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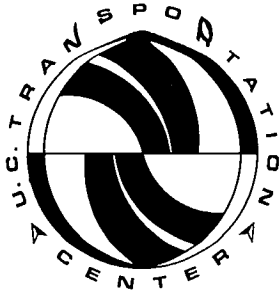
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And Car Ownership Decisions**

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The University of California Transportation Center  
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## THE DYNAMICS OF HOUSEHOLD TRAVEL TIME EXPENDITURES AND CAR OWNERSHIP DECISIONS†

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**Abstract**—A dynamic (panel data) structural equations model is developed that links four dependent travel behavior variables at two points in time, one year apart. The four dependent variables are: car ownership, travel time per week by car, travel time by public transit, and travel time by nonmotorized modes. Exogenous variables include 13 household characteristics and variables accounting for period effects over the 1985 to 1987 time frame in the Netherlands. The model treats car ownership as ordered-response probit variables and all travel times as censored (tobit) continuous variables. The model accounts for serially-correlated errors and panel conditioning biases. Results are interpreted in terms of recommendations for forecasting procedures.

### OBJECTIVES AND SCOPE

The objective of this research is to establish causality in the interrelationships among household travel time expenditures by mode and car ownership, conditional upon exogenous changes in factors such as income, the numbers of household workers and drivers, and stage in the family life cycle. A longitudinal data set, the Dutch Mobility Panel (1984–1988), provides the information necessary to test whether travel time expenditures by mode are mutually interdependent with car ownership. Car travel time, and consequently travel time by competing modes, is clearly a function of the level of household car ownership. However, on a longer-term basis, car ownership is quite possibly a function of travel time expenditures. This “reverse” causality is an important principle in the UMOT Model of Zahavi (1979b; 1982) and has been supported by utility theory models of travel demand (Golob *et al.*, 1981; Zahavi and McLynn, 1983; Downes and Emmerson, 1985). The postulate is that households with high levels of travel time expenditures will be motivated to decrease their time expenditures by switching some travel to a higher speed, but costlier mode. This amounts to trading off time and money expenditures, and does *not* necessarily imply constant time or money “budgets.” Such a trade-off of travel time and money expenditures has also been recognized in utility-based models of car ownership and usage (e.g. Beckmann *et al.*, 1973; Burns *et al.*, 1976; Fowkes and Button, 1977; Button *et al.*, 1982; Mogridge, 1989).

If some travel decisions are made in a manner that is consistent with a household utility-maximizing process subject to constraints associated with time or money budgets, then households will react to changing exogenous conditions in predictable ways. Invoking such reactions would be exogenous changes in income, levels of service of transport modes, and compulsory travel requirements (caused by changes in factors such as the employment status of household members). Travel time and money expenditures can be adjusted by modifying trip rates, trip distances (destination choices), and choice of mode for each trip. As an example of travel adjustments that might be made by households, suppose that money available for transportation is increased by either a decrease in the real costs of travel or an increase in disposable income. A household might react to such a change in the short term by: (1) making more of the same type of trips (to similarly located destinations by the same mode), (2) substituting trips to further (more desirable) locations, or (3) switching some travel to a more expensive (and presumably faster) mode, or by various combinations of these and other actions. In the intermediate term, the switch to a

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more expensive mode would typically involve an increase in the level of car ownership; and in the long term, adjustments might be made in residential location.

The testing of alternative hypotheses of cause and effect among these variables is accomplished using longitudinal structural equation models. The advent of longitudinal structural equation models—simultaneous equations applied to panel data—has made it possible to test competing hypotheses of cause and effect without relying on assumptions that effect is instantaneous in time. Tests can include both contemporaneous relationships, in which the cause and its effect occur synchronously within the same year, and lagged relationships, in which a significant portion of the effect is manifested in the year or years following the change in the causal variable. Recent methodological advances in structural equation modeling can lead to the reduction of estimation biases associated with non-normally distributed dependent variables; and longitudinal structural equations can be tailored to account for panel conditioning effects and period effects.

#### DATA SOURCE AND SAMPLE FORMATION

The source of the data is the Dutch National Mobility Panel (Golob *et al.*, 1985; van Wissen and Meurs, 1989). This panel, instituted in 1984, involves weekly travel diaries, household, and personal questionnaires collected at biannual and annual intervals, with travel diaries completed by all household members over eleven years of age. The refreshed sample consists of approximately 1,800 households stratified by life-cycle group, income category, and community type. In the Netherlands an appropriate breakdown of travel modes is: car (driver and passenger), public transport (including bus, tram, subway, and train), and nonmotorized modes (including bicycle and walking). Travel times by mode are computed as household weekly totals calculated from the diaries, with correction procedures applied to estimate times associated with missing diary entries.

The data used in the present study are from waves 3, 5, 7, and 9 of the panel, collected in the spring of each of the years 1985, 1986, 1987, and 1988. These data were organized as a pooled wave-pair sample. The configuration of this pooled wave-pair sample is shown in Table 1. There are three wave-pair subsamples, each representing observations at two

Table 1. Composition of the pooled wave-pair sample

YEARS IN PANEL	WAVE-PAIR SUBSAMPLE			DIAGONAL TOTALS	
	1985-86	1986-87	1987-88		
1	475	343	401		Year Initiated
2	859	355	305	401	1987
3		684	327	648	1986
4			656	1,168	1985
				2,199	1984
Wave-Pair Subsample Totals	1,334	1,393	1,689		
<b>GRAND TOTAL:</b>				<b>4,416</b>	

points in time one year apart: 1985–86, with 1,334 households; 1986–87, with 1,393 households; and 1987–88, with 1,689 households. The breakdown of each of these three subsamples by the number of years each household participated in the panel, up to and including the second year of the wave pair (panel tenure) is given in Table 1. Also shown is a breakdown of the pooled wave-pair sample by the year in which the household was introduced into the panel, given by the diagonal totals of the panel tenure by wave-pair cross tabulation.

The 4,416 total household wave-pair observations represent 2,119 separate households; 782 households (36.9%) are observed for only one of the year pairs; 381 households (18.0%) are observed for two of the year pairs; and 956 (45.1%) are observed for all three year pairs.

The alternative to pooled wave-pair samples for panels with more than two waves is to restrict the sample to only those households which participate in all waves spanning the time frame of analysis. For the Dutch Mobility Panel for the period 1985–1988, such a pure “stayers” sample would include in the 1987–1988 wave-pair only the 656 households in Table 1 which have four years’ tenure in the panel. These households represent only 23.4% of the 2,805 different households that participated in any of the 1985–1988 panel waves (van Wissen and Meurs, 1989). In comparison, the 2,119 separate households in the pooled wave-pair sample represent 75.5% of all 1985–1988 panel households. Most panel-based travel demand analyses have used a “stayers” sample. The use of pooled wave-pair sampling is less common in travel demand analysis, but it was advocated by van der Eijk (1987) and was used by Golob and van Wissen (1989).

There are advantages and disadvantages in using a pooled wave-pair sample compared to a sample of stayers. There are at least three major advantages: First, the effects of panel attrition bias are minimized because households that drop out after their second and subsequent waves of participation are included in the sample, as are multi-wave households added to the panel as refreshment after each wave; such households are excluded from a “stayers” sample. This is a substantive advantage if drop-out or refreshment households are different from households that participate in all panel waves under study. Kitamura and Bovy (1987) and Meurs *et al.* (1989) reported that, in the case of the Dutch Mobility Panel, drop-out and refreshment differences *are* associated with levels of mobility.

A second advantage lies in the ability to separate panel conditioning effects from period effects, which uniformly affect all observational units at the same point in time. A pooled wave-pair sample constructed from at least three waves of a panel with attrition and refreshment will provide a variance of panel tenure over time, allowing a separation of panel conditioning and period effects. Meurs *et al.* (1989) has shown that the Dutch Mobility Panel is characterized by substantial conditioning effects with regard to mobility levels.

