Title
Simultaneous Model of Household Activity Participation and Trip Chain Generation

Author
Golob, Thomas F.

Publication Date
1999-03-01

UCI-ITS-AS-WP-99-3

Simultaneous Model of Household Activity Participation and Trip Chain Generation

UCI-ITS-AS-WP-99-3

Thomas F. Golob

Institute of Transportation Studies
University of California, Irvine
tgolob@uci.edu

March 1999

Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697-3600, U.S.A.
http://www.its.uci.edu

A Simultaneous Model of Household Activity Participation and Trip Chain Generation

Thomas F. Golob
Institute of Transportation Studies
University of California
Irvine, California 92660-3600
tgolob@uci.edu

Abstract

A trip generation model has been developed using a time-use perspective, in which trips are generated in conjunction with out-of-home activities, and time spent traveling is another component of overall time use. The model jointly forecasts three sets of endogenous variables – (1) activity participation and (2) travel time (together making up total out-of-home time use), and (3) trip generation -- as a function of household characteristics and accessibility indices. It is estimated with data from the Portland, Oregon 1994 Activity and Travel Survey. Results show that the basic model, which has ten endogenous time use and trip generation variables and thirteen exogenous variables, fits well, and all postulated relationships are upheld. Test show that the basic model, which divides activities into work and nonwork, can be extended to a three-way breakdown of subsistence, discretionary and obligatory activities. The model can also capture the effects of in-home work on trip chaining and activity participation. We use the model to explore the effects on time use and trip chaining of GIS-based and zone-based accessibility indices.

BACKGROUND AND OBJECTIVES

From a standpoint of consumer behavior, time is the ultimate resource constraint. Financial constraints can be overcome by increasing income and wealth, but there are severe limits in how far one can go in reducing time constraints by purchasing time-saving goods and services. Engel, *et al.* (1990) note that more money allows consumers to *buy* more of everything, but consumers cannot conceivably *do* more of everything.

In the 1970's, researchers in the field of travel demand modeling began to realize the potential of incorporating travel within a more comprehensive view of time use divided into activity participation and travel. Transportation researchers began to discover general studies of time use by individuals and households (e.g., Szalai, 1973; Robinson, 1977), and work began in earnest on modeling travel as a demand derived from the demand for activity participation (Damm, 1980; Kostyniuk and Kitamura, 1982; Kitamura, 1984; Pas, 1984). About the same time, Zahavi (1979) exposed patterns of time use in travel that are consistent with a joint activity and travel time setting (Zahavi and McLynn, 1983; Zahavi and Talvitie, 1980; Golob, *et al.,* 1981). The advantages of modeling travel demand based on activity demand are provided by Kitamura (1988), Jones, *et al.* (1990) and others.

The objective of this research is to develop and test a household trip generation model that jointly forecasts three sets of endogenous variables -- activity participation, trip chaining, and travel time -- as a function of household characteristics and accessibility indices. We also want our model to determine the relationships among each of these three sets of endogenous variables, so that we can use the system to investigate interrelationships among activity demand, travel time use, and trip chaining.

When analyzing travel within a time use context we must subdivide activities into different types and there are numerous ways to do this. Traditionally, activities were divided into two types: work and leisure (Voss and Blackwell, 1979), and this two-way classification has been used in activity-based trip generation modeling (e.g., Supernak, *et al.*, 1983 and Munshi, 1993) and analyses of travel times and costs (Gunn, 1981). However, modern consumer theory typically uses a three-way classification of activities into (1) subsistence (income-producing or paid time, i.e., work), (2) nondiscretionary (obligated, maintenance or compulsory activities, e.g., eating meals, certain shopping, and child care), and (3) discretionary or leisure activities (Reichman, 1977, and Lane and Lindquist, 1988). Golob, et al. (1994), Golob (1998) and Golob and McNally (1997) use this classification in modeling relationships between activity and travel time. But other classifications have also been shown to be useful. Pas, *et al.* (1995) and Pas and Lu (1997) use a four-way classification of activities: subsistence, maintenance, recreation and "other," where "other" includes visiting, school, cultural, and civic activities. Here, we initially use the old-fashioned simple classification of activities into work and nonwork, then expand the model by subdividing nonwork activities into nondiscretionary (maintenance) and discretionary components.

Joint models of activity participation and travel have also been developed by Golob *et al.,* (1994), Golob (1998), Golob and McNally (1997) and Lu and Pas (1997). All of these previous models were individual-based, while the present model is household-based. Golob, et al. (1994) developed a joint model of out-of-home time use for workers, where time use was broken down into commuting time, time spent in nondiscretionary activities, time spent in discretionary activities, and total nonwork travel time. Applying their model to a national sample of workers in the Netherlands, they determined that there were 'time-budget' feedbacks from commute time to activity times and subsequently to induced nonwork travel.

Golob (1998) and Golob and McNally (1997) model the activity and travel behavior of male and female heads, employing a four-way breakdown of activities into work, discretionary, nondiscretionary (all for out-of-home activities) and in-home work. The Golob (1998) model then includes car and non-car travel time by each head, as well as car ownership and vehicle miles of travel by all household vehicles. These models includes travel times for each separate activity. In contrast, Lu and Pas (1997) develop a joint model involving a four-way classification of both in-home and out-of-home activities on the activity side, and travel time, car mode share, number of trips and number of trip chains on the travel side.

THE MODEL CONCEPT

Our models are based on a three-level causal structure, which is depicted in Figure 1. We propose that the demand for activities generates trips. Trips then generate travel time. Trip chaining behavior provides a feedback loop from trip demand to activity demand, as people find ways of satisfying activity demand by arranging their travel. Finally, time spent traveling cuts into time available for certain activities, thus limiting activity demand. This last set of feedback loops can be called "time budget" effects.

While it is also generally possible to demonstrate these basic relationships within the context of utility theory, as demonstrated by Golob, *et al.* (1981), Kitamura (1984), Munshi, (1993), and Kraan (1997), we do not see any advantages in doing so at this stage in the development of the model system. The simplifying assumptions necessary in justifying a particular behavioral paradigm apply too many limits to a model that attempts to capture complicated household time use and trip generation phenomena involving the interrelated behavior of multiple household members.

For activity demand in Figure 1, the model uses time spent on out-of-home work and out-of-home nonwork activities aggregated across all household members. Later, we expand the model by adding time spent on in-home work. For trip demand, the model uses counts of home-based trip chains (called "tours") made by all household members, classified according to activity and complexity. Finally, for travel time, we separate time traveling to an out-of-home activity site by the type of the initial activity at that site, while keeping return-home time separate. Having a separate return-home category avoids the problem of assigning return-home travel time on complex trip chains to separate activities. Specific variables are defined in the next Section.

