport supply models. The model system can be estimated, tested and validated using readily available statistical procedures.

2.1. The day activity schedule

Demand for activity and travel is viewed as a choice among all possible combinations of activity and travel in the course of a weekday. The model uses a day timeframe 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 shown in Fig. 1, the day activity schedule consists of a set of tours tied together by an overarching activity pattern (pattern). The activity pattern extends the linkage beyond that of a tour-based model to include all the tours that occur in a single day, thereby explicitly representing the ability of individuals to make inter-tour and at-home vs on-tour trade-offs. For example, the model can capture the choice between combining activities into a single tour and spreading them among multiple tours, incorporating the factors that influence this type of decision. Many situations of interest, such as demand management programs, ITS deployment and increased fuel prices, can induce these kinds of activity and travel schedule responses.

In the model, tour decisions are conditioned, or constrained, by the choice of activity pattern. This is based on the notion that some decisions about the basic agenda and pattern of the day's

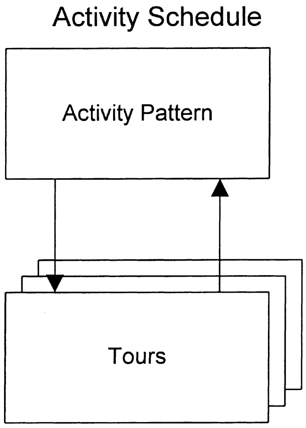

Fig. 1. The activity schedule model framework. An individual's multidimensional choice of a day's activities and travel consists of tours interrelated in an activity pattern.

activities take precedence over details of the travel decisions. The probability of a particular activity schedule is therefore expressed in the model as the product of a marginal pattern probability and a conditional tours probability

$$p(\text{schedule}) = p(\text{pattern})p(\text{tours}|\text{pattern}), \tag{1}$$

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

But the choice of pattern is not independent of the conditional tours decisions. Rather, the relative attractiveness – or utility – of a pattern depends on the expected value of the maximum utility to be gained from its associated tours. Through the expected utility, the pattern's choice probability is a function of the attributes of all its available tours alternatives. This relation captures sensitivity of pattern choice – including inter-tour and at-home vs on-tour trade-offs already mentioned – to spatial characteristics and transportation system level of service, and is the most important feature of the proposed model system.

At a minimum, the pattern is characterized by (a) the primary activity, with one alternative being to remain at home for all the day's activities (b) the type of tour for the day's primary activity, including the number, purpose and sequence of activity stops, and (c) the number and purpose of secondary tours. The tours decision involves the selection of activity location for the activities in each tour, as well as the time of day and modes of travel.

Inherent in this definition of the pattern is the notion of activity priority, or importance, and the assumption that people use a priority-based decision process. Accordingly, more definition is given to the tour on which the primary activity occurs. Other tours are considered secondary.

2.2. Example

Fig. 2 shows how a particular implementation of the activity schedule model might explicitly represent the dimensions of a person's activity and travel itinerary. The hypothetical itinerary (Fig. 2a) shows that this person departed for work at 7:30 AM, driving alone from home in traffic

(a) Itinerary

7:30 AM	Drive alone from from home in zone A to work in zone B.
noon	Walk for lunch and personal business, returning to work
4:40 PM	Depart for home, stopping at the bank in zone C
5:00 P.M.	Depart for home from the bank.
7:00 PM	Drive with family to mall in zone C for shopping.
10:00 PM	Return home.

(b) Model Representation

Activity Pattern

Primary activity	work
Primary tour type	home-work-other-work-other-home
Number and purpose of secondary tours	1 tour, purpose 'other'

Primary Tour

Primary stop	destination	zone B
	mode	drive alone
	time of day	AM peak
		PM peak
work-based subtour	destination	zone B
	mode	walk
	time of day	midday
		midday
after work stop	destination	zone C
	time of day	PM peak

Secondary Tour

Primary stop	destination	zone D
	mode	drive with passenger
	time of day	evening
		evening

Fig. 2. Hypothetical activity schedule: (a) A 24 h itinerary; (b) a corresponding model representation.

zone A to work in zone B. At noon they walked out for lunch and personal business, returning to work for the afternoon. At 4:40 PM they departed for home, stopping on their way at the bank in zone C, where they departed for home at 5:00 PM. That evening at 7:00 PM they drove with other family members to the mall in traffic zone C for shopping, and drove home at 10:00 PM that evening.

Fig. 2b shows how one implementation of the proposed model might represent the choice. In the marginal pattern model, the primary activity is work; the primary tour type is the sequence "home-work other-work other-home", reflecting the purpose and sequence of the activity stops in the tour; and one secondary tour is undertaken, with a purpose of "other" (i.e., other than work or school). In the conditional tours model system, the work destination is zone B, the mode of the primary activity is drive alone, and departures to and from the activity occur during the AM and PM peak periods, respectively; the destination, mode and departure times of day of the work-based subtour are zone B, walk, and midday/midday; the representation of the after work stop includes only destination in zone C and departure from the activity during the PM peak; and finally, the destination, mode and times of day of the secondary tour are zone C, auto with passenger, and evening/evening.

The example can be used to point out two important features of the model system. First, it includes time of day decisions as the choice of departure times to and from the activity, providing a categorization of travel time of day and an implicit representation of activity duration. Second, temporal–spatial constraints can be captured by the restriction of choice sets. In this example, the work-based subtour could not occur in the early morning or late evening, because in the higher priority pattern decision the traveler chose to pursue this activity as a subtour during the daytime work activity. Likewise the secondary tour could not occur during the midday period.

The example defines categories for the subchoices of the activity schedule, as must any particular implementation of the model system, although the design accommodates a variety of categorizations. The categories chosen for implementation significantly affect the complexity of the model system, as well as its ability to provide usable, policy-sensitive forecasts. The prototype described in the next section has a less detailed representation than this example, excluding secondary stops on tours. A subsequent operational pilot implementation for the Portland, Oregon, metropolitan has more detail; it explicitly represents at-home primary activities, incorporating trade-offs between on-tour and at-home activity participation for work, maintenance and discretionary activities (Bowman et al., 1998).

2.3. Nested logit model form

Nested logit models, first estimated 25 years ago by Ben-Akiva (1973), effectively model multidimensional choice processes where a natural hierarchy exists in the decision process, using conditionality and expected utility as described above. In addition to the hierarchy between pattern and tours, the marginal pattern model and the conditional tours model system each involve multiple dimensions and can be specified as nested logit models.

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, ch. 10).

Nesting the model helps capture correlation among alternatives that is common with multidimensional choice sets. However, for a decision as complex as the activity schedule it is impossible with simple nesting to fully capture the correlations – such as spatial correlation in destination choice dimensions. On the other hand, the correlation conditions required by the nested logit model are statistically testable (Ben-Akiva and Lerman, 1985, chs. 7 and 10; McFadden, 1987), enabling the modeler to seek a specification that satisfies them.