A third advantage of a pooled wave-pair sample is in increasing the observational frequency of rare events. Events such as the formation of new households, residential relocation across community types, changes in the number of adults in the household, or other “life cycle shocks” provide information on behavioral adaptation and change that is extremely valuable for long-term travel demand forecasting (Clark and Dix, 1982; Clark *et al.*, 1982; Goodwin *et al.*, 1987). Wave pooling increases the sample sizes of such events.

There is also a major disadvantage of wave-pair pooling: There is redundant information in the repeated measurements of the same observational units over successive wave pairs, and this redundancy is not easily compensated for in statistical tests. It is possible to deflate the number of cases by a repetition factor, but this is in general only a lower bound on sample size, reflecting perfect autocorrelation of the repeated measurements (van der Eijk, 1987). Alternatively, it may be possible to separate error terms into within-observation and between-observation components, but the statistical methodology to accomplish this becomes cumbersome when extended beyond the case of single-equation models with a normally-distributed dependent variable.

The actual sample size of the pooled wave-pair sample used was 4,002, resulting from random subsamples of 1,334 households drawn from each of the wave-pairs. This even

breakdown of sample size by wave pair facilitates the comparison of period effects for the three years.

#### PRELIMINARY DESCRIPTIVE ANALYSES

A descriptive dynamic analysis was performed by investigating the travel time expenditures at two points in time (designated at  $t_1$  and  $t_2$ , one year apart) of seven household dynamic car ownership segments. These segments are defined according to car ownership levels at  $t_1$  and  $t_2$ , as described in Table 2. The use of a pooled wave-pair sample results in segment sample sizes sufficient to support these descriptive analyses.

The mean weekly car travel time expenditures for  $t_1$  and  $t_2$  are plotted for the dynamic car ownership segments as a function of car ownership level (0, 1, or 2 cars) in Fig. 1. For each of the four segments with changes in car ownership, the lines in Fig. 1 connect the means for the same segment at the two points in time; for the segments that are temporally stable in terms of car ownership levels, the lines connect the three ownership levels at each point in time.

The means for the three segments with temporal stability are nearly identical for  $t_1$  and  $t_2$ . However, the segment that increases from 0 cars at  $t_1$  to 1 car at  $t_2$  (segment "0 to 1 Car") exhibits a higher level of car travel time (presumably mostly car passenger time) at  $t_1$  (3.60 hours/week) than does the remainder of zero-car households (1.62 hours/week). That is, prior to owning a car, these households stand out from other households in the same cross-sectional state. Moreover, this "0 to 1 Car" segment reaches a time expenditure level at  $t_2$ , after purchasing a car, that is less than that of households that were stable one-car owners at both  $t_1$  and  $t_2$  (6.82 hours/week versus 8.21 hours/week), indicating a lagged effect of car ownership on car travel time. This is evidence of dynamic phenomena not detectable in cross-sectional analyses. The reverse change exhibited by the "1 to 0 Car" segment is almost a pure reflection, with only slight (statistically insignificant) differences between the segments at their one-car state.

Changes between one and two cars reveal similar dynamic phenomena: The initial and final states are statistically different than, and numerically bounded by, the corresponding state values of the temporally stable segments (nonchangers). Moreover, there is asymmetry in the changes between one and two cars. The reduction from two to one cars results in the same *change* in car travel time as does the increase from one to two cars, but the *levels* are different (the lines in Fig. 1 are parallel but displaced). Households that increase from one car to two cars start from, and change to, higher levels of car travel time, compared to households that decrease from two cars to one car. Thus, Fig. 1 displays

Table 2. The dynamic car ownership segments

CAR OWNERSHIP		NUMBER OF HOUSEHOLD OBSERVATIONS	PERCENT OF POOLED WAVE-PAIR SAMPLE OF 4,416 OBSERVATIONS
$t_1$	$t_2$		
0	0	945	21.4
0	1	112	2.5
1	0	87	2.0
1	1	2,658	60.2
1	2	148	3.4
2	1	98	2.2
2	2	357	8.1
Any other combination (not included)		11	0.3



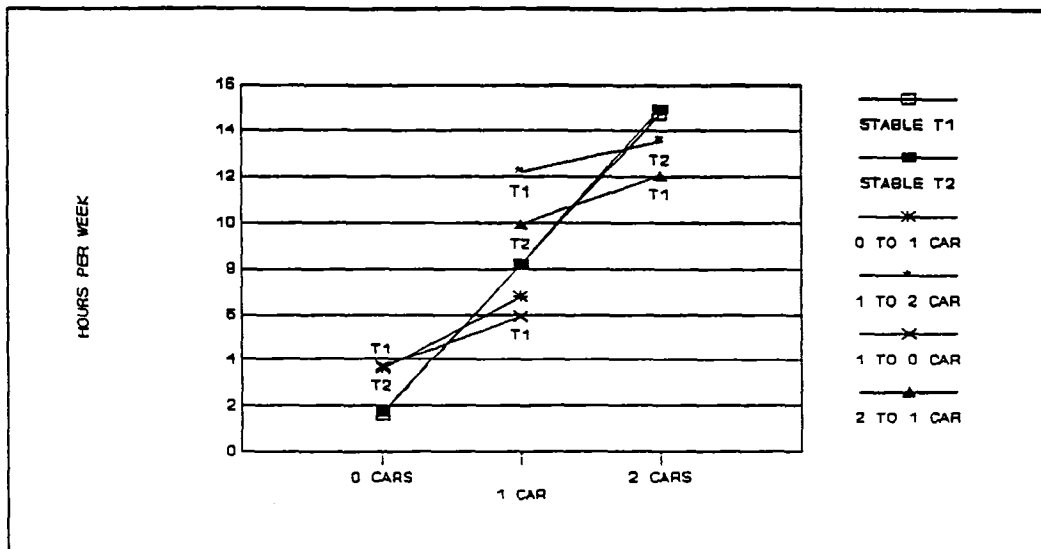


Fig. 1. Household car travel times by dynamic ownership segment.

path dependency and asymmetry (irreversibility) (Goodwin, 1987; Kitamura, 1986, 1987), as well as lagged effects (Golob and van Wissen, 1989).

A similar plot of public transport times by dynamic car ownership segment is provided in Fig. 2. Here, the "0 to 1 Car" and the "1 to 0 Car" segments exhibit equal changes in public transport times, but the amounts of change are significantly less than the differences between the stable "0 Car" and "1 Car" segments, revealing a lagged effect. The "2 to 1 Car" segment exhibits no change over time in public transport travel time, which is identical to the cross-sectional comparison of stable "1 Car" and "2 Car" segments at time  $t_1$  (the slight difference at time  $t_2$  being potentially due to nonrandom panel conditioning bias, as found in the results of the structural equation model). However, the "1 to 2 Car" segment exhibits a significant reduction in public transport time from a high base level. This is entirely consistent with trade-offs of time and money expenditures. Cross-sectional models based on these data would underestimate the reduction in public transport travel time that accompanies a change in car ownership from one to two cars. (All cited differences in Figs. 1 and 2 are statistically at the  $p = .05$  level.)

