Title

How Households Use Different Types of Vehicles: A Structural Driver Allocation and Usage Model

Authors

Golob, Thomas F.
Kim, Seyoung K.
Ren, Weiping (Willliam)

Publication Date

1995-06-01

UCI-ITS-AS-WP-95-2

How Households Use Different Types of Vehicles: A Structural Driver Allocation and Usage Model

Thomas F. Golob
Seyoung Kim
Weiping Ren

UCI-ITS-AS-WP-95-2

Institute of Transportation Studies
University of California, Irvine; Irvine, CA 92697-3600 U.S.A.
tgolob@uci.edu

June 1995

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

How Households Use Different Types of Vehicles: A Structural Driver Allocation and Usage Model

by

Thomas F. Golob

Seyoung Kim

Weiping Ren

Institute of Transportation Studies
University of California
Irvine, CA 92717

December 7, 1994

Revised: June 9, 1995

Published in

Transportation Research – Part A: Policy and Practice, 30: 103-118

How Households Use Different Types of Vehicles: A Structural Driver Allocation and Usage Model

by

Thomas F. Golob
Seyoung Kim
Weiping Ren

ABSTRACT

The vehicle miles of travel for each vehicle in multi-vehicle households is modeled as a function of household characteristics, vehicle characteristics, and the matches of vehicle to driver in the satisfaction of travel desires. A structural equations model is developed in which principal driver characteristics, as well as vehicle miles of travel, are endogenous. There are links between how each vehicle is used and who in the household is each vehicle's principal driver. Each vehicle's usage can then be expressed in reduced-form equations as a function of exogenous household and vehicle type variables for forecasting purposes. The model is estimated on a 1993 sample of approximately 2000 multi-vehicle households in California.

INTRODUCTION

We are concerned here with household vehicle usage behavior, and the focus is on predicting vehicle miles of travel by type of vehicle, where we define type by combinations of size and body style and model year (vintage). Usage by vehicle type is important for forecasting vehicle emissions. Vehicle usage is also a key component in forecasting demand for alternative-fuel vehicles and environmentally-friendly vehicles with limited range or other such distinguishing vehicle attributes.

Households acquire different vehicles to satisfy both specific transportation needs and the preferences of the household members. For single-vehicle households with more than one driver, vehicle usage results from each driver's use of the household vehicle to satisfy his or her travel desires. For multi-vehicle households, usage behavior involves distributing total travel across the vehicles. Each household driver can either use one of the household's vehicles exclusively, or he or she can use different vehicles for different trip purposes. The level of usage of each vehicle depends on how total household usage is allocated among the drivers and vehicles.

Forecasts of usage by vehicle type thus depends on: (1) household characteristics, (2) characteristics of the principal driver or drivers of the vehicle, and (3) the characteristics of the vehicle itself. Potentially important household characteristics include income, residential location, number of vehicles, number of drivers, number of workers, and number of household members by age group. Driver characteristics might include age, gender, and employment status. And vehicle characteristics might include vehicle age, operating cost, passenger and cargo capacity, body style, and value.

Exogenous forecasts of household characteristics using Census projections or sociodemographic models used in regional planning. Exogenous forecasts of household vehicle holdings by type of vehicle are also obtainable using vehicle type choice models, such as those developed by Lave and Train (1979), Manski and Sherman (1980), Hensher and Manefield (1982), Hocherman, et al. (1983), Berkovec (1985), Hensher and Le Plastrier (1985), Mannering and Winston (1985), Train (1986), McCarthy and Tay (1989), Hensher, et al. (1992), or Ren, et al. (1995). In principle, household and vehicle characteristics are all that are needed to forecast vehicle usage for single-vehicle households with only one driver. However, for the majority of households -- multi-vehicle households and for single-vehicle households with more than one driver -- a driver allocation model is needed to forecast usage by specific vehicle type.

Usage of a specific vehicle depends heavily on which member or members of the household typically drives the vehicle. Workers, younger persons, and males are likely to drive more, as demonstrated in several studies (e.g., Hensher, 1985; Hensher, et al., 1992; Mannering, 1983; Mannering and Winston, 1985; and Train, 1986). However, exogenous forecasts of principal driver characteristics for individual vehicles in multi-vehicle and multidriver households are not feasible. Consequently, the present model treats principal driver characteristics as endogenous.

The current model is similar to previous models of vehicle allocation and use in multi-vehicle households (Mannering, 1983; Hensher, 1985; Train, 1986; and Hensher, et al., 1992) in that separate equations with correlated error terms are developed for each vehicle in the household. Our approach deviates from previous efforts, because we specify additional equations for principal-driver characteristics that cannot be readily forecast and need to be “solved out” of the problem. We also believe that the present approach is unique because the reduced-form equations needed for forecasting purposes are developed through a structural specification of vehicle allocation to drivers.

The household’s choices of the number of vehicles to own and the types of these vehicles are taken as given in this model. This is theoretically incorrect, because a household’s travel requirements will influence its choice of vehicle type. If the error terms of the discrete vehicle type choice model and the vehicle usage model are correlated, the parameter estimates will be biased. A linear correction term involving a transformation of predicted vehicle type choice probabilities can be applied to the usage model to account for self selectivity bias (McFadden et al., 1985; Mannering and Winston, 1985; Train, 1986; Hensher, et al., 1992). Empirically, however, the selectivity corrections applied in utilization models to account for endogeneity bias have not had substantial effects on estimation results (Train, 1986; Hensher, 1992). The structural equation system developed here can be estimated jointly with vehicle type choice, or it can accept correction terms that are linear-in-parameters, but this is relegated to future research.

We model is for two vehicles in multi-vehicle households. In two-vehicle households, we thus model use of both vehicles. In households with more than two vehicles, we model use of the two newest vehicles only, but the model takes account of the total number of household vehicles as additional variables explaining use of the two newest vehicles.

DATA

The Survey

The data are from a 1993 survey of approximately 4750 households. The sample was identified using pure random digit dialing and was geographically stratified into 79 areas covering most of the urbanized area of California excluding San Diego County. The survey was composed of three distinct components. First, 7,387 households completed an initial computer-aided telephone interview (CATI), which collected information on household structure, vehicle inventory, housing characteristics, employment data, commuting for all workers and students, and information about the intended next vehicle transaction. Second, the data from the initial CATI interview were used to produce a customized mail-out questionnaire. This questionnaire asked more detailed questions about each household member's commuting and vehicle usage, including information about sharing vehicles in multiple-vehicle and multiple-driver households. The mail-out questionnaire also contained two "stated preference" experiments for each household. Each of these experiments described three hypothetical vehicles, from which households were asked to choose their preferred vehicle (Ren, *et al.,* 1995). A final CATI interview was used to collect the responses to the mail-out questions.

Of the approximately 7,200 households that completed the initial CATI survey, 66%, or 4747 households, successfully completed the mail-out portion of the survey. A comparison with Census data reveals that the sample is slightly biased toward home-owning larger households with higher incomes, and weights are being developed to balance the sample to the known population (Brownstone et al., 1994). An unweighted sample is used here.