2.4. Model system operation

A Monte-Carlo procedure is used to produce aggregate predictions. In other words, the model makes predictions with disaggregate data. The model is applied to each decision maker in the population – or a representative sample – yielding either a simulated activity schedule or a set of probabilities for alternatives in the choice set. Sequence, timing, mode and destination information in each activity schedule is translated into a set of trips. These are aggregated in time-and mode-specific trip matrices and assigned to the transport network, resulting in a prediction of transport system level of service. This process may require replications to achieve statistically reliable predictions. It may also require trip matrix adjustment to include trips not explicitly represented in the model, using factors for each origin–destination pair derived by comparing modeled and actual trips in the estimation data set. A successful implementation of the proposed model system would require a sufficiently detailed representation of the activity schedule so that the important policy sensitive travel responses are modeled explicitly rather than relying on the policy insensitive matrix adjustment procedure.

3. Prototype model system

3.1. Introduction

In this section we present a prototype of the day activity schedule model system, developed using data from the Boston metropolitan area, including a 24 h household travel diary survey collected in 1991, as well as zonal and time-of-day-specific transportation system attributes from the same time period. Survey respondents reported activities requiring travel, and details of the associated travel.

Section 3.2 presents a description of the model specification and associated data preparation issues, starting with an overview, then proceeding to describe the pattern and finally the tours models. In the subsequent subsection we present the results of model parameter estimation, this time starting with the tours models and proceeding to the pattern. The section concludes with a critique of the prototype, focusing on the implications of its limitations and the prospects for an operational implementation.

3.2. Prototype specification

To implement the basic structure of (1), the prototype groups the elemental decisions of the activity schedule into five major tiers, including (a) activity pattern, which is the marginal model of Eq. (1), plus four tiers that together constitute the conditional tours model system: (b) primary tour time of day, (c) primary destination and mode, (d) secondary tour time of day, and (e) secondary tour destination and mode, as shown in Fig. 3.

Activity pattern model. The activity pattern is a nested logit model as depicted in Fig. 4. It represents the choice between a pattern with travel and one without. Given the choice of a pattern with travel it also includes the conditional choice among 54 patterns with travel.

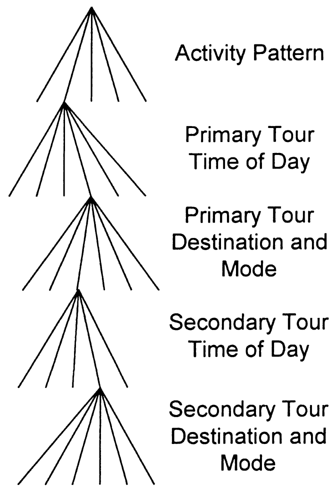

Fig. 3. Activity Schedule hierarchy. Lower tier models are conditioned by decisions in higher tiers.

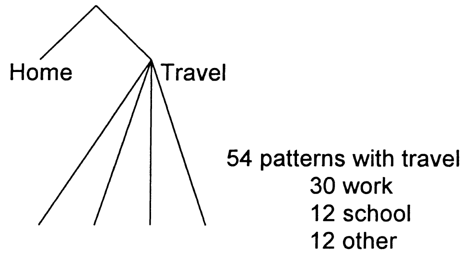

Fig. 4. Nested logit model of the choice of activity pattern. The upper level is a binary choice between staying at home all day and a pattern with travel. The lower level is a choice among 54 alternatives with travel.

The utility function of each pattern includes the expected maximum utility variable from the lower level tours model alternatives, providing the link that makes the entire activity schedule a sequentially estimated nested logit model system.

Each activity pattern with travel is defined by a primary activity, a primary tour type and the number and purpose of secondary tours. The primary activity is defined as the most important activity of the day. If it occurs on a tour, this tour is designated the primary tour and all other tours are designated as secondary.

With this definition it is necessary to identify in the estimation data set the most important activity of the day, information not available in the Boston data. Lacking this information, a deterministic rule is used based on the research of Hague Consulting Group (Antonisse et al., 1986) who investigated the ability of various deterministic rules and a stochastic model to match priorities reported by survey respondents. They found a simple deterministic rule worked best, but it matched the reported priority in only 76% of the cases, and did not report the success rate for nonwork patterns, which we suspect were even lower. If, as we propose, the model design should be based on activity priority, it would be advisable to collect activity priorities directly in activity/travel surveys.

In the selected rule, all the activities within a tour are ranked by priority, with work being the highest priority, followed in order by work related, school, and all other purposes. Ties are broken by assigning higher priority to activities of longer duration. Within an individual's activity pattern the tours are assigned relative priorities by giving highest priority to the tour containing the highest priority activity, and so on until all tours are assigned a priority.

Each dimension of the activity pattern is discussed below. The primary activity is classified as home, work, school or other. This classification is somewhat arbitrary and quite limited. A more customary classification distinguishing subsistence (work or school), maintenance (household or personal business activities) and leisure (activities engaged in for pleasure, recreation or refreshment) may be more appropriate.

Tour type is defined by the number, purpose and sequence of activity stops on the tour. The prototype partitions the observed work tour types into five categories. The three predominant categories are (a) the tour from home to work and back again with no additional stops (hwh), (b) the tour with at least 1 additional stop for another activity (hwh+), and (c) the tour with a work-based subtour for another activity as well as any number (including zero) of additional stops for other activities (hw + wh). Two additional work tour categories involve mid-tour returns home, one with no additional activity stops (hwhwh) and another with one or more additional stops (hwhwh+). School and other tours received a simpler categorization involving only the analogs of the first two work tour types. We subsequently sometimes refer to type (a) tours as simple and all other tour types as complex.

The prototype classification lacks important sequence and purpose information. For example, it is unable to distinguish a pattern with a maintenance stop on the way to work from one with a leisure stop after work, two patterns that would have significantly different utilities. A better method would distinguish tour types by the presence or absence of purpose-specific secondary stops at three temporal locations on the tour – before the primary stop, after the primary stop and, for work tours, a work-based subtour (see Bowman, 1998 for details). This would enable the model specification to significantly improve its explanation of pattern choice, and allow the use of more accurate availability constraints in secondary stop models.

The prototype's classification of the activity pattern decision by number and purpose of secondary tours distinguishes 2 purposes and 3 frequencies. The first purpose category – constrained – includes purposes that usually involve tight schedule constraints, including work, work related, school, and banking/personal business; the second category – unconstrained – includes all other purposes. The 3 frequencies are 0, 1 and 2 or more secondary tours. The feasible combinations of purpose and number yield a set of six alternatives, including (a) 0 secondary tours, (b) 1 secondary tour with schedule constrained purpose, (c) 1 secondary tour with schedule unconstrained purpose, (d) 2 or more secondary tours with schedule constrained purposes, (e) 2 or more secondary tours with schedule constrained and unconstrained purposes, and (f) 2 or more secondary tours with schedule unconstrained purposes. An improved representation would use the same purpose categories for primary and secondary tours – subsistence, maintenance and discretionary – making it easier to capture purpose-specific inter-tour trade-offs.