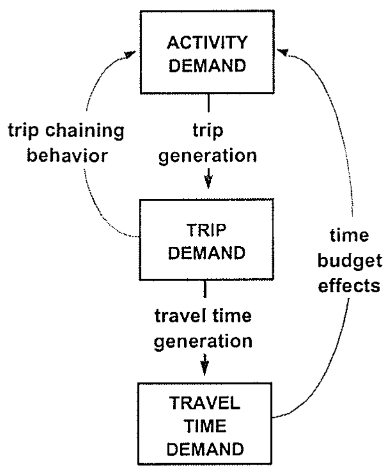

Figure 1. Conceptual Flow Diagram

THE DATA

The data are from the Portland, Oregon *1994 Activity and Travel Survey,* conducted in the spring and autumn of 1994 and the winter of 1995. This survey involved a two-day activity diary, which was designed to record all activities involving travel and all in-home activities with a duration of at least 30 minutes, for all individuals in the household. Our sample consists of 3,217 households with 6,872 individuals (an average of 2.14 persons per household). This sample represents all of the households with complete data on our demographic and socioeconomic variables and activity diaries with no discernible reporting errors in time sequences. Households with incomplete tours (i.e., tours with an overnight stay away from home at the start of the diary or at the end of the second diary day) were also excluded from the sample.

The Time Use Variables

Time use varies substantially by day of week, and the two-day Portland diaries allow us to capture weekend versus weekday behavior. Our model's time use variables, with the addition of aggregate out-of-home time per household and per person, are listed together with their descriptive statistics broken down by weekday versus weekend in Table 1. The differences between weekdays and weekends highlight the need to account for day of week in datasets such as this one where there is an unequal distribution of diaries over day of week.

Table 1. Household Time Use by Day of Week (In hours per day, and weighted by starting day of diary to represent all days of the week equally)

Time use category	All days	Weekdays	Weekends
out-of-home work activity duration	5.73	7.48	1.37
out-of-home nonwork activity duration	6.07	5.84	7.28
in-home work activity duration	0.31	0.34	0.18
travel to work activities	0.35	0.45	0.09
travel to nonwork activities	1.01	0.92	1.30
return-home travel	0.94	0.93	0.99
total out-of-home time	14.10	15.62	11.03
total out-of-home time per person	6.60	7.31	5.17

Trip Generation Variables

The four household trip generation variables used in the model are listed in Table 2. This set is not quite symmetric about activity type (work versus nonwork), because there are not enough complex (multiple sojourn) tours involving only work activities to justify separating simple and complex work tours. Thus, there are two variables for nonwork tours, one for simple tours that involve only one nonwork activity site away from home, and one for complex tours involving more than one nonwork activity site. There is only one variable for work-only tours, with any number of work activity sites, and a variable for tours involving both work and nonwork activities (which are complex tours by definition).

Table 2. Household Trip Generation per Day by Day of Week (In tours per day, and weighted by starting day of diary to represent all days of the week equally)

Trip generation	All days	Weekdays	Weekends
work-only tours (simple & complex)	0.36	0.44	0.13
work/nonwork tours (complex)	0.44	0.56	0.11
simple nonwork tours	1.36	1.23	1.73
complex nonwork tours	0.71	0.60	1.01
total tours	2.87	2.83	2.98
total tours per person	1.34	1.32	1.40

The present research highlights the importance of multi-day diaries (Pas, 1986; 1995 and Pas and Koppelman, 1987). The two-day Portland diaries allow us to observe a greater proportion of households engaging in an activity or generating a trip chain of a particular type. This has ramifications for model estimation (discussed below). Two days also result in a greater proportion of completed tours, because tours involving overnight stays spanning the two diary days can be included in the analysis. The rate of generation of tours (home-based trip chains) is almost identical on weekdays and weekends, being just less than 3.0 tours per household, or 1.33 tours per person (of all ages). Of course, the breakdown of tours by activity varies by day of week.

Summed together, the four trip chaining variables account for all movements from home. Multiplying the variables by average trips per chain accounts for all trips generated by all household members. For the Portland sample, the trips per chain factors are listed in Table 3. There are slightly less than 2.0 trips in simple nonwork tours because some tours (walking, jogging, and bicycling for recreation) involve only one trip starting and ending at home, where the activity and the travel time are identical. In the Portland sample, 3.1% of all tours, or 8.0% of simple nonwork tours, were single-trip tours of this type.

Table 3. Trip Rates for the Four Types of Tours
(Weighted by staring day of diary to represent all days of the week equally)

Trip generation	Mean trips per tour
work-only tours (simple & complex)	2.14
work/nonwork tours (complex)	3.76
simple nonwork tours	1.93
complex nonwork tours	3.62

The Combined Time Use and Trip Generation Variables

The complete set of endogenous time use and trip generation variables is listed in Table 4. These statistics are over two days. The variables are arranged in order of Figure 1, with the exception that in-home work activity participation is last, because that variable is added to the model system at a later stage in the analysis.

Table 4. Descriptive Statistics on the Endogenous Household Activity Participation and Travel Variables over Two Days (Weighted by starting day of diary to to represent all days of the week equally; N = 3217)

	% cases	For cases > 0		
	> 0	mean	median	std.dev.
1 out-of-home work activity duration (hours)	69 %	17.7	16.5	9.9
2 out-of-home nonwork activity duration (hours)	94 %	12.6	8.7	11.7
3 work-only tours (simple and complex)	42 %	1.8	2.0	1.0
4 work/nonwork tours (complex)	50 %	1.9	2.0	1.0
5 simple nonwork tours	75 %	3.5	3.0	2.8
6 complex nonwork tours	56 %	2.4	2.0	1.8
7 travel time to work activities (hours)	68 %	1.1	0.8	0.9
8 travel time to nonwork activities (hours)	93 %	2.1	1.6	1.8
9 return-home travel time (hours)	98 %	1.9	1.5	1.5
10 in-home work activity duration	13 %	5.0	3.9	3.8

The Exogenous Variables

We selected thirteen exogenous variables, based on extensive prior research (e.g., Kostyniuk and Kitamura, 1982, Supernak, 1983, Pas, 1984, Townsend, 1987, Strathman and Dueker, 1994, and Lu and Pas, 1997) and exploratory analyses. The exogenous variables can be divided into three groups: household demographics (six variables), socioeconomic variables (five variables), and variables to account for differences in time use by day of week. This last group (two dummy variables, distinguishing Saturdays and Sundays from the base category of weekdays) is necessary to control for the uneven distribution of starting days for the two-day activity diaries. These exogenous variables are described in Table 5.

Table 5. Descriptive Statistics on the Exogenous Variables (N = 3217)

Exogenous variable	Mean	Std.dev.	= 0	= 1
1 number of household heads (1 or 2)	1.53	0.50		46.9%
2 number of children under 6	0.15	0.46	88.7%	
3 number of children 6-11 years of age	0.16	0.48	88.2%	
4 number of children 12-17 years of age	0.13	0.40	89.8%	
5 number of non-heads 18+ years of age	0.15	0.42	86.4%	
6 average age of household heads	47.5	16.0		
7 vehicles per driver (no drivers ≡ 0)	0.87	0.30	8.8%	81.5%
8 zero-vehicle dummy			91.2%	8.8%
9 income < \$20,000			83.8%	16.2%
10 income ≥ \$60,000			83.7%	16.3%
11 number of workers	1.16	0.82	22.9%	
12 one diary day Saturday			76.3%	23.7%
13 one diary day Sunday			77.7%	22.3%

Household demographics are obviously important because aggregate household time use will depend heavily on household membership. For individuals, time use is very much a function of age, so we propose that a combination of counts of household members by age group with average age of the household heads jointly captures both number and age effects at the aggregate household level. We argue that a breakdown of the membership into all its component groups (which add up to household size) is more informative than using household size, and we count children under eighteen years of age by age groups, and also count the number of non-heads eighteen or older. Using the mean age of the household heads (or age of the single head) avoids the problem of having to choose which age to use in households with two (married or unmarried) heads, because it is not feasible to use ages of both heads due to their high multicollinearity.

