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Abstract

With modern multivariate statistical methods and activity-diary (time-use) data sets, it is possible to model household mobility decisions as being derived from decisions to participate in activities at various locations. We show how this can be accomplished by specifying activity participation by activity type and location as endogenous variables, with a simple locational distinction of "at home" versus "out of home." The activity participation variables are then combined in a model system of simultaneous equations with variables that measure mobility demand: travel times by mode, household vehicle ownership and household vehicle utilization. We specify the model in terms of latent, multivariate normally distributed choice variables, and this treatment solves estimation problems associated with censored and ordinal observed endogenous variables. The estimation method provides accurate goodness-of-fit model evaluation and hypothesis testing. Results are shown from a model estimated using two-day activity diary data for male and female household heads and associated accessibility data collected in the Portland, Oregon, U.S.A. Metropolitan Area in 1994. The model system can be used in conjunction with conventional travel demand models, to provide forecasts of the effects of factors such as accessibility and in-home work, on travel demand by mode, car ownership, and car vehicle miles of travel. This type of model system has the potential of replacing some existing demand forecasting models.

1. Objectives and Scope

The travel choice model system introduced here is founded on the principle that personal travel choices involve an integrated set of decisions involving what activity to participate in, where and when to participate in that activity, and how to travel between activity locations. In this model system, we treat mobility decisions, involving household car ownership, car usage, and travel by different modes, as the direct results of demands by household members to participate in activities at different locations. But we also recognize that mobility allows a person to engage in activities at different locations. Thus, the model must also capture feedbacks from mobility demand to activity demand.

Despite the indisputable linkages between activity participation demand and travel demand, the vast majority of travel choice behavior models assume that most aspects of activity participation demand are given. Almost all travel behavior models are based on trips or trip chains, with the endogenous variables of interest being a selection from the list that includes: destination, mode, route, time of day, and frequency of repetition. If we assume that the reasons for making a trip will remain unchanged, then the most important travel choices are already made, and we are left modeling only the minor details. Granted, these details are of interest to planners, because they impact traffic flows on transportation networks, but it is foolish to assume that the motivations for trips do not change. This is why conventional trip-based models fail to account for increased demand for travel due to enhanced accessibility and improved transportation system levels of service; and this is why trip-based models are inappropriate for evaluating the effects of telecommunications on travel (Kitamura, 1991).

One basic group of activity participation decisions is whether or not to work, whether to work full-time or part-time, and whether or not to conduct some or all of the work at home. 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. This might be acceptable only if all of the following were true: (1) We have reliable exogenous forecasts of detailed employment characteristics, which we do not. (2) Working does not affect other travel, which, of course, it does. (3) There are no feedbacks from mobility to employment, which there are. And (4), working at home, versus away from home, is not important, but it is. Likewise, we should not assume a fixed demand for activities such as shopping and personal business (banking, medical services, etc.), because we know that accessibility and mobility substantially influence patterns of demand for these activities. Moreover, home-based shopping and conduct of personal business are major aspects of the telecommunications revolution.

We must also recognize that an individual's activity participation and mobility choices are not made in isolation. Activities are typically shared among household members, and household members and non-household members alike engaged in many activities and travel together. For this reason, we should strive to model the activity and travel choices of household members simultaneously.

The objective here is to develop a choice model system that can explain some basic causal relationships between household activity participation, travel to out-of-home activity sites, car ownership, and household vehicle utilization. The effects of residential location on activity and mobility demand were investigated by Golob and McNally (1996); it was concluded that, as a first approximation, residential location could be treated as an exogenous variable.

The behavioral units in this case study application of the proposed choice model system are the two married or unmarried male and female adults who can be identified as heads of a household in which there might be any number of other members, such as children or other persons. Thus, the focus in this application is on the activity and travel demand of adult heads of household, and their household car ownership and utilization demand.

The case study documented here is viewed as an initial test of a model system that can be expanded to meet many policy evaluation needs related to travel demand. The exogenous variables in the model can be expanded to encompass essentially any variables that have been used in conventional models. The difference is, the current model system is designed to explain the effects of exogenous variables on both activity and mobility demand. This includes network and other spatial data related to residential locations and transportation levels of service. Activity demand in this model system can be measured in terms of any set of activity categories; the extent of the division is limited only by the sample size and the quality of the data. Mobility demand can be measured in terms of travel demand by mode, car ownership demand, and car usage demand. Modal travel demand, in turn, can be measured in terms of travel times, trip rates, rates of journeys or tours, or travel distances. Again, the travel demand component of the model system is, in principle, limited only by data availability.

Another important feature of this model system is its ability to estimate the influences of any endogenous variable on the other endogenous variables. For example, the model system can be used to investigate the effects of an independent increase or decrease in certain activities, such as in-home working or in-home shopping, on all other activity and mobility demands.

The model system could be used to generate household demand for travel (in terms of trips or trip chains by mode), car ownership, and car usage for spatial aggregations of households. As such, it could feed some combination of destination choice, route choice, or traffic assignment models.

2. Background

Travel behavior models based on activity demand makes use of the time-use data collection and analysis techniques developed by sociologists and regional scientists (e.g., Hägerstrand, 1970; Chapin, 1974; Robinson, 1977). The trick is to apply these techniques in a way that usefully improves traditional travel demand forecasting methods. The principle of basing travel demand models on activity patterns was endorsed in the 1970's and early 1980's, by van der Hoorn (1979), Jones, *et al.* (1983), Pas (1985), and others; and several conferences, workshops, and special sessions were held on the subject, leading to numerous publications (e.g., Carpenter and Jones, 1983). Kitamura (1988 and 1996) and Pas (1996) provide comprehensive review of the pioneering efforts in activity analysis for transportation planning.

Overall interest in new activity-based models has waned over the last decade. However, there have been efforts to make incremental improvements to conventional planning models by using principles originally developed in activity analyses. For example, Purvis, Iglesias, and Eisen (1996) used early results on "feedback" relationships between travel and activities (Golob, Kitamura and Lula, 1994) to modify a conventional travel demand model system to incorporate work trip accessibility in non-work trip generation models for the San Francisco Bay Area. Further examples of advances based on activity analyses are Goulias, Pendyala and Kitamura (1990) and Pas (1988).

Development of activity-based models has been held up in part by the lack of time-use data. Trip diaries do not provide the necessary data; activity diaries are needed. Progress has also been held up by the lack of familiarity in the travel demand modeling community with methods to handle multivariate problems with endogenous variables that are not multivariate normally distributed (e.g., variables measuring activity durations, which have high concentrations of observations at zero and are otherwise constrained to the positive domain). Travel choice modeling has been ruled by the paradigm of a single-equation discrete choice variable.

Today, there are enhanced opportunities for activity-based models. The conventional four-step or five-step (UTPS) transportation planning process in use today was established in all essential aspects 40 years ago. These travel demand models are inappropriate for forecasting latent demand, or for assessing the role of accessibility on car ownership, mode choice, and residential location (Kitamura, 1991). Planners are now being forced to abandon this planning process because it does not meet the requirements of the relatively recent changes to requirements for federal funding in the United States. Also, plans based on the four-step process have been successfully challenged in court by environmental groups concerned with induced demand caused by improvements in levels of service for car travel.

Activity-based models are a potential way out of this dilemma, and metropolitan planning organizations (MPOs) and the U.S. Federal technical support bureaucracy have expressed recent interest in such models. Several MPOs, such as Portland, Oregon, Dallas-Fort Worth Texas, and Raleigh-Durham, North Carolina, have conducted extensive activity diary surveys. In principle, activity-based models applied to such rich datasets can deal with many of today's critical planning issues, if they can be made practical.