The categorization of the activity pattern by purpose, primary tour type and number and purpose of secondary tours, as described above, yields a choice set of 55 alternatives in the Boston prototype, including the home pattern, 30 work tour patterns, 12 school tour patterns and 12 other tour patterns. Table 1 describes the choice alternatives for the 3 dimensions of

Table 1
Activity pattern alternatives in the Boston prototype

Decision	Choice alternative	Description
Primary activity	Home	At home all day
	Work	The activity pattern includes at least 1 work activity
	School	The activity pattern includes no work activities and at least 1 school activity
	Other	The activity pattern includes no work or school activities
Primary tour type	HWH	Simple tour from home to work and back
	HWH+	Work tour with at least 1 additional stop for another activity
	HW + WH	Work tour with a work-based subtour, and any number of additional stops
	HWHWH	Work tour with an intermediate stop at home
	HWHW-H+	Work tour with an intermediate stop at home, plus 1 or more additional stops
	HSH	Simple tour from home to school and back
	HSH+	School tour with at least 1 additional stop for another activity
	HOH	Simple tour with purpose other than work or school
	HOH+	Tour with purpose other than work or school, with at least 1 additional stop for another activity
Number and purpose of secondary tours	0	No secondary tours
	1, C	One secondary tour, with a purpose (i.e. the primary activity of the tour) that is time constrained (work, work related, school, banking/personal business)
	1, U	One secondary tour with a purpose that is not time constrained (social, recreational, eat out, shopping)
	2+, C	Two or more secondary tours, all time constrained
	2+, CU	Two or more secondary tours, 1 or more time constrained and 1 or more not time constrained
	2+, U	Two or more secondary tours, none time constrained

the activity pattern, and Table 2 lists all 55 alternatives and their relative frequency in the sample.

The collection in the diary survey of information about activities conducted at home would enable a more detailed categorization of patterns with at-home activities, and could lead to a restructuring of the model's hierarchy. For example, the model might distinguish the primary activity of the day not only by three purposes, but also by whether it is conducted at home or on a tour, allowing for the possibility of secondary tours in all six cases.

Tours model structure. As defined in the Boston prototype, any activity schedule with travel always has a primary tour, and may have zero, one or more secondary tours. The conditional tours probability of (1) consists of the joint probability of all modeled dimensions of all the tours in the schedule. The secondary tours are modeled conditional on the primary tour outcome, so the tours probability is expressed as the product of the primary tour probability and the conditional probability of the secondary tour outcomes, given the primary tour

Table 2
Activity pattern alternatives and their relative frequency in the estimation data set

Primary activity	Primary tour type	Number and purpose of secondary tours	Percentages		
			Workers	Non-workers	Total
At home			9.95	28.17	15.08
Work	hwh	0	13.76		9.88
		1 constrained	3.86		2.77
		1 unconstrained	5.83		4.19
		2 + constrained	0.59		0.42
		2 + constrained and unconstrained	1.33		0.96
		2 + unconstrained	0.80		0.57
	hwh+	0	17.24		12.39
		1 constrained	2.47		1.78
		1 unconstrained	5.59		4.01
		2 + constrained	0.56		0.40
		2 + constrained and unconstrained	1.46		1.05
		2 + unconstrained	0.56		0.40
	hw + wh	0	11.79		8.47
		1 constrained	1.36		0.97
		1 unconstrained	5.14		3.69
		2 + constrained	0.21		0.15
		2 + constrained and unconstrained	0.40		0.29
		2 + unconstrained	0.27		0.19
	hwhwh	0	0.72		0.52
		1 constrained	0.13		0.10
		1 unconstrained	0.43		0.31
		2 + constrained	0.03		0.02
		2 + constrained and unconstrained	0.11		0.08
		2 + unconstrained	0.08		0.06
	hwhwh+	0	1.14		0.82
		1 constrained	0.19		0.13
		1 unconstrained	0.53		0.38
		2 + constrained	0.05		0.04
		2 + constrained and unconstrained	0.00		0.00
		2 + unconstrained	0.08		0.06
School	hsh	0	0.64	3.12	1.34
		1 constrained	0.08	0.54	0.21
		1 unconstrained	0.51	2.04	0.94
		2 + constrained	0.05	0.34	0.13
		2 + constrained and unconstrained	0.19	0.54	0.29
		2 + unconstrained	0.11	0.41	0.19
	hsh+	0	0.88	3.67	1.66
		1 constrained	0.24	0.75	0.38
		1 unconstrained	0.43	1.90	0.84
		2 + constrained	0.00	0.34	0.10
		2 + constrained and unconstrained	0.11	0.41	0.19
		2 + unconstrained	0.16	0.27	0.19
Other	hoh	0	1.57	11.74	4.44
		1 constrained	0.80	4.07	1.72

Table 2 (*Continued*)

Primary activity	Primary tour type	Number and purpose of secondary tours	Percentages		
			Workers	Non-workers	Total
		1 unconstrained	0.80	7.06	2.56
		2 + constrained	0.35	2.31	0.90
		2 + constrained and unconstrained	0.67	4.07	1.62
		2 + unconstrained	0.21	1.83	0.67
	hoh+	0	2.45	13.10	5.45
		1 constrained	0.75	3.87	1.62
		1 unconstrained	1.25	4.68	2.22
		2 + constrained	0.21	0.81	0.38
		2 + constrained and unconstrained	0.64	3.19	1.36
		2 + unconstrained	0.29	0.75	0.42
Total			100.00	100.00	100.00

$$p(\text{tours}|\text{pattern}) = p(\text{primary tour}|\text{pattern})p(\text{secondary tours}|\text{primary tour}). \tag{2}$$

Secondary tours are considered to be mutually independent and the conditional secondary tours probability is expressed as

$$p(\text{secondary tours}|\text{primary tour}) = \prod_{t=1}^{T} p(\text{secondary tour}_t|\text{primary tour}), \tag{3}$$

where $p(\text{secondary tour}_t|\text{primary tour})$ is the conditional probability of the dimensions of secondary tour t given the primary tour, $t = 1, \ldots, T$ and T is the number of secondary tours in the schedule. All secondary tour probabilities are calculated from the same secondary tour model. This approach ignores time constraints and correlation across secondary tours, but simplifies the model structure, which would otherwise involve repeated conditional tour nesting via a secondary tour, tertiary tour, etc.