Plotted in Fig. 3 is the temporal change in public transport travel time versus the temporal change in car travel time for the seven dynamic car ownership segments. The

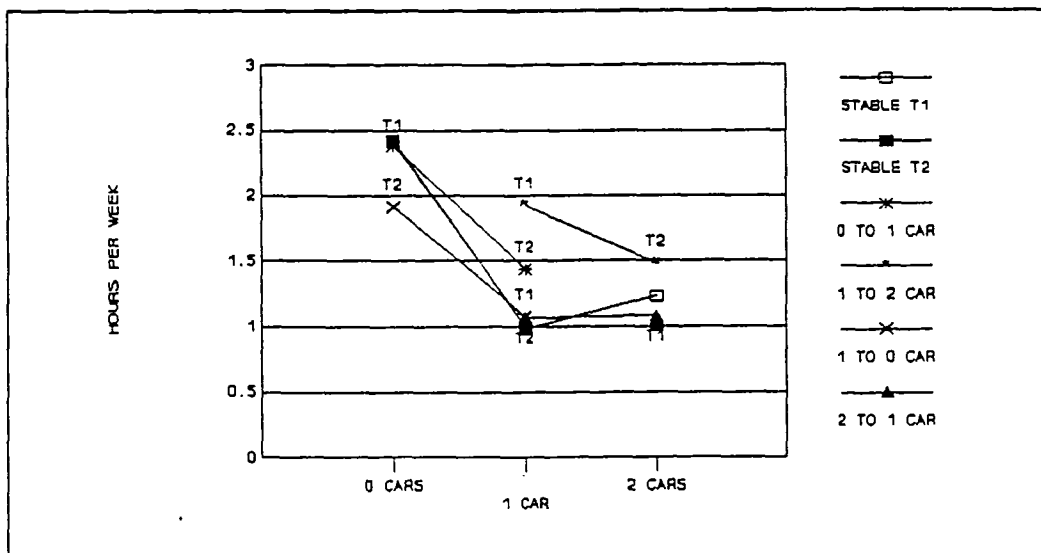


Fig. 2. Household public transport travel times by dynamic car ownership segment.

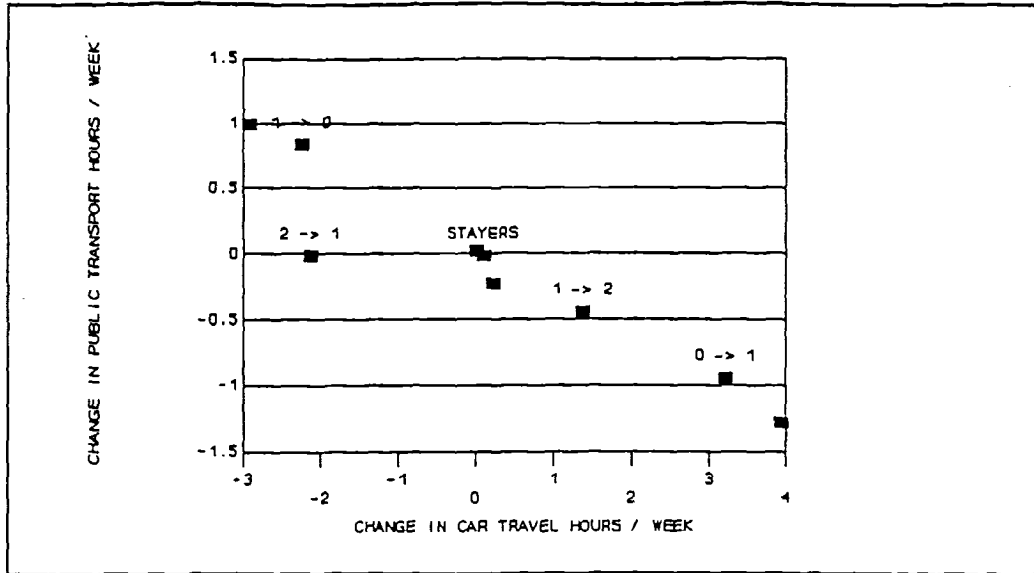


Fig. 3. Temporal changes in household car and public transport travel times by dynamic ownership segment.

three segments with stable ownership levels are located in the vicinity of the origin of the plot. The segments defined by changes between zero and one car are at the extremes of the plot, and the "2 to 1 Car" segment is the only one not located on a regression line through the origin.

The equation of this regression is:

$$\Delta PT = -0.253 \Delta CAR \quad (R^2 = 0.75) \quad (1)$$

where  $\Delta PT$  denotes change in public transport time, and  $\Delta CAR$  denotes change in car travel time. This regression result does not change significantly if an intercept term is allowed.

Similarly, temporal change in travel time by nonmotorized modes is plotted against temporal change in car travel time in Fig. 4. In this case, there is somewhat less alignment of the segments, but the "2 to 1 Car" segment is still the most atypical. There also appears to be a panel conditioning bias displayed in terms of a uniform reduction in reported travel time by nonmotorized modes by all segments. The regression equation is

$$\Delta NMOT = -0.857 - 0.316 \Delta CAR \quad (R^2 = 0.58) \quad (2)$$

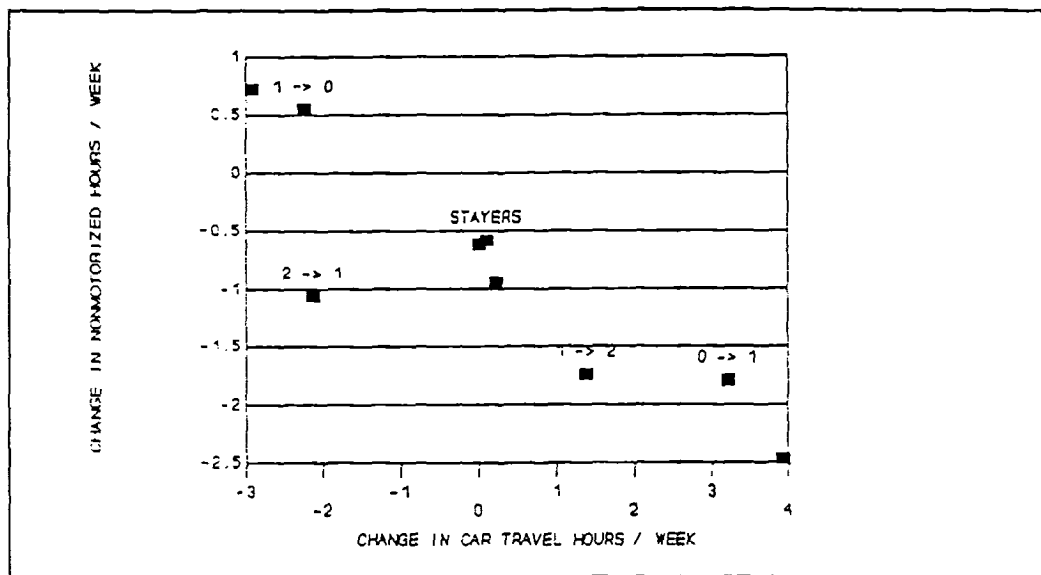


Fig. 4. Temporal changes in household car and nonmotorized times by dynamic ownership segment.

where  $\Delta NMOT$  denotes change in time by nonmotorized modes.

Finally, a complementary relationship between public transport and nonmotorized travel time expenditures is shown by the plot of their changes, in Fig. 5. The linear regression equation between the two change variables is

$$\Delta NMOT = -0.725 + 1.4 \Delta PT \quad (R^2 = 0.90). \quad (3)$$

The three-way interrelationship among the changes in modal travel time expenditure (Figs. 3, 4, 5) indicates that nonmotorized time is more sensitive to car travel time than is public transport time. Another consistent result is that the changes between zero and one car dominates the scale, while the changes between one and two cars are smaller in magnitude and less consistent. This is evidence in support of a nonlinear treatment of car ownership level in modeling its causal interrelationships with travel times.

#### METHODOLOGY

The method used to model the dynamics of travel time expenditures was one which satisfied eight requirements: (1) The model must accommodate multiple endogenous variables that are potentially interrelated in terms of causal structure. (2) There must be the capability of testing alternative directions of causality between any two endogenous variables. (3) The model must accommodate two types of exogenous variables: dynamic variables that exhibit significant yearly changes for the sample, and static variables that tend to remain the same over the one-year horizon for the vast majority of the sample. (4) In addition to contemporaneous causal relationships, the model must accommodate temporal lags and leads in causality. (5) The model must accommodate period effects that account for the influences of factors such as nationwide fuel prices and public transport fares that are uniform cross-sectionally. (6) Compensation for biases resulting from panel conditioning must be explicitly included in the model. (7) There must be the potential for a dynamic structure among disturbance terms (i.e. autocorrelated error terms). Finally, (8) the model must account for biases in estimation resulting from non-normal distributional properties of the endogenous variables.