METHODOLOGY

Structural equations modeling (SEM) with observed variables is defined by the system:

$$y = \mathrm{B}y + \Gamma x + \zeta \qquad (1)$$

where y is a column vector of *p* endogenous variables, x is a column vector of *q* exogenous variables, and ζ is a column vector of the error terms. The structural parameters are the elements of the three matrices:

B = matrix (*pxp*) of direct effects between pairs of the *p* endogenous variables,

Γ = matrix (*pXq*) of regression effects of the *q* exogenous variables, and

$\Psi = E(\zeta\zeta')$ = symmetric variance-covariance matrix (*p* by *p*)of the error terms.

A necessary condition for identification of system (1) is that (I - B) must be non-singular, where **I** denotes the identity matrix of rank *p*. A sufficient condition for the identification of system (1) is that the (*p* by *pxq*) matrix C, defined by

$$\mathrm{C} = \left[(\mathrm{I} - \mathrm{B}) \,|\, -\Gamma\right] \qquad (2)$$

is of rank *p* (Fox, 1984).

For an identified SEM, it can be shown that the total effects of the endogenous variables implied by system are given by

$$\mathrm{T}_{yy} = (\mathrm{I} - \mathrm{B})^{-1} - \mathrm{I} \qquad (3)$$

and the total effects of the exogenous variables on the endogenous variables are given by the parameters of the so-called reduced-form equations

$$\mathrm{T}_{xy} = (\mathrm{I} - \mathrm{B})^{-1}\Gamma \qquad (4)$$

Structural equations models of this type are estimated using variance analysis methods (also known as methods of moments). The method proceeds by defining the sample variance-covariance matrix of the combined set of endogenous and exogenous variables, partitioned with the endogenous variables first:

$$\mathrm{S} = \begin{bmatrix} \mathrm{S}_{yy} & \mathrm{S}_{yx} \\ \mathrm{S}'_{yx} & \mathrm{S}_{xx} \end{bmatrix}, \qquad (5)$$

where S_{yy} denotes the variance-covariance matrix of the endogenous variables, S_{yx} denotes the covariance matrix between the endogenous and exogenous variables, and S_{xx} denotes the variance-covariance matrix of the exogenous variables. It can be easily shown using matrix algebra that the corresponding variance-covariance matrix replicated by model system (1), denoted by

$$\Sigma = \begin{bmatrix} \Sigma_{yy} & \Sigma_{yx} \\ \Sigma'_{yx} & \Sigma_{xx} \end{bmatrix} \tag{6}$$

is:

$$\Sigma_{yy} = (I - B)^{-1}(\Gamma S_{xx}\Gamma' + \Psi)\left((I - B)^{-1}\right)' \tag{7}$$

and

$$\Sigma_{yx} = (I - B)^{-1}\Gamma S_{xx} \tag{8}$$

where $\Sigma_{xx} = S_{xx}$ is exogenous. The structural equation system is estimated using the variance-analysis normal-theory maximum likelihood method (Bollen, 1989). The fitting function for structural equations maximum likelihood (ML) estimation is

$$F_{ML} = \mathrm{Log}|\Sigma(\theta)| - \mathrm{Log}|S| + \mathrm{tr}[S\Sigma(\theta)] - (p + q) \tag{9}$$

where $\Sigma(\theta)$ represents Σ (equations 6-8) implied by the vector of model parameters, θ. This fitting function F_{ML} is (-2/n) times the log of the likelihood, where n is the sample size. Under the assumption of multivariate normality, $(n-1)F_{ML}$ is chi-square distributed, providing a test of model rejection and criteria for testing hierarchical models.

Other SEM estimation methods are available when we cannot or should not assume that the endogenous variables are distributed multivariate normally. Golob and McNally (1997) describe the use of the asymptotically distribution-free ADF-WLS estimation method in SEM of time use. ADF-WLS relies on the use of Tobit models for censored variables, resulting in asymptotically correct standard errors and model goodness-of-fit measures. However, in SEM with censored and discrete choice variables estimated using ADF-WLS, the variances of the latent endogenous variables are not identified, so the estimates are standardized. Here, we would like the estimated parameters to be in the (time) scales of the variables, because this aids greatly in interpreting the results.

The choice of the ML estimation method is supported by research that has demonstrated that, while ML potentially yields biased error estimates, the coefficient estimates will be consistent even with censored endogenous variables, and estimates have been shown to be robust under violations of multivariate normality (Boomsma, 1987). Furthermore, after comparing ML and ADF-WLS estimates of the same SEM, Golob and McNally (1997) concluded that "we showed that the main conclusions in our model are consistent between a linear model estimated using the normal-theory maximum likelihood (ML) method and a Tobit model estimated using ADF-WLS." ADF-WLS estimation of the present model is left as a fruitful topic for further research.

RESULTS

The Base Model

Our base model has the first nine endogenous variables listed in Table 4 and the thirteen exogenous variables listed in Table 5. There are 28 direct effects among the nine endogenous variables, and each of these effects is shown as an arrow in the flow diagram of Figure 2; these are freely estimated elements in the B matrix of system (1). In addition, there are 58 regression effects from the thirteen exogenous variables (Γ matrix elements), nine error-term variances (diagonal elements in the Ψ matrix), and one error-term covariance (an off-diagonal element in the Ψ matrix). This freely estimated error-term covariance allows the unexplained portions of travel time to work and travel time to nonwork to be correlated.

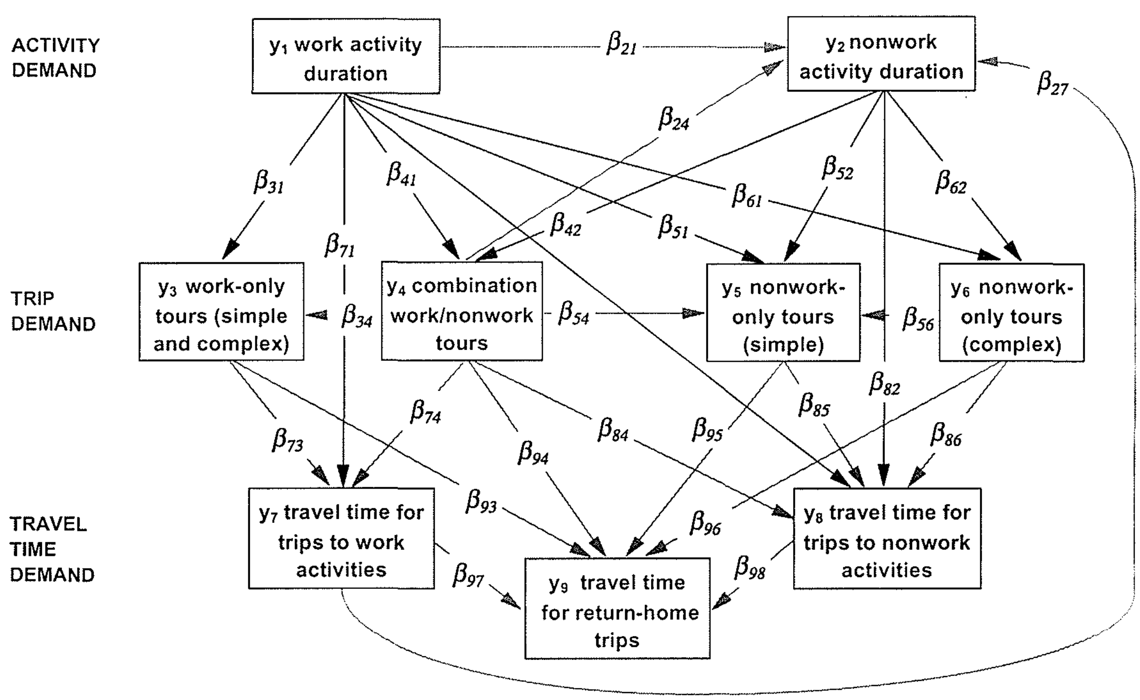

Figure 2
Causal Structure Linking the Endogenous Variables in the Base Model
(Each arrow represents a direct effect of one variable upon another)