Regarding vehicle usage behavior, the breakdown by vehicle ownership level was: 1% zero vehicles, 34% one vehicle, 47% two vehicles, 13% three vehicles, and 5% four or more vehicles. The corresponding population statistics from the US Census is: 2% zero vehicle, 36% one vehicle, 43% two vehicles, 13% three vehicles, and 6% four or more vehicles. On this criterion, our sample is representative, with the exception of zero-vehicle households. For one-vehicle households, 75% had exactly one driver, while 25% had two or more drivers. Thus, approximately 73% of the households in the sample were either multi-vehicle or single-vehicle/multiple-driver, where driver allocation behavior is relevant.

Data for the present model

The sample used to estimate the model reported here is 1869 households. This sample met the following requirements: (1) the household has two or more vehicles driven at least 500 miles per year; (2) the vehicle make, model, and vintage is known for the two newest vehicles in the household; (3) the principal driver is identified for both of these vehicles; and (4) each driver's gender, age and employment status is known.

The model contains 46 variables, as defined in Table 1. These variables are divided into three groups: (1) *behavioral* vehicle usage characteristics, capturing the ways in which households use their vehicles, (2) *physical* vehicle characteristics and (3) household structural characteristics. We selected these variables on the basis of published vehicle usage model results (Mannering, 1983; Hensher, 1985; Mannering and Winston, 1985; Hensher and Smith, 1986; Train, 1986; Golob, 1990; Hensher, at al., 1992; van Wissen and Golob, 1992). Vehicle usage is self-reported in terms of "How many miles per year is this vehicle driven?" It would be more accurate to calculate annual usage from vehicle odometer readings one year apart, but such data are not available in a cross-sectional survey.

Table 1: Definitions of the Model Variables

Behavioral Vehicle Usage Variables	
Natural log of annual VMT - veh. 1	Natural log of annual VMT - veh. 2
Principal driver age (yrs.) - veh. 1	Principal driver age (yrs.) - veh. 2
Principal driver gender - veh. 1	Principal driver gender - veh. 2
Principal driver employment status - veh. 1	Principal driver employment status - veh. 2
Physical Vehicle Variables	
Vehicle Age (in yrs. from 1993) - veh. 1	Vehicle Age (in yrs. from 1993) - veh. 2
Mini class dummy - veh. 1	Mini class dummy - veh. 2
Subcompact car class - veh. 1	Subcompact car class - veh. 2
Compact car class - veh. 1	Compact car class - veh. 2
Mid-size or full-size car class dummy - veh. 1	Mid-size or full-size car class dummy - veh. 2
Full-size (standard) car class dummy - veh. 1	Full-size (standard) car class dummy - veh. 2
Sports car dummy - veh. 1	Sports car dummy - veh. 2
Compact pickup truck dummy - veh. 1	Compact pickup truck dummy - veh. 2
Full-size (std.) pickup truck dummy - veh. 1	Full-size (std.) pickup truck dummy - veh. 2
Minivan (compact van) dummy - veh. 1	Minivan (compact van) dummy - veh. 2
Full-size (standard) van dummy - veh. 1	Full-size (standard) van dummy - veh. 2
Compact sport utility vehicle dummy - veh. 1	Compact sport utility vehicle dummy - veh. 2
Full-size sport utility vehicle dummy - veh. 1	Full-size sport utility vehicle dummy - veh. 2
Operating cost per mile - veh. 1	Operating cost per mile - veh. 2
Household Variables	
Number of household members aged 16-20	
Total number of drivers in household	
Number of children in household aged 1 to 5	
Total number of children in household	
Household income more than $60,000 (dummy)	
Household head(s) are retired (dummy)	
Mean age of household heads	
Total Number of workers in household	
Household has three vehicles (dummy)	
Household has four or more vehicles (dummy)	

SPECIFICATION

A distinguishing feature of this model is the endogenous treatment of driver allocation behavior. In order to avoid omitted-variables bias, vehicle miles of travel (VMT) is specified as a function of principal driver characteristics in addition to exogenous household and vehicle type characteristics. However principal driver characteristics are also specified as a function of the exogenous variables. This allows the principal driver characteristics, for which no exogenous forecasts are available, to be replaced by their predictors in the final forecasting equations for VMT.

The model has eight endogenous variables. These are listed in Table 2. The two vehicles in each household are arranged such that the newer of the two vehicles in the two-vehicle household is defined as “vehicle 1,” described by the first four endogenous variables and the first group of 14 vehicle-type exogenous variables. The older of the two vehicles, defined to be the “vehicle 2,” is described by the last four endogenous variables and the last group of 14 vehicle-type exogenous variables. If the two vehicles are of the same model year, the order of listing by the respondent is preserved.

Table 2: The Endogenous Variables

Variable	Acronym
Natural log of vehicle miles traveled per year - 1st vehicle	$Ln(VMT_1)$
Age of principal driver - 1st vehicle	Driver Age_1
Gender of principal driver (+ = female) - 1st vehicle	Driver $Gender_1$
Employment status of principal driver (+ = working) - 1st vehicle	Driver Empl St_1
Natural log of vehicle miles traveled per year - 2nd vehicle	$Ln (VMT_2)$
Age of principal driver - 2nd vehicle	Driver Age_2
Gender of principal driver (+ = female) - 2nd vehicle	Driver $Gender_2$
Employment status of principal driver (+ = working) - 2nd vehicle	Driver Empl St_2

The exogenous variables are divided into two blocks: physical vehicle characteristics and household characteristics. The first block is made up of the 28 physical vehicle characteristics from Table 1, 14 for each of the two household vehicles. These variables are listed in Table 3 together with their acronyms.

The second block of exogenous variables is comprised of the ten household characteristics listed in Table 1. This list is reproduced with associated acronyms for further reference in Table 4.

[Table 3: Exogenous Variables for each of the two vehicles

Variable	Acronym
Vehicle Age (in years from 1993)	Vehicle Age
Mini class (dummy)	Type Mini
Subcompact car class (dummy)	Type: Subcompact
Compact car class (dummy)	Type: Compact
Mid-size or full-size car class (dummy)	Type: Mid-size
Full-size (standard) car class (dummy)	Type: Full-size
Sports car (dummy)	Type: Sports Car
Compact pickup truck (dummy)	Type: Small Truck
Full-size (standard) pickup truck (dummy)	Type: Std. Truck
Minivan (compact van) (dummy)	Type: Van
Full-size (standard) van (dummy)	Type: Van
Compact sport utility vehicle (dummy)	Type: Compact SUV.
Full-size (standard) sport utility vehicle (dummy)	Type: Full-size SUV.
Operating cost per mile (in cents)	Operating Cost

Table 4: Exogenous Variables - Household Characteristics

Variable	Acronym
Number of household members aged 16-20	No. of 16-20 yr. olds
Total number of drivers in household	No. of drivers
Number of children in household aged 1 to 5	No. of 1- 5 yr. olds
Total number of children in household	Total no. of children
Household income more than $60,000 (dummy)	Income > $60k
Household head(s) are retired (dummy)	Retired household
Mean age of household heads	Ave. age of heads
Total Number of workers in household	No. of workers
Household has three vehicles (dummy)	3 veh household
Household has four or more vehicles (dummy)	4+ veh household

The model is specified, estimated, and tested using the standard structural equations model (without latent variables), which is given by

$$\mathbf{y} = \mathrm{B}\mathbf{y} + \mathrm{G}\mathbf{x} + \mathrm{z} \qquad (1)$$

where **y** is an (m by 1) column vector of endogenous variables, and **x** is an (n by 1) column vector of exogenous variables. Here, m = 8 and n = 38. The structural parameters are the elements of the (8 by 8) B matrix of causal links between the endogenous variables, and the (8 by 38) G matrix of direct causal (regression) effects from the exogenous variables to the endogenous variables. In addition, we can specify error-term parameters, which are elements of the variance-covariance matrix $\Psi = E\left(\zeta\zeta¢\right)$. For identification of system (1), it must be assumed that **B** is chosen such that **(I-B)** is non-singular, where **I** denotes the identity matrix of rank m.

