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The Dynamics of Household Travel Time Expenditures and Car Ownership Decisions

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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. Panel data with extended travel diary periods (of, say, a week's duration) provide a unique opportunity to understand how households balance their levels of time expenditures and car ownership, and how they adjust these levels in response to exogenous changes. Such an opportunity is provided by the Dutch National Mobility Panel (1984-1988), and 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).

A basic tenet of this research is that travel time expenditures by mode are mutually interdependent with car ownership. It is obvious that car household travel time, and consequently travel time by competing modes, is 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, conditional on the exogenous influences of income, number of drivers and workers, and other household characteristics. 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; it does *not* imply constant time or money "budgets." The trade-off of travel time and money expenditures has also been recognized in certain 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 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. Which, if any, of these changes are made depends on the household's values, particularly leisure time versus money, current expenditure levels, and environmental conditions, including transport levels of service and the locations of activity sites.

The testing of alternative hypotheses of cause and effect among these variables is accomplished using longitudinal structural equation models. A simultaneous equations approach is called for because multiple endogenous variables are likely to be affected by any exogenous change, and there are inherent interrelationships among the endogenous variables. The advent of longitudinal structural equation models -- structural 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. Hypothesis 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. Moreover, 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, period effects, and certain misspecification errors. Some of these advances are applied here in the specification and testing of mutual interdependencies among travel time expenditures and car ownership.

DATA SOURCE AND SAMPLE FORMATION

The source of the data is the ongoing Dutch National Mobility Panel (J. Golob, et al., 1985; van Wissen and Meurs, 1989). This panel, instituting 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. The travel time expenditure variables are computed as household weekly totals of travel times 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 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 breakdowns 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 entire 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.

TABLE 1

COMPOSITION OF THE POOLED WAVE-PAIR SAMPLE

YEARS IN PANEL	WAVE-PAIR SUBSAMPLE 1985-86	1986-87	1987-88	DIAGONAL TOTALS	Year Initiated
1	475	343	401		
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		
GRAND TOTAL:				**4,416**	

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 first panel wave (1984) was excluded from the pooled sample, because it is important to separate panel conditioning (tenure) and period effects, and these effects are confounded for the 1984-85 period. This is a manifestation of the initial conditions problem in panel analysis.

The alternative to pooled wave-pair samples for panels with more than two waves is to restrict the sample to only those households (or other units of observation) 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. The "stayers" sample is the most widely used approach in panel-based travel demand analyses, and was employed by, among others, Golob and Meurs, (1987), Kitamura (1987), Golob (1988), Hensher (1988), and Meurs (1989a). 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. These results argue for the use of pooled wave-pair samples, which reduces but does not eliminate attrition and refreshment bias.

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 (panel wave). A pooled wave-pair sample constructed from at least three waves (excluding the initial wave) of a panel with attrition and refreshment will provide a variance of panel tenure over time. This allows a separate accounting of panel conditioning and period effects, as was attempted in the present study. Meurs, et al. (1989) has shown that the Dutch Mobility Panel is characterized by such 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). Sample sizes can be crucial in the analyses of the consequences of such events: an event occurring with the probability of .01 in one year has an expectation of 19 times on the "stayers" sample of 656 Dutch Panel households observed over four years (1985-1988); while the same event is likely to be observed 44 times in the pooled wave-pair sample of 4,416 household-year pairs.

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 (in the present study: 2,119 households, divided by 4,416 wave-pair observations = 0.48), 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. Given the objective in the present study of determining causal structure, there is no known evidence that the repeated measurements problem will bias model coefficients representing strength of effect in a systematic way, but the unweighted standard errors of estimates will be underestimated due to the inflated sample size.

The actual sample size of the pooled wave-pair sample used was approximately 4,000 (4,002). An even breakdown of sample size by wave pair facilitates the comparison of period effects for the three years, accomplished by including variables comparing each of the latter years (1987 and 1988) to the base year (1986). Consequently, random subsamples of 1,334 households were drawn from each of the two wave-pairs with the larger sample sizes (Table 1), resulting in a total wave-pair sample of 4,002. Due to the repeated-measurements overestimation of sample size, the sample of approximately 4,000 was considered to be an effective sample of only 3,000 for upward adjustment of standard errors of the estimates (or downward adjustment of the t-scores or z-scores).

This represents a mid-point correction between the bounds of an effective sample size of approximately 2,000 (assuming perfect autocorrelation or complete redundancy in the repeated measurements on the same households) and the pooled wave-pair total of 4,000 (assuming no redundancy in the repeated measurements).