Substituting (2) and (3) into (1) we obtain the expression of the activity schedule probability as specified in the Boston prototype:

$$p(\text{schedule}) = p(\text{pattern})p(\text{primary tour}|\text{pattern})\prod_{t=1}^{T} p(\text{secondary tour}_t|\text{primary tour}). \tag{4}$$

For the primary tour and each of the secondary tours, the time of day, primary destination and mode are modeled, with the choice of mode and destination conditioned by the time of day choice

$$p(\text{tour}) = p(\text{timing})p(\text{mode, destination}|\text{timing}). \tag{5}$$

A weakness of the Boston prototype is the lack of explicit models of secondary tour stops, an important feature for accurately capturing trip chaining behavior and inter-tour trade-offs. To handle this (5) might be enhanced by modeling secondary stops conditional on the primary stop choice, representing the tour probability as

$$p(\text{tour}) = p(\text{timing})p(\text{mode, dest}|\text{timing})p(\text{secondary stops}|\text{timing, mode, dest}). \tag{6}$$

Tour time of day models. Two similar MNL models of the choice of tour time of day are estimated, one each for secondary and primary tours. Each of the 16 alternatives is comprised of

1 of 4 time periods for departure from home to the primary destination and 1 of 4 time periods for departure from the primary destination returning home. These 4 time periods include AM peak (6:30–9:29 AM), midday (9:30 AM–3:59 PM), PM peak (4:00–6:59 PM), and other (7:00 PM–6:29 AM). All time periods are considered available to all persons for primary tours. For secondary tours, times that overlap with the chosen primary tour time are removed from the choice set.

Tour destination and mode choice models. The destination and mode choice model involves the choice of a mode for the tour instead of the usual choice of mode for a trip. The Boston survey respondents did not report their travel mode on a tour basis, but instead reported every mode used, in sequence, sometimes reporting several modes for a single trip, with different sets of modes used for different trips in the same tour. Thus, the modeling of a tour mode choice required a decision rule for translating a large set of potentially complex sequences of reported modes into a smaller choice set of tour mode alternatives. The rule selected was able to automatically assign over 98% of the sample to one of six modes, including auto drive alone, auto shared ride, transit with auto access, transit with walk access, walk and bicycle. Additional rules were used to judge which of the 6 mode alternatives were available to each person in the estimation data set. For more details see Bowman (1995).

The definition of mode alternatives could be enhanced within the proposed model system framework to include more sophisticated mixes of intermodal travel, as is sometimes done in mode choice models. It would also be possible to define some alternatives in terms of two modes, namely the modes used for the outgoing and return trips, respectively. If secondary tour stops were explicitly modeled, mode choice could be modeled if it was likely to occur, such as for work-based subtours.

An important difference between the primary and secondary tour model specifications is the inclusion in the primary tour model of the expected maximum utility variable, computed from the secondary tour model. This link turns the models into an informal nested logit system. The calculation of the expected maximum utility requires a special application of the theory of the nested logit model to capture the expected maximum utility from a multiple number of secondary tours. The resulting expected maximum utility of all secondary tours is equal to the sum of the expected maximum utility of each of the tours. Since the expected maximum utility of a single tour is equal to the logarithm of the sum of the exponentiated systematic utilities of all available tour alternatives (logsum), the expected maximum utility among multiple tours is simply the sum of the logsums across all secondary tours in the pattern.

3.3. Prototype model estimation results

Model parameters were estimated simultaneously within each tier and sequentially across tiers. Three factors prevented the simultaneous estimation of the model's parameters across two or more tiers. These include (a) the independent nesting of multiple conditional secondary tours, (b) the use of alternative sampling for destination choice, described later, and (c) our desire to work within the capacity limits of commercially available nested logit estimation software (all models were estimated with ALOGIT, by Hague Consulting Group). The sequential estimation procedure yields consistent parameter estimates that are different than simultaneously estimated parameters. It also yields inconsistent estimates of the standard errors of the parameter estimates;

they are usually underestimated, especially for the parameters of the expected utility variables. In this paper the reported standard errors have not been corrected.

We present estimation results first for the destination and mode choice models, followed by time of day, and finally the activity pattern.

Destination and mode choice. The tour destination and mode choice models are estimated as multinomial logit (MNL) models with alternative sampling. A sample of up to 48 alternatives is constructed for each tour in the data set, using stratified importance sampling (Ben-Akiva and Lerman, 1985, p. 266). The sample includes 8 of 786 possible geographic zones, with up to 6 modes available for each destination. Details of the sampling procedure are provided in Bowman (1995).

Estimation of the destination and mode choice model requires the definition of transportation system level of service variables and preparation of such data for all of the mode alternatives, by the four time of day categories used in the time of day choice models. Interzonal roadway distance is used as the transportation system level of service measure for walk and bicycle modes, since the data set provides no good level-of-service attributes such as travel times, bikeway availability or sidewalk connectivity. Costs and travel times are defined in traditional ways, although the models require values of these attributes by time of day.

Table 3 shows the complete estimation results of the destination and mode choice models for primary and secondary tours. The specification reflects a substantial amount of testing and re-specification, and is adequate for demonstrating the proposed model system design, but retains some important deficiencies that would need to be corrected in an operational implementation. In particular, although the coefficient signs for the level of service variables are correct, they imply unreasonable values of time in some cases, indicating the need to check further for data problems and improve the model specification. For instance, for a household with annual income of \$54,000, the value of auto in-vehicle time on secondary tours is too high at \$114 per hour, and for transit the value of out-of-vehicle time is lower than that of in-vehicle time.

The following discussion highlights differences in behavior between primary and secondary tours, a feature of the model system that differentiates it from typical trip and tour-based models. The presence of cost (coefficient 6 in Table 3) in the primary work tour model, accompanied by cost/income (coefficient 10) that is smaller for the work tour, indicates that low income does not increase cost sensitivity as much for primary work tours as it does for non-work and secondary tours. Coefficient 7 in both work and non-work models indicates that the presence of any or all of the employer incentives of mileage allowance, subsidized parking or company car tends to offset the disutility of the cost of driving alone. Coefficients 8 and 9 yield similar, but even stronger effects on the disutility of transit costs in the presence of employer subsidized transit passes, but this effect occurs only for work tours. The socioeconomic variables of auto availability and income have substantially different mode choice effects for primary tours than for secondary tours.