The total effects of the exogenous variables on the endogenous variables in a structural equations model of this type are given by:

$$T_{yx} = (\mathbf{I} - \mathrm{B})^{-1}\,\mathrm{G}. \qquad (2)$$

These are the so-called reduced-form equations. The total effects of the endogenous variable on each other is given by

$$T_{yy} = (\mathbf{I} - \mathrm{B})^{-1} - \mathbf{I}. \qquad (3)$$

The model specification can be subdivided into endogenous effects (the **B** matrix in equation system 1), exogenous effects (the G matrix), and error-term variance-covariances (the Y matrix). The postulated structure of the **B** matrix is depicted in Table 5.

There are two types of direct effects in the postulated **B** matrix: within vehicle effects and between-vehicle effects. The within-vehicle effects are those in the upper left-hand (first vehicle) and lower right-hand (second vehicle) quadrants of the matrix. Each of these effects is expected to be identical for the two vehicles, and equality restrictions are specified for corresponding pairs of parameters. Use is postulated to be less for vehicles primarily driven by older persons ($\beta_{1,2} = \beta_{5,6}$), and women ($\beta_{1,3} = \beta_{5,7}$), and use is postulated to be greater for vehicles primarily driven by employed persons ($\beta_{1,3} = \beta_{5,8}$). Male principal drivers are more likely to be employed ($\beta_{4,3} = \beta_{8,7}$), as are younger principal drivers ($\beta_{4,2} = \beta_{8,6}$), and older drivers are expected to be male ($\beta_{3,2} = \beta_{7,6}$). An important feature of this specification is that, for each of the two household vehicles, VMT is postulated to be a function of all three of the principal driver variables. Thus, while driver allocation is endogenous, VMT is specified as a function of driver characteristics.

Regarding the between-vehicle effects, we expect strong negative relationships between the gender and employment status of the two principal drivers, and this is accomplished by specifying equated pairs of reciprocal effects ($\beta_{3,7} = \beta_{7,3}$) and ($\beta_{4,8} = \beta_{8,4}$). Ages of the two drivers are expected to be positively related ($\beta_{2,6} = \beta_{6,2}$), and the usage levels of the two vehicles are expected to be positively related due to spatial location and life style factors ($\beta_{1,5} = \beta_{5,1}$).

Table 5: Postulated Direct Effects Between Endogenous Variables

Influenced variable	Influencing Variable							
	Ln (VMT_1)	Driver Age_1	Driver $Gender_1$	Driver Empl St_1	Ln (VMT_2)	Driver Age_2	Driver $Gender_2$	Driver Empl St_2
Ln (VMT_1)		$b_{1,2}$ **(-)**	$b_{1,3}$ **(-)**	$b_{1,4}$ **(+)**	$b_{1,5}$ **(+)**			
Driver Age_1						$b_{2,6}$ **(+)**		
Driver $Gender_1$		$b_{3,2}$ **(-)**					$b_{3,7}$ **(-)**	
Driver Empl St_1		$b_{4,2}$ **(-)**	$b_{4,3}$ **(-)**					$b_{4,8}$ **(-)**
Ln (VMT_2)	$b_{5,1}=b_{1,5}$					$b_{5,6}=b_{1,2}$	$b_{5,7}=b_{1,3}$	$b_{5,8}=b_{1,4}$
Driver Age_2		$b_{6,2}=b_{2,6}$						
Driver $Gender_2$			$b_{7,3}=b_{3,7}$			$b_{7,6}=b_{3,2}$		
Driver Empl St_2				$b_{8,4}=b_{4,8}$		$b_{8,6}=b_{4,2}$	$b_{8,7}=b_{4,3}$	

This is a parsimonious structure, because it has only ten free parameters in the **B** matrix, representing 20 endogenous paired effects. This specification will in general result in an identified system.

The postulated structure of the exogenous effects is shown in is depicted in Table 6. This represents a transposed version of the Γ matrix of structural equation system (1). The hypothesized effects of the vehicle characteristics (Sub-matrices A and D in Table 6) capture driver stereotypes. For example, there are typically more male principal drivers of compact and full-size pickup trucks; subcompact cars might have younger principal drivers; and minivans are likely to be driven by females. Logically, older vehicles and higher operating cost vehicles should be driven less, holding all else constant. The major restrictions applied in specifying these exogenous vehicle type influences are that the effects be the same for the two vehicles ($\gamma_{i,,j} = \gamma_{i+4,j+14}$ for i = 1 to 4, j = 1 to 14).

It is possible that the characteristics of the first vehicle can affect the VMT and principal driver characteristics of the second vehicle, and conversely. The model was initially specified by setting all such cross-vehicle effects to zero (elements in Sub-matrices B and C in Table 6). Tests were then conducted to ascertain whether cross-vehicle effects significantly improved model fit.

Table 6: Postulated Direct Effects from the Exogenous Variables

<table>
<tr><th rowspan="2">Exogenous Variable</th><th colspan="8">Endogenous Variable</th></tr>
<tr><th>Ln (VMT_1)</th><th>Driver Age_1</th><th>Driver $Gender_1$</th><th>Driver Empl St_1</th><th>Ln (VMT_2)</th><th>Driver Age_2</th><th>Driver $Gender_2$</th><th>Driver Empl St_2</th></tr>
<tr><td>Vehicle Age_1</td><td colspan="4" rowspan="14">Sub-matrix A:
within-vehicle effects of vehicle characteristics on VMT and relationships between vehicle characteristics and principal driver characteristics for first vehicle

(equated to Sub-matrix D)</td><td colspan="4" rowspan="14">Sub-matrix B:
cross-vehicle effects of characteristics of the first vehicle on VMT and principal driver characteristics of the second vehicle