3. Theory

The choice model system has four sets of endogenous demand variables:

1. **Activity Participation**: Choices concerning whether or not to participate in various activities, at home and away from home, and how long to engage in such activities are considered to be the basic determinants of household mobility. In turn, activity participation will be influenced by all of these components of mobility, because access to activity sites and the time available for out-of-home activities is dependent on the accessibility of activity sites and travel times. Activities must be divided into upon categories in order to specify an operational choice model. Categories such as "work and work-related," "shopping and personal business" and "discretionary" have been used in time-use studies (Chapin, 1974; Robinson, 1977).

2. **Travel Times**: Travel will be strongly and directly determined by activity participation. But travel time will also be determined by vehicle ownership, because some activity sites are more accessible to households with a higher level of vehicle availability. In turn, travel times affect activity participation due to pressures on time budgets. Travel times can also influence vehicle ownership decisions through the link with activity participation. We can group travel times into times for travel to a particular category of activities (Golob and McNally, 1997), or travel times by category of travel mode, such as "car," "public transport" and "non-motorized modes."

3. **Vehicle Ownership**: Decisions concerning household vehicle ownership level will be influenced by all of the above sets of demand variables because households acquire vehicles in order to satisfy demands for travel to activity sites, and demand for activity participation depends in part on vehicle availability.

4. **Vehicle Miles of Travel (VMT):** This is a variable that is key in many policy assessments. Consequently, why not measure it directly and include it in the demand model system as an endogenous variable? Here we do.

These four sets of demand variables are depicted in Figure 1 together with the expected direct effects between the sets. In this flow diagram, six sets of direct causal effects are identified:

1. **Travel Demand** (causal links from *Activity Participation* to *Travel Times*)**:** In this choice model system, demand for travel is derived from demand for activity participation. Consequently, there will be strong direct effects from demand for an out-of-home activity to the travel times needed to access the sites for that activity. Travel times will be determined by mode choice decisions, by land use patterns, and by network architecture and performance.

2. **Time Budget Effects** (links from *Travel Times* to *Activity Participation*): The total amount of time available for both out-of-home activities and the travel to and from these activities is relatively fixed, assuming that household members have responsibilities at home or desire to be at home for certain minimum periods. If accessibility improves, say, by infrastructure improvements or by reducing congestion, travel times associated with activities might initially decrease. But the individuals engaged in the activities will have more time available. Some of the saved time is likely to be consumed by increasing the duration of the activity at that site. However, some of the saved time might also be consumed by other out-of-home activities, or by substitution of more preferred destinations for the same activities, either of which would lead to increased travel (an effect typically called “latent demand”). Such “feedback” effects from travel to activity duration were captured in a more limited way in the budget models of travel originally proposed by Zahavi (1979) and studied by Downes and Emmerson (1984) and Golob, *et al.* (1981).

3. **Mobility Demand** (links from *Activity Participation* to *Vehicle Ownership*): Activity participation choices, and the life style choices that underlie activity participation choices, will influence car ownership demand (Burns and Golob, 1976). Households that choose to live in areas well served by transit and pedestrian networks will exhibit less need for vehicles, while households in residential areas that are auto-oriented will generally strive to acquire one vehicle for every driver.

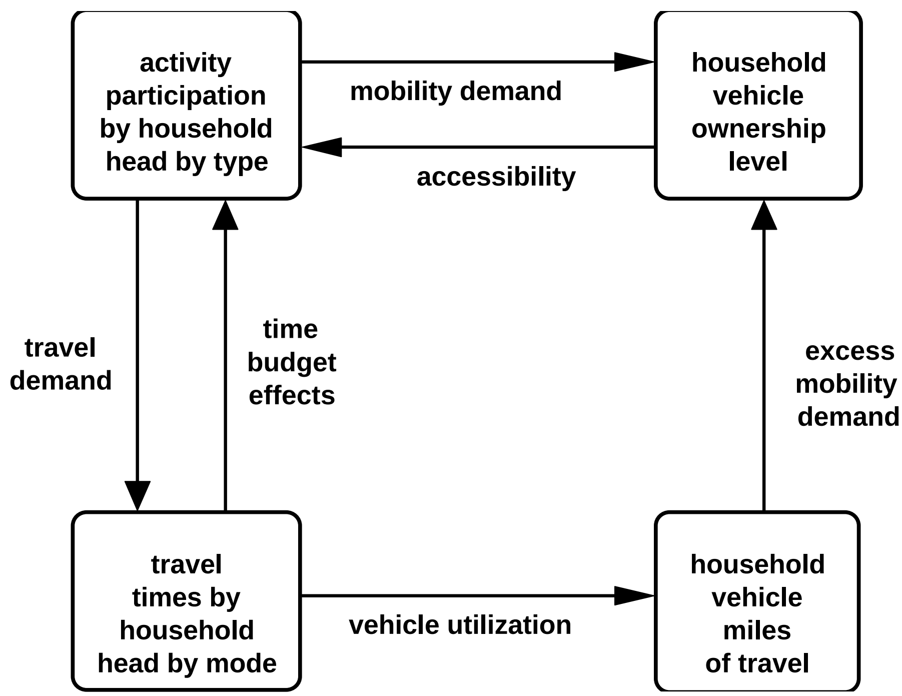
4. **Accessibility** (links from *Vehicle Ownership* to *Activity Participation*): Potentially, access to vehicles can enhance activity participation, if certain activity sites are not well served by alternative modes of transportation, so that travel times to such sites are substantially less by car. Also, some household members might forego certain activities, if household vehicles are being used by other household members and there is no vehicle available when they want to pursue the activity.

5. **Vehicle Utilization** (links from *Travel Times* to *Vehicle Miles of Travel*): Household vehicle miles of travel (VMT) will be a function of travel time dependent on how households split their travel times between driving a household vehicle and all other modes. Households in which most travel is by solo driving will exhibit a high multiplier between travel times and VMT, while households with more car passenger, public transport, bicycle, and pedestrian trips will put fewer miles on their vehicle(s) per hour of total travel.

6. **Excess Mobility Demand** (links from *Vehicle Miles of Travel* to *Vehicle Ownership*): For households in which there are fewer vehicles than drivers, intensive use of the household vehicle(s) will pressure the household to acquire an additional vehicle. This effect will be mitigated to the extent that vehicle ownership is “saturated” with at least one vehicle per driver.

The six hypothesized sets of direct causal effects between the sets of endogenous variables effects listed above and portrayed in Figure 1, provide numerous paths by which each set of variables can have a total effect or influence on any of the other sets of variables. For example, there are no hypothesized direct effects between vehicle ownership and travel times, but vehicle ownership can influence travel times via the path combining the accessibility and travel demand links through activity participation, and travel times can influence vehicle ownership via the path combining the time budget and mobility demand effects. The identification of the strengths and directions of total effects is one of the objectives in our modeling.

Figure 1: Conceptual Flow Diagram of the Model System



4. Methodology

We can test these hypotheses by specifying and estimating a system of activity participation and mobility choice models using the analytical framework of structural equation models with latent choice variables. Other applications of structural equations to data on activity participation and travel are found in Golob, *et al*., (1994 and 1996), Golob and McNally (1997), Lu and Pas (1997) and Fujii, *et al.* (1997).