The causal structure of this model is by no means arbitrary. A comparison of Figures 1 and 2 shows that the model makes operational the three-level concept that activity trips are derived for the demand for activities, thus generating travel time. Activity demand is divided into two parts (work and nonwork) trip demand is divided into four parts (based on the two activity classes and tour complexity), and travel time into three parts (time traveling to work activities, to nonwork activities, and return-home time). Regarding casual relationships between the variables at each of the three levels, the link from work activity demand to nonwork activity demand, postulated as being negative, captures the activity hierarchy modeled by Golob and McNally (1997), among others. The relationships between the trip demand variables capture a similar hierarchy that trip chaining reduces the need for simple tours. At the third level, the two links to return-home travel time from work travel time and nonwork travel time simply account for total tour travel time.

Regarding links from conceptual level one to level two, there are eight possible causal links from the two activity demands to the four trip demands, and only the one from nonwork activity to simple work tours is left out. From level two to level three, the structure is merely straightforward accounting, linking tours involving trips to one of the two classes of activities to travel time for those types of trips, plus return-home travel. There are also three links from level one variables to level three variables; these are adjustments to proportional relationships through the intermediate tour demand variables. Finally, two feedback loops were postulated based on the findings of Golob and McNally (1997) and Golob (1998). One feedback, from tours involving work and nonwork activities to nonwork activity time (postulated to be positive), is meant to capture efficiencies that can be gained by chaining trips. The second feedback, from work travel time to nonwork activity time captures the well-accepted postulate that excess commuting time reduces time available for other out-of-home activities.

The structure of the model is also centered on the postulate that work activity duration is the major driving force in time use and trip generation. This postulate is depicted in Figure 2 by the presence of arrows (direct effects) from variable y_1 to all of the other variables, with the exception of return-home travel time (which is a function of work through the other paths).

Empirically, the base model fits well. The model log-likelihood ratio chi-square is 79.50 with 66 degrees of freedom, corresponding to a probability of 0.123. This indicates that we cannot reject, at the p = .05 level, the hypothesis that the sample variance-covariance matrix was drawn from a distribution for which the model captures the true relationships among the variables. In other words, we cannot reject the hypothesis that the differences between the model replicated variance-covariances and the true variance-covariances are zero.

The R^2 values for each of the endogenous variables are shown in Table 6. The model is least able to explain demand for complex home-based trip chains involving nonwork activities. The number of household work tours is most readily explainable.

All 28 parameters corresponding to direct effects among the endogenous variables (structural parameters that are elements of the B matrix in system (1), depicted in Figure 1) are significant at the p = .05 level, with one exception. All 58 effects of the exogenous variables (Γ matrix parameters) are significant at the p = .05 level, as is the error-term covariance linking travel times to work and nonwork activities. The postulated feedback from trip chaining to activity participation is upheld by the estimation of a statistically significant link from variable y_4 (combination work/nonwork tours) to variable y_2 (nonwork activity duration). Likewise, the postulated feedback from work travel time to nonwork activity duration is confirmed by estimation of a statistically significant negative coefficient for the direct effect from variable y_7 to variable y_2; longer work times leave less time for out-of-home nonwork activities. Since nonwork activities require travel (the chains of direct positive effects from y_2 to y_8 and y_9) this confirms the previous results of Golob, *et al.* (1994), Golob (1998) and Golob and McNally that improvements in commuters' travel time induces more travel, as predicted by Zahavi (1979) and his colleagues. Purvis, *et al.* (1996) have modified a conventional urban transportation planning travel demand forecasting method to accommodate this consequence.

Table 6
Percent Variances Accounted for in the Base Model

	Endogenous variable	R^2
1	work activity duration	0.61
2	nonwork activity duration	0.58
3	work-only tours (simple and complex)	0.73
4	work/nonwork tours (complex)	0.46
5	simple nonwork tours	0.50
6	complex nonwork tours	0.41
7	travel time to work activities	0.58
8	travel time to nonwork activities	0.60
9	return-home ravel time	0.54

The base model was next expanded by adding in-home work activity. Interpretation of the estimation results is performed on the expanded model.

Including Working at Home in an Expanded Model

If our model is an effective representation of causal relationships among time use and trip generation variables, it should be capable of expansion to further subdivision of activities and travel by activity purpose. To date, we have tested expanding the model on two fronts: (1) subdividing in-home activities (the missing category that is equal to two days minus the sum of out-of-home work and out-of-home nonwork in the base model) into in-home work and all other in-home activities, and (2) subdividing out-of-home nonwork activities into maintenance and discretionary activities, using the definition proposed by Golob and McNally (1997). Both expansions were successful. Because of length restrictions on this paper, we are able to present only one set of results, and we selected the model with in-home work activities.

Only 13% of the households in the Portland dataset registered in-home work activities over two days, and the mean in-home work activity duration for these households was 5.0 hours (Table 4). We postulated that in-home activity demand would have a negative direct effect on both out-of-home activities, but the total effect of in-home work on out-of-home nonwork time use would be neutral, due to compensating effects.

The expanded model has 103 parameters, seven more than the base model. Three parameters were added to the Γ matrix in a feeble attempt to explain in-home work participation in terms of the exogenous variables, and four parameters were added to the B matrix of direct effects among the endogenous variables. These endogenous variable linkages are shown as the arrows labeled $\beta_{1,10}$, $\beta_{2,10}$, $\beta_{3,10}$ and $\beta_{10,7}$ in Figure 3. The first two (negative) effects indicate that in-home work cuts into other activities, and the third (positive) effect indicates that in-home workers still make work-related trips (i.e., work tours do not go down as much as predicted by a simply switching of in-home for out-of-home work). The last effect, $\beta_{10,7}$, tells us that workers with longer commutes are more likely to work at home, *ceteris paribus*. All the other endogenous variable effects remained significant as they were in the base model. This is stability we were looking for in the model.

The Chi-square statistic for the fit of the expanded model is 94.40 with 81 degrees of freedom, corresponding to a probability of p = .146, indicating that the model cannot be rejected at the p = .05 level. The estimated direct effects among the endogenous variables are listed in Table 7; each cell in Table 7 corresponds to an arrow in Figure 3.