Since the secondary tour destination and mode choice model is conditioned by the choice of destination and mode for the primary tour, the actual choices of mode and destination in the primary tour are used to explain choices in the secondary tour. Coefficients 25–27 indicate a tendency for people who choose drive alone, shared ride or bicycle in their primary tour to choose the same mode again for their secondary tours, with the effect being dramatically strong for the bicycle mode; the effect is insignificant for the other modes. Coefficient 28 indicates a similar effect in destination choice for work tours, with persons tending to choose the same destination zone for

Table 3
Tour destination and mode choice models

Variable name (units), alternatives		Coefficient estimates (uncorrected standard errors)					
		Secondary tours		Primary work tours		Primary nonwork tours	
Mode constants (*base case is drive alone* (*da*))							
1	Shared ride (sr)	1.16	(0.21)	−0.113	(0.32)	0.893	(0.24)
2	Transit w/auto (ta)	−4.06	(0.73)	−1.06	(0.43)	−1.86	(0.52)
3	Transit w/walk (tw)	−1.08	(0.51)	1.09	(0.36)	0.849	(0.36)
4	Walk (wa)	−0.337	(0.33)	0.742	(0.35)	1.26	(0.32)
5	Bicycle (bi)	−4.67	(0.96)	−1.46	(0.54)	−1.66	(0.54)
Level of service variables							
6	Cost ($), motorized modes			−0.0505	(0.024)		
7	Cost for persons w/da incentive ($), da			0.192	(0.029)	0.264	(0.038)
8	Cost for persons w/employer transit incentives ($), ta			0.482	(0.082)		
9	Cost for persons w/employer transit incentives ($), tw			0.382	(0.080)		
10	Cost/inc (/10,000), motorized modes	−0.276	(0.065)	−0.232	(0.064)	−0.440	(0.056)
11	In-vehicle time (min), auto	−0.0976	(0.0020)	−0.0416	(0.0016)	−0.0596	(0.0015)
12	In-vehicle time (min), transit	−0.0653	(0.0094)	−0.0192	(0.0028)	−0.0277	(0.0034)
13	Out-of-vehicle time (min), auto	−0.115	(0.015)	−0.0656	(0.015)	−0.0864	(0.014)
14	Out-of-vehicle time (min), transit	−0.0261	(0.0096)	−0.0283	(0.0046)	−0.0279	(0.0050)
15	Distance squared (mi^2), walk	−0.416	(0.031)	−0.190	(0.022)	−0.416	(0.034)
16	Distance (mi), bicycle	−0.845	(0.19)	−0.443	(0.085)	−0.537	(0.11)
Socioeconomic variables							
17	Autos per driver, shared ride	−0.442	(0.21)	−1.94	(0.35)	−1.03	(0.24)
18	Autos per driver, transit w/auto	−2.12	(0.84)	−1.29	(0.41)	−0.913	(0.51)
19	Autos per driver, transit w/walk	−2.84	(0.49)	−3.73	(0.32)	−4.01	(0.34)
20	Autos per driver, walk	−1.52	(0.29)	−3.16	(0.38)	−2.71	(0.33)
21	Autos per driver, bicycle	0.483	(0.89)	−3.02	(0.62)	−3.57	(0.64)
22	Household income ($10,000), tw	−0.132	(0.069)				
23	Household income ($10,000), wa	−0.0541	(0.033)				
24	Household income ($10,000), bi	−0.230	(0.14)				

Alternative specific dummies							
25	Mode matches primary tour mode, da	0.330	(0.11)				
26	Mode matches primary tour mode, sr	0.506	(0.14)				
27	Mode matches primary tour mode, bi	5.48	(0.73)				
28	Work tour, destination matches primary tour destination	1.11	(0.27)				
29	Age under 20, bicycle			2.46	(1.1)	1.22	(0.78)
30	Simple tour, transit w/walk			0.356	(0.16)		
31	Simple tour, transit w/auto					−1.06	(0.36)
Size and logsum variables							
32	Size: employment (100,000), CBD zones	0.822	(0.10)	0.806	(0.074)	0.905	(0.084)
33	Size: employment (100,000), non-CBD	0.656	(0.029)	0.999	(0.033)	0.870	(0.031)
34	Logsum: expected maximum utility from secondary tours			0.556	(0.23)	0.515	(0.26)
Summary statistics							
Number of observations		2068		1901		1929	
$\mathscr{L}(0)$		−11,163		−7740		−9126	
$\mathscr{L}(\hat{\beta})$		−4773		−3733		−4641	
$\bar{\rho}^2$		0.570		0.514		0.489	

secondary work tours as they choose for their primary (work) tour. Coefficients 30 and 31 capture trip chaining tendencies.

Finally, coefficient 34 is the logsum coefficient associated with the expected maximum utility of secondary tours. It is in the acceptable range for nested logit models, and reveals a strong influence of secondary tour utility on the choice of alternatives in the primary tour. Activity patterns with more secondary tour travel, due either to more or longer tours, generally have smaller values (less positive or more negative) of the logsum variable. Thus, the positive sign of this coefficient means that primary tour alternatives that are linked in an activity pattern with a substantial amount of secondary tour travel will have lower utility than those with little or no secondary tour travel, all other things being equal.

Time of day models. The time of day models are estimated as MNL models. The utility functions were initially specified with the expected maximum utility variable from the corresponding destination and mode choice model. However, these parameter estimates did not fit in the theoretically acceptable range of 0–1 and also had very high standard errors. That is, the data did not indicate a clear effect of mode and destination accessibility on the time of day choice. This might be caused by inaccuracy of the transportation system level of service data by time of day, the coarse granularity of the time of day choice categories, or improper specification of the nesting hierarchy. The logsum variables are therefore excluded from the model. The prototype nested logit model system therefore excludes the time of day models from the logsum linkages, although the destination and mode choice models are still conditioned by their respective time of day choices.

Tables 4 and 5 show the estimation results of the time of day choice models for secondary tours and primary tours, respectively. In the secondary tour model, coefficients 1–8 are alternative specific constants, with a base case of travel to and from the primary destination occurring after the PM peak. Coefficients 9 and 10 indicate worker preferences of conducting the secondary tour during a peak period or after the evening peak. Coefficients 11–16 indicate the preference of several types of people to conduct secondary tour(s) before the evening, including those whose primary tour involves a single activity, whose primary activity of the day is not school or work, or who conduct 2 or more secondary tours. Coefficient 17 indicates a tendency for secondary tours of short duration if there are 2 or more in the activity pattern.

In the primary tour time of day model, shown in Table 5, coefficients 1–12 are the alternative specific constants, with a base case of travel to and from the primary destination during the midday time period. Coefficients 13 and 14 capture commuter peak period tendencies. Coefficient 15 captures a strong tendency to shift the work tour schedule so travel occurs before or after the AM and PM peak periods, and coefficient 16 captures a slight tendency for the work tour to occur during the night. Coefficients 17–19 reveal preferences when the primary tour involves more than one activity stop: there is a tendency to avoid tours that span a peak period or occur in the evening, and a slight tendency to start the tour during the AM peak. Coefficients 20–22 indicate time of day preferences when there are no secondary tours in the pattern, with a tendency to avoid evening tours and those that require peak period travel, and to choose a schedule that fully spans the midday period.