4.1 Structural Equation Models

Structural equations model systems are generally defined by the matrix equation system:

$$\mathbf{y} = \mathbf{B}\mathbf{y} + \boldsymbol{\Gamma}\mathbf{x} + \boldsymbol{\zeta} \tag{1}$$

where **y** is a column vector of endogenous variables, **x** is a column vector of exogenous variables, and $\boldsymbol{\zeta}$ is a column vector of unexplained portions of the endogenous variables (error terms). The structural parameters are the elements of the three matrices:

$\mathbf{B}$ = matrix of causal links between the endogenous variables,
$\boldsymbol{\Gamma}$ = matrix of regression effects of the exogenous variables,

and

$\boldsymbol{\Psi} = E(\boldsymbol{\zeta}\boldsymbol{\zeta}')$ = symmetric variance-covariance matrix of the error terms.

A necessary condition for identification of system (1) is that **(I - B)** must be non-singular, where $\mathbf{I}$ denotes the identity matrix.

The total effects of the endogenous variables on one other, $\mathbf{T_{yy}}$, implied by system (1) are:

$$\mathbf{T_{yy}} = (\mathbf{I} - \mathbf{B})^{-1} - \mathbf{I} \tag{2}$$

And the total effects of the exogenous variables on the endogenous variables, $\mathbf{T_{xy}}$, are given by

$$\mathbf{T_{xy}} = (\mathbf{I} - \mathbf{B})^{-1}\boldsymbol{\Gamma} \tag{3}$$

which are the parameters of the so-called reduced-form equations.

If the endogenous variables in the structural equation system can all be considered to be continuous and multivariate normally distributed, the estimation of the system is straightforward, using normal-theory maximum likelihood (Bollen, 1989). However, in the present case, the endogenous variables represent imperfectly observed choices, and this requires the use of special estimation methods (Golob and McNally, 1997).

4.2 Specification of the Choice Variables

Demand for participation in any activity type can be observed in terms of the duration of time spent in that activity. Likewise, demand for travel on a category of modes can be observed in terms of time spent traveling on those modes. However, durations data must be gathered through the use of survey instruments such as activity or time use diaries (or logs), and these diaries typically cover time periods of from one day to one week, with two-day diaries becoming popular with transportation planners. With such restricted time periods of observation, we can expect to detect many individuals with zero durations for many activity types and travel times. The probability of observing an individual participating in an activity will be directly related to the frequency pattern with which the individual engages in that activity. Extensive examinations of the day-to-day variability in activity and travel patterns are provided by Pas(1986), Pas and Koppelman (1986), and others (reviewed in Kitamura, 1988).

We can get around this problem of limited observation time by treating the activity participation, travel time, and VMT choice variables as being censored. We assume that each of these observed choice variables $\mathbf{y_i}$ is associated with a latent (unobserved) normally distributed variable $\mathbf{y_i^*}$ with mean μ and variance σ^2. The observed and latent variables are related such that:

$$\begin{aligned} \mathbf{y_i} &= \mathbf{y_i^*} \quad \textbf{if } \mathbf{y_i^*} > \mathbf{0} \\ \mathbf{y_i} &= \mathbf{0} \quad \textbf{otherwise} \end{aligned} \tag{3}$$

For observed durations (or mileage) of zero, all we know is

$$\boldsymbol{P(}\,\mathbf{y_i} = \mathbf{0}\boldsymbol{)} = \boldsymbol{P(}\,\mathbf{y_i^*} \le \mathbf{0}\boldsymbol{)} \tag{4}$$

The likelihood function for estimation of the unknown parameters is thus

$$\boldsymbol{L(}\mu\boldsymbol{,}\sigma^2|\mathbf{y_i}\boldsymbol{)} = \prod_{\mathbf{y_i}>\mathbf{0}} \frac{\mathbf{1}}{\sigma}\phi\left(\frac{\mathbf{y_i}-\mu}{\sigma}\right)\prod_{\mathbf{y_i}\le\mathbf{0}}\Phi\left(\frac{-\mu}{\sigma}\right) \tag{5}$$

Where ϕ and Φ denote the density and distribution functions of the standard normal. Estimation of μ and variance σ^2 for each censored endogenous variable in the choice model system is accomplished using the Tobit model described in standard econometric references, such as Maddala (1983). The Tobit model was introduced by Tobin (1958), and was further developed by Amemiya (1973) and Fair (1977).

We can treat all endogenous choice variables this way, with the exception of vehicle ownership. For this variable, we observe the number of vehicles available to the household, from zero on up, and this distribution can have a long tail, with a few households having large numbers of vehicles. Econometricians have determined that estimations of such observed ordered choice variables can be improved by defining a normally distributed latent variable that is cut by thresholds to generate the observed ordered categories. The latent variable itself is not observed, but the ordinal indicator is related to it in the following way

$$\begin{aligned} \mathbf{y_i} &= \mathbf{1} \ \text{ if } \quad \mathbf{y_i^*} \le \alpha_1 \\ \mathbf{y_i} &= \mathbf{2} \ \text{ if } \ \alpha_1 < \mathbf{y_i^*} \le \alpha_2 \\ &\ \vdots \\ \mathbf{y_i} &= \mathbf{c} \ \text{ if } \ \alpha_{c-1} < \mathbf{y_i^*} \end{aligned} \tag{6}$$

where $\alpha_1 < \alpha_2 < \cdots < \alpha_{c-1}$ are the unknown threshold values.

These thresholds are estimated corresponding to the marginal distribution of the population over the categories using the ordered-response probit regression model, developed by Aitchison and Silvey (1957) and Ashford (1959) as an extension of the binomial probit model (Maddala, 1983).

4.3 Estimation of the Structural Equations Model with Latent Choice Variables

Structural equations systems are estimated using methods of moments (also called: variance analysis methods). We begin by defining the sample variance-covariance matrix of the combined set of endogenous and exogenous variables, partitioned with the endogenous variables first:

$$\mathbf{S} = \begin{bmatrix} \mathbf{S_{yy}} & \mathbf{S_{yx}} \\ \mathbf{S'_{yx}} & \mathbf{S_{xx}} \end{bmatrix} \tag{7}$$

where $\mathbf{S_{yy}}$ denotes the variance-covariance matrix of the endogenous variables, $\mathbf{S_{xy}}$ denotes the covariance matrix between the endogenous and exogenous variables, and $\mathbf{S_{xx}}$ denotes the variance-covariance matrix of the exogenous variables, which is taken as given.

It can be easily shown using matrix algebra that the corresponding variance-covariance matrix replicated by model system (1) with parameter vector θ (denoting all parameters in the B, Γ, and Ψ matrices) is

$$\Sigma(\theta) = \begin{bmatrix} \Sigma_{\mathbf{yy}} & \Sigma_{\mathbf{yx}} \\ \Sigma'_{\mathbf{yx}} & \Sigma_{\mathbf{xx}} \end{bmatrix} \tag{8}$$

where

$$\boldsymbol{\Sigma}_{\mathbf{yy}} = (\mathbf{I} - \mathbf{B})^{-1}(\Gamma \mathbf{S}_{\mathbf{xx}} \Gamma' + \Psi)\left((\mathbf{I} - \mathbf{B})^{-1}\right)' \tag{9}$$

$$\boldsymbol{\Sigma}_{\mathbf{yx}} = (\mathbf{I} - \mathbf{B})^{-1} \Gamma \mathbf{S}_{\mathbf{xx}} \tag{10}$$

and $\boldsymbol{\Sigma}_{\mathbf{xx}} = \mathbf{S}_{\mathbf{xx}}$ is taken as given for the exogenous variables.