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 Figure 1. For each of the four segments with changes in car ownership, the lines in Figure 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

TABLE 2

THE DYNAMIC CAR OWNERSHIP SEGMENTS

CAR OWNERSHIP t_1	t_2	NUMBER OF HOUSEHOLD OBSERVATIONS	PERCENT OF POOLED WAVE-PAIR SAMPLE OF 4,416 OBSERVATIONS
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

(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

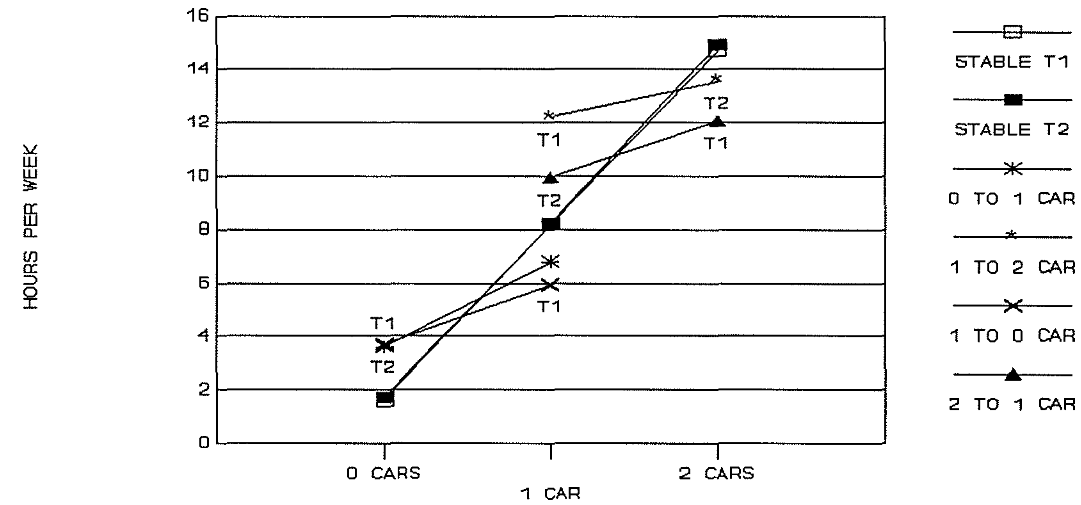

FIGURE 1

HOUSEHOLD CAR TRAVEL TIMES
BY DYNAMIC OWNERSHIP SEGMENT

corresponding state values of the temporally stable segments (non-changers). 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 Figure 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, Figure 1 displays path dependency and asymmetry (irreversibility) (Goodwin, 1987; Kitamura, 1986, 1987), as well as lagged effects (Golob and van Wissen, 1989).

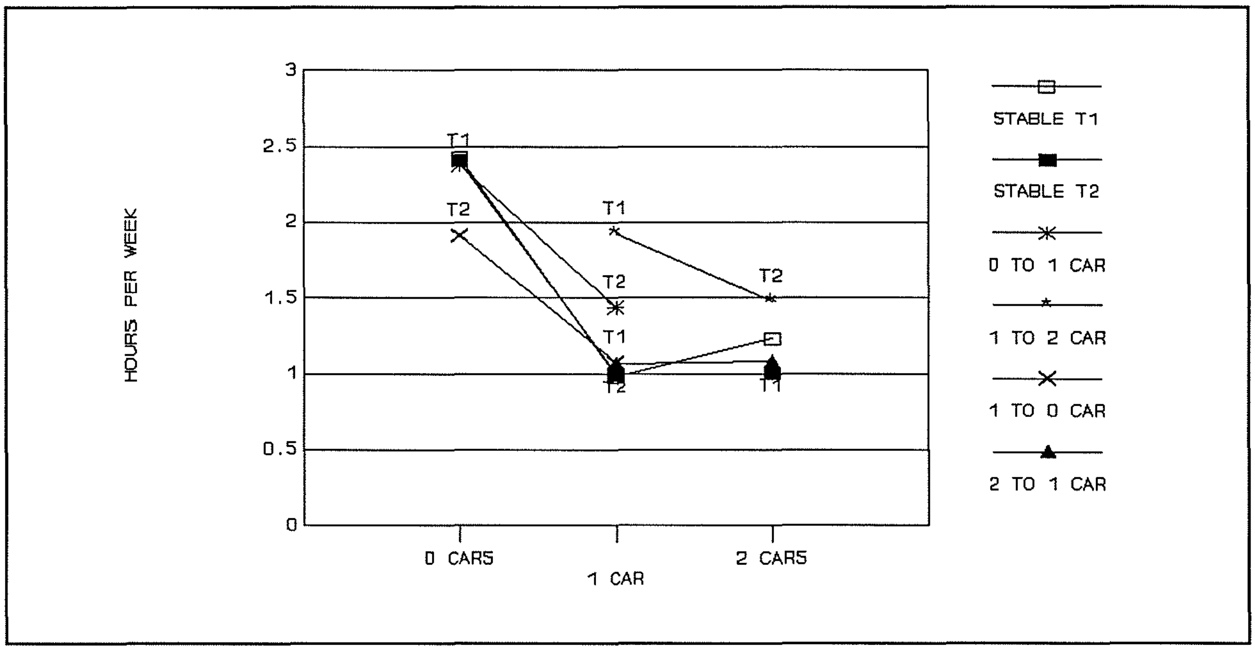

FIGURE 2

HOUSEHOLD PUBLIC TRANSPORT TRAVEL TIMES BY DYNAMIC CAR OWNERSHIP SEGMENT

A similar plot of public transport times by dynamic car ownership segment is provided in Figure 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 Figures 1 and 2 are statistically at the $p = .05$ level).