(sparse sub-matrix, initially specified null)</td></tr>
<tr><td>$Type_1$: Mini car</td></tr>
<tr><td>$Type_1$: Subcompact</td></tr>
<tr><td>$Type_1$: Compact car</td></tr>
<tr><td>$Type_1$: Mid-size car</td></tr>
<tr><td>$Type_1$: Full-size car</td></tr>
<tr><td>$Type_1$: Sports car</td></tr>
<tr><td>$Type_1$: Small Truck</td></tr>
<tr><td>$Type_1$: Std. Truck</td></tr>
<tr><td>$Type_1$: Minivan</td></tr>
<tr><td>$Type_1$: Std. Van</td></tr>
<tr><td>$Type_1$: Small SUV</td></tr>
<tr><td>$Type_1$: Std. SUV.</td></tr>
<tr><td>Operating $Cost_1$</td></tr>
<tr><td>Vehicle Age_2</td><td colspan="4" rowspan="14">Sub-matrix C:
cross-vehicle effects of characteristics of the second vehicle on VMT and principal driver characteristics of the first vehicle

(sparse sub-matrix, initially specified null)</td><td colspan="4" rowspan="14">Sub-matrix D:
within-vehicle effects of vehicle characteristics on VMT and relationships between vehicle characteristics and principal driver characteristics for second vehicle

(equated to Sub-matrix A)</td></tr>
<tr><td>$Type_2$: Mini car</td></tr>
<tr><td>$Type_2$: Subcompact</td></tr>
<tr><td>$Type_2$: Compact car</td></tr>
<tr><td>$Type_2$: Mid-size car</td></tr>
<tr><td>$Type_2$: Full-size car</td></tr>
<tr><td>$Type_2$: Sports car</td></tr>
<tr><td>$Type_2$: Small Truck</td></tr>
<tr><td>$Type_2$: Std. Truck</td></tr>
<tr><td>$Type_2$: Minivan</td></tr>
<tr><td>$Type_2$: Std. Van</td></tr>
<tr><td>$Type_2$: Small SUV.</td></tr>
<tr><td>$Type_2$: Std. SUV.</td></tr>
<tr><td>Operating $Cost_2$</td></tr>
<tr><td>No.of 16-20 yr. olds</td><td colspan="4" rowspan="10">Sub-matrix E:
effects of household characteristics on VMT and principal driver characteristics of the first vehicle
(equated to Sub-matrix F)</td><td colspan="4" rowspan="10">Sub-matrix F:
effects of household characteristics on VMT and principal driver characteristics of the second vehicle
(equated to Sub-matrix E)</td></tr>
<tr><td>No. of drivers</td></tr>
<tr><td>No. of 1-5 yr. olds</td></tr>
<tr><td>Total no. of children</td></tr>
<tr><td>Income>$60k</td></tr>
<tr><td>Retired household</td></tr>
<tr><td>Ave. age of heads</td></tr>
<tr><td>No. of workers</td></tr>
<tr><td>3 veh household</td></tr>
<tr><td>4+ veh household</td></tr>
</table>

Examples of the postulated exogenous effects of the household characteristics, represented in Table 6 by the elements of Sub-matrices E and F, include: Principal drivers in households with more workers and in high-income households are more likely to be employed. Usage is higher in households with more children and in high-income households. Principal drivers are younger in households with young children. Drivers in retired households are older and are less likely to be employed (although some drivers in retired households, such as adult children living with their parents, could be employed). Finally, households with three or more vehicles have lower levels of usage on their first and second vehicles, *ceteris paribus*. We initially attempt to equate all of these effects between the two vehicles (coefficient $\gamma_{i,,j} = \gamma_{i+4,,j}$ for i = 1 to 4, j = 29 to 38).

Finally, the we postulate a Ψ matrix of error-term variance-covariances that is diagonal (no error-term covariances). If the unique component of any one of the four endogenous variables of the first vehicle is correlated with the unique component of the corresponding variable for the second vehicle, then we should find statistically significant coefficients for the Ψ matrix terms $\psi_{5,1}$, $\psi_{6,2,}$ $\psi_{7,3}$, or $\psi_{8,7}$. That is, if what is not explained about a variable for one vehicle is correlated with what is not explained about the same variable for the other vehicle, these sub-diagonal parameters should be found to be significant. However, we attempt to capture between-vehicle effects as structural components in the B matrix, rather than as error term covariances, so covariances are specified as zero terms initially. The freely estimated main-diagonal variances produce R^2 values:

$$R^2 = (s_{j,j} - \psi_{j,j}) / s_{j,j} \tag{4}$$

where $s_{j,j}$ is the sample variance of endogenous variable j, and $\psi_{j,j}$ is the estimated error-term variance.

ESTIMATION

Estimation Method

Structural equations systems of this type can be generally estimated using methods of moments (also known as, variance analysis methods). 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:

$$\mathbf{S} = \begin{bmatrix} S_{\mathbf{yy}} & S_{\mathbf{yx}} \\ S_{\mathbf{yx}}' & S_{\mathbf{xx}} \end{bmatrix}, \tag{5}$$

where $\mathbf{S_{yy}}$ denotes the variance-covariance matrix of the endogenous variables, $\mathbf{S_{yx}}$ denotes the covariance matrix between the endogenous and exogenous variables, and $\mathbf{S_{xx}}$ denotes the variance-covariance matrix of the exogenous variables. In the present application, there are 8 endogenous variables and 38 exogenous variables, so $\mathbf{S}$ is a (46 by 46) symmetric matrix.

It can be easily shown using matrix algebra that the corresponding variance-covariance matrix replicated by model system (1), denoted by

$$\Sigma = \begin{bmatrix} \Sigma_{\mathbf{yy}} & \Sigma_{\mathbf{yx}} \\ \Sigma'_{\mathbf{yx}} & \Sigma_{\mathbf{xx}} \end{bmatrix}, \qquad (6)$$

is:

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

$$\Sigma_{yx} = \left(I - B\right)^{-1}\Gamma S_{xx}, \qquad (8)$$

and $\Sigma_{xx} = S_{xx}$ is taken as given, which is the definition of exogenous variables.

The structural equation system here is estimated using the normal-theory maximum likelihood method (Bollen, 1989). The fitting function for structural equations maximum likelihood (ML) estimation is

$$F_{ML} = \mathrm{Log}\left|\Sigma(\theta)\right| - \mathrm{Log}\left|S\right| + \mathrm{tr}\left[S\Sigma^{-1}(\theta)\right] - (m + n) \quad . \qquad (9)$$

This fitting function $\mathbf{F}_{\mathbf{ML}}$ is two times the log-likelihood ratio divided by the sample size, n. Consequently, under assumptions of multivariate normality, $n\mathbf{F}_{\mathbf{ML}}$ is Chi-square distributed, providing a test of model rejection and criteria for testing hierarchical models. Function (9) is minimized in the LISREL8 program using a modified Fletcher-Powell algorithm (Jöreskog and Sörbom, 1993a).

Because four of the eight endogenous variables are dichotomous, the coefficient estimates will be consistent, but the estimates of parameter standard errors for certain coefficients and the overall model Chi-square goodness-of-fit will be biased (Bentler and Bonett, 1980). Unbiased estimates can be generated using the asymptotically distribution-free weighted least squares method (Browne, 1982, 1984), but this requires a much larger sample size. (The rule-of-thumb is that the sample size must be at least three times greater than the number of free entries in the asymptotic variance-covariance matrix of the correlation matrix, the fourth order moments; with 36 variables, this requires approximately 3,250 observations.) However, ML estimates will be consistent, and they have been shown to be fairly robust (Boomsma, 1983). Furthermore, the two endogenous variables of most interest are continuous.