The parameters of the $\mathbf{B}$, $\boldsymbol{\Gamma}$, and $\boldsymbol{\Psi}$ matrices are estimated by making $\boldsymbol{\Sigma(\theta)}$ be as close as possible to $\mathbf{S}$. With latent choice variables corresponding to censored and ordered categorical (ordinal) observed endogenous variables, this is accomplished using the method known as asymptotically distribution-free weighted least squares, or ADF-WLS. This method produces consistent and asymptotically efficient parameter estimates and unbiased estimates of standard errors and goodness-of-fit (Browne, 1982, 1984).

The ADF-WLS estimation method proceeds in two distinct steps after estimation of the means and variances of the latent variables corresponding to the observed censored variables, and the thresholds of the latent variable corresponding to the ordinal variable.

The first step is to estimate the correlations between the latent endogenous variables, and the correlations between each of the latent variables and the continuous exogenous variables in the system. For pairs of censored endogenous variables, the problem is to determine the unknown correlation coefficient between the latent variables that maximizes the likelihood of observing the cross-products where below-censoring level observations are assigned normal scores determined by the Tobit model (Des Raj, 1953). For endogenous variable pairs involving the ordinal endogenous variable and a censored variable, the polyserial correlation coefficient is method is used (Olsson, et al., 1982).

The final step in the ADF-WLS method is to estimate the parameters of the structural equation model by making the model-implied correlation matrix as close as possible to the sample correlation matrix, where the sample matrix is determined in the previous steps. The fitting function is then:

$$\mathbf{F}_{\mathbf{WLS}} = [\mathbf{s} - \boldsymbol{\sigma}(\theta)]' \, \mathbf{W}^{-1} \, [\mathbf{s} - \boldsymbol{\sigma}(\theta)] \tag{11}$$

where $\mathbf{s}$ is a vector of censored correlation coefficients for all pairs of endogenous and exogenous variables, $\sigma(\theta)$ is a vector of model-implicated correlations for the same variable pairs, and $\mathbf{W}$ is a positive-definite weight matrix. Minimizing F_{WLS} implied that the parameter estimates are those that minimize the weighted sum of squared deviations of s from $\sigma(\theta)$. This is analogous to weighted least squares regression, but here the observed and predicted values are variances and covariances rather than raw observations.

The best choice of the weight matrix is a consistent estimator of the asymptotic covariance matrix of $\mathbf{s}$:

$$\mathbf{W} = \mathbf{ACOV}\left(\mathbf{s}_{ij}, \mathbf{s}_{gh}\right). \tag{12}$$

Under very general conditions

$$\mathbf{W} = \frac{\mathbf{1}}{\mathbf{N}}\left(\mathbf{s}_{ijgh} - \mathbf{s}_{ij}\,\mathbf{s}_{gh}\right) \tag{13}$$

is a consistent estimator, where $\mathbf{s}_{ijgh}$ denotes the fourth-order moments of the variables around their means, and $\mathbf{s}_{ij}$ and $\mathbf{s}_{gh}$ denote covariances. Brown (1982, 1984) demonstrated that $F_{\mathbf{WLS}}$ with such a weight matrix will yield consistent estimates which are asymptotically efficient with correct parameter z-statistics and correct chi-square test values. These properties hold for very general conditions, and consequently such estimators are known as asymptotically distribution free (ADF) estimators (also called: arbitrary distribution function estimators).

ADF-WLS estimators are available in several structural equation model packages. The LISREL/PRE-LIS (Versions 8/2 for Windows) programs (Jöreskog and Sörbom, 1993) are used here.

5. The Portland Case Study

The choice model system has been implemented using the Portland Oregon and Southwest Washington Metropolitan Area as a case study.

5.1 Data

The data are from the Portland, Oregon *1994 Activity and Travel Survey,* conducted in the spring and autumn of 1994. 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. Only the spring portion of the sample was used, because the autumn portion is concentrated on weekdays, and we prefer that the model system deals with activities and travel on *all* days of the week. This portion of the survey involved 2,230 households with 5,120 individuals. The importance of a multi-day diary for this type of analysis is made clear by Pas(1986), Pas and Koppelman (1987), and Pas (1995).

The sample used here was composed of households in which there are two persons eighteen years or older living in the same residence, one male and one female, who we can identify as household heads. The household heads need not be married. After processing for missing data, particularly exogenous environmental data, the sample of 1,318 such households (approximately 60% of the 2,230 total household) was reduced to a final sample of 1,047. This is a subset of the same sample of 1,292 households used in the analyses reported by Golob and McNally (1997).

5.2 The Endogenous Variables

Specific variables were computed for each of the four sets of demand variables depicted in Figure 1. Multiple variables were used in three of the four sets, resulting in a total of fourteen endogenous variables. Each set of variables is described below.

5.2.1 Activity Participation

Total activity duration was computed over each individual's two diary days, divided into three categories of out-of-home activities and a single category of in-home activities. The three categories of out-of-home activities represent a hierarchy that has been used in many time-use studies. At the top of the hierarchy is (1) out-of-home work (subsistence activities). This is followed by (2) out-of-home maintenance, which includes activities that households typically need to perform on a regular basis. Finally, we define (3) out-of-home discretionary, which includes social, recreational, and entertainment activities. This hierarchy was originally proposed in the travel demand context by Reichman (1977), and Gunn (1981) found the distinction between mandatory and discretionary activities to be important in explaining travel budgets.

Our only in-home activity is work. Theoretically, the demand model structure can handle multiple categories of in-home activities, but we are constrained by limitations in the data and the desire for a simple initial model. The specific activity categories utilized in collecting the Portland activity diaries are assigned to our four activity categories as follows:

> Out-of-home work is comprised of the two activities coded as “work” and “work-related” at non-home locations.
>
> Out-of-home maintenance is comprised of activities coded as “meals,” “shopping (general),” “shopping (major),” “personal services,” “medical care,” “professional services,” “household or personal business,” “household maintenance,” “household obligations,” “pick up or drop off passenger,” “school,” and “religious” at non-home locations.
>
> Out-of-home discretionary is comprised of activities coded as: “visiting,” “culture,” “civic,” “amusements,” “hobbies,” “exercise or athletics,” “rest and relaxation,” “spectator athletic events,” “incidental trips,” and “tag-along trips” at non-home locations.
>
> In-home work is comprise of activities coded as “work” and “work-related” at the home location.

It is possible to use other activity categorizations within the same demand model structure. For example, several studies have focused on shopping activities and activities involving picking up or dropping off passengers (the so-called “serve-passenger” trip purpose), and our maintenance category could be subdivided to preserve categories such as these. However, it is wise to evaluate the performance of the model system at its current level of complexity before expanding the detail of its activity demand component.

These activity participation variables were computed for both the male and female heads of spousal households. Thus we have a total of eight activity duration variables, four for each household head, allowing us to capture interactions between the male and female household heads (Damm, 1978; Hanson and Hanson, 1978; Kostyniuk and Kitamura, 1982; van Wissen, 1989; Golob and McNally, 1997).

The endogenous activity participation variables are listed with descriptive statistics in Table 1. Over 62 percent of male heads recorded some out-of-home work activity over the two days; and for those men participating in work activities, the two-day mean activity participation was 13.4 hours. In comparison, almost 48 percent of female heads worked outside the home during the two diary days, and the mean duration of 12.0 hours for those participating in work activities was slightly less than that of the male heads. For both men and women working outside the home, as expected, the median duration was less than the mean, indicating a distribution skewed to the right.