Plotted in Figure 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 **three** segments with stable ownership levels are located in the vicinity of the origin

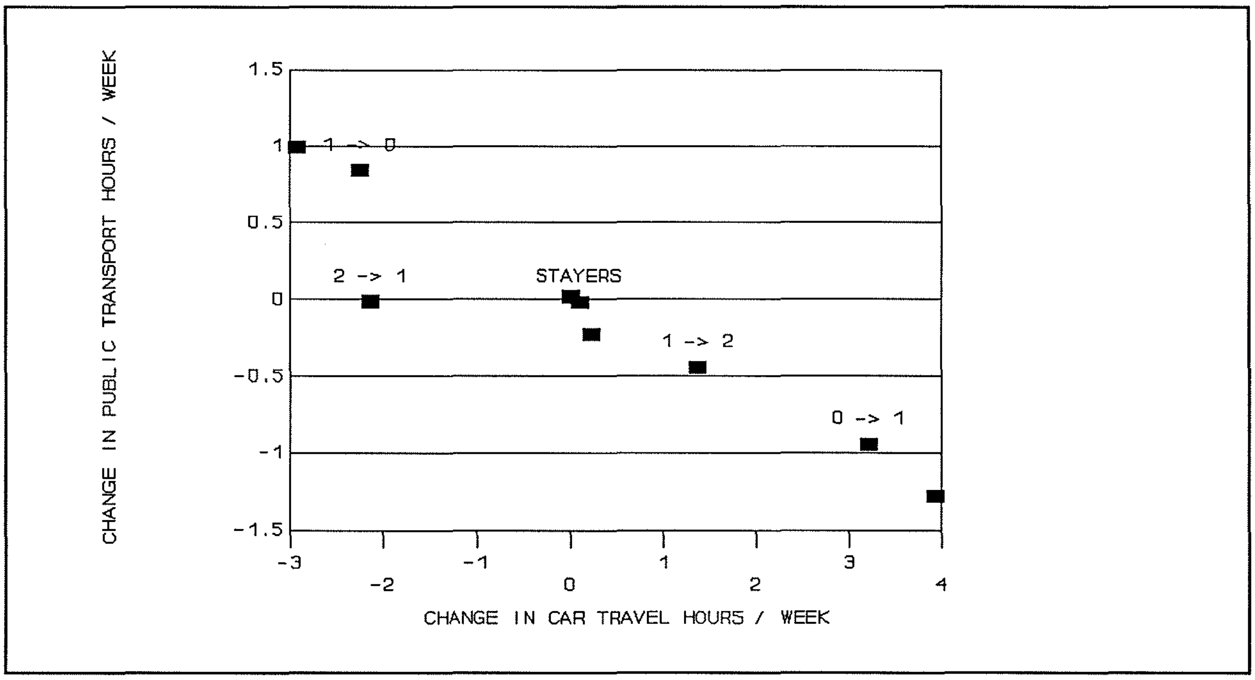

FIGURE 3

TEMPORAL CHANGES IN
HOUSEHOLD CAR AND PUBLIC TRANSPORT TRAVEL TIMES
BY DYNAMIC OWNERSHIP SEGMENT

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:

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

where ΔPT denotes change in public transport time, and ΔCAR 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 Figure 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

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

where ΔNMOT 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 Figure 5. The linear regression equation between the two change variables is