There is at least one modeling method that appears to satisfy these eight requirements: longitudinal structural equations with limited and categorical dependent variables. The method can be implemented by adapting a procedure developed by Muthén (1979, 1983, 1984), which is an extension of linear structural equations modeling with unlimited

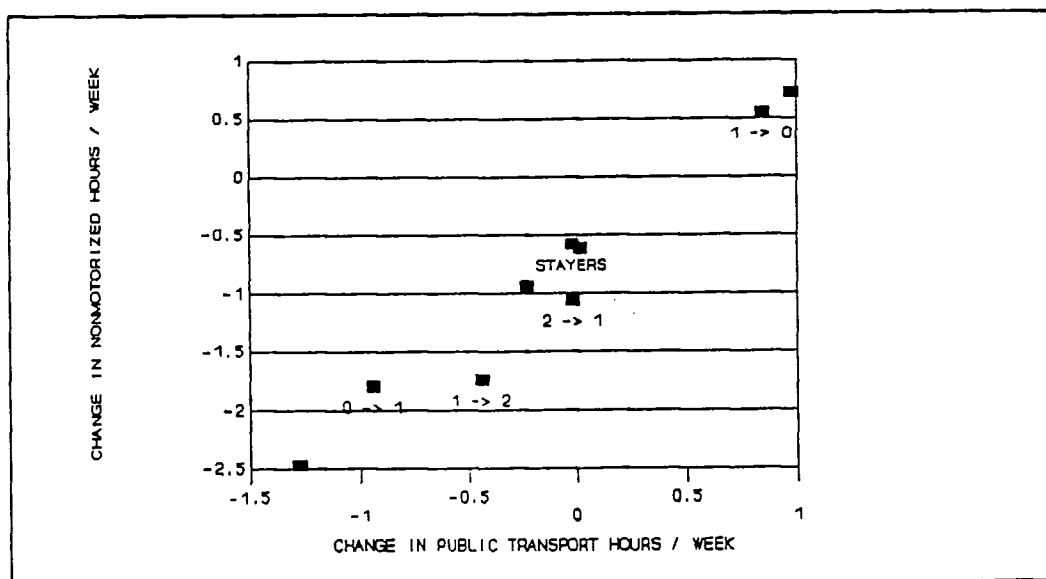


Fig. 5. Temporal changes in household public transport and nonmotorized mode times by dynamic ownership segment.

continuous variables (Jöreskog, 1973) to situations in which the dependent variables are non-normal in any or all of four ways: (1) truncated, (2) censored, (3) ordered polytomous (ordered and categorical), or, as a special case of ordered polytomous, (4) dichotomous. Closely related methods are provided by Bentler (1985) and Jöreskog and Sörbom (1987).

Longitudinal structural equations modeling with limited and categorical variables has been applied in travel demand modeling by Golob (1990) and by Golob and van Wissen (1989). In the special case of dichotomous variables, van Wissen and Golob (1990) compare this method to the conditional logit model in an investigation of simultaneous equation systems involving binary choice variables.

Precursors to the current research are Golob (1989, 1990) and Golob and van Wissen (1989). In Golob (1989), a static structural equation model was developed to explain the contemporaneous relationships among three income-class exogenous dummy variables and four endogenous variables: car ownership, car trips, public transit trips, and bicycle trips in the Netherlands. All endogenous variables were continuous and there were no dynamic relationships. In Golob (1990), dynamic relationships were modeled among four variables treated either as ordered categorical or limited variables: income, car ownership, car trips, and public transit trips. This was expanded in Golob and van Wissen (1989) to dynamic relationships among seven ordered categorical and limited variables using a pooled wave-pair data set. Neither of the Golob (1989, 1990) and Golob and van Wissen (1989) models included exogenous variables, nor were disturbance term autocorrelations, period effects, or panel conditioning effects considered in any previous models.

Structural equations modeling is defined for the purposes of the present application, where there are  $p$  limited and categorical dependent variables, as a  $p$ -equation system:

$$y^* = By^* + \Gamma x + \zeta \quad (4)$$

where  $y^*$  is a  $(p \times 1)$  vector of endogenous latent variables,  $B$  is a  $(p \times p)$  matrix of structural (causal) effects among the  $y^*$  variables (with a main diagonal of zeros),  $\Gamma$  is a  $(p \times m)$  matrix of regression effects of the  $(m \times 1)$  exogenous  $x$  variables, and  $\zeta$  is a  $(p \times 1)$  vector of disturbance or residual terms with variance-covariance matrix  $\Psi = \zeta\zeta'$ . In limited and categorical variable modeling, there are additional equations specifying the relationship between each endogenous latent variable  $y_i^*$  and its corresponding non-normal observed variable,  $y_i$ . In the present application, there are two types of non-normal  $y_i$  variables: censored variables and ordered polytomous variables.

Travel time expenditures are assumed to be censored endogenous variables in the present application. For each such travel time variable,  $y_i$ , it is presumed that there is a latent variable  $y_i^*$ , which measures the true propensity of a household to expend time on the mode in question. If this latent variable is greater than zero, the actual time expended is observed; if it is zero or less, no time is observed:

$$\begin{aligned} y_i &= y_i^* \text{ if } y_i^* > 0 \\ y_i &= 0 \text{ otherwise.} \end{aligned} \quad (5)$$

These latent time expenditure variables  $y_i^*$  are conditional on the exogenous  $x$  variables in the equation system, representing background household characteristics and period effects:

$$y_i^* = \pi'x + u_i \quad (6)$$

where  $\pi$  is a vector of reduced-form regression coefficients and  $u_i$  is normally-distributed residual with mean zero and unknown variance  $\sigma_u^2$ . The problem at this stage of the estimation is to determine  $\pi$  and  $\sigma_u^2$  when the only available information concerning an observation  $j$  for which  $y_{ij}^* \leq 0$  is  $y_{ij} = 0$ :

$$\begin{aligned} P(y_{ij} = 0) &= P(y_{ij}^* \leq 0) \\ &= P(\pi x_j \leq -u_{ij}) \end{aligned} \quad (7)$$

apparent from substituting (6) into (5). A maximum-likelihood solution to the problem of estimating  $\pi$  and  $\sigma_u^2$  was first proposed by Tobin (1958) and was subsequently refined by

Amemiya (1973) and Fair (1977). It is known as the tobit model, or as Tobin's probit (Goldberger, 1964; Maddala, 1983) and is used to establish the variances and covariances of the latent time expenditure variables in the first stages of the structural equations estimation. The appropriate maximum likelihood estimation procedures are described in Maddala (1983).

The remaining endogenous variables — car ownership levels measured at two points in time and the number of years a household participates in the panel, the latter used to control for panel conditioning bias — are assumed to be ordered polytomous (i.e. categorical, with an unknown ordinal scale relating the categories). For each of these variables, it is presumed that there is a latent variable that is translated into the categorical observations through an unknown set of thresholds  $k_{i1}, k_{i2}, \dots, k_{i,c-1}$  (Muthén, 1984; Golob and van Wissen, 1989):

$$y_i = \begin{cases} c-1 & \text{if } k_{i,c-1} < u_i^* \\ c-2 & \text{if } k_{i,c-2} < u_i^* \leq k_{i,c-1} \\ \vdots & \\ 1 & \text{if } k_{i1} < u_i^* \leq k_{i2} \\ 0 & \text{if } y_i^* \leq k_{i1} \end{cases} \quad (8)$$

For the car ownership variables, there are  $c = 3$  categories (corresponding to 0, 1, and 2 cars, as there are very few households with more than two cars in the Dutch Mobility Panel); for the panel tenure variable, there are  $c = 4$  categories (corresponding to 1 through 4 years of panel participation).