Almost 89 percent of the male heads and over 94 percent of the female heads participated in some non-work out-of-home activities over two days. The mean non-work activity durations for both men and women were approximately 5.5 hours, and the conditional distributions are skewed to the right. Finally, only 11.5 percent of the male heads and 8.4 percent of the female heads recorded any in-home work activities.

Table 1: The Endogenous Activity Participation Variables (units of hours per two days)

Activity Duration Variable	% Cases > 0	For Cases > 0		
		Median	Mean	Std. Dev.
Total two-day **out-of-home work** activity duration - **male** head	62.6%	15.1	13.4	5.75
Total two-day **out-of-home maintenance** activity duration - **male** head	82.8%	2.0	2.9	2.7
Total two-day **out-of-home discretionary** activity duration: male head	54.1%	3.0	4.2	3.8
Total two-day **in-home work** activity duration: male head	12.8%	4.0	6.4	5.9
Total two-day **out-of-home work** activity duration - **female** head	47.7%	12.8	12.0	5.8
Total two-day out-of-home **maintenance** activity duration - **female** head	89.0%	2.6	3.4	3.0
Total two-day **out-of-home discretionary** activity duration - **female** head	57.4%	2.7	3.8	3.2
Total two-day **in-home work** activity duration - **female** head	8.9%	3.8	5.6	5.2

5.2.2 Travel Times

Travel demand can be measured in various ways, including numbers of trips, number of trip destinations (often called sojourns), number of home-based trip chains (often called tours), travel time, or travel distance. Each of these measures can be broken down by mode, where modes are defined in terms of combinations of car driver, car passenger, car travel by driving alone (solo driver), car travel by multiple-occupancy car (carpool), bus, rail, and other forms of public transportation, pedestrian, bicycle, etc. We chose to measure travel in terms of total travel time, over two days, for each household head broken down into (1) total travel times by car, and (2) total travel times by all other modes. The use of travel time is consistent with the measurement of activity demand in terms of activity durations, and all out-of-home time can be accounted for by the addition of the three out-of-home activity durations and two travel times for each individual. It is entirely possible to add trip-based travel measures within the same demand model structure, but this is relegated to future research.

The four travel time variables are listed in Table 2. The distributions of the travel time variables are similar for males and females. Thus, even though males and females have substantially different activity patterns, they spend similar times traveling.

Table 2: The Endogenous Travel Time Variables (units of hours per two days)

Travel Time Variable	% Cases > 0	For Cases > 0		
		Median	Mean	Std. Dev.
Total two-day travel time by **car (driver and passenger)** - **male** head	92.6%	2.0	2.2	1.3
Total two-day travel time by all other **non-car travel** - **male** head	27.7%	0.8	1.1	1.1
Total two-day travel time by **car (driver and passenger)** - **female** head	93.2%	2.0	2.1	1.2
Total two-day travel time by all other **non-car travel** - **female** head	28.6%	0.8	1.1	1.0

5.2.3 Vehicle Ownership

Vehicle ownership for the sample (of 1.047) households breaks down into: 3.3% zero-car, 13.8% one-car, 57.5% two-car, 18.9% three-car, and 6.4% more than three cars.

5.2.4 Vehicle Miles of travel (Household VMT)

VMT was calculated from network distances. More than 96% of the households used at least one of their household vehicles during the two diary days. The median VMT for these households was 53.4 miles, and the mean was 61.6 miles, with a standard deviation of 41.7 miles.

5.3 The Exogenous Variables

The exogenous variables used in the choice model system are similar to those used in conventional travel demand models, with the exception that we exclude employment status. We endeavor to forecast work activities endogenously. The thirteen exogenous variables used in the model is listed in Table 3. Household characteristics include age of the male head, household membership in terms of the number of children by age category, number of drivers, housing tenure, and income. It was not possible to include ages of both of the household heads because of strong multicolinearity problems. Detailed personal characteristics, such as education, occupation, and personal income were not included, because it is generally not possible to obtain exogenous forecasts of such variables for planning purposes.

One exogenous accessibility variable (variable 13 in Table 3) is also included in the model, as a test of policy sensitivity. This variable was created by Metro, the Portland MPO, using sophisticated geographical information system (GIS) computations. It measures the total retail employment within one mile of each residential location, based on x-y coordinates, using the actual street network, and land-use data accurate down to quarter acre parcels. This accessibility variable should explain significant portions of activity demand and the split of mobility demand between car and other modes.

Table 3: The Exogenous Variables

No.	Variable
1	Number of children under 6 years of age
2	Number of children 6-11 years of age
3	Number of children 12-21 years without driving license
4	Number of drivers in household
5	Household in current home 1 year or less (dummy)
6	Household is renting (dummy)
7	Age of male head
8	Male head less than 31 years of age (dummy)
9	Male head 70 years of age or older (dummy)
10	Household Income less than $20,000 (dummy)
11	Household income $20,000 to $30,000 (dummy)
12	Household Income $60,000 or more (dummy)
13	Total retail employment within 1 mile of residence

6. Model Specification

The structural equations model system with latent demand variables was specified with forty-six direct effects between endogenous variables. Each of these effects represents a free parameter in the beta matrix of equation system (1). The postulated matrix is depicted in Figure 2, where $+\beta$ indicates an expected statistically significant positive effects from the variable of the column to the variable of the row, and $-\beta$ indicates an expected negative effect. Table 4 provides a key to the numbered endogenous variables. There are postulated effects that correspond to the six types of effects listed in Section 3:

1. **Travel Demand** (from *Activity Participation* to *Travel Times*)**:** These are operationalized in the effects from variables 1 through 4 to variables 9 and 10 (for the male head) and from variables 5 through 8 to variables 11 and 12 (female head). For each household head, the effects from a given out-of-home activity to the two modes will measure the modal split for that activity. We also hypothesize that in-home work will cause a reduction in car travel, but an increase in non-car travel. In addition, we initialize the model estimation by constraining all eight pairs of these travel demand coefficients to be equal across the two household heads.

2. **Time Budget Effects** (from *Travel Times* to *Activity Participation*): Based on the findings of Golob and McNally (1997), we expect that the maintenance and discretionary activities of the female household head will be most sensitive to feedbacks from car travel time. We also expect that both male and female heads will exhibit more demand for in-home work as a direct function of their car travel time. These effects are in rows 4 through 8 and columns 9 and 11 in the beta matrix of Figure 2.

3. **Mobility Demand** (from *Activity Participation* to *Vehicle Ownership*): We postulate that the major pressures on vehicle ownership demand will come from the out-of-home activities of the male head. These effects are in row 13, columns 1 through 4.

4. **Accessibility** (from *Vehicle Ownership* to *Activity Participation*): We postulate that the vehicle availability will positively influence the maintenance and discretionary activities of female heads. These effects are in column 13.

5. **Vehicle Utilization** (from *Travel Times* to *Vehicle Miles of Travel*): These effects are in row 14.

6. **Excess Mobility Demand** (from *Vehicle Miles of Travel* to *Vehicle Ownership*): This effect is in cell (13,14).