Activity pattern model. The two dimensions of the nested logit activity pattern model are estimated jointly. Because of expected differences in choice behavior between employed persons (workers) and those who are not employed (non-workers), we divide the data set and estimate two

Table 4
Secondary tour time of day model

Variable number	Variable name	Coefficient estimate	Uncorrected stand. error	*t*-Statistic
Basic alternative specific constants (*base case is after PM peak to after PM peak*)				
1	Before AM peak to AM peak constant	−4.042	0.266	−15.2
2	AM peak to AM peak constant	−2.606	0.158	−16.5
3	AM peak to midday constant	−2.770	0.147	−18.8
4	midday to midday constant	−1.411	0.144	−9.8
5	Midday to PM peak constant	−2.874	0.149	−19.3
6	PM peak to PM peak constant	−1.438	0.140	−10.3
7	PM peak to after PM peak constant	−0.5182	0.110	−4.7
8	Constant for other alternatives other than after PM peak to after PM peak	−5.953	0.282	−21.1
Activity pattern dummy variables				
9	Primary activity of activity pattern (AP) is work, alternatives with travel during at least 1 peak period	0.5508	0.114	4.8
10	Primary activity of AP is work, alternative is after PM peak to after PM peak	0.3869	0.155	2.5
11	primary tour type is HPH, alternatives in which activity ends during AM peak	0.5967	0.151	3.9
12	Primary tour type is HPH, alternative is PM peak to PM peak	0.3697	0.120	3.1
13	Primary tour type is HPH, alternatives other than those ending in AM peak, or starting and ending during or after PM peak	0.8468	0.099	8.6
14	Primary activity of AP is other than work or school, alternative is before PM peak to before or during PM peak	2.158	0.129	16.7
15	Primary activity of AP is other than work or school, alternative is PM peak to PM peak	1.274	0.152	8.4
16	AP has 2 or more secondary tours, alternatives in which activity ends before or during PM peak	0.7866	0.088	8.9
17	AP has 2 or more secondary tours, alternatives with a long tour (i.e., fully spanning a time period)	−1.992	1.03	−1.9

Summary statistics
Number of observations = 2873
$\mathscr{L}(0) = -7966$
$\mathscr{L}(C) = -5404$, $\bar{\rho}^2 = 0.321$ (restricted model: variables 1–8 only)
$\mathscr{L}(\hat{\beta}) = -4953$, $\bar{\rho}^2 = 0.376$

models, one for workers and another for non-workers. The non-worker model includes only the 25 non-work activity pattern alternatives.

Tables 6 and 7 show the estimation results for workers and non-workers, respectively. In the worker model the first 33 coefficients are alternative specific constants, with some of the 54 alternatives combined because early versions of the model revealed insignificant differences between the estimated coefficients. Coefficients 34–44 are for various socioeconomic characteristics associated with particular subsets of the population and particular subsets of the activity pattern alternatives. Coefficients 34–36 are associated with the simplest non-home activity pattern,

Table 5
Primary tour time of day model

Variable number	Variable name	Coefficient estimate	Uncorrected stand. error	*t*-Statistic
Basic alternative specific constants (*base case is midday to midday*)				
1	Before AM peak to AM peak	−3.621	0.175	−20.7
2	Before AM peak to midday	−3.200	0.153	−21.0
3	Before AM peak to PM peak	−2.644	0.110	−24.1
4	AM peak to AM peak	−3.118	0.149	−21.0
5	AM peak to midday	−0.4446	0.084	−5.3
6	AM peak to PM peak	−2.533	0.140	−18.0
7	AM peak to after PM peak	−2.522	0.106	−23.9
8	Midday to PM peak	−1.527	0.088	−17.4
9	Midday to after PM peak	−3.205	0.165	−19.4
10	PM peak to PM peak	−2.396	0.162	−14.8
11	PM peak to after PM peak	−1.050	0.107	−9.8
12	After PM peak to after PM peak	−1.065	0.128	−8.3
Activity pattern dummy variables				
13	Work purpose, alternatives with travel during at least 1 peak period	2.473	0.133	18.7
14	Work purpose, alternative is AM peak to PM peak	2.559	0.129	19.9
15	Work purpose, alternative is before AM peak to before PM peak, or after AM peak to after PM peak	4.347	0.190	22.9
16	Work purpose, alternative is after PM peak to after PM peak	0.6183	0.301	2.1
17	Complex primary tour, alternative is before AM peak to midday or midday to after PM peak	−0.5478	0.125	−4.4
18	Complex primary tour, alternative is in the evening (i.e., from during or after PM peak to before or during AM peak)	−1.201	0.129	−9.3
19	Complex primary tour, alternative is AM peak to midday or PM peak	0.3115	0.079	3.9
20	No secondary tours, alternative involves travel during or after PM peak	−1.118	0.144	−7.8
21	No secondary tours, alternative is daytime with peak period travel	−0.2271	0.085	−2.7
22	No secondary tours, alternatives that fully span midday	0.5977	0.088	6.8
Summary statistics				
Number of observations = 4546				
$\mathscr{L}(0) = -12{,}604$				
$\mathscr{L}(C) = -9214,\ \bar{\rho}^2 = 0.268$ (restricted model: variables 1–12 only)				
$\mathscr{L}(\hat{\beta}) = -7940,\ \bar{\rho}^2 = 0.368$				

involving only a single commute to the primary activity location, revealing a tendency of 1 adult households and students to have complex patterns, while men with more children tend to have simple patterns. Coefficients 37 and 38 deal with patterns involving secondary tours, with school aged children causing more secondary tours, and females with young children making less secondary tours. Coefficients 39 and 40 show the tendency toward more trip making among higher income, part-time employees. Coefficients 41–44 show socioeconomic variations in the choice of

Table 6
Activity pattern model: workers

Variable number	Variable name	Coefficient estimate	Uncorrected stand. error	*t*-Statistic
Alternative specific constants for HWH patterns (*base case is HWH with* 0 *secondary tours*)				
1	1 secondary tour with constrained purpose	−1.362	0.107	−12.8
2	1 secondary tour with unconstrained purpose	−0.9497	0.0952	−10.0
3	2 + secondary tours with the same (c or u) purpose	−2.945	0.172	−17.1
4	2 + secondary tours with mixed purpose categories	−2.405	0.176	−13.6
Alternative specific constants for HWH + patterns				
5	0 secondary tours	0.2224	0.0760	2.9
6	1 secondary tour with constrained purpose	−1.626	0.132	−12.3
7	1 secondary tour with unconstrained purpose	−0.8107	0.107	−7.6
8	2 + secondary tours with the same (c or u) purpose	−2.874	0.192	−15.0
9	2 + secondary tours with mixed purpose categories	−2.091	0.182	−11.5
Alternative specific constants for HW + WH patterns				
10	0 secondary tours	−0.08887	0.0792	−1.1
11	1 secondary tour with constrained purpose	−2.167	0.162	−13.4
12	1 secondary tour with unconstrained purpose	−0.8356	0.108	−7.7
13	2 + secondary tours with the same (c or u) purpose	−3.662	0.261	−14.0
14	2 + secondary tours with mixed purpose categories	−3.264	0.283	−11.5
Alternative specific constants for HWHWH and HWHWH + patterns				
15	HWHWH	−3.965	0.168	−23.6
16	HWHWH+	−3.349	0.157	−21.3
Alternative specific constants for HSH patterns				
17	0 secondary tours	0.4971	0.267	1.9
18	1 secondary tour with constrained purpose	−2.233	0.588	−3.8
19	1 secondary tour with unconstrained purpose	−0.3875	0.255	−1.5
20	2 + secondary tours	−1.932	0.309	−6.2
Alternative specific constants for HSH + patterns				
21	0 secondary tours	0.1021	0.206	0.5
22	1 secondary tour with constrained purpose	−1.191	0.355	−3.4
23	1 secondary tour with unconstrained purpose	−0.6154	0.279	−2.2
24	2 + secondary tours	−2.207	0.351	−6.3