The unknown parameters in (8) are estimated using the ordered-response probit model of Aitchison and Silvey (1957) and Ashford (1959):

$$P(y_i = j|x) = P(k_{ij} < y_i^* \leq k_{i,j+1}) = \Phi[(k_{i,j+1} - \pi'x) - (k_{ij} - \pi'x)] \quad (9)$$

where  $\Phi$  is the standard cumulative normal distribution function, and  $\pi$  and  $x$  are as in (6). The parameters in (9) can be estimated using a maximum likelihood technique (Maddala, 1983).

The entire model, consisting of equation system (4) and the tobit and probit submodels for the non-normal endogenous variables, is estimated using a multi-stage procedure outlined in Golob and van Wissen (1989). It was developed by Muthén (1983, 1984, 1987). In the first stage of the procedure, the first- and second-order sample statistics of the non-normal endogenous variables are estimated using the conventional maximum-likelihood tobit and ordered probit techniques, followed by a limited-information maximum-likelihood technique to estimate the covariances between all pairs of these endogenous variables. In this way, the probabilities that the endogenous variables are multivariate normally-distributed are maximized conditional on the exogenous variables in system (4). In the second stage of the procedure, a generalized least-squares (GLS) iterative technique is used to estimate the structural parameters of the beta, gamma, and psi ( $\Psi = \zeta\zeta'$ ) matrices of system (4) using the estimated second-order sample statistics as weights. It has been shown that these GLS estimators are asymptotically distribution free (Browne, 1974, 1984; Bentler, 1983a, 1983b).

#### MODEL SPECIFICATION

##### *The endogenous behavioral variables*

There are eight endogenous behavioral variables, comprised of four variables measured on the same households at two points in time one year apart. The four variables, their scale properties, and model treatments are listed in Table 3.

The postulated causal structure among these eight endogenous variables is depicted in the flow diagram of Fig. 6. There are sixteen causal relationships in this structure, each

Table 3. The behavioral endogenous variables, each measured on households at two points in time

VARIABLE	ABBREVIATION	SCALE	TREATMENT
Travel time/week by car	T CAR	Ratio	Continuous, censored at 0
Travel time/week by public transport	T P.T.	Ratio	Continuous, censored at 0
Travel time/week by nonmotorized modes	T NMOT	Ratio	Continuous, censored at 0
Number of cars	NCARS	Ordinal	Ordered Probit

relationship denoted by an arrow in Fig. 6. Fourteen of these sixteen relationships are contemporaneous, implying that one variable influences another variable at the same point in time (synchronously). Such relationships are analogous to those in cross-sectional models.

The fourteen contemporaneous relationships represent the identical seven relationships at two points in time. They can be interpreted as four sets of relationships:

1. The level of household car ownership has a positive direct effect on travel time expenditures by car and negative direct effects on travel time expenditures by public transport and by nonmotorized modes (accounting for three of the seven contemporaneous relationships).
2. Car travel time has a further negative effect on both public transport and nonmotorized times. That is, conditional upon the level of car ownership, higher car use also implies less use of the competing modes (accounting for two more of the relationships).
3. Public transport travel time has a positive influence on car travel time. This relationship is postulated as a contemporaneous manifestation of the principle of travel time and money trade-offs (Zahavi, 1979b; Golob *et al.*, 1981; Zahavi and McLynn, 1983): households expending higher levels of travel time by a slower, less expensive mode (public transport) are likely to switch some travel to a faster, more expensive mode (car) in order to reduce travel time expenditures at the cost of increasing travel money

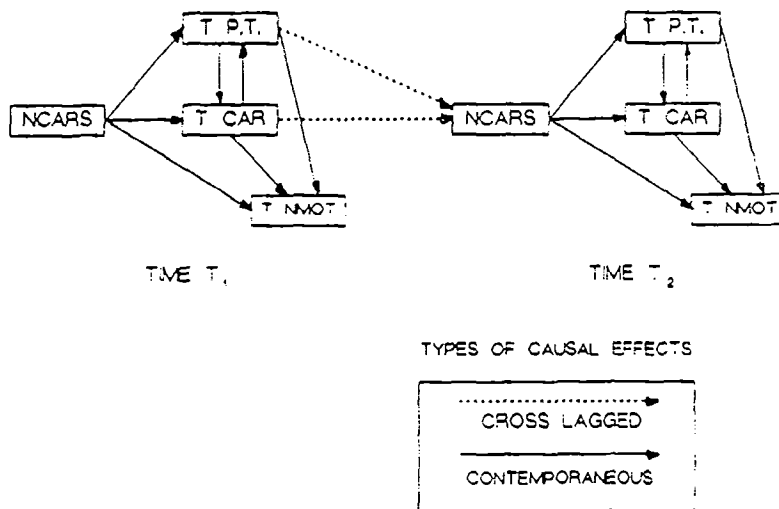


Fig. 6. Flow diagram of causal linkages between endogenous behavioral variables.

expenditures. This contemporaneous relationship is likely to be relatively weak, because it is conditional on a given level of car ownership.

4. The final contemporaneous relationship implies that public transport travel time has a positive influence on nonmotorized time. This specifies a hierarchical complementarity between these modes (Golob and Meurs, 1987).

Two important lagged relationships are postulated in addition to these contemporaneous relationships. These lagged relationships imply that travel time expenditures in the base year affect car ownership in the following year:

1. Public transport travel time expenditures have a positive lagged influence on future car ownership. This is a dynamic manifestation on the principle of time and money trade-offs involving comparative speeds and costs of travel by mode.
2. Car travel time expenditures also have a positive influence on future car ownership; extensive use implies the need for more cars, as evidenced in the descriptive analyses documented above as part of the present study. The causal structure depicted in Fig. 6 is implemented in the model in terms of free and constrained nonzero elements of the beta matrix of equation system (4). The sixteen relationships lead to nine free model parameters, because the seven contemporaneous relationships are constrained to be equal in the two points in time. Thus, there are seven free contemporaneous parameters, plus two lagged diachronal parameters.

#### *Corrections for panel conditioning*

The influence of panel conditioning bias is accounted for by introducing an ordered polytomous variable measuring the number of years each household had participated in the panel at each point in time. This variable, labeled "tenure," takes on the integer values 1 through 4 and is treated as an ordered probit (expression (9)). In this way the ordinal observed variable is transformed into a continuous latent variable with the ability to capture the expected nonlinear effects of diminishing marginal conditioning over panel waves. Furthermore, the specification of panel tenure as an endogenous variable allows the inclusion of ordered probit regression effects from the exogenous variables to tenure; allowing identification of differences in attrition by household characteristic.

It is postulated that the tenure variable has a causal influence on each of the three travel time expenditure variables at each of the two points in time. These influences, expected to all be negative in sign, partially control for the increase over time in reporting errors and omissions in the travel diaries documented by Meurs *et al.* (1989). No panel conditioning effects are expected on the car ownership variables due to the much simpler reporting requirements, and this absence of panel bias on the car ownership variable is confirmed by Hensher (1988).

These six additional causal effects complete the structural relationships among the endogenous variables expressed in the beta matrix of equation system (4). There are nine endogenous variables, eight of which are the behavioral variables described in the previous section (travel time expenditures by three modes plus car ownership at each of two points in time), the ninth variable being tenure, accounting for panel conditioning biases.

#### *The explanatory variables*

The explanatory background household characteristics were divided into two types: dynamic characteristics which change over the course of a year for a substantial proportion of households, and static characteristics which are relatively stable over time. To qualify as a dynamic exogenous variable, at least 5% of the observations had to exhibit temporal change, corresponding to an autocorrelation of a value no greater than 0.89, depending on the variable distribution. High autocorrelations must be avoided because they lead to estimation problems due to near-singular matrices.

The exogenous variables are listed in Table 4. There are nine dynamic variables, which account for eighteen exogenous variables through their measurement at two points in time.