Table 4: Model Endogenous Variables

No.	Set	Variable
1	Activity Participation	out-of-home work - male
2		out-of-home maintenance - male
3		out-of-home discretionary - male
4		in-home work - male
5		out-of-home work - female
6		out-of-home maintenance - female
7		out-of-home discretionary - female
8		in-home work - female
9	Travel Time	car (driver and passenger) - male
10		non-car travel - male
11		car (driver and passenger) - female
12		non-car travel - female
13	Vehicle Ownership	number of household vehicles
14	Vehicle Miles of Travel	total VMT on all household vehicles

Figure 2: Postulated Direct Effects Between Endogenous Variables
(beta matrix specification; no effects are allowed in the diagonal cells)

		activity participation demand								travel demand					
		male				female				male		female		**vehs**	**VMT**
Variable		1	2	3	4	5	6	7	8	9	10	11	12	13	14
male act.	1	--			-β										
	2	-β	--		-β										
	3	-β	-β	--	-β										
	4				--					+β					
fem. act.	5					--			-β						
	6					-β	--		-β			-β		+β	
	7					-β	-β	--	-β			-β		+β	
	8								--			+β			
male travel	9	+β	+β	+β	-β					--	-β				
	10	+β	+β	+β	+β					-β	--				
fem. travel	11					+β	+β	+β	-β			--	-β		
	12					+β	+β	+β	+β			-β	--		
vehs.	13	+β	+β	+β										--	+β
VMT	14									+β	-β	+β	-β		--

Finally, the model specification needs to cover interactions among the activity and travel demand variables:

1. **Activity Hierarchy** (*Within-Activity Participation* effects): These effects, based on the findings of Golob and McNally (1997), determine an activity-based time-use hierarchy for both male and female heads. Individuals who spend more time in work activities have less time available for all other out-of-home activities, and individuals who spend more time in out-of-home maintenance activities have less time available for discretionary activities. All within-activity effects for were equated for male and female household heads.

2. Modal Substitution (*Within-Travel Time* effects): Modal substitution is operationalized by the symmetric effects in cells (10,9) and (9,10) and in cells (12,11) and (11,12). As in the case of within-activity effects, the within-travel effects were specified to be the same for males and females.

The exogenous effects (determined by the free elements in the gamma matrix in system (1)) were initially specified to capture relationships found in empirical studies (e.g., Kostyniuk and Kitamura, 1982; Solomon and Ben-Akiva, 1982). Independent Tobit and ordered-response probit model regressions were also computed for each of the endogenous variables to identify important exogenous effects.

We also specified free disturbance-term correlations between corresponding pairs of variables for male and female heads (the error terms being free off-diagonal elements in the Ψ matrix of equation system (1)). We assume that the unexplained portion of an activity or travel demand of the male head is positively correlated with the unexplained portion of the corresponding activity or travel demand of the female. These error-term correlations, shown to be statistically significant by McNally and Golob (1997), are important for unbiased estimation of causal effects.

It can be shown that such a structural equations model is identified. The model was then estimated using the ADF-WLS method described in Section 4, and the model structure was optimized by performing nested hypothesis testing common in simultaneous equation modeling.

7. Results

7.1 Model Fit

The chi-square value for the final model was 135.35 with 165 degrees of freedom, corresponding to a probability value of $p = 0.956$. This indicates that the model *cannot* be rejected at the $p = .05$ level. The overall fit of the model is excellent, as measured by all generally accepted goodness-of-fit criteria for structural equations models (Bollen, 1989).

The endogenous variable causal structure of the final model, shown in Figure 3, differed in some details from the postulated structure of Figure 2. Thirty-eight (83%) of the postulated forty-six direct causal effects were found to be significant at the $p = .05$ level with the correct sign. One coefficient (shown in parentheses in Figure 3) was significant at only the $p = .12$ level, but we judged its inclusion to be theoretically justified. Seven of the postulated effects were rejected at the $p = .05$ level, and these are shown by shaded empty cells in Figure 3. On the other hand, four unanticipated effects were found to be important in explaining the causal structure. These are shown as shaded cells with positive or negative beta coefficient indicators in figure 3. We can conclude that the postulated endogenous variable structure was essentially upheld.

Figure 3: Direct Effects Between Endogenous Variables (beta matrix coefficients)
(boxed cells indicate different structure than hypothesized)

		activity participation demand								travel demand					
		male				female				male		female		**vehs**	**VMT**
Variable		1	2	3	4	5	6	7	8	9	10	11	12	13	14
male act.	1				$-\beta$										
	2	$-\beta$			$-\beta$										
	3	$-\beta$	$-\beta$		$-\beta$	$\boxed{-\beta}$									
	4					$\boxed{+\beta}$				$+\beta$					
fem. act.	5								$-\beta$						
	6					$-\beta$			$-\beta$			$-\beta$		$+\beta$	
	7					$-\beta$	$-\beta$		$-\beta$						
	8	$+\beta$										$+\beta$			
male travel	9	$+\beta$	$+\beta$	$+\beta$	$-\beta$		$+\beta$				$-\beta$				
	10		$+\beta$		$+\beta$										
fem. travel	11					$+\beta$	$+\beta$	$+\beta$	$-\beta$				$-\beta$		
	12					$+\beta$	$+\beta$	$+\beta$				$-\beta$			
vehs.	13	$+\beta$		$+\beta$											$(+\beta)$
VMT	14				$+\beta$					$+\beta$	$-\beta$	$+\beta$	$-\beta$		

The exogenous variable regression structure involved sixty-four effects (each effect corresponding to a free parameters in the gamma matrix of system (1)).

The freely estimated main-diagonal variances of the error-term correlation matrix Ψ produce R^2 values for the endogenous variables. These R^2 estimates are listed in Table 7. The model does a good job of explaining demand for cars, followed by car travel demand for both male and female household heads. Demand for male and female out-of-home work activities is also fairly well explained, as is total vehicle utilization. The least well explained variables are demand for male and female in-home work activities, as well as females' demand for out-of-home maintenance activities and males' demand for non-car travel.

Table 7: Estimated Endogenous Variable R^2 values

Endogenous Variable	R^2
out-of-home work activities - male	0.25
out-of-home maintenance activities - male	0.13
out-of-home discretionary activities - male	0.12
in-home work activities - male	0.01
out-of-home work activities - female	0.19
out-of-home maintenance activities - female	0.01
out-of-home discretionary activities - female	0.11
in-home work activities - female	0.02
car (driver and passenger) travel - male	0.29
non-car travel - male	0.07
car (driver and passenger) travel - female	0.30
non-car travel - female	0.15
number of household vehicles	0.45
total VMT on all household vehicles	0.21

7.2 Relationships Between the Endogenous Variables

7.2.1 Travel Demand

The estimated total effects on the travel demand variables from the activity demand variables, calculated according to equation system (2), are listed in Table 8. The strongest causes of demand for car travel are demands for out-of-home maintenance activities by both male and female heads. Out-of-home work activities impose less demand on car travel, because less work time implies more time for other activities which require travel. In fact, the total effect of out-of-home work on car travel is insignificant for female heads. In-home work leads to reduced car travel for both males and females, but it leads to increased non-car travel time for males, but not for females. There are also some cross-person effects, in which male travel demand is sensitive to female work and maintenance activities, confirming the descriptive findings of Hanson and Hanson (1978), and female car travel demand is sensitive to male non-work activities.