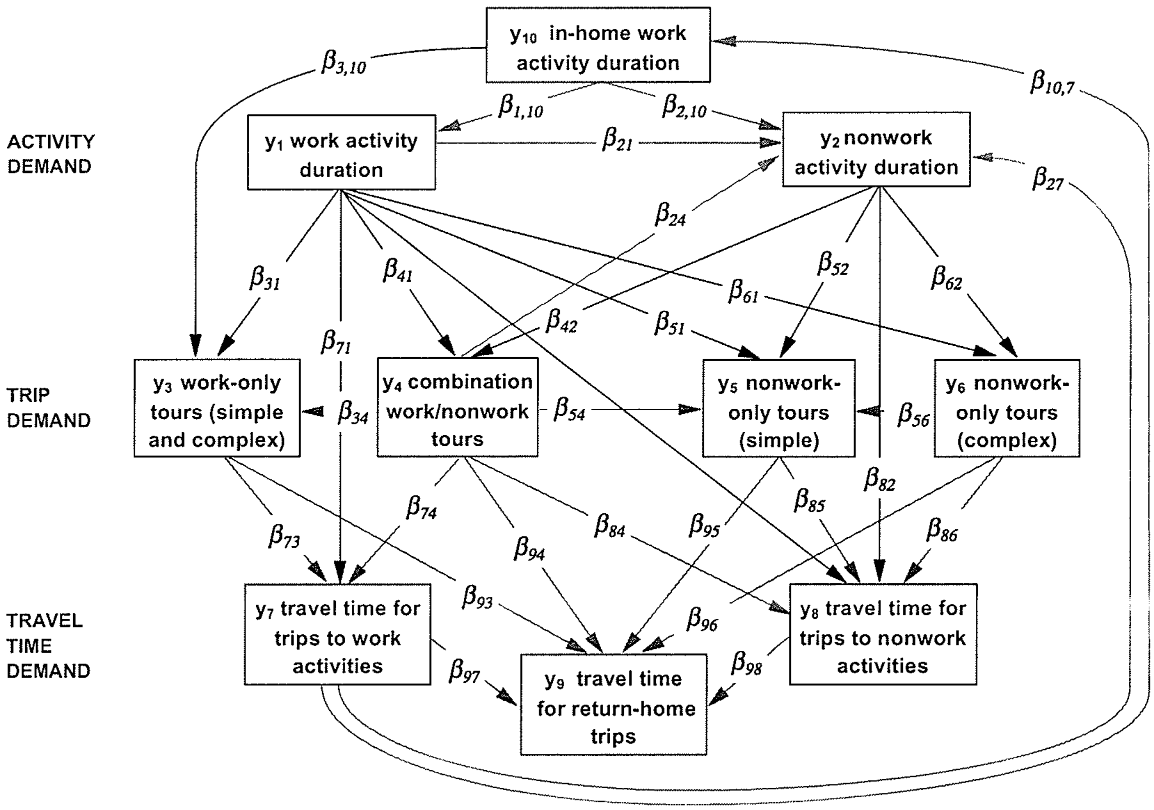

Figure 3. Endogenous Causal Structure of the Enhanced Model that Includes In-home Work Activities (Each arrow represents a direct effect of one variable upon another)

A structural equations model must be built by specifying the B, Γ and Ψ matrices in system (1), which is equivalent to postulating all of the direct effects and error-term correlations. However, it is the total effects, given by equation system (3) and (4), that are of interest in forecasting. The total effect of one variable upon another might even have a different sign than the direct effect when there are paths for indirect effects. For example, consider a three-variable recursive model with direct effects [from A to B], [from B to C], and [from A to C]. If [from A to B] is positive [from B to C] is positive, and [from A to C] is negative, the total effect from A to C will be positive if [from A to B] multiplied times [from B to C] is greater than the direct effect [from A to C]; it will be negative otherwise. The total effects among the endogenous variables are listed in Table 8.

Table 7. Estimated Direct Effects Among the Endogenous Variables
(*t*-statistics in parentheses)

	FROM									
TO	1 work activity duration	2 non-work activity duration	3 work-only tours	4 work/ nonwork tours	5 simple nonwork tours	6 complex nonwork tours	7 travel time to work activities	8 travel time to nonwork activities	9 return-home travel time	10 in-home work act duration
1 work activity duration										-.799 (-11.5)
2 nonwork activity duration	-.239 (-9.57)			1.557 (5.87)			-.601 (-2.56)			-.257 (-4.05)
3 work-only tours	0.095 (60.1)	-.003 (-2.69)		-.789 (-67.4)						0.024 (4.70)
4 work/nonwork tours	0.058 (27.3)	0.003 (1.19)								
5 simple non-work tours	-.047 (-9.66)	0.127 (24.4)		-.367 (-8.68)		-.492 (-19.1)				
6 complex non-work tours	-.030 (-13.2)	0.083 (35.8)								
7 travel time to work activities	0.016 (7.29)		0.256 (14.9)	0.326 (18.3)						
8 travel time to nonwork acts.	-.017 (-5.38)	0.050 (15.6)		0.253 (10.1)	0.133 (13.5)	0.455 (29.7)				
9 return-home travel time			0.118 (5.21)	-.046 (-1.96)	0.152 (18.7)	-.033 (-2.33)	0.380 (11.8)	0.322 (21.6)		
10 in-home work activity duration							0.155 (2.44)			

The total effects (Table 8) reveal some intriguing interrelationships in time use and trip chaining that expand previous results (Pant and Bullen, 1980, Supernak, *et al.*, 1983, Kitamura, 1984, Pas, 1984, Goulias and Kitamura, 1990, Pendyala and Kitamura, 1991, Levinson and Kumar, 1995). But this type of joint model also reveals some new results. For instance, work activities and work travel time are found to be self-regulating: The model predicts that if a household shocks the system by increasing either out-of-home or in-home work by an certain amount, that initial increase will be reduced through feedback after all other time uses are adjusted. And if work travel time is increased independently, say by reducing travel speeds due to congestion, the model predicts that the initial increase will be moderated. Part of the moderation is due to a shift to in-home work.

Table 8
Estimated Total Effects Among the Endogenous Variables
(*t*-statistics in parentheses and showing only effects significant at the p = .05 level)

	FROM									
TO	1 work activity duration	2 non-work activity duration	3 work-only tours	4 work/ nonwork tours	5 simple nonwork tours	6 complex nonwork tours	7 travel time to work activities	8 travel time to nonwork activities	9 return-home travel time	10 in-home work act duration
1 work activity duration	-.006 (-2.15)		-.032 (-2.19)	0.019 (2.39)			-.123 (-2.19)			-.795 (-11.7)
2 nonwork activity duration	-.179 (-11.7)		-.160 (-2.62)	1.502 (5.70)			-.623 (-2.64)			
3 work-only tours	0.050 (23.2)	-.005 (-2.13)		-.797 (-67.0)						-.015 (-2.30)
4 work/nonwork tours	0.057 (27.9)		-.002 (-2.37)				-.009 (-2.38)			-.047 (-10.7)
5 simple non-work tours	-.068 (-16.7)	0.085 (17.2)	-.012 (-2.25)	-.239 (-5.00)		-.492 (-19.1)	-.046 (-2.27)			0.032 (4.10)
6 complex non-work tours	-.045 (-17.0)	0.084 (35.5)	-.012 (-2.42)	0.126 (5.65)			-.048 (-2.44)			0.014 (2.21)
7 travel time to work activities	0.047 (35.2)		0.255 (14.9)	0.123 (10.3)			-.005 (-1.97)			-.032 (-8.06)
8 travel time to nonwork acts.	-.041 (-12.4)	0.101 (34.2)	-.015 (-2.49)	0.355 (9.95)	0.133 (13.5)	0.389 (25.8)	-.060 (-2.51)			
9 return-home travel time		0.042 (23.7)	0.208 (10.1)		0.195 (23.6)		0.354 (10.5)	0.322 (21.6)		
10 in-home work activity duration	0.007 (2.41)		0.039 (2.45)				0.154 (2.46)			-.0049 (-2.05)

Exogenous differences in time use and trip generation are captured by the model in the total effects from the exogenous variables (equation(4)). The total effects of the household demographic variables are listed in Table 9. Essentially all of the demographic variables are powerful explanatory variables of time use in terms of in-home and out-of-home work and out-of-home nonwork.