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

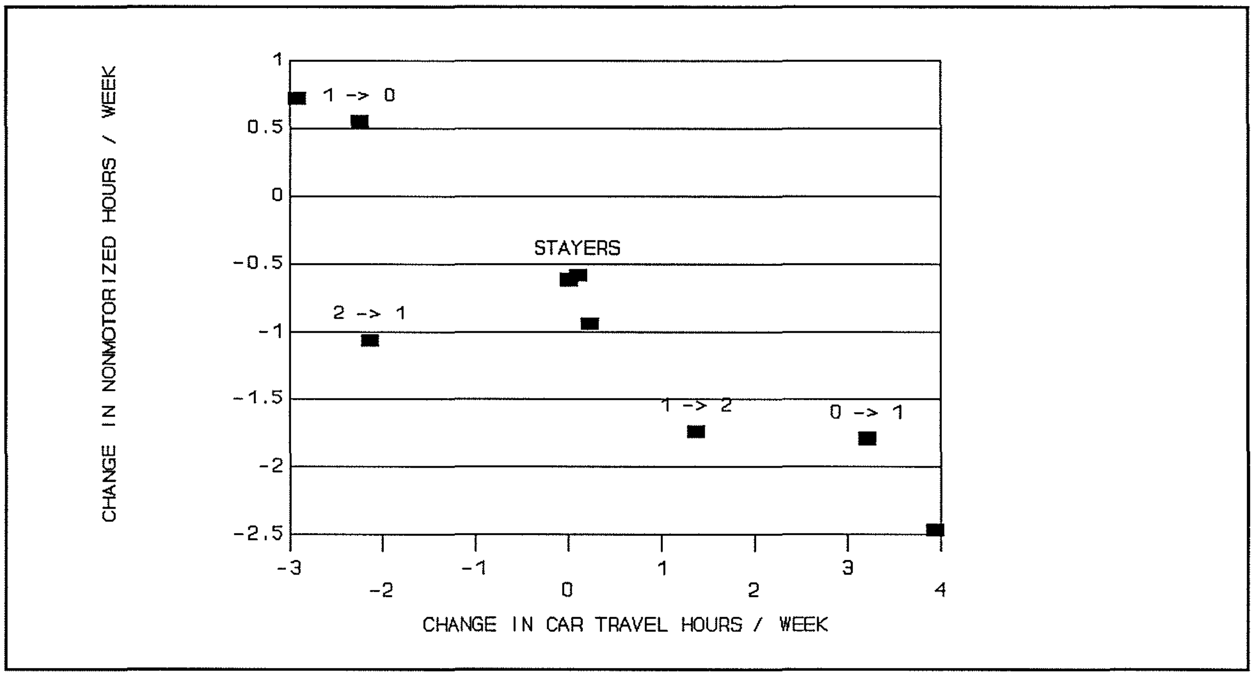

FIGURE 4

TEMPORAL CHANGES IN
HOUSEHOLD CAR AND NONMOTORIZED TIMES
BY DYNAMIC OWNERSHIP SEGMENT

The three-way interrelationship among the changes in modal travel time expenditure (Figures 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.

It is also possible to describe lagged and path-dependent relationships among exogenous household characteristics and travel time expenditures and car ownership.

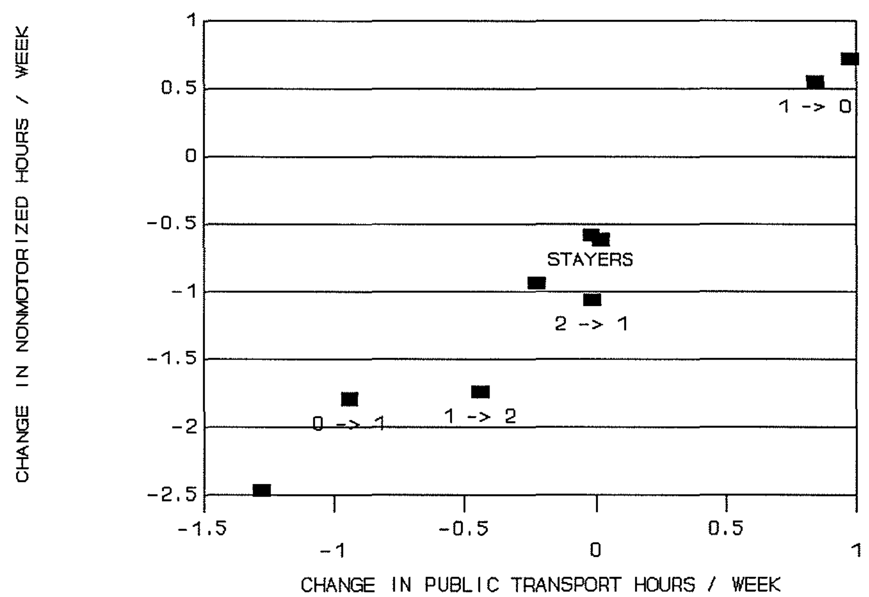

FIGURE 5

TEMPORAL CHANGES IN
HOUSEHOLD PUBLIC TRANSPORT AND NONMOTORIZED MODE TIMES
BY DYNAMIC OWNERSHIP SEGMENT

Some examples are documented elsewhere (e.g., Goodwin, 1987; Kitamura and van der Hoorn, 1987). An important relationship for the present research objectives is that between the number of drivers in the household (license holding) and the level of car ownership. The dynamic phenomena involved in this relationship is apparent in a comparison of car ownership breakdowns at two points in time for the seven dynamic license-holding segments defined in Table 3. Breakdowns of car ownership by segment are given in Figure 6a for time t_1 and in Figure 6b for time t_2 one year later.

TABLE 3

THE DYNAMIC LICENSE HOLDING SEGMENTS

NUMBER OF DRIVERS t_1	t_2	NUMBER OF HOUSEHOLD OBSERVATIONS	PERCENT OF POOLED WAVE-PAIR SAMPLE OF 4,416 OBSERVATIONS
0	0	572	13.0
0	1	62	1.4
1	1	1,329	30.1
1	2	146	3.3
2	2	1,847	41.8
2	3	49	1.1
3	3	104	2.4
Any other combination (not included)		307	7.0

Three of the four segments with temporal stability in license holding (zero, one, and two drivers) exhibit nearly identical breakdowns by car ownership level at times t_1 (Figure 6a) and time t_2 (Figure 6b). The fourth temporally stable segment (three drivers) exhibits an increase in car ownership, from 51.1 percent two-car households to 62.8 percent two-car households, an indication of where some of the growth in car ownership