Table 8: Total Effects of Activity Demand on Demand for Travel by Mode (showing only effects significant at the p = .05 level)

Causal variable	Affected variable	Total effect	*z*-statistic
out-of-home work - male	car travel - male	0.092	4.19
out-of-home maintenance - male	car travel - male	0.226	7.99
out-of-home discretionary - male	car travel - male	0.353	13.00
in-home work - male	car travel - male	-.241	-4.60
out-of-home work - female	car travel - male	-.086	-5.90
out-of-home maintenance - female	car travel - male	0.100	4.09
out-of-home discretionary - female	car travel - male		
in-home work - female	car travel - male		
out-of-home work - male	non-car travel - male	-.042	-5.69
out-of-home maintenance - male	non-car travel - male	0.130	6.56
out-of-home discretionary - male	non-car travel - male		
in-home work - male	non-car travel - male	0.065	3.27
out-of-home work - female	non-car travel - male	0.005	2.07
out-of-home maintenance - female	non-car travel - male		
out-of-home discretionary - female	non-car travel - male		
in-home work - female	non-car travel - male	-.001	-2.08
out-of-home work - male	car travel - female		
out-of-home maintenance - male	car travel - female	-0.001	-2.08
out-of-home discretionary - male	car travel - female	0.012	3.25
in-home work - male	car travel - female		
out-of-home work - female	car travel - female		
out-of-home maintenance - female	car travel - female	0.438	14.37
out-of-home discretionary - female	car travel - female	0.328	12.31
in-home work - female	car travel - female	-.149	-4.25
out-of-home work - male	non-car travel - female		
out-of-home maintenance - male	non-car travel - female		
out-of-home discretionary - male	non-car travel - female		
in-home work - male	non-car travel - female		
out-of-home work - female	non-car travel - female		
out-of-home maintenance - female	non-car travel - female		
out-of-home discretionary - female	non-car travel - female		
in-home work - female	non-car travel - female		

7.2.2 Time Budget Effects

Significant time budget effects were found for car travel, but not for non-car travel (Table 9). These results imply that all male activities are sensitive to the male car travel time, and all female activities, with the exception of discretionary activities, are sensitive to female car travel time. Importantly, demand for in-home work is a positive function of car travel time for both males and females. There are also some effects of female car travel time on male activities. These results indicate that budget models of travel (Zahavi, 1979; Gunn, 1981; Downes and Emmerson, 1984; and Golob, *et al.,* 1981) are credible if the time-budget concept is expanded to incorporate both activity and travel time (Kraan, 1996).

Table 9: Total Effects of Car Travel Demand on Activity Participation Demand (showing only effects significant at the p = .05 level)

Causal variable	Affected variable	Total effect	*z*-statistic
car travel - male	out-of-home work - male	-.026	-2.70
car travel - male	out-of-home maintenance - male	-.016	-2.17
car travel - male	out-of-home discretionary - male	-.020	-2.18
car travel - male	in-home work - male	0.172	3.19
car travel - male	out-of-home work - female		
car travel - male	out-of-home maintenance - female		
car travel - male	out-of-home discretionary - female		
car travel - male	in-home work - female		
car travel - female	out-of-home work - male	0.001	2.06
car travel - female	out-of-home maintenance - male		
car travel - female	out-of-home discretionary - male	0.002	2.83
car travel - female	in-home work - male	-.004	-2.30
car travel - female	out-of-home work - female	-.015	-3.24
car travel - female	out-of-home maintenance - female	-.138	-2.95
car travel - female	out-of-home discretionary - female		
car travel - female	in-home work - female	0.131	3.87

7.2.3 Mobility Demand

All significant total effects of activity demand on vehicle ownership are from activities of the male head (Table 10). Out-of-home work and discretionary activities are positively related to vehicle demand, while in-home work and out-of-home maintenance activities are negatively related to vehicle demand. The causal effect of maintenance activities reflects the fact that maintenance activities negatively affect discretionary activities, and the link from discretionary demand to vehicle demand is strong.

Table 10: Total Effects of Activity Demand on Car Ownership Demand (showing only effects significant at the p = .05 level)

Causal variable	Affected variable	Total effect	*z*-statistic
out-of-home work - male	car ownership demand	0.189	5.47
out-of-home maintenance - male	car ownership demand	-.016	-2.91
out-of-home discretionary - male	car ownership demand	0.218	5.70
in-home work - male	car ownership demand	-.058	-5.89
out-of-home work - female	car ownership demand		
out-of-home maintenance - female	car ownership demand		
out-of-home discretionary - female	car ownership demand		
in-home work - female	car ownership demand		

7.2.4 Accessibility

The only important total effect of vehicle ownership on activity demand concerns female out-of-home maintenance activities. Enhanced car availability encourages shopping, personal business, child care, and related activities by the female head.

7.2.5 Vehicle Utilization

There is a slightly stronger total effect on VMT from car travel time of the female head, than from car travel time of the male head (Table 11). This is probably due to lower mean speeds for trips made by the female head.

Table 11: Total Effects of Travel Demand on Car Utilization
(showing only effects significant at the p = .05 level)

Causal variable	Affected variable	Total effect	*z*-statistic
car travel - male	total VMT on all household vehicles	0.102	7.86
non-car travel - male	total VMT on all household vehicles	-.125	-14.51
car travel - female	total VMT on all household vehicles	0.137	9.65
non-car travel - female	total VMT on all household vehicles	-.112	-11.98

7.2.6 Excess Mobility Demand

There is a positive link from VMT to vehicle ownership, as expected, but the total effect (0.116) is not significant at the p = .05 level (z-statistic = 1.08).

7.2.7 Error-term Correlations

The estimated correlations of the unexplained portions of the endogenous variables (off-diagonal terms in the ψ matrix of system (1)), are listed in Table 12. The strengths of these correlations underscores the importance of including them in the model specification.

Table 12: Estimated Error-term Correlations

Between	And	Correlation	*z*-statistic
out-of-home work - male	out-of-home work - female	0.17	7.63
out-of-home maintenance - male	out-of-home maintenance female	0.38	15.20
out-of-home discretionary - male	out-of-home discretionary - female	0.43	18.53
in-home work - male	in-home work - female	0.16	5.65
car travel - male	car travel - female	0.20	8.77
non-car travel - male	non-car travel - female	0.24	8.48

7.3 Effects of the Exogenous Variables

Every one of the thirteen exogenous variables is present in the fourteen reduced-form equations (one for each of the endogenous variables) because of the extensive endogenous links between the endogenous variables. Most of the effects are consistent with earlier findings (e.g., Pas, 1984 and 1988; Golob and McNally, 1997; Lu and Pas, 1997), but there appear to be some new insights. The strongest effects for each exogenous variable are:

1. **Number of children under 6 years of age** negatively influences female out-of-home work demand, female demand for non-car travel, and male demand for in-home work. It positively influences male and female demand for discretionary activities and VMT.

2. **Number of children 6-11 years of age** also negatively influences female out-of-home work demand and male in-home work demand, and it positively influences female demand for both maintenance and discretionary activities and VMT, but it has no significant total effect on male demand for discretionary activities.

3. **Number of children 12-21 years without driving license** has a positive influence on male demand for out-of-home work, and it has a negative influence on male demand for in-home work and female demand for out-of-home discretionary activities.

4. **Number of drivers in household** strongly explains car travel times, car ownership demand, and VMT.

5. **Households in current home 1 year or less** exhibit higher levels of discretionary activities, lower levels of in-home work for both males and females, lower female car travel, and lower VMT.

6. **Households renting** exhibit lower car demand for travel, ownership, and VMT, but higher demand for out-of-home discretionary and maintenance activities, for both males and females, and higher demand for in-home female work activities.

7. **Age of the male head** is related to all activity and mobility demand *except* demand for maintenance activities (male and females) and demand for male non-car travel.

8. **Household in which the male head less than 31 years of age** exhibit more demand for more out-of-home non-work activities (male and female) and more intensive use of vehicles.