Table 9. Estimated Total Effects From the Exogenous Demographic Variables
(t-statistics in parentheses and showing only effects significant at the p = .05 level)

	FROM					
TO	number of heads (1 or 2)	number of children under 6	Number of children 6-11	number of children 12-17	number of non- heads 18+	average age of heads
1 work activity duration	0.967 (3.21)	-1.169 (-4.00)	-1.20 (-4.29)	-1.178 (-3.59)	0.0249 (3.24)	-.0630 (-6.41)
2 nonwork activity duration	5.41 (17.0)	5.07 (16.0)	8.95 (29.3)	11.49 (32.1)	6.14 (18.1)	-.0730 (-7.52)
3 work-only tours	0.108 (3.35)	-.834 (-4.41)	-.105 (-4.13)		0.103 (3.21)	-.0025 (-4.62)
4 work/nonwork tours		-.051 (-2.34)		-.191 (-4.41)	-.130 (-3.25)	-.0039 (-6.19)
5 simple nonwork tours	1.81 (19.3)	1.29 (13.7)	1.38 (15.9)	2.01 (19.9)	1.68 (17.9)	-.0103 (-3.79)
6 complex non-work tours	0.700 (11.4)	0.885 (14.3)	0.782 (22.3)	0.993 (23.4)	0.504 (15.9)	-.0042 (-4.46)
7 travel time to work activities	0.031 (2.04)	-.057 (-4.01)	-.059 (-4.25)	0.079 (-4.71)		-.0019 (-2.30)
8 travel time to nonwork activities	0.952 (15.0)	0.836 (18.7)	0.686 (11.9)	0.908 (13.2)	0.855 (12.9)	-.0068 (-6.11))
9 return-home travel time	0.919 (19.1)	0.406 (16.1)	0.372 (13.3)	0.874 (16.0)	0.747 (14.1)	-.0085 (-6.11)
10 in-home work activity duration		-.009 (-2.07)	-.009 (-2.11)	-.012 (-2.16)	-.312 (-3.37)	0.0081 (3.07)

Finally, the estimated total effects of the remaining exogenous variables are listed in Table 10. As expected, number of household workers is omnipresent. In fact, it can be argued that labor force participation should not be treated as exogenous in travel demand forecasting, because we may not be able to obtain reliable exogenous forecasts (Golob, 1996). Rather we should forecast work activity demand in our own models. That can be accomplished here by simply removing exogenous variable x_{11}. The model itself will then forecast work activity demand as a function of all the other exogenous variables.

Table 10. Estimated Total Effects From the Exogenous Car Ownership, Income and Day-of-week Variables (*t*-statistics in parentheses and showing only effects significant at the p = .05 level)

TO	FROM: vehicles per driver	zero-vehicle dummy	Income < $20,000	income ≥ $60,000	number of workers	one diary day is Saturday	one diary day is Sunday
1 work activity duration			-1.254 (-3.46)	1.451 (4.00)	9.006 (43.1)	-5.74 (-19.3)	-5.92 (-19.5)
2 nonwork activity duration	2.315 (5.10)		0.216 (3.16)		-1.53 (-9.88)	1.445 (4.43)	
3 work-only tours				-.127 (-2.62)	0.587 (23.0)	-.277 (-6.96)	-.287 (-7.04)
4 work/nonwork tours			-.072 (-3.43)	0.232 (4.80)	0.709 (27.0)	-.429 (-10.8)	-.449 (-11.1)
5 simple non-work tours	0.195 (4.90)		0.085 (3.35)	-.137 (-4.83)	-.679 (-17.0)	0.383 (7.67)	0.374 (8.83)
6 complex non-work tours	0.193 (5.05)	-.311 (-3.40)	0.056 (3.34)	-.049 (-2.73)	-.401 (-15.3)	0.461 (7.07)	0.199 (5.92)
7 travel time to work activities			-.044 (-2.35)	0.125 (3.69)	0.571 (32.0)	-.303 (-17.2)	-.365 (-12.7)
8 travel time to nonwork activities	0.232 (5.05)	-.170 (-4.22)	0.051 (3.27)		-.234 (-6.27)	0.444 (6.84)	0.139 (3.39)
9 return-home travel time	0.096 (4.99)		0.014 (2.11)		0.088 (3.75)	0.057 (2.38)	
10 in-home work activity duration				0.019 (2.04)	0.562 (10.4)	-.047 (-2.40)	-.056 (-2.41)

The model indicates that personal vehicle mobility leads to increased participation in nonwork activities, as shown by the effects of vehicles per driver and the zero-vehicle dummy variable (Table 10). Vehicles per driver is positively associated with nonwork activity duration, simple and complex nonwork tours and return-home time. In addition households without vehicles make simpler and shorter tours to nonwork activities.

Effects of Accessibility

As a final exercise of the model, we tested the explanatory powers of different accessibility measures by estimating four separate models, each with one of four different accessibility indices as an additional (fourteenth) exogenous variable. These four accessibility indices were computed by Portland Metropolitan Service District

(Metro), the Portland regional government, for general use in their transportation modeling. Two of the indices are network-based GIS computations of total employment and total retail employment within one mile of each household's residence. The other two indices are zone-based, being travel time-weighted sums over all zones of logs of attractions from multinomial logit destination choice models, one with total employment as the attraction, and one with total households as the attraction.

One measure of the how well the accessibility variables improve explanation of the time use and trip chain generation variables is given by the improvement in overall goodness of fit. The model log-likelihood ratio chi-square values before and after inclusion of the each exogenous variable are listed in Table 11. (The initial model log-likelihood ratios are different, because each is based on a different dataset due to the inclusion of the additional exogenous accessibility variable.) The difference in the number of degrees-of-freedom for each model is equal to the number of statistically significant direct effects found for each accessibility index (two for each of the GIS-based measures and seven for each of the zone-based measures). Each of four of the indices make a significant contribution to model explanatory power, but the zone-based measures are more effective in explaining household time use and trip chaining.