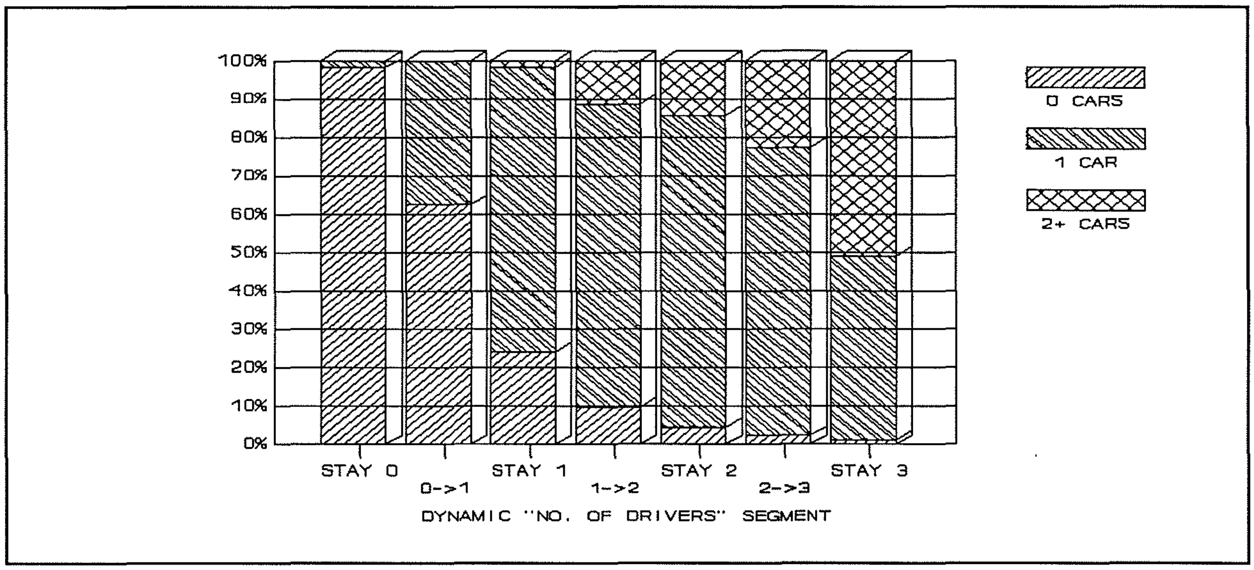

FIGURE 6a

CAR OWNERSHIP LEVELS AT TIME T_1
BY DYNAMIC "NO. OF DRIVERS" SEGMENT

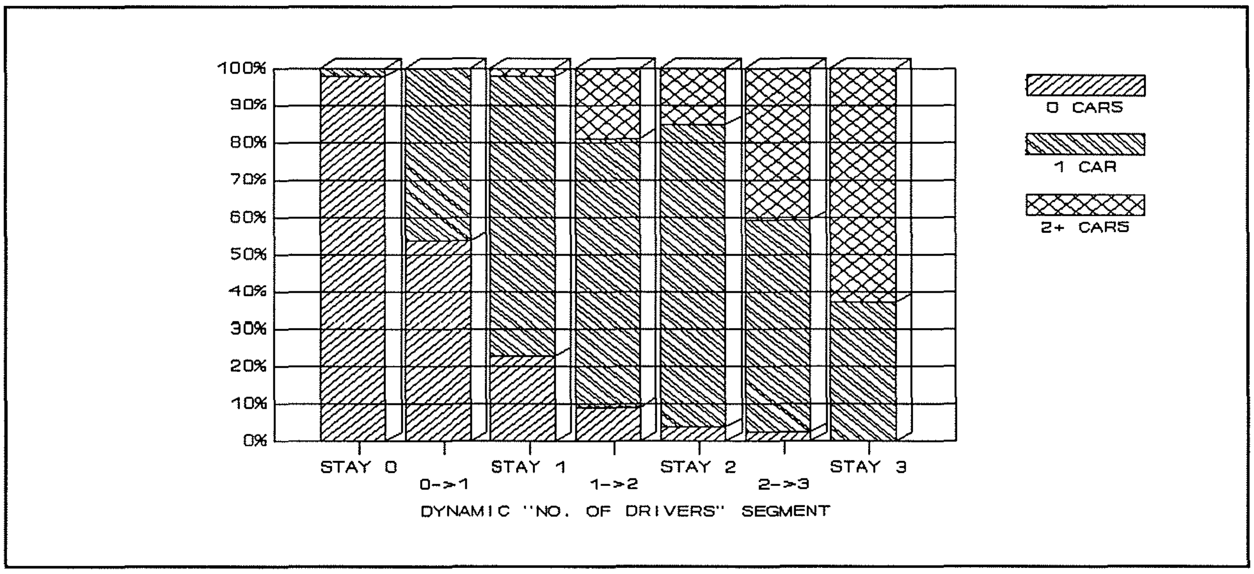

FIGURE 6b

CAR OWNERSHIP LEVELS AT TIME T_2
BY DYNAMIC "NO. OF DRIVERS" SEGMENT

in the Netherlands might be concentrated. However, the most important evidence in Figures 6a and 6b concerns a leading influence of the number of drivers on car ownership: For the "0 to 1 Driver" segment, 37.5 percent of households own a car *prior* to obtaining a driver's license; this increases to 46.4 percent at time t_2, which is short of the 77.4 percent of stable "1 Driver" households (representing a potential time lag in adjustment). For the "1 to 2 Driver" segment, the same lead is evident in that 11.4 percent of these households own two cars in the "before" period, compared to only 1.7% of stable "1 Driver" households; there is also a lag in the eventual elimination of the zero-car state for these households. Finally, for households with increases from two to three drivers, the same lead and lags are apparent in the breakdown of one versus two cars when comparisons are made to the stable "2 Driver" segment in the "before" period and the stable "3 Driver" segment in the "after" period.

These and other results from dynamic descriptive analyses were used to guide the specification of structural model hypotheses.

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 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 (1988) and by Golob and van Wissen (1989). In the special case of dichotomous variables, van Wissen and Golob

(1988) compare this method to the conditional logit model in an investigation of simultaneous equation systems involving binary choice variables.