Table 4. The exogenous background variables

TYPE	VARIABLE DEFINITION	ABBREVIATION	SCALE
Dynamic	Household Income in highest category	INCHIGH	Dummy
	Household Income in lowest category	INCLOW	Dummy
	Number of persons 18 or older in household	NADULTS	Continuous
	Number of persons 12-17 in household	NKIDS12	Continuous
	Household composed of 2 adults	COUPLES	Dummy
	Presence of children less than 12 years old	W/KIDS	Dummy
	Number of household drivers	NDRIVERS	Continuous
	Presence of 3 or more drivers	3+DRIVERS	Dummy
	Number of household workers	NWORKERS	Continuous
Static	Residence located in either of the 2 largest metropolitan areas	LOCBIG	Dummy
	Residence located in regional center	LOCREGCEN	Dummy
	Residence located in suburb with commuter rail service	LOCSUB	Dummy
	Residence located in rural area	LOCRURAL	Dummy

In addition, there are four static variables, making a total of 22 exogenous background variables. These variables were chosen according to conceptual arguments and empirical evidence concerning the relationships between household characteristics and travel time "budgets" (cf. Szalai, 1972; Zahavi, 1979a, 1979b, 1982) and the relationships between household characteristics and car ownership and mode usage (cf., Button *et al.*, 1982; Golob and Burns, 1978; Goodwin, 1987; Heggie, 1979; Kitamura and van der Hoorn, 1987).

The levels of temporal change in the dynamic household characteristics are reflected in comparisons of the variables at the two points in time. Among the continuous variables, 17.2% of the households exhibited changes in the number of workers; 12.5% had changes in the number of adults; and 12.1% had changes in the number of drivers. Among the dummy variables, 13.3% of households changed states with respect to high income; 6.7% changed states with respect to low income; and 6.0% changed states regarding their life-cycle classification as couples.

The static variables capture four of the six categories of residential location used in the panel cluster sampling (Golob *et al.*, 1985). Residential location reflects differences in densities of population and activity sites and public transport levels of service, and these differences have been shown to be important in explaining both travel time expenditures (e.g. Chapin, 1974; van der Hoorn, 1979; Golob *et al.*, 1981) and car ownership levels (e.g. Beckmann *et al.*, 1973; Fowkes and Button, 1977). These residential location variables are treated as static because most residential relocations occur within the same community type; an average of only about 0.5% of households change classification on these four dummy variables.

The regression structure linking these exogenous background variables and the endogenous variables is specified in terms of nonzero elements in the gamma matrix of equation system (4). This specification was guided by results of previous studies and by results of regressions conducted separately for each dependent variable. As in the case of the structure among the endogenous variables, these parameters are constrained to be equal in the two time periods. In addition, diachronal effects representing temporal lags and leads were specified for the causal influences of income and number of drivers on car ownership; the importance of these dynamic influences is evaluated in the discussion of the results.



*Exogenous period effects*

It is probable that there are temporal changes in travel time expenditures and car ownership levels that are due to factors affecting all panel households uniformly. Such factors could include fuel prices, public transport fares, general levels-of-service (e.g. congestion effects on travel times), and influences on disposable income from tax rates and costs of living.

These factors, here called "period effects," are accounted for by introducing dummy variables for two of the three wave-pair time periods. Regression effects (free parameters in the gamma matrix of eqn (4)) are then specified from each of the two period dummy variables to each of the four time period  $t_2$  behavioral endogenous variables. These effects thus represent period effects for the two latter years in the last two wave pairs, 1987 and 1988, and relative to the latter year of first (base) wave pair, 1986. These period effects are conditional on the effects of static and dynamic household characteristic and are also conditional on the panel bias effects captured by the tenure variable. These two period effects bring the total number of exogenous variables to 24.

*Disturbance term dynamics*

The covariances of the  $\zeta$  error terms in the structural equation system (4) comprise an important part of the model because the eight behavioral endogenous variables represent four travel demand variables measured at two points in time. The autocorrelations between these four pairs of endogenous variables are accommodated in the model by allowing the corresponding covariances in the  $\Psi = \zeta\zeta'$  variance-covariance matrix to be freely estimated. This and other means of accounting for repeated measurement structure in longitudinal data are discussed in Jöreskog (1979).

The full specification of the  $\Psi$  disturbance-term variance-covariance matrix involves these four off-diagonal autocovariance parameters, plus six free diagonal (variance) parameters for the continuous endogenous variables: travel time expenditures by the three modes at two points in time. The variances of the ordered polytomous variables—car ownership at two points in time and the panel tenure variable reflecting panel conditioning—are not identified and are standardized to unity, which is a consequence of the probit model (Maddala, 1983).

## RESULTS

*Overview of model fit*

The model is extremely parsimonious due to the limited number of effects and the restrictions involving equal contemporaneous effects at the two points in time (given the number of  $x$  and  $y$  variables, it is possible to have up to 180 more free parameters than are specified in the model). In light of this parsimony, the fit of the model was judged to be very good. The parameter estimates corresponding to the postulated structure among the endogenous variables, depicted in the flow diagram of Fig. 7, were all of the correct sign and were, with a single exception, significantly different from zero at the  $p = .05$  one-tailed level. The constraints that the seven contemporaneous relationships among the behavioral endogenous variables are equal at the two points in time were found to be realistic because subsequent releases of each constraint did not lead to substantially better fitting models.

The structure of the exogenous effects on the endogenous variables was also largely as expected: The 18 dynamic (nine variables at two points time) and four static background variables (or 22 exogenous variables in total) had 66 significant effects on the endogenous behavioral variables, an average of three effects per variable. As in the case of the endogenous contemporaneous structure, the simplification of equivalent relationships at the two points in time was successful; and the postulated lag and lead effects were all statistically significant, as described in the next section.

The structure capturing the influences of panel conditioning biases yielded results that were entirely consistent with expectation and with previous results (Meurs *et al.*, 1989;



public transport. Importantly, the (positive) lagged effects of car travel time and public transport travel time on future car ownership are both statistically significant. This confirms the hypothesis that, controlling for exogenous influences, excess motorized travel times at time  $t_1$  lead to an increase in car ownership demand at time  $t_2$ .

Another important estimation result is that the tenure variable accounting for panel conditioning (through an ordered probit formulation) has the expected effects: The variable most subject to panel conditioning bias is travel time by nonmotorized modes, with the biases on travel by the two motorized modes being relatively similar, but stronger on public transport. Furthermore, the levels of bias are stronger on time period  $t_1$  than on time period  $t_2$ , indicating diminishing effects over time for a given panel tenure, particularly for the reporting of travel by nonmotorized modes (bicycle and walking). The estimated thresholds ( $k_{ij}$  in expression (9)) in the probit translation of the number of years of panel participation also indicate a diminishing marginal panel-conditioning effect by tenure.

The standardized structural parameters interrelating the endogenous variables are listed in Table 6. Each of these parameters relates two variables with unit variance, which removes scale differences in their comparison. The strongest relationships are those from car ownership to travel times. The next strongest relationship is the (positive) influence of public transport travel time on car travel time, followed by the (negative) influence of car travel time on nonmotorized time and the lagged influence of car travel time on future car ownership. The influences of car and public transport travel times on nonmotorized time are similar in importance to the influence of panel conditioning biases on nonmotorized time, emphasizing the need to include such bias effects.

The estimated structural regression parameters relating the endogenous variables to the exogenous variables are listed in Table 7a (exogenous variables of time period  $t_1$ ), Table 7b (variables of time period  $t_2$ ), and Table 7c (static and period effect variables). All parameters are statistically significant at the  $p = .05$  one-tailed level, with the exception of some of the period effects. Importantly, the lagged effects of the high income dummy variable and number of drivers on future car ownership are both significant (Table 7a), as are the lead effects of future high income and future number of drivers on present car ownership. Regarding exogenous influences on the panel tenure variable, only three significant effects were found: panel attrition is less for households located in rural villages and towns and for households with a greater number of drivers; panel attrition is higher for households located in the two largest cities (Amsterdam and Rotterdam). The relationships between panel tenure and the period variables merely account for time expiration. The most important regression effects, determined through a comparison of standardized coefficients (not shown) are: from number of adults and number of kids aged 12–17 to car ownership; and from number of adults and residential location in the two largest cities to time by public transport.