Table 11. Effects on Model Goodness of Fit of Adding Four Different Accessibility Indices

Accessibility index	Model without index effects		Model with index effects		Model improvement	
	X^2	d-of-f *	X^2	d-of-f *	ΔX^2	d-of-f *
Retail employment within 1 mi.	127.55	91	106.95	89	20.60	2
Total employment within 1 mi.	124.06	91	107.87	89	16.19	2
Zonal employment attractions	189.76	91	111.98	84	77.78	7
Zonal household attractions	178.69	91	96.95	84	81.74	7

* degrees of freedom

All significant total effects from the accessibility indices in the four separate models are listed in Table 12. (The number of significant total effects is generally different from the number of direct effects.) The scales of the indices are arbitrary so we focus on the statistical significance of the parameters. All accessibility indices are positively related to (1) participation in out-of-home nonwork activities, (2) generation of simple home-based trip chains for nonwork purposes, and negatively related to (3) work travel time. However, households with higher levels of the two zone-based accessibility measures also exhibit more complex trip chaining. We conclude that the model does a good job of identifying influences of accessibility on time use and trip generation.

Table 12
Estimated Total Effects From the Exogenous Accessibility Indices in Four Different Models (*t*-statistics in parentheses and showing only effects significant at p = .05 level)

Endogenous variable	retail employment within 1 mile	total employment within 1 mile	zonal employment attractions	zonal household attractions
1 work activity duration				
2 nonwork activity duration	0.0082 (2.05)	0.0008 (1.98)	0.0107 (2.50)	0.0127 (3.76)
3 work-only tours				-.0040 (-3.14)
4 work/nonwork tours				
5 simple nonwork tours	0.0512 (3.19)	0.0048 (2.72)	0.0056 (4.43)	0.0130 (3.56)
6 complex nonwork tours			0.0030 (3.54)	0.0072 (3.03)
7 travel time to work activities	-.0131 (-3.26)	-.0013 (-3.00)	-.0018 (-5.26)	-.0058 (-5.40)
8 travel time to nonwork activities	0.0075 (3.37)	0.0007 (2.92)	0.0027 (4.75)	
9 return-home travel time				-.0051 (-2.59)
10 in-home work activity duration	-.0020 (-1.96)		-.0003 (-2.16)	-.0009 (-2.22)

SUMMARY AND CONCLUSIONS

Summary

These models are founded on the testable hypothesis that demand for out-of-home activities, broken down by type, causes households to generate trips in simple and complex chains, and the combination of demand for different activities determines, in part, the complexity of trip chaining. The trip chains in turn distribute travel time, broken down by travel to sites for the different types of activities and return-home travel. The activity demand and travel time variables account for all household out-of-home time use, and all trips are accounted for by the trip chaining variables. We specified a simultaneous equation model in which all of the time use and trip generation variables are functions of themselves and of exogenous household characteristics, including location-specific characteristics. We then estimated the model and its variants using data from the 1994 Portland *Activity and Travel survey* (data that were generously provided for research purposes by Portland Metro).

So far, we have estimated models that subdivided out-of-home activities into (1) work and (2) nonwork, and also into (1) work, (2) household maintenance (compulsory obligations), and (3) discretionary (leisure activities). In another extension, we have added in-home work as an activity category. The model structure allows us to forecast how increasing any one type of activity (for instance, working at home) will affect demand for other activities, as well as trip generation and travel time.

Trip generation is handled to-date in terms of home-based trip chains (tours) of four types: (1) work-only (simple and complex), (2) work plus nonwork (complex by definition), (3) simple nonwork, and (4) complex nonwork. Added together, these account for movements from home. Multiplying the variables by average trips per chain accounts for all household trips. For the Portland sample, the trips per chain factors are given in Table 4.

We next added location-specific exogenous variables. These were four different accessibility indices developed by Portland Metro for general use in travel demand estimation. Two of these indices focused on the immediate neighborhood of each household and were generated by a GIS using microscopic network data. Two other indices were zone based, computed from destination choice model data. Each index added significant explanatory power, and the results show how accessibility influences time use and trip generation. The zone-based measures had more ubiquitous effects.

Conclusions

Based on these initial tests results, we propose that it is not difficult to specify and estimate a family of trip generation models that provide insights about travel behavior that are not obtainable using conventional approaches that treat trip generation as an isolated set of events. Our approach is to model trip generation jointly with time use. The models can reveal how the generation of simple and complex trip chains is interrelated with demand for out-of-home and in-home activities, and how travel "time budget" effects can affect activity demand and trip generation. The models reveal how the time-use and trip generation interrelationships are affected by household characteristics and by residential accessibility.

Joint models of time use and trip generation can also be used to forecast the effects of exogenous shocks to the endogenous variables, because they capture the effects of activity participation, trip chaining, and travel times on all the endogenous variables. For example, we can trace the effects of increases in telecommuting on demand for all other activities, trip generation, and travel times. Or, we can trace the effects of travel time changes due to congestion on activity participation and trip generation. Sensitivity to network variables has been demonstrated, and it will not be difficult to apply additional exogenous accessibility variables. We can also expand the model to break down travel by mode, adding network-based levels-of-service exogenous variables. With such a model, forecasts of trip generation would be sensitive to network link volumes and other location-dependent measures of transportation system attributes.

Directions for Further Research

This family of models requires further development and testing in order to evaluate its full potential in travel demand forecasting. Several enhancements could make the models more useful to planners: First, the definitions of the time use and trip generation variables can be changed according to forecasting and policy evaluation needs. Instead of work and nonwork time use, and trip chains distinctions based on combinations of work and nonwork activities, we can use any other subdivisions of activities. We have proved that three, rather than two categories are possible, and four categories might also be possible without making the model too complicated. Different definitions of the activity categories are certainly possible (e.g., singling out shopping, in the manner of Gould and Golob, 1997).

Second, we can break travel down by mode. For example, we could divide trip generation into tours using household vehicles versus tours by public transport and non-motorized modes. This would internalize mode choice into the time use and trip generation model in an aggregate fashion, and it would allow us to incorporate exogenous variables representing mode-specific levels-of-service for the household location. However, as in the case of activity categorization, a breakdown into too many modes could lead to unwieldy model structures, and the modeling in the end must be subject to Occam's razor.

Fifth, we can restructure the trip chaining variables. One alternative would be to add total trips as an additional endogenous variable, structured as a function of all of the tour variables. The direct effects from the tour variables would then measure trips per chain.

Fourth, we can internalize explanation of labor force participation within the model system by eliminating "number of household workers" as an exogenous variable in some future models. Work activity duration would then need to be a function of the remaining exogenous household variables. This circumvents the problem of obtaining reliable forecasts of household labor force participation. It was argued in an earlier paper that, if we assume that employment status, work schedules, and work locations are given in our travel choice models, we have abdicated forecasting responsibility for a great portion of travel behavior.(Golob, 1996).

Fifth, car ownership can be converted from an exogenous to an endogenous variable. Golob (1998) did this in a model of time use that excluded trip generation. However, this requires using the more complicated distribution-free estimation procedure for structural equation models in order to treat car ownership as a discrete choice variable and avoid estimation biases. This has sample size ramifications and prevents direct interpretation of coefficients in terms of the scales of the variables (Golob and McNally, 1997).

Overall, it would be most instructive to estimate a model of this type embedded in a zone and network system. Forecast trip generation rates could then be observed spatially and compared to those of conventional models.