Model Fit

The structure of the final model is basically in accordance with the hypotheses depicted in the previous tables, with some exceptions. The model fits extremely well according to all goodness-of-fit criteria. The chi-square distributed, -2 log likelihood ratio is 216.96 with 266 degrees of freedom, corresponding to a probability value of 0.988. Thus, the model *cannot* be rejected at the p = .05 level.

Error-term Variance-Covariances

The variance-covariance estimates for the endogenous variable unique terms (the Y matrix parameters) are listed in Table 7. The estimated R^2 value for VMT of the first (newest) vehicle is 0.172, and that of the second (oldest) vehicle is 0.197. An unexpected, significant positive error-term covariances was found between principal driver ages. Otherwise, there were no significant error-term covariances. Importantly, the error terms for VMT of the first and second vehicles were not found to be significantly correlated. This relationship was captured in the structural parameters of mutual direct effects between the VMT variables.

Table 7: Estimated Endogenous Variable Error-term Variance-covariances
(*t*-statistics in parentheses)

Endogenous variable	Endogenous Variable							
	Ln (VMT_1)	Driver Age_1	Driver $Gender_1$	Driver Empl St_1	Ln (VMT_2)	Driver Age_2	Driver $Gender_2$	Driver Empl St_2
Ln (VMT_1)	0.382 (30.1)							
Driver Age_1		70.2 (30.2)						
Driver $Gender_1$			0.150 (29.9)					
Driver Empl St_1				0.0750 (29.9)				
Ln (VMT_2)					0.426 (30.1)			
Driver Age_2						82.7 (30.3)		
Driver $Gender_2$			0.138 (15.2)				0.149 (24.4)	
Driver Empl St_2								0.0771 (29.9)

Endogenous Variable Structure

The estimated direct effects between endogenous variables are listed with their *t*-statistics in Table 8. All five of the within-vehicle effects postulated in Table 5 for each vehicle are statistically significant and equal across the two vehicles. Vehicle usage is greater for principal drivers who are younger, male, or employed.

As anticipated, there are also a strong reciprocal linkage between the usage levels of the first and second vehicles, and the two principal drivers are negatively and symmetrically linked in terms of gender and employment status. However, the ages of the two drivers were found to be linked only in one direction: the age of the driver of the newer vehicle is a predictor of the age of the driver of the second vehicle, but the opposing effect from the second driver's age to the first driver's age was not close to being statistically significant and was removed from the final model. This could be due to the mix of first-driver spouses and children as second drivers.

Table 8: Estimated Direct Effects Between Endogenous Variables
(*t*-statistics in parentheses)

Influenced variable	Influencing Variable							
	Ln (VMT_1)	Driver Age_1	Driver $Gender_1$	Driver Empl St_1	Ln (VMT_2)	Driver Age_2	Driver $Gender_2$	Driver Empl St_2
Ln (VMT_1)		-0.0046 (-5.74)	-0.158 (-6.38)	0.221 (8.39)	0.153 (13.6)		0.0809 (2.43)	
Driver Age_1								
Driver $Gender_1$		-0.0024 (-5.35)					-0.847 (-18.8)	
Driver Empl St_1		-0.0019 (-5.07)	-0.109 (-11.7)					-0.233 (-21.3)
Ln (VMT_2)	0.153 (13.6)					-0.0046 (-5.75)	-0.158 (-6.38)	0.221 (8.39)
Driver Age_2		0.0011 (3.00)						
Driver $Gender_2$			-0.847 (-18.8)			-0.0024 (-5.35)		
Driver Empl St_2				-0.233 (-21.3)		-0.0019 (-5.07)	-0.109 (-11.7)	

One unexpected between-vehicle effect is that from gender of the driver of the second vehicle to use of the first vehicle (coefficient $\beta_{1,7}$): use of the first vehicle is greater if the principal driver of the second vehicle is female and less if the driver of the second vehicle is male.

Effects of the Exogenous Variables

The estimated direct effects from the exogenous variables are listed along with their *t*-statistics in Table 9. Ten of the effects of the vehicle characteristics are identical for the two vehicles. However, ten effects for vehicle one and eleven effects for vehicle two are unique to the vehicle from which they emanate. Five of the unique effects are cross-vehicle effects: three representing influences of the type of the household's first vehicle on the use and driver allocation of the second vehicle, and two representing influences of the type of the household's second vehicle on the use and driver allocation of the first vehicle.

Table 9: Estimated Direct Effects of the Exogenous Variables
(*t*-statistics in parentheses)

Exogenous Variable	Endogenous Variable							
	Ln (VMT_1)	Driver Age_1	Driver $Gender_1$	Driver Empl St_1	Ln (VMT_2)	Driver Age_2	Driver $Gender_2$	Driver Empl St_2
Vehicle 1 Age	-0.0229 (-4.57)		-0.0036 (-2.58)	-0.0048 (-2.32)				
Vehicle 1 Type: Mini car								
Vehicle 1 Type: Subcompact		-3.30 (-7.19)						
Vehicle 1 Type: Compact car		-1.68 (-3.41)				1.07 (2.06)		
Vehicle 1 Type: Mid-size car								
Vehicle 1 Type: Full-size car								
Vehicle 1 Type: Sports car		-2.40 (-4.33)		0.0659 (2.66)				
Vehicle 1 Type: Small truck	-0.244 (-3.90)		-0.118 (-5.26)					
Vehicle 1 Type: Std. Truck	-0.0959 (-1.98)		-0.131 (-5.23)					
Vehicle 1 Type: Minivan			0.0446 (3.42)					0.0498 (2.15)
Vehicle 1 Type: Std. Van			-0.0445 (-2.07)					
Vehicle 1 Type: Small SUV.		-1.86 (-3.06)	-0.052 (-3.77)					
Vehicle 1 Type: Std. SUV.			-0.0945 (-4.24)					
Vehicle 1	-0.0081				0.0195			