Table 6 (*Continued*)

Variable number	Variable name	Coefficient estimate	Uncorrected stand. error	*t*-Statistic
Alternative specific constants for HOH patterns				
25	0 secondary tours	−1.042	0.161	−6.5
26	1 secondary tour with constrained purpose	−1.853	0.211	−8.8
27	1 secondary tour with unconstrained purpose	−1.853	0.211	−8.8
28	2 + secondary tours	−2.532	0.197	−12.8
Alternative specific constants for HOH + patterns				
29	0 secondary tours	−0.7726	0.148	−5.2
30	1 secondary tour with constrained purpose	−1.896	0.221	−8.6
31	1 secondary tour with unconstrained purpose	−1.378	0.185	−7.4
32	2 + secondary tours	−2.529	0.209	−12.1
33	Alternative specific constant for home patterns	−1.736	0.302	−5.7
Socioeconomic variables				
34	Dummy: 1-adult households, simple patterns (HWH, HSH or HOH with no secondary tours)	−0.7299	0.165	−4.4
35	Dummy: students with simple patterns	−0.5822	0.189	−3.1
36	Ratio of children to adults, males with simple patterns	0.1981	0.0867	2.3
37	Number of children age 5–15 in household, patterns with 1 + secondary tours	0.2567	0.0394	6.5
38	Dummy: females with children under 5 and no secondary tours	0.2642	0.177	1.5
39	Income ($10,000), part-time workers with 2 + secondary unconstrained tours	0.1238	0.0205	6.0
40	Income ($10,000), part-time workers with extra stops on primary tour	0.07644	0.0150	5.1
41	Dummy: full-time workers with work patterns	1.673	0.112	14.9
42	Dummy: children under 5 in household, work patterns	−0.3674	0.135	−2.7
43	Dummy: homemaker with 'other' primary tour purpose	0.4766	0.205	2.3
44	Dummy: children age 5–15 in household, home patterns	−0.6696	0.135	−5.0
Logsum variables				
45	Logsum: expected maximum utility from primary tour destination and mode alternatives, patterns with simple primary tours	0.04868	0.0175	2.8
46	Logsum: expected maximum utility from primary tour destination and mode alternatives, patterns with complex primary tours	0.09213	0.0176	5.2
47	Logsum: expected maximum utility from activity patterns involving travel	0.09965	0.103	1.0
Summary statistics				
Number of observations = 3758				
$\mathscr{L}(0) = -14{,}263$				
$\mathscr{L}(C) = -10{,}837,\ \bar{\rho}^2 = 0.238$ (restricted model: multinomial logit with variables 1–33 only)				
$\mathscr{L}(\hat{\beta}) = -10{,}585,\ \bar{\rho}^2 = 0.255$				

Table 7
Activity pattern model: non-workers

Variable number	Variable name	Coefficient estimate	Uncorrected stand. error	*t*-Statistic
Alternative specific constants for HOH patterns (*base case is HOH with* 0 *secondary tours*)				
1	1 secondary tour with constrained purpose	−1.087	0.179	−6.1
2	1 secondary tour with unconstrained purpose	−0.5373	0.158	−3.4
3	2 + secondary tours	−1.589	0.238	−6.7
Alternative specific constants for HOH + patterns				
4	0 secondary tours	0.09310	0.172	0.5
5	1 secondary tour with constrained purpose	−1.169	0.242	−4.8
6	1 secondary tour with unconstrained purpose	−0.9782	0.236	−4.1
7	2 + secondary tours	−2.146	0.315	−6.8
Alternative specific constants for HSH patterns				
8	0 secondary tours	1.689	0.227	7.4
9	1 secondary tour with constrained purpose	−0.08377	0.406	−0.2
10	1 secondary tour with unconstrained purpose	1.271	0.268	4.7
11	2 + secondary tours	−0.4455	0.350	−1.3
Alternative specific constants for HSH + patterns				
12	0 secondary tours	1.832	0.256	7.2
13	1 secondary tour with constrained purpose	0.1809	0.392	0.5
14	1 secondary tour with unconstrained purpose	1.115	0.313	3.6
15	2 + secondary tours	−0.7189	0.412	−1.7
16	Alternative specific constant for home pattern	−0.5606	0.157	−3.6
Socioeconomic variables				
17	Number of children age 5–15 in household, patterns with 1 + secondary tours	0.2885	0.0755	3.8
18	Dummy: children under 5 in household, patterns with 1 + secondary tours	0.3087	0.173	1.8
19	Ratio of children to adults, males with simple patterns	0.6308	0.248	2.5
20	Income ($10,000), patterns with 2 + secondary unconstrained tours	0.1154	0.0200	5.8
21	Income ($10,000), patterns with extra stops on primary tour	0.03409	0.0211	1.6
22	Children 5–15 in household, home patterns	−0.5896	0.148	−4.0
Logsum variables				
23	Logsum: expected maximum utility from primary tour destination and mode alternatives, patterns with simple primary tours	0.03764	0.0390	1.0
24	Logsum: expected maximum utility from primary tour destination and mode alternatives, patterns with complex primary tours	0.05467	0.0415	1.3
25	Logsum: expected maximum utility from activity patterns with travel	0.1249	0.0794	1.6

Summary statistics
Number of observations = 1474
$\mathscr{L}(0) = -4006$
$\mathscr{L}(C) = -3354$, $\bar{\rho}^2 = 0.159$ (restricted model: multinomial logit with variables 1–16 only)
$\mathscr{L}(\hat{\beta}) = -3274$, $\bar{\rho}^2 = 0.176$

primary activity, with full-time workers tending to choose work, parents with young children choosing not to work, homemakers choosing travel for other purposes and individuals with school-aged children choosing not to stay home.