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:

$$y^* = B\,y^* + \Gamma x + \zeta \qquad (4)$$

where y* is a (p x 1) vector of endogenous latent variables, B is a (p x p) matrix of structural (causal) effects among the y* variables (with a main diagonal of zeros), Γ is a (p x m) matrix of regression effects of the (m x 1) exogenous x variables, and ζ is a (p x 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:

$$y_i = y_i^* \quad \text{if} \quad y_i^* > 0$$

$$y_i = 0 \quad \text{otherwise.} \qquad (5)$$

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:

$$y_i^* \quad = \quad \pi' x + u_i \tag{6}$$

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

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

apparent from substituting (6) into (5). A maximum-likelihood solution to the problem of estimating π and σ_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 $k_{i1}, k_{i2}, \ldots k_{c-1}$ (Muthén, 1984; Golob and van Wissen, 1989):

$$y_i = \left\{ \begin{array}{llllll} c-1 & \text{if} & k_{i\,c-1} & < & u_i^* & \\ c-2 & \text{if} & k_{i\,c-2} & < & u_i^* & \leq & k_{i\,c-1} \\ \vdots & & & & & \\ 1 & \text{if} & k_1 & < & u_i^* & \leq & k_{i2} \\ 0 & \text{if} & & & y_i^* & \leq & k_{i1} \end{array} \right. \tag{8}$$

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):

$$\begin{aligned} P(y_i = j \mid x) &= P(k_{ij} < y_i^* \leq k_{ij+1}) \\ &= \Phi\,[(k_{ij+1} - \pi' x) - (k_{ij} - \pi' x)] \end{aligned} \tag{9}$$

where Φ is the standard cumulative normal distribution function, and π 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 ($\psi = \varsigma \varsigma'$) 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 4.

The postulated causal structure among these **eight** endogenous variables is depicted in the flow diagram of Figure 7. There are **sixteen** causal relationships in this structure, each relationship denoted by an arrow in Figure 7. **Fourteen** of these sixteen relationships are contemporaneous, implying that one variable influences another variable

TABLE 4

THE BEHAVIORAL ENDOGENOUS VARIABLES,
EACH MEASURED ON HOUSEHOLDS
AT TWO POINTS IN TIME

VARIABLE	ABBRE-VIATION	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

at the same point in time (synchronously). Such relationships are analogous to those in cross-sectional models (Golob and Meurs, 1987; Kitamura, 1987).

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

> 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).

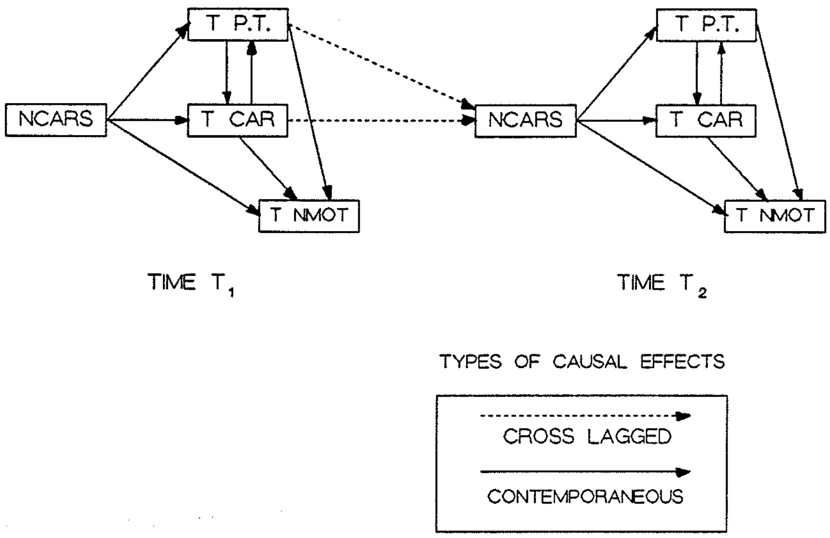

FIGURE 7

FLOW DIAGRAM OF CAUSAL LINKAGES
BETWEEN ENDOGENOUS BEHAVIORAL VARIABLES

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).

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

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:

Public transport travel time expenditures have a positive lagged influence on future car ownership. This is a dynamic manifestation of the principle of time and money trade-offs involving comparative speeds and costs of travel by mode.

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 Figure 7 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 five percent 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 5. There are **nine** dynamic variables, which account for **eighteen** exogenous variables through their measurement at two points in time. 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)

TABLE 5

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

and the relationships between household characteristics and car ownership (cf., Golob and Burns, 1978; Heggie, 1979; Button, et al., 1982).

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 (J. 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 equation (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 characteristics 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 ζ 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 Ψ 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).

INTERPRETATION OF 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 Figure 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; van Wissen and Meurs, 1989; Kitamura and Bovy, 1987). Also, the separation of period effects from panel conditioning biases led to estimates of period effects that appear to be consistent with increased levels of car ownership and mobility in the Netherlands in recent years.