Operating Cost	(-0.94)				(2.07)			
Vehicle 2 Age					-0.0409 (-9.47)		-0.0077 (-4.90)	
Vehicle 2 Type: Mini car	0.123 (1.90)				-0.134 (-1.94)	-2.60 (-2.74)		
Vehicle 2 Type: Subcompact						-3.30 (-7.19)		
Vehicle 2 Type: Compact car						-1.68 (-3.41)		
Vehicle 2 Type: Mid-size car							0.0316 (2.43)	
Vehicle 2 Type: Full-size car						2.23 (1.87)		
Vehicle 2 Type: Sports car						-3.53 (-4.46)		
Vehicle 2 Type: Small truck						-2.40 (-4.33)	-0.118 (-5.26)	
Vehicle 2 Type: Std. Truck					-0.0959 (-1.98)		-0.131 (-5.23)	
Vehicle 2 Type: Minivan							0.0446 (3.42)	
Vehicle 2 Type: Std. Van							-0.0445 (-2.07)	
Vehicle 2 Type: Small SUV.						-1.86 (-3.06)	-0.0522 (-3.77)	
Vehicle 2 Type: Std. SUV.							-0.0945 (-4.24)	
Vehicle 2 Operating Cost	0.0184 (2.29)				-0.0128 (-1.40)			
No.of 16-20 yr. olds						-4.70 (-8.41)		
No. of drivers		1.90 (6.07)		-0.266 (-18.7)	0.104 (3.26)	1.90 (6.07)		-0.266 (-18.7)
No. of 1 to 5 yr. olds		-0.707 (-2.07)		-0.0355 (-3.01)		-0.707 (-2.07)		
Total no. of children	0.0338 (3.13)	-0.453 (-2.41)			0.0338 (3.13)	-0.453 (-2.41)		
Income>$60k	0.0795 (3.25)			0.0429 (2.99)	0.0795 (3.25)			
Retired household		5.91 (9.78)		-.286 (-12.5)		5.91 (9.78)		-.286 (-12.5)
Ave. age of heads		0.747 (48.0)				0.695 (41.5)		
No. of workers				0.405 (47.0)			0.0082 (1.70)	0.405 (47.0)
3 veh household	-0.0267 (-0.69)		-0.0236 (-2.30)		-0.0935 (-2.18)			
4+ veh household	-0.0275 (-0.464)			-0.146 (-7.05)		2.37 (2.59)		-0.146 (-7.05)

Regarding VMT, the negative relationship between vehicle age and usage is significant for both vehicles, but it is much stronger for second vehicles than for first vehicles. Standard trucks are driven less, controlling for all other factors, regardless of whether they are first or second vehicles. Compact trucks are driven less than average only if they are the household's first (newest) vehicle, and when mini cars are the second vehicle in a household they are both driven less and the first car is driven more than otherwise expected.

The relationships between usage and operating cost are consistent but not numerically identical across the two vehicles. The signs of the direct effects of operating cost on usage are negative as expected for both vehicles. The relationship is stronger for the second vehicle, but neither coefficient is statistically significant. These effects are maintained in the model because they are theoretically justified. However, there are strong and comparable operating cost substitution effects between the vehicles. A higher operating cost of either vehicle causes an increase in usage of the other vehicle.

Regarding driver allocation to vehicle type, most of the influences that are consistent across both vehicles involve driver gender. Males are more likely to be the principal drivers of compact trucks, full-size trucks, full-size vans, and sport utility vehicles. On the other hand, females are more likely to be the principal drivers of minivans, and, for second vehicles only, of mid-size cars. Males also drive older second cars.

Younger persons are more likely to drive subcompact cars, compact cars, compact sport utility vehicles, and sports cars; and the relationship between driver age and sports cars is stronger for second cars than for first cars. For second cars only, drivers of mini cars are younger, while drivers of full-size cars are older. Finally, employed persons are more likely to drive first vehicles that are newer and ones that are sports cars.

Ten of the direct effects of the household characteristics are equal across the two vehicles. There are also six unique effects for each vehicle. The strong relationships between the mean age of the household heads and the ages of the two principal drivers are similar for the two vehicles, but the equality constraint is rejected at the $p = .05$ level (the difference in chi-square values being 5.12 with one degree of freedom), indicating that the improvement in the model fit due to releasing the constraint is significant.

For each vehicle, there are two vehicle-consistent effects of household characteristics on VMT. The total number of children in the household is directly related to increased VMT of both vehicles, as is the effect of annual household gross income in excess of $60,000. The number of drivers significantly affects VMT of the second vehicle only. Regarding the total number of vehicles owned by the household, ownership of three vehicles reduces VMT of the second vehicle more than it reduces VMT of the first vehicle, and only the effect of the additional vehicle on usage of the second vehicle is statistically significant. A comparable effect is found for four or more vehicles on usage of the first vehicle, but the coefficient of the link is imprecisely measured. The effect of four or more vehicles on usage of the second vehicle is almost identically zero, causing that link to be removed from the model.

All of the other effects of the household characteristics are readily interpretable. Many of the household characteristics will have an indirect effect on VMT through these direct effects on the other endogenous variables, combined with the effects of the endogenous variables on each other. For example, both principal drivers in households with children, particularly in households with children 1 to 5 years of age, are younger than otherwise expected; usage is higher for younger drivers. Also, drivers in retired households are older and less likely to be employed; usage is lower for both older and unemployed drivers. Reduced-form equations are used to capture the accumulation of all paths of causality between the exogenous and endogenous variables.

INTERPRETATION OF RESULTS

The total effects of the endogenous variables on the VMT variables are listed in Table 10. The total age effects on VMT are significant both within and between vehicles for both principal drivers. Having a younger principal driver on either vehicle means that both vehicles are used more. And the strongest of these influences is that of age of the principal driver of the second vehicle on usage of this vehicle.

Table 10: Total Effects of the Other Endogenous Variables on the VMT Variables

Influencing Variable	Influenced variable			
	Ln (VMT_1)		Ln (VMT_2)	
	Total effect	*t*-statistic	Total effect	*t*-statistic
Ln (VMT_1)	0.0239	6.66	0.157	13.0
Driver Age_1	-0.0029	-3.41	-0.0020	-7.10
Driver $Gender_1$	-0.664	-4.92	0.331	3.77
Driver Empl St_1	0.231	8.39	-0.0192	-4.29
Ln (VMT_2)	0.157	13.0	0.0239	6.66
Driver Age_2	-0.0021	-6.73	-0.0041	-4.95
Driver $Gender_2$	0.593	4.16	-0.440	-4.51
Driver Empl St_2	-0.0192	-4.29	0.0574	10.1

The gender effects are also consistent for the first and second vehicle: If the principal driver of either vehicle is a female, that vehicle is driven less and the other vehicle is driven more. The strongest gender effects are on usage of the first vehicle. Employment status has a similar pattern of effects similar to gender. If either driver is employed, that vehicle is driven more and the other vehicle is driven less. But in the case of employment status, the strongest effects are on the driver's own vehicle.

The total effects of the exogenous variables on the usage endogenous variables are listed in Table 11. These are the coefficients of the reduced-form equations for two of the eight endogenous variables. For simplicity, the total effects for the other six endogenous variables are not shown because focus here is on forecasts of vehicle use.

Vehicle Ages

The older the vehicle, the less it is used, all else held constant. Vehicle age also negatively affects use of the other vehicle, but the between-vehicle effect is weaker than the within-vehicle effect for both the first and second vehicles. The forecasting implication of this is reduced usage of the household fleet over time if no vehicle transactions occur. If household structure also does not change, the reduction in fleet will be further accentuated through the negative total effect on usage of driver age.

Operating cost

For either of a household's first two vehicles, the total effect of operating cost is a shift in usage between the two vehicles. An increase in operating cost for a vehicle results primarily in a shift of usage to the other vehicle, accompanied by a marginal reduction in usage on the vehicle with the increased operating cost.