Focusing on the period effects, there is a uniform increase in both car ownership and

Table 6. Estimated standardized structural parameters linking endogenous variables (beta matrix estimates for standardized variables)

	TENURE	T CAR 1	T PT 1	T NMOT 1	NCARS 1	T CAR 2	T PT 2	T NMOT 2	NCARS 2
TENURE	0	0	0	0	0	0	0	0	0
T CAR 1	-0.023	0	0.104	0	0.399	0	0	0	0
T PT 1	-0.032	-0.054	0	0	-0.262	0	0	0	0
T NMOT 1	-0.061	-0.072	0.063	0	-0.238	0	0	0	0
NCARS 1	0	0	0	0	0	0	0	0	0
T CAR 2	-0.017	0	0	0	0	0	0.101	0	0.389
T PT 2	-0.022	0	0	0	0	-0.056	0	0	-0.263
T NMOT 2	-0.004	0	0	0	0	-0.079	0.066	0	-0.252
NCARS 2	0	0.070	0.025	0	0	0	0	0	0

Table 7a. Estimated structural parameters linking dynamic exogenous variables of time period  $t_1$  to the endogenous variables (certain gamma matrix estimates) with z-statistics in parentheses

	TIME PERIOD 1								
	INC HIGH	INC LOW	NADULTS	NKIDS12	COUPLES	W/KIDS	NDRIVERS	3+DRVRS	NWORKERS
TENURE	0	0	0	0	0	0	0	0	0
T CAR 1	0	0	0.66 (3.65)	0.91 (6.63)	0	0	0.88 (6.35)	0	0.55 (4.69)
T PT 1	0.97 (5.22)	0	1.84 (12.9)	0.79 (3.62)	1.07 (4.67)	1.53 (4.36)	-0.39 (-2.29)	1.98 (5.30)	0.39 (2.96)
T NMOT 1	0	0	3.29 (28.9)	4.26 (37.3)	0	0	0	0	0.39 (4.23)
NCARS 1	0.41 (5.94)	-0.32 (-5.47)	0	-0.11 (-2.93)	0.17 (3.43)	0.18 (2.61)	0.66 (12.5)	0	0.11 (3.90)
T CAR 2	0	0	0	0	0	0	0	0	0
T PT 2	0	0	0	0	0	0	0	0	0
T NMOT 2	0	0	0	0	0	0	0	0	0
NCARS 2	0.21 (3.21)	0	0	0	0	0	0.34 (6.83)	0	0

Table 7b. Estimated structural parameters linking dynamic exogenous variables of time period  $t_2$  to the endogenous variables (certain gamma matrix estimates) with z-statistics in parentheses

	TIME PERIOD 2								
	INC HIGH	INC LOW	NADULTS	NKIDS12	COUPLES	W/KIDS	NDRIVERS	3+DRVRS	NWORKERS
TENURE	0	0	0	0	0	0	0.076 (3.27)	0	0
T CAR 1	0	0	0	0	0	0	0	0	0
T PT 1	0	0	0	0	0	0	0	0	0
T NMOT 1	0	0	0	0	0	0	0	0	0
NCARS 1	0.12 (1.79)	0	0	0	0	0	0.42 (7.89)	0	0
T CAR 2	0	0	0.66 (3.65)	0.91 (6.63)	0	0	0.88 (6.35)	0	0.55 (4.69)
T PT 2	0.97 (5.22)	0	1.84 (12.9)	0.79 (3.62)	1.07 (4.67)	1.53 (4.36)	-0.39 (-2.29)	1.98 (5.30)	0.39 (2.96)
T NMOT 2	0	0	3.06 (28.5)	3.86 (35.6)	0	0	0	0	0.39 (4.23)
NCARS 2	0.24 (3.43)	-0.32 (-5.47)	0	-0.11 (-2.93)	0.17 (3.43)	0.18 (2.61)	0.71 (14.0)	0	0.11 (3.90)

Table 7c. Estimated structural parameters linking static and period effect exogenous variables to endogenous variables (certain gamma matrix estimates) with z-statistics in parentheses

	STATIC				-- PERIOD EFFECTS --	
	LOC BIG	LOC MID	LOC SUB	LOC RURL	1987	1988
TENURE	-0.34 (-5.04)	0	0	0.13 (2.98)	0.74 (10.5)	1.357 (20.7)
T CAR 1	0	0	0.94 (3.64)	0.76 (3.49)	0	0
T PT 1	3.25 (9.85)	1.23 (4.52)	1.14 (4.08)	-0.65 (-2.69)	0	0
T NMOT 1	0	0	0	-0.67 (-4.17)	0	0
NCARS 1	0	-0.36 (-5.35)	0	0.27 (5.33)	0	0
T CAR 2	0	0.00	0.94 (3.64)	0.76 (3.49)	0.11 (0.48)	0.46 (1.72)
T PT 2	3.25 (9.85)	1.23 (4.52)	1.14 (4.08)	-0.65 (-2.69)	-0.04 (-0.19)	0.42 (1.60)
T NMOT 2	0	0	0	-0.67 (-4.17)	-0.31 (-1.82)	-0.17 (-0.90)
NCARS 2	0	-0.36 (-5.35)	0	0.27 (5.33)	0.07 (1.62)	0.08 (1.90)

travel time in 1988, relative to 1986. The increase in car ownership is also indicated by a marginally significant increase in 1987 which, together with the significant effects for the 1988 period, indicates a steady increase from 1986 through 1987 and 1988 in car ownership in the Netherlands. This increase is over and above that explained by changes in household characteristics. The increase in car *travel time* is relatively more concentrated in 1988, compared to 1987, possibly indicating a lagged effect of car *ownership*. Also detected in the period effects is a marginally significant increase in public transport travel time in 1988, following essentially no change between 1986 and 1987.

Further interpretation of results is facilitated by investigating the total effects on the endogenous variables.

### Total effects

The total effect of one variable on another variable might be different than the direct effect of the first variable on the second if the first variable also affects other variables that in turn, directly or indirectly, affect the second variable. There also might be total effects between variables when there is no direct effect, but only indirect "paths" through intermediate variables. The total effects are the coefficients of the reduced-form equations of structural equation system (4):

$$y^* = (I - B)^{-1}\Gamma x \quad (10)$$

so the total effects of  $x$  on  $y^*$  are given in the matrix  $(I - B)^{-1}\Gamma$ . The total effects of  $y^*$  on  $y^*$  are given by  $(I - B)^{-1} - I$ .

The total effects on each of the four endogenous variables at the second point in time are listed in Table 8. Shown are the total effects of the *standardized* solution (unit-variance variables), allowing comparisons to be made free of scale differences. A variable-by-variable interpretation of these results follows.

Car ownership at time  $t_2$ : The dominant explanatory variable is the number of household drivers at the same point in time. There is also an important lagged effect from the