ACKNOWLEDGEMENTS

This research was sponsored by the University of California Transportation Center. The author wishes to thank his colleague Mike McNally of the University of California, Irvine, for his intellectual stimulus and technical support in the conduct of this and related research conducted under the auspices of the Center for Activity Systems Analysis of the Institute of Transportation Studies. The author also wishes to thank Keith Lawton and the staff of Portland Metropolitan Service District (Portland Metro) for generously providing the data and for their encouragement. Naturally, all opinions expressed here are solely those of the author, who is also the only one responsible for any errors. An earlier version of this paper was presented at the meeting of the International Association of Travel Behavior Research in Austin, Texas, September 21-25, 1997.

REFERENCES

Bollen, K.A. (1989). *Structural Equations with Latent Variables.* Wiley, New York.

Boomsma , A. (1987). The robustness of maximum likelihood estimation in structural equation models. In P. Cuttance and R. Ecob, eds., *Structural Modeling by Example.* Cambridge University Press, New York.

Damm, D. (1980). Interdependencies in activity behavior. *Transportation Research Record,* No. 750: 33-40.

Engel, J.F., R.D. Blackwell and P. W. Miniard (1990). *Consumer Behavior.* Dryden, Chicago.

Fox, J. (1984). *Linear Statistical Models and Related Methods.* Wiley, New York

Golob, T.F. (1998). A model of household demand for activity participation and mobility. In T. Gärling, T. Laitila and K. Westin, eds., *Theoretical Foundations of Travel Choice modeling*, 365-398. Pergamon, Oxford.

Golob, T.F., M.J. Beckmann and Y. Zahavi (1981). A utility-theory travel demand model incorporating travel budgets. *Transportation Research*, 15B: 375-390.

Golob, T.F. R. Kitamura and C. Lula (1994) "Modeling the Effects of Commuting Time on Activity Duration and Non-Work Travel." Presented at Annual Meeting of Transportation Research Board, Washington, DC, January.

Golob, T.F. and M.G. McNally (1997). A model of household interactions in activity participation and the derived demand for travel. *Transportation Research*, 31B: 177-194.

Gould, J. and T.F. Golob (1997). Shopping without travel or travel without shopping? An investigation of electronic home shopping. *Transport Reviews,* 17: 355-376.

Goulias, K., R.M. Pendyala and R. Kitamura (1990). Practical method for the estimation of trip generation and trip chaining. *Transportation Research Record No. 1285*: 47-56.

Gunn, H.F. (1981). An analysis of travel time budgets into mandatory and discretionary components. Presented at the PTRC 9th Summer Annual Meeting, University of Warwick, England.

Jones, P., F. Koppelman and J-P Orfeuil (1990). Activity analysis: State-of-the-art and future directions. In P. Jones, ed., *Developments in Dynamic and Activity-Based Approaches to Travel Analysis.* Gower, Aldershot, UK.

Kitamura, R. (1984). A model of daily time allocation to discretionary out-of-home activities and trips. Transportation Research, 18B: 255-266.

Kitamura, R. (1988). An evaluation of activity-based travel analysis. *Transportation,* 15, 9-34.

Kitamura, R., J.P. Robinson, T.F. Golob, M.A. Bradley, J. Leonard and T. van der Hoorn (1992). A comparative analysis of time use data in the Netherlands and California. *Proceedings of the PTRC Summer Annual Meeting,* PTRC Education and Research Services, London.

Kostyniuk, L.P. and R. Kitamura (1982). Life cycle and household time-space paths: Empirical investigation. *Transportation Research Record No. 879:* 28-37.

Kraan, M. (1997). In search for limits to mobility growth with a model for the allocation of time and money. In D. Ettema nd H. Timmermans, eds., *Activity-Based Approaches to Travel Analysis.* Pergamon, Elsevier Science, Oxford.

Lane, P. M. and J.D. Lindquist (1988). Definitions for the fourth dimension: A proposed time classification system. In K.D. Bahn, ed., *Developments of Marketing Science II.* Academy of Marketing Science, Blacksburg, VA.

Levinson, D. and A. Kumar (1995). Activity, travel and the allocation of time. *Journal of the American Planning Association*, 61: 458-470.

Munshi, K. (1993). Urban passenger demand estimation: A household activity approach. *Transportation Research*, 27A: 423-432.

Pant, P.D. and A.G.R. Bullen (1980). Urban activities, travel and time: Relationships from National Time-Use Survey. *Transportation Research Record,* No. 750: 1-6.

Pas, E.I. (1984). The effects of selected sociodemographic characteristics on daily travel-activity behavior. *Environment and Planning A*, 16: 571-581.

Pas, E.I. (1986). Multiday samples, parameter estimation precision, and data collection costs for least squares regression, trip-generation models. *Environment and Planning, A*, 18: 73-87.

Pas, E.I. (1995). Intrapersonal variability in daily urban travel: Some additional evidence. Transportation, 22: 135-150.

Pas, E.I. and F.S. Koppelman (1987). An examination of the determinants of day-to-day variability in individuals' urban travel behavior. *Transportation*, 14: 3-20.

Pendyala, R.M., K.G. Goulias and R. Kitamura (1991). Impact of telecommuting on spatial and temporal patterns of household travel. *Transportation,* 18: 383-409.

Purvis, C.L., M. Iglesias, and V.A. Eisen (1996). Incorporating work trip accessibility in non-work trip generation models in the San Francisco Bay Area. Presented at the 75th Annual Meeting of the Transportation Research Board, Jan. 7-11, Washington, DC.

Reichman, S. (1977). Instrumental and life style aspects of urban travel behavior. *Transportation research Record No. 649:* 38-42.

Robinson, J.P. (1977). *How Americans use time: A Social-Psychological Analysis of Everyday Behavior*, Praeger, New York.

Saxena, S. and P.L. Mokhtarian (1997). The impact of telecommuting on the activity spaces of participants. *Geographical Analysis*, 29: 124-144.

Strathman, J.G., K.J. Dueker and J.S. Davis (1994). Effects of household structure and selected travel characteristics on trip chaining. *Transportation*, 21: 23-45.

Supernak, J., A. Talvitie and A. DeJohn (1983). Person-category trip generation model. *Transportation research Record* No. 944: 74-83.

Szalai, A., *et al.* (1973). *The Use of Time: Daily Activities of Urban and Suburban Populations in Twelve Countries.* Mouton, The Hague.

Townsend, T.A. (1987). The Effects of Household Characteristics on the Multi-day Time Allocations and Travel - Activity Patterns of Households and Their Members. Unpublished Ph.D. Dissertation, Northwestern University, Evanston, IL.

Voss, J. and R. Blackwell (1979). The role of time resources in consumer behavior . In O.C. Ferrell, S. Brown and C. Lamb, eds., *Conceptual and Theoretical Developments in Marketing:* 296-311. American Marketing Association, Chicago.

Zahavi, Y. (1979). *The UMOT Project.* Report for U.S. Department of Transportation, Research and Special Programs Administration, and the Federal Republic of Germany Ministry of Transport. DOT-RSA—DPW-20-79-3, August 1979.

Zahavi, Y. and J.M. McLynn (1983). Travel choices under changing constraints as predicted by the UMOT Model. Presented at the Tenth Transportation Planning Research Colloquium, Dec. 14-16, Zandvoort, the Netherlands.

Zahavi, Y. and A. Talvitie (1980). Regularities in travel time and money expenditures. *Transportation Research Record,* No. 750: 13-19.