Vehicle Types

Mini cars have approximately average usage. Subcompact cars are driven more than average as either first or second cars, and if the either vehicle is a subcompact car, another vehicle in the household is also driven more. The within-vehicle direct effect could be explained by relatively low operating costs, and the cross-vehicle effect could be explained by the household's desire for a larger or more specialized vehicle for certain trip purposes. Compact cars have greater than average usage only if they are the second car in the household. As second cars, they also indicate greater than average use of the first car. Mid-size car usage also involves the second vehicle; if it is a mid-size car it is used less than average and the first car is used more than average. Use of full-size (standard) cars is approximately average.

Sports cars are similar to subcompact cars in that households tend to make heavy use of both the sports car and the other car in the household as well. The effect on use of another vehicle could definitely be explained by the household's desire for a larger or vehicle for certain trip purposes.

Small (compact) pickup trucks are driven less than average if they are the first vehicle, but more than average if they are a second vehicle. As a second vehicle, apparently usage is also shifted to the first vehicle. Conversely, full-size (standard) pickup trucks are consistently used less than average, both as first vehicles and as second vehicles.

Table 11: Total Effects of the Exogenous Variables on the VMT Variables (Coefficients of the Reduced-form Equations)

Influencing Variable	Influenced variable			
	Ln (VMT_1)		Ln (VMT_2)	
	Total effect	*t*-statistic	Total effect	*t*-statistic
Vehicle 1 age	**-0.0222**	**-4.24**	**-0.0047**	**-4.93**
Vehicle 1 type: Mini car	0.0	0.0	0.0	0.0
Vehicle 1 type: Subcompact	**0.0096**	**3.08**	**0.0065**	**5.05**
Vehicle 1 type: Compact car	0.0026	1.14	-0.0011	-0.42
Vehicle 1 type: Mid-size car	0.0	0.0	0.0	0.0
Vehicle 1 type: Full-size car	0.0	0.0	0.0	0.0
Vehicle 1 type: Sports car	**0.0222**	**3.47**	**0.0035**	**2.45**
Vehicle 1 type: Small truck	**-0.0171**	**-2.69**	**-0.0774**	**-6.19**
Vehicle 1 type: Std. Truck	-0.0113	-0.23	**-0.0584**	**-5.05**
Vehicle 1 type: Minivan	**-0.0305**	**-3.89**	**0.0262**	**3.75**
Vehicle 1 type: Std. Van	**0.0295**	**2.14**	**-0.0147**	**-2.08**
Vehicle 1 type: Small SUV.	**0.0401**	**4.92**	**-0.0136**	**-3.08**
Vehicle 1 type: Std. SUV.	**0.0627**	**5.07**	**-0.0313**	**-4.34**
Vehicle 1 operating Cost	-0.0052	-0.58	**0.0187**	**1.97**
Vehicle 2 age	**-0.0110**	**-9.01**	**-0.0385**	**-8.73**
Vehicle 2 type: Mini car	0.111	1.64	-0.107	-1.50
Vehicle 2 type: Subcompact	**0.0070**	**4.92**	**0.0136**	**4.08**
Vehicle 2 type: Compact car	**0.0033**	**2.41**	**0.0064**	**2.29**
Vehicle 2 type: Mid-size car	**0.0188**	**2.47**	**-0.0139**	**-2.45**
Vehicle 2 type: Full-size car	-0.0047	-1.80	-0.0092	-1.75
Vehicle 2 type: Sports car	**0.0075**	**3.72**	**0.0145**	**3.32**
Vehicle 2 type: Small truck	**-0.0652**	**-5.74**	**0.0620**	**6.48**
Vehicle 2 type: Std. Truck	**-0.0927**	**-5.83**	-0.0405	-0.82
Vehicle 2 type: Minivan	**0.0264**	**3.56**	**-0.0196**	**-3.48**
Vehicle 2 type: Std. Van	**-0.0264**	**-2.10**	**0.0196**	**2.08**
Vehicle 2 type: Small SUV.	**-0.0270**	**-3.57**	**0.0307**	**4.74**
Vehicle 2 type: Std. SUV.	**-0.0560**	**-4.58**	**0.0416**	**4.40**
Vehicle 2 operating Cost	**0.0168**	**2.00**	-0.0102	-1.08
No. of 16-20 yr. olds	**0.0099**	**5.26**	**0.0193**	**4.27**
No. of drivers	**-0.0496**	**-5.58**	0.0386	1.16
No. of 1-5 yr. olds	-0.0046	-1.33	**0.0050**	**2.27**
Total no. of children	**0.0422**	**3.33**	**0.0427**	**3.37**
Income>$60k	**0.104**	**3.59**	**0.0931**	**3.23**
Retired household	**-0.0901**	**-9.40**	**-0.0964**	**-9.82**
Ave. age of heads	**-0.0036**	**-5.19**	**-0.0043**	**-6.44**
No. of workers	**0.0905**	**8.45**	**0.0820**	**7.76**
3 veh HH	-0.0263	-0.65	**-0.108**	**-2.42**
4+ veh HH	-0.0640	-1.05	**-0.0448**	**-3.90**

Minivans are also driven less as either first or second vehicles, and there is a higher than otherwise expected level of usage of another vehicle in the household fleet. Conversely, full-size (standard) vans are driven more than average as either first or second vehicles, and there is a lower than otherwise expected level of usage of another vehicle in the household. Minivans and full-size vans take on very different vehicle-usage roles.

Finally, compact sport utility vehicles and full-size sport utility vehicles have usage patterns similar to full-size vans. They are used heavily and their presence in the household fleet implies that usage is lower on at least one other vehicle in the household fleet.

Household characteristics

With regard to the membership of the household, the number of household members between 16 and 20 years old has a positive influence on VMT of both the first and second vehicle, but the effects on second-vehicle VMT are considerably greater than effects on first-vehicle VMT. The number of drivers in the household has a negative effect on VMT of the first vehicle. This seemingly counter-intuitive result could indicate a shift of usage toward third and fourth vehicles in the household. The number of drivers does have a positive effect on second-vehicle VMT, but this effect is not statistically significant. The number of children 1 to 5 years old positively influences VMT of only the second vehicle. There is also evidence of a shift in VMT from the first to the second vehicle, but the negative effect on first-vehicle VMT is not significant. Finally, the total number of children positively influences VMT of both the first and second vehicles.

There is an important positive high-income effect on the VMT of both vehicles. On the other hand, retired households exhibit lower usage of both vehicles. Regarding mean age of the household heads, usage of both vehicles is higher for households headed by younger persons. Vehicle usage for both vehicles is also a positive function of the number of workers in the household. Finally, the presence of three household vehicles and four or more household vehicles reduces VMT of the second vehicle. There is also evidence of a reduction in first-vehicle VMT, but the relationships are not statistically significant at the $p = .05$ level.

DIRECTIONS FOR FURTHER RESEARCH

Estimation methodology

Selectivity bias can be accounted for in this usage model by linking the model to a discrete type-choice model, and adding into the structural equation system a correction term variable involving a transformation of the household's predicted type vehicle choice probabilities (McFadden et al., 1985; Mannering and Winston, 1985; Train, 1986; Hensher, et al., 1992). It is doubtful that such a correction term would have any pronounced effect on the results.