Table 8. Standardized total effects for endogenous variables

EXOGENOUS VARIABLE	ENDOGENOUS VARIABLE			
	T CAR	T P.T.	T NMOT	NCARS
INC HIGH 1	0.025	-0.019	-0.021	0.075
INC LOW 1	-0.001	0.001	0.001	-0.002
NADULTS 1	0.002	-0.001	-0.001	0.005
TIME HKIDS12 1	-0.001	0.001	0.001	-0.003
T1 COUPLES 1	0.001	-0.001	-0.001	0.004
W/KIDS 1	0.002	-0.001	-0.002	0.005
NDRIVERS 1	0.087	-0.069	-0.075	0.267
3+DRVRS 1	0.000	0.000	0.000	0.001
NWORKERS 1	0.003	-0.002	-0.002	0.009
INC HIGH 2	0.034	0.055	-0.019	0.086
INC LOW 2	-0.033	0.026	0.028	-0.100
NADULTS 2	0.124	0.269	0.493	0.000
TIME NKIDS12 2	0.075	0.093	0.505	-0.065
T2 COUPLES 2	0.030	0.076	-0.012	0.067
W/KIDS 2	0.039	0.123	-0.013	0.083
NDRIVERS 2	0.365	-0.271	-0.179	0.525
3+DRVRS 2	-0.002	0.097	0.015	-0.029
NWORKERS 2	0.116	0.038	0.028	0.059
LOC BIG	0.020	0.206	0.014	0.005
STATIC LOC MID	-0.059	0.117	0.037	-0.094
EFFECTS LOC SUB	0.058	0.071	-0.002	0.006
LOC RURL	0.085	-0.104	-0.115	0.106
PERIOD PERIOD=87	0.016	-0.020	-0.036	0.021
EFFECTS PERIOD=88	0.049	0.012	-0.023	0.034
PANEL BIAS	-0.011	-0.025	-0.007	-0.001

number of drivers in the previous year. The high income dummy has both contemporaneous and lagged effects, but the low income dummy has only a contemporaneous effect. The income effects, while important, are no greater than the effects from two of the residential location dummy variables: households located in rural towns and villages have higher car ownership levels, while those located in cities which are regional centers (principally the cities of Groningen and Nijmegen, due to the clustering of the Dutch Panel sample) have lower car ownership, *ceteris paribus*. At the next level of importance are four additional household composition variables, followed by the period effects. These period effects indicate that there are increases in car ownership in 1987 and (with a slight acceleration) in 1988, relative to 1986, that are uniform across all panel households.

For car travel time at time  $t_2$ , the number of household drivers at the same point in time plays a dominant role, as in the case of car ownership, but there is a greater contribution from other household composition variables. Particularly, both the number of workers and the number of adults are major contributors to the explanation of car travel time expenditures; and the number of children 12 to 17 years of age has a positive effect on car travel time. The influences of residential location are also different than for car ownership: households located in rural areas expend greater car travel time, but so do households located in suburban cities and towns, and to a lesser extent, so do households located in the largest cities (Amsterdam and Rotterdam) (the reference group being location in either nonsuburban medium-sized cities or in suburbs without rail service). The period effects exhibit an increase in car travel time that is accelerating over the 1986-1988 period. However, panel conditioning has a negative total effect on car travel time. Consequently, analyses in which period and conditioning effects are confounded are likely to display little or no systematic change in car travel time across the sample, due to the opposing period and panel conditioning influences.

These results for *car ownership* and *car travel time* expenditures reveal that the two endogenous variables have both common and unique explanations. The number of household drivers is the most important explanator of both variables, and this explanatory variable has both contemporaneous and dynamic influences on both endogenous variables. The dynamic influences are stronger for car ownership than for car travel time, which is logical considering the longer-term nature of car ownership decisions. Income also exhibits both contemporaneous and dynamic influences on both variables. Both variables demonstrate period effects, but car travel time increases at an increasing rate over the 1986-1988 period, while car ownership increases at a constant or diminishing rate.

The principal differences in the explanation of car ownership and car travel time expenditures are with regard to household composition and residential location. Car travel time is more sensitive to both of these sets of explanatory variables. In particular, the number of adults, conditional on the number of drivers and the number of workers, has an influence on car travel time but not on car ownership. The number of children aged 12 to 17 actually has a negative influence on car ownership (presumably through a reduced car purchasing power) and a positive influence on car travel time (possibly through increased household car passenger time *and* increased car driver time for serve-passenger purposes), *ceteris paribus*. Regarding residential location, the relationship between car travel time and community type is more pervasive than the relationship between car ownership and community type. For instance, suburban locations imply higher car usage in terms of travel times but not higher car ownership, *ceteris paribus*. These differences can be important in policy evaluations.

The two most important total effects on travel time by public transport at time  $t_2$  are due to the number of adults and the number of drivers, with the (negative) influence of number of drivers being both direct and indirect. The indirect effects are through the positive effect of drivers on car ownership and use and through negative effects of these two endogenous variables, particularly car ownership, on public transport travel time. Number of drivers also has a lagged effect on public transport time. Residential location variables are also very important in explaining public transport time, there being a direct relationship between city size and public transport use. Finally, there are dynamics in the relationship between the high income dummy variable and public transport time: The

contemporaneous relationship is positive, indicating that public transport is a superior economic good; but the lagged relationship is negative as a consequence of adjustments in car ownership. This is a clarification of the results cited in Golob (1989). Public transport time also exhibits a negative panel conditioning effect and period effects that indicate a decrease in public transport usage from 1986 to 1987, followed by an increase in 1988 compared to both previous years.

Finally, regarding the total effects on nonmotorized mode time, the two critical explanatory variables are the number of adults and the number of children aged 12 to 17, which together add to the total number of diary keepers, a variable used in several other studies (e.g. Kitamura, 1987; Meurs, 1989a). This effect of number of diary keepers is entirely contemporaneous, but the negative effect of the number of drivers includes both contemporaneous and lagged dynamic components. Income also has a lagged dynamic effect. There is also a substantial panel conditioning bias effect and an apparent real period decline in nonmotorized mode time.

#### CONCLUSIONS AND A DIRECTION FOR FURTHER RESEARCH

The principal conclusion is that the three household travel demand variables—car ownership and total travel times by car and by public transport—are mutually interdependent. A demand model that specifies any one of these variables as a function of one or more of the others (say, car usage as a function of car ownership) without additional “feedback” equations is subject to endogeneity bias; the error term will be correlated with an explanatory variable. The mutual causality among these variables is consistent with the principle of travel time and money trade-offs: households expending high levels of travel time are likely to expend more money in order to reduce this travel time.

A second conclusion is that the interrelationships among car ownership and travel times by mode *and* the relationships between exogenous household characteristics and car ownership are not all contemporaneous. There are important dynamic effects. These involve lagged effects of travel times on car ownership and lagged effects of income and number of household drivers on car ownership. There are also anticipatory effects of the future income and number of drivers on present car ownership. Furthermore, there are dynamic effects on travel times manifested through causal chains. For instance, high income implies higher public transport at the same point in time, *ceteris paribus*, but the same variable implies lower public transport use one year later due to adjustments in car ownership and use.

A third conclusion is that it is possible to control for panel conditioning biases, so that period effects, capturing the influences of factors such as fuel prices that are uniform across the sample cross-sectionally can be estimated. For the Netherlands, it was estimated that there was a period increase in car ownership and use in 1987 compared to 1986, followed by an increase in public transport use and an accelerated increase in car use in 1988. The separation of panel bias and period effects is important because, in such a situation of positive period effects, panel bias and period effects counteract each other, leading to potentially misleading conclusions.

A fourth conclusion is that there are important similarities and differences in the explanations of car ownership and mode use in terms of household characteristics. Particularly, car ownership and car use are shown to have both common and unique predictors: for instance, the number of adults in the household, conditional on the number of drivers and the number of workers, explains car usage, but not car ownership; also, households located in suburban communities exhibit higher levels of car use, but not car ownership, *ceteris paribus*. Such comparisons are facilitated by the simultaneous equations approach.

Further conclusions can be drawn regarding methodology. Longitudinal structural equation models appear to be capable of handling travel behavior variables that involve either ordered discrete choices or continuous positive measurements with a high proportion of observations at the value zero. The models can also be used to impose dynamic causal effects and disturbance term autorelationships. There certainly appear to be further

capabilities not taken advantage of in the present research. A fruitful direction for further research lies in the marriage of approaches to dynamic travel behavior analysis that are rich in causal structure with those that are sophisticated in the handling of error terms and their influences on parameter estimation. The present research is of the former type, with a minimum of endogeneity assumptions and a built-in ability to test alternative cause and effect relationships. The latter type of approach, overviewed by Maddala (1987) and represented by Hensher (1988) and Meurs (1989a; 1989b), can account for the effects of disruptions such as individual-specific disturbances, but at the expense of dealing with limitations on presumed cause and effect; in fact, the models are usually limited to a single dependent variable. Clearly, future research will glean important material from both types of approaches. The result *should* be improved methods for travel demand forecasting.

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