The success of the model structure in replicating the variance-covariance matrices $\mathbf{S}_1$ = y* x' and $\mathbf{S}_2$ = y* y*' is measured by a χ^2 statistic calculated as a product of the sample size and objective function of the GLS estimation (Browne, 1974; Bentler and Bonett, 1980), with degrees of freedom equal to the difference of the number of free elements in the $\mathbf{S}_1$ and $\mathbf{S}_2$ matrices and the number of free parameters in the model. For the present model, χ^2 = 488.9 with 181 degrees of freedom. This indicates that the model *can* be rejected at the p = .05 level. However, this statistic is not trustworthy in the evaluation of large problems, as discussed by Bentler and Bonett

(1980). One problem with all χ^2 statistics is inflation with large sample sizes, and the repeated measurements aspect of the pooled wave-pair sampling scheme used here exacerbates the problem by an artificially large sample size. (If the statistic were based on the number of separate households in the sample, rather that the number of wave-pair observations on households, the model would be associated with a probability in the neighborhood of $p = .01$.) The model χ^2 statistic can be improved by releasing parameter equalities at the two points in time, but this would be at too great a cost in terms of interpretability.

There are two aspects to the interpretation of the model results: First, the *direct* causal effects of each endogenous and exogenous variable on each endogenous variable are represented by the estimated parameters of the structural equation system (4). Second, the *total* effect of each exogenous variable on each endogenous variable are represented by the estimated coefficients of the reduced-form equations. These two aspects are examined in the next two sections.

Direct Effects

The estimated parameters of the beta and gamma matrices of equation system (4) represent all direct causal effects in the model. The parameters of all matrices (including the psi residual term variance-covariance matrix) are estimated *simultaneously*, but are presented here separately for purposes of clarity.

The estimated structural parameters interrelating the endogenous variables (i.e., beta matrix parameters) are listed together with their z-statistics (estimate/standard error ratios) in Table 6. All of the relationships linking pairs of behavioral variables are

TABLE 6

ESTIMATED STRUCTURAL PARAMETERS LINKING ENDOGENOUS VARIABLES
(BETA MATRIX ESTIMATES)
WITH CORRESPONDING Z-STATISTICS IN PARENTHESES

	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	-0.130 (-1.52)	0 -	0.120 (2.04)	0 -	2.29 (21.6)	0 -	0 -	0 -	0 -
T PT 1	-0.160 (-1.71)	-0.047 (-1.11)	0 -	0 -	-1.30 (-11.0)	0 -	0 -	0 -	0 -
T NMOT 1	-0.300 (-3.86)	-0.062 (-6.53)	0.062 (5.06)	0 -	-1.17 (-18.4)	0 -	0 -	0 -	0 -
NCARS 1	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -
T CAR 2	-0.100 (-0.94)	0 -	0 -	0 -	0 -	0 -	0.120 (2.04)	0 -	2.29 (21.5)
T PT 2	-0.110 (-1.08)	0 -	0 -	0 -	0 -	-0.047 (-1.11)	0 -	0 -	-1.30 (-11.0)
T NMOT 2	-0.020 (-0.22)	0 -	0 -	0 -	0 -	-0.062 (-6.53)	0.062 (5.06)	0 -	-1.76 (-18.4)
NCARS 2	0 -	0.012 (6.02)	0.005 (1.66)	0 -	0 -	0 -	0 -	0 -	0 -

significant, with the exception of the (negative) direct effect from time by car to time by public transport, which is significant only at $p > .10$. 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 7. Each of these parameters relates two variables with unit variance,

TABLE 7

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

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 8a (exogenous variables of time period t_1), Table 8b (variables of time period t_2), and Table 8c (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 8a), 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.

TABLE 8a

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	HKIDS12	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 8b

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 8c

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

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

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

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 graphed in Figures 8 through 11. In each figure, total effects are displayed for explanatory variables grouped into five categories: (1) dynamic exogenous t_1 (lagged) variables, (2) dynamic exogenous t_2 (contemporaneous) variables, (3) exogenous static variables, (4) exogenous period effects, and (5) endogenous panel conditioning bias. This last explanatory variable is endogenous, rather than exogenous, but is included in the graphs for comparison purposes. 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 second point in time (Figure 8): 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 number of drivers in the previous year. The high income dummy has both contemporaneous and lagged effects, but the low income