The known biases in the normal-theory maximum likelihood estimation method applied to dichotomous endogenous variables are concentrated on coefficient standard errors and overall goodness-of-fit criteria. The fit of the model is not in question, and hypothesis testing is subordinate to forecasting capability in this research. However, it would be possible to use unbiased generally weighted least squares estimation (Browne, 1982, 1984), as implemented in LISREL8 with PRE-LIS2 (Jöreskog and Sörbom, 1993b), with an increased sample size. Alternatively, the number of variables could be reduced by combining vehicle type classifications. Results show that compact sport utility vehicles might be combined with full-size (standard) sport utility vehicles and full-size (standard) vans.

Extension to other vehicle ownership levels

A simplified model, not reported here, has been estimated for single-vehicle households. That model has only four endogenous and 24 exogenous variables for one vehicle rather than two vehicles.

For explaining usage behavior for more than two vehicles, the present model structure could be exploded to add a third vehicle in a manner consistent with the first two vehicles. However, the sample size for three-vehicle households in the survey used here will not support estimation of such an extended model. The present model contains 74 free parameters, so an extended three-vehicle model might contain in excess of 100 free parameters. If the rule-of-thumb of six observations per free parameter is applied, the three-sample size called for is in excess of 600 households. Extension of the model structure to more than three household vehicles is probably not feasible.

Use in Forecasting

This model can be applied as a marginal change model in a dynamic microsimulation forecasting system, such as the one outlined in Brownstone, et al. (1994): Accompanying sociodemographic change and vehicle transactions models are used to forecast changes in a household's sociodemographic structure and composition of the household's vehicle fleet. The usage model is then exercised to forecast VMT for both the before- and after-situations for the household. The calculated change in forecasts is then applied as a percentage change to the actual base levels of usage for the household in the before-situation.

Even if the dynamic sociodemographic model predicts no change in household characteristics (household composition, employment status, or income), and the vehicle transactions model predicts no vehicle transactions for the household for the period in question, the present usage model will in general predict changes in VMT. This will be due to aging of the household heads, aging of the vehicles, and possible changes in the age categories of children and subsequent increases numbers of drivers in the household, and.

ACKNOWLEDGMENTS

This research is part of the project aimed at developing a model system to forecast demand for clean fuel vehicles in California, conducted by researchers at the University of California, Irvine and University of California, Davis. This research has been sponsored by the Southern California Edison Company, in cooperation with the California Energy Commission. The authors wish to thank their colleagues, who have made the research reported here possible: David Brownstone, Soheila Crane, and Jane Torous of the University of California, Irvine; David Bunch and Ryuichi Kitamura of the University of California, Davis; and Mark Bradley of the Hague Consulting Group. In addition, Ernest Morales, Richard Rice, and Debbie Brodt of Southern California Edison Co., and Gary Occhiuzzo and Mike Jaske of the California Energy Commission have worked diligently on behalf of the project. None of these kind people or their organizations are responsible for any errors or for the views expressed here.

An earlier version of this paper will be presented at the Annual Meeting of the Transportation Research Board, Washington, DC, January 24, 1995.

REFERENCES

Bentler, P.M. and Bonett, D.G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, 88: 558-606.

Berkovec, J. (1985). Forecasting automobile demand using disaggregate choice models. *Transportation Research,* 19B: 315-329.

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

Boomsma, A. (1983). *On the Robustness of LISREL (Maximum Likelihood Estimation) against Small Sample Sizes and Nonnormality*. Amsterdam: Sociometric Research Foundation.

Browne, M.W. (1982). Covariance structures. In D.M. Hawkins, ed., *Topics in Multivariate Analysis:* 72-141. Cambridge: Cambridge University Press.

Browne, M.W. (1984). Asymptotic distribution free methods in analysis of covariance structures. *British Journal of Mathematical and Statistical Psychology*, 37: 62-83.

Brownstone, D., D.S. Bunch and T.F. Golob (1994). A demand forecasting system for clean-fuel vehicles. Presented at the OECD International Conference "Towards Clean Transport: Fuel Efficient and Clean Motor Vehicles," Mexico City, march 28-30..

Golob, T.F. (1990). The dynamics of travel time expenditures and car ownership decisions. *Transportation Research*, 24A: 443-463.

Hensher, D.A. (1985). An econometric model of vehicle use in the household sector. *Transportation Research*, 19B: 303-314.

Hensher, D.A. and V. Le Plastrier (1985). Towards a dynamic discrete-choice model of household automobile fleet size and composition. *Transportation Research,* 19B: 481-495.

Hensher, D.A. and Manefield, T. (1982). A structured-logit model of automobile acquisition and type choice. *Proceedings of the 7th Australian Transport Research Forum, Hobart, Tasmania:* 625-654.

Hensher, D.A. and N.C. Smith (1986). A structural model of the use of automobiles by households: a case study of urban Australia. *Transport Reviews,* 6: 87-111.

Hensher, D.A., N.C. Smith, F.W. Milthorpe and P.O. Bernard (1992). *Dimensions of Automobile Use: A Longitudinal Study of Automobile Ownership and Use*. Amsterdam: North Holland.

Hocherman, I., J. Prashker, and M. Ben-Akiva (1983). Estimation and use of dynamic transaction models of automobile ownership, *Transportation Research Record No. 944:* 134-141.

Jöreskog, K.G. and D. Sörbom (1993a). *LISREL 8 User's Reference Guide.* Scientific Software, Chicago.

Jöreskog, K.G. and D. Sörbom (1993b). *PRELIS 2 User's Reference Guide.* Scientific Software, Chicago.

Lave, C.A. and K. Train (1979). A disaggregate model of auto-type choice. *Transportation Research,* 13A: 1-9.

Mannering, F. (1983). An econometric analysis of vehicle use in multi-vehicle households. *Transportation Research,* 17A: 183-189.

Mannering, F. and C. Winston (1985). Dynamic empirical analysis of household vehicle ownership and utilization. *Rand Journal of Economics,* 16: 215-236.

McFadden, D. L., C. Winston and A. Borsch-Supan (1985). Joint estimation of freight transportation decisions under non-random sampling. In A.F. Daugherty, ed. *Analytical Studies in Transport Economics:* 137-160. Cambridge University Press, Cambridge.

McCarthy, P.S. and R. Tay (1989). Consumer valuation of new car attributes: an econometric analysis of the demand for domestic and Japanese and Western European imports. *Transportation Research,* 23A: 367-375.

Ren, W., D. Brownstone, D.S. Bunch and T.F. Golob (1995). A personal vehicle transactions choice model for use in forecasting demand for future alternative-fuel vehicles. *Research in Transportation Economics* (in press).

Train, K. (1986). *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand*. Cambridge: MIT Press.

van Wissen, L.J. and T.F. Golob (1992). A dynamic model of car fuel type choice and mobility. *Transportation Research*, 26B: 77-96.