Coefficients 45 and 46 are the logsum coefficients capturing the effect of expected utility from the tour models in the conditional choice among 54 patterns with travel. Coefficient 47 is the logsum coefficient capturing the effect of the conditional model's expected utility on the marginal choice between a pattern with travel and a pattern that stays home all day. The values, between 0 and 1, fall within the theoretically acceptable range for the nested logit structure, and the small size indicates a rather small influence of travel utility on the choice of activity pattern. Nevertheless, the effect of these variables is one of the key features of the activity schedule model system. Suppose, for example, that this model was being used to predict the effect of an increase in fuel prices. A fuel price increase would manifest itself in the secondary and primary tour models as negative utility. Negative utility in these lower level models would reduce the size of variables 45–47, affecting activity patterns with more travel more than other patterns, with the stay at home alternative being totally unaffected. Thus, this model system would predict a shift toward patterns with less travel in response to an increase in fuel prices. This might take various forms, depending on the values of the estimated parameters and the magnitude of the change in fuel prices. For example, it might predict a shift toward simpler primary tours (i.e., less stops and/or shorter distances) and a reduction in the number of secondary tours. It might, however, predict a reduction in the number of secondary tours with a partially offsetting addition of stops chained to the primary tours. A closer look at this effect in the model system explains the relative size of coefficients 45 and 46. The larger value of coefficient 46 indicates that, given a particular logsum variable value, patterns with complex primary tours are affected more than those with simple primary tours. This is because the formulation of the tour models does not explicitly capture the differences in utility between simple and complex primary tours because secondary stops are not modeled explicitly. The greater effect of a fuel price increase, for example, on patterns with complex primary tours is captured by the larger size of coefficient 46, rather than by a larger value of the logsum variable. This stands in contrast to the effect of a fuel price increase on the number of tours, where the calculation of the logsum variable captures a greater effect among patterns with more tours.

The non-worker model, shown in Table 7, provides results similar to those of the worker model, but with a smaller number of alternative specific constants, a somewhat different set of socioeconomic variables, and some differences in the magnitude of coefficients. The logsum coefficients are somewhat smaller in magnitude than those of the worker model, which means the predicted response to changes in factors affecting travel utility would be smaller for non-workers than for workers. The estimates also have a higher standard error, which can be partially explained by the substantially smaller estimation sample size.

3.4. Evaluation of the prototype

The purpose of the prototype is to demonstrate the concept of the activity schedule model system, test important features, and gain an initial evaluation of the method's potential for further research and operational implementation. A number of simplifications were introduced that may limit the prototype's prediction capabilities. Here we summarize these limitations, giving special attention to impact on model performance and the prospects for remedies in subsequent development.

Time of day models. The weakest components of the model system are the time of day models because level of service variables are not included. However, these models interact with other policy sensitive dimensions of the activity schedule via the conditionality hierarchy. As a result, while timing choices are not influenced by transportation system level of service via travel accessibility, they are affected indirectly by accessibility's influence on the activity pattern, and the conditioning of time of day on the pattern choice. The time of day dimension is defined very coarsely so that, even if the model specification was enhanced to include accessibility's direct influence, the responsiveness to level of service would be crude. Effectively incorporating time of day choice requires finer resolution of the time of day dimension, accessibility linkages with the other dimensions of the model system, and better explanation of time of day choice. The lack of a strong time of day component does not, however, undermine the ability to capture inter-tour trade-offs in the activity schedule, an important improvement over tour-based models.

Secondary stops on tours. This dimension is missing entirely from the prototype, and reduces the ability of the model to accurately represent inter-tour trade-offs involving trip chaining, one of the important features of the model design. Without secondary stops, the model relies too heavily on matrix adjustments for unmodeled stops during model system operation. For example, it cannot capture correlation among destinations of stops on a tour. This simplification is not inherent to the proposed design, and the secondary stops can be included in an enhanced implementation, as they are included in existing tour-based model systems.

Activity pattern model. This model explains very little of the observed variability in pattern choice, with measurable but small responsiveness to transportation policy via the accessibility variable. The proposed system structure provides an excellent context for further research and development into the factors influencing pattern choice, such as demographic outcomes and lifestyle decisions. Prospects of improving the measurement of activity and travel accessibility's influence are also good, through the enhancement of the tours portion of the model structure.

Nesting hierarchy. Although the hierarchical relation of activity pattern to tours is statistically established in the prototype, and provides a clear advantage over existing operational econometric models, several important structural issues were not fully analyzed, including (a) the relation of the time of day decision to the mode and destination choice, (b) correlations within tiers, (c) cross-correlations not accommodated by nested logit. Further research and development may lead to important structural model enhancements.

Values of time. Unrealistic values of time indicate model specification errors and/or data deficiency that were not resolved in the prototype. As specified the model would produce counter-intuitive predictions in some cases. Achieving realistic values is a reasonable pre-requisite for final acceptance of the model, calling for more specification testing with new data.

Mutually independent secondary tours. This simplifying assumption unrealistically violates temporal constraints, spatial correlation, and conditionality arising from priority-based behavior. The simplification is not inherent to the proposed design. Some relaxation of the assumption may be possible, such as introduction of a tertiary tour, but a complete representation of relationships among secondary tours may produce a model of unmanageable size.

Coarse classification within choice dimensions. Many of the prototype's classifications of alternatives are arbitrary and/or very coarse. These include activity purposes (work, school, other), tour type (did not identify purpose or tour placement of secondary stops), secondary tour purposes (inconsistent with primary tour purposes), mode (few mixed mode alternatives), destination (traditional zonal aggregation) and time of day (four time periods). Redefining inferior or inconsistent classifications poses no problem, but refining resolution, especially desirable for destination and time of day choices, 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 prototype for destination choices, and might be employed to handle extremely fine resolution of destination and time of day dimensions. Sampling of alternatives and simplification from a pure nested logit structure – mentioned in the previous paragraph – preclude the use of existing simultaneous estimation procedures. Sequential procedures are required that yield less efficient estimates and make testing cumbersome, not only because the usual standard error estimates are inconsistent, but also because they increase the effort required to test alternative structures. If these complications can be overcome, then the use of fine resolution, especially in the destination and time of day dimensions, may significantly improve the proposed model system.

At-home activities. The prototype does nothing with at-home activities because such information was not collected in the Boston survey. This limits the ability of the prototype to fully capture the activity basis of travel demand, but does not prevent the capture of basic at-home vs on-tour trade-offs and inter-tour trade-offs. Data availability is an important concern, and further research and development may sharpen understanding of data requirements enabling more efficient collection of the most important at-home information.

4. Summary

This paper presents a disaggregate discrete choice activity schedule model system that can be specified and estimated from available diary survey and transportation system level of service data. It can generate time and mode specific trip matrices for prediction, similar to some of the existing trip and tour-based model systems, without relying on exogenous predictions for any of the major dimensions of the activity schedule. The model is designed to capture interactions among an individual's decisions throughout a 24 h day by explicitly representing tours and their interrelationships in an activity pattern. These features give the model potential to improve travel forecasts by capturing activity-based policy responses involving inter-tour and at-home vs on-tour trade-offs that are likely in many circumstances. A prototype demonstrates the system concept and statistically verifies the basic structure of the model system. However, an operational implementation would require further empirical tests and model refinements.

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