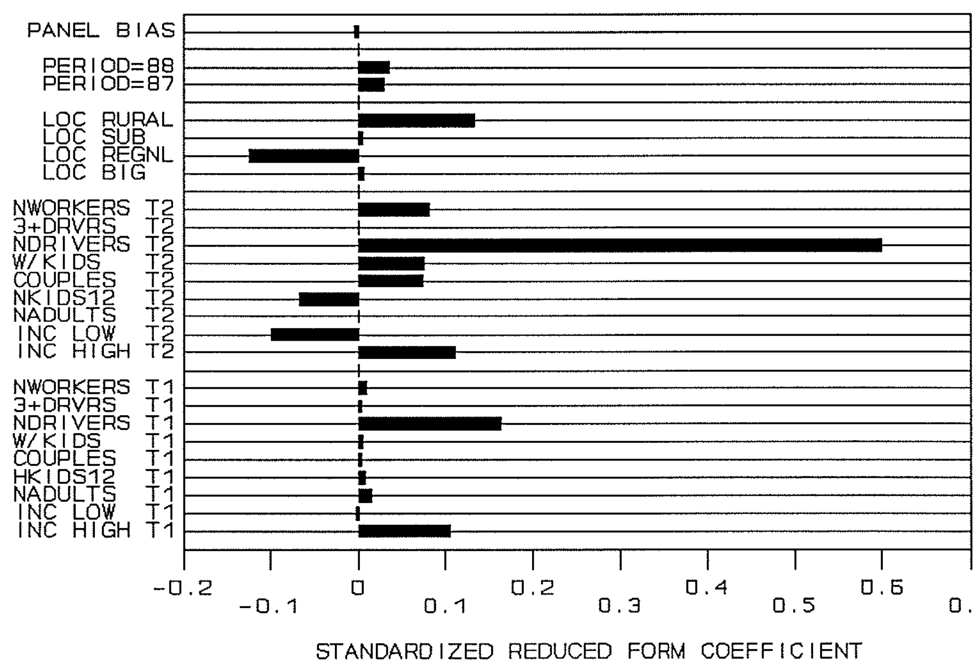

FIGURE 8

STANDARDIZED TOTAL EFFECTS
FOR CAR OWNERSHIP AT TIME t_2

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. Finally, there are a few minor lagged effects that are channeled through the direct lagged travel time influences on car ownership (i.e., through the lagged causal effects between the endogenous variables).

These results indicate that in forecasting car ownership, it is most important to predict license holding, followed by income, labor force participation, and household composition (in terms of the number of children 12 to 17 years of age and a breakdown of households by life-cycle categories). Residential location is also important. Beyond these influences, there is an upward trend in car ownership over the 1986-1988 period that can be traced to factors affecting the household population uniformly.

The total effects on **car travel time** at time t_2 are graphed in Figure 9. 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 less er 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

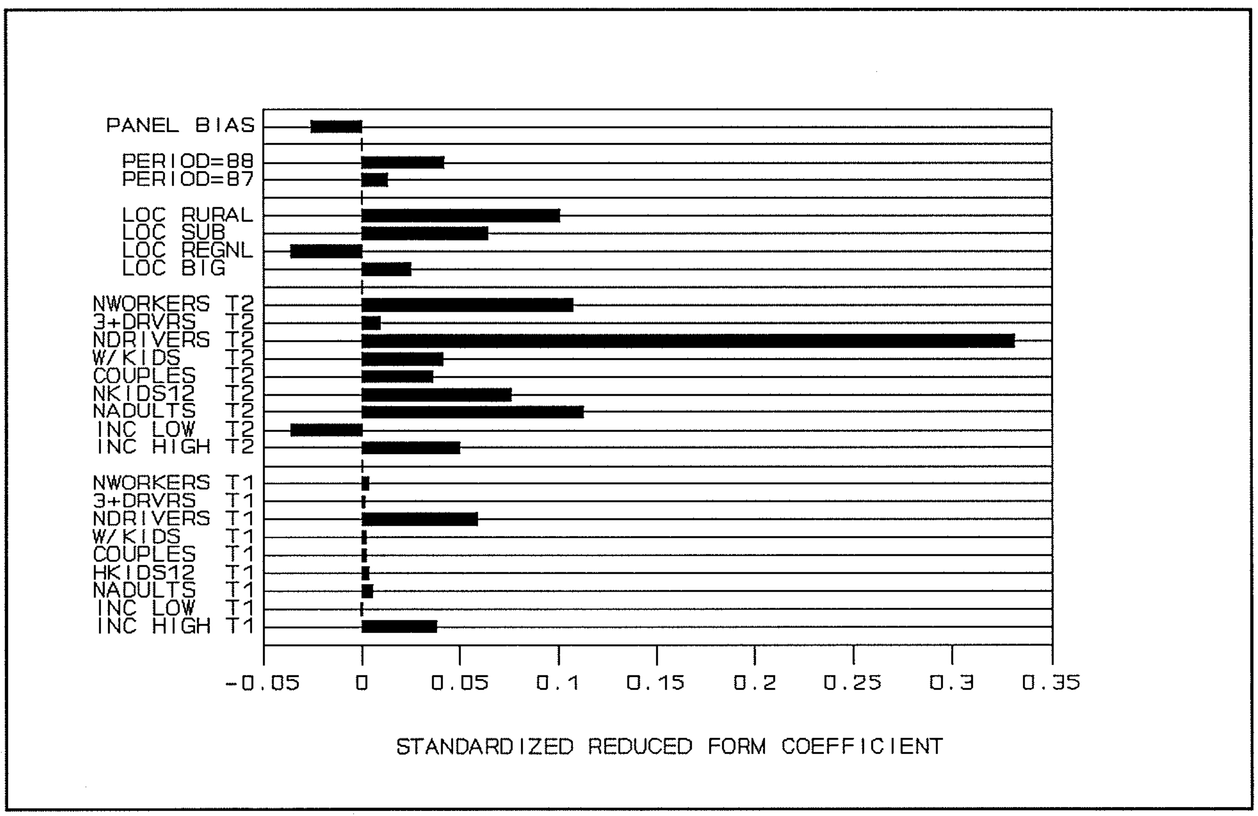

FIGURE 9

STANDARDIZED TOTAL EFFECTS
FOR CAR TRAVEL TIME AT TIME t_2

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. Moreover, this explanatory variable has both contemporaneous