9. **Households in which the male head 70 years of age or older**, as expected, have less work activities, car ownership, and usage. However, there is positive effects on demand for other activities, and there are no significant affects on travel demand, with the exception of lower car travel demand for female heads.

10. **Households with Income less than $20,000** exhibit lower levels of demand for work activities, car travel, ownership, and usage, but they maintain high levels of demand for non-work out-of-home activities.

11. **Household with income $20,000 to $30,000** are similar to households with lower incomes, but they travel more.

12. **Household with Income $60,000 or more** are opposite to low income households in most aspects, with the exception that high income households also exhibit strong demand for female out-of-home discretionary activities, and lower demand for male non-car travel.

13. **Total retail employment within 1 mile of residence** was extremely effectual as an exogenous variable. Twelve of the fourteen total effects of this variable, which are listed in Table 13, were significant at the p = .05 level. Controlling for all other exogenous effects, both men and women in households with higher levels on this accessibility index demonstrated less car travel, and more non-car travel. Accessibility was associated with substantially less VMT, but the affect on car ownership was insignificant, indicating that households with better neighborhood accessibility own

essentially the same numbers of vehicles, but they use them less. This measure of neighborhood accessibility also predicted a higher level of demand for maintenance activities among male heads, and lower levels of in-home work for both males and females.

Table 13: Estimated Total Effects of Retail Accessibility

Endogenous Variable	Coefficient	*z*-statistic
out-of-home work activities - male	0.0034	2.23
out-of-home maintenance activities - male	0.1293	5.91
out-of-home discretionary activities - male	-0.0094	-2.31
in-home work activities - male	-0.0228	-2.48
out-of-home work activities - female	0.0445	1.97
out-of-home maintenance activities - female	-0.0054	-0.61
out-of-home discretionary activities - female	-0.0139	-1.93
in-home work activities - female	-0.0112	-2.77
car (driver and passenger) travel time- male	-0.1484	-6.75
non-car travel time- male	0.1677	6.33
car (driver and passenger) travel time - female	-0.0829	-3.78
non-car travel time - female	0.2109	8.83
number of household vehicles	-0.0249	-1.12
total VMT on all household vehicles	-0.2040	-23.90

The performance of these exogenous variables indicates that the demand for *both* activities and mobility is highly sensitive to household demographic and economic factors, as well as to environmental factors such as accessibility. This bodes well for the use of such models in forecasting and policy evaluation.

8. Summary and Directions for Further Research

We were successfully able to develop and estimate a joint model of demand for activity participation and mobility. The observed endogenous variables are out-of-home and in-home activity durations and travel times by mode for each of two household heads, household vehicle ownership, and household vehicle utilization. The model system of simultaneous equations involves latent demand variables that represent these observed censored and ordinal variables. The distribution-free estimation method provides accurate goodness-of-fit model evaluation and hypothesis testing capabilities. The goodness-of-fit is excellent, using activity-diary and accessibility data from the Portland Metropolitan Area. This model system can be used to replace or augment conventional travel demand models for certain planning purposes. It can provide forecasts of the effects on activity participation and mobility of factors that are difficult to include in trip-based models.

The demand model system can be expanded to be made more useful in numerous ways. First, we can test the effects of additional exogenous variables on activity and mobility demand, the most interesting candidates for testing being different types of accessibility measures. Second, we can subdivide activities differently, possibly adding non-work in-home activities if reliable time-use data are available. Third, we can modify or expand the set of mobility variables, using trip-based measures, to see how trip and trip chain generation is related to activity participation and other mobility measures. Fourth, we can divide travel demand differently, by separating car travel into solo driving and carpool modes, or by separating non-car travel into public transport and non-motorized modes. Finally, we can divide activity and travel demand into different periods of the week, if we are anxious to know how weekdays differ from weekends. Such a model system can evolve in many ways while preserving its fundamental assumptions and basic causal structure.

8.1 Exogenous Variables

Adding additional exogenous variables to a structural equation model such as this will generally not be a problem, as long as the sample size is sufficient, and the exogenous variables correlation matrix is positive definite (the variables are not collinear). Thus, the set of potential exogenous variables is limited only by data availability. The most productive new variables might be spatial accessibility indices and levels of service associated with residential location. One such accessibility variable, computed using a GIS as retail employment within one mile of the residential location, was found to have substantial explanatory power in the case study application. Many other variables that can capture changes in accessibility for different types of activities and different modes should be useful in evaluating the effects of changes in such things as traffic flows, land-uses, or pedestrian or bicycle facilities, on activity and mobility demand. The next logical step would be to study how people associate changes in activity patterns and mobility with their perceived quality of life.

8.2 Activity Demand Variables

The demand model system can accommodate other activity categorizations. Several trip chaining studies have focused on shopping activities and activities involving picking up or dropping off passengers (the so-called “serve-passenger” trip purpose), and the maintenance category used in the case study could be subdivided to analyze demand for these more specific activities. However, a large number of activity categories will require a large sample size, because: (1) minimum sample size is proportional to the number of estimated free parameters, (2) the estimation method relies on asymptotic theory, and (3) we need to observe sufficient demand for each category of activity (as discussed in Section 8.4 below).

We anticipate that the greatest potential will be in expanding the set of in-home activity categories. This would allow us to analyze the effects on activity and mobility demand of the substitution of in-home for out-of-home activities. We could thus forecast the travel demand consequences of advances in telecommunication that provide opportunities for in-home shopping and banking services, as well as in-home work activities.

8.3 Travel Demand Variables

Many measurements of travel demand are possible without changing the basic structure of the model system. We used travel time, by mode, in the case study. Some other obvious candidates are:

1. trip rates (numbers of sojourns, or destinations visited);
2. numbers of home-based trip chains (or, tours);
3. numbers of trip chains by type (simple out-and-back tours, versus multiple destination tours of different kinds).
4. travel distance.

Due to potential collinearity problems and complexity of the endogenous variable causal structure, it might not be possible to accommodate multiple travel demand variables, such as travel times and trip-chain rates, within the same model. Rather, separate models could be estimated for each travel demand measure of interest.

8.4 Modal Definitions

Any of these travel demand variables could be divided according to mode, where modal definitions can be tailored to policy evaluation needs. The car mode used in the case study could be broken down into: (1) solo driving, and (2) car travel with two or more occupants. Our non-car mode could be broken down into: (1) public transport, (2) pedestrian, and (3) bicycle. Once again, the detail is dictated mainly by the extent of the data. Empirically ,we have found that censored endogenous variables with less than five percent non-zero observations can cause problems in estimation of this type of structural equation model. Thus, we can avoid estimation problems if activity and mode categories are defined so that we observe at least five percent of our sample engaging in the activity or using the mode within the activity diary period. A longer diary period is also effective in increasing the incidence of relatively rare activity or travel demand, so the sample size requirement can be partially offset by a longer diary period.

8.5 Time Periods

We do not think that it is wise to estimate separate models for weekdays and weekend days, because there are complex activity patterns related to day of the week, and separate models will not allow analyses of the substitution of weekday for weekend activities. For example, compressed work weeks potentially alter the activity relationships between weekdays and weekend days. However, some activity diary surveys conducted by MPOs have concentrated on weekdays, so equal representation of all days of the week is not always possible. If we estimate our model system using only data on weekday activities and travel, we will weaken the explanation of the car ownership and usage components, because we are only considering the mobility needs emanating from weekday activities. If we have data for all days of the week and planners are interested in distinguishing activity and travel by weekday versus weekend day, it is possible to divide the activity and travel demand variables by time period, if we have sufficient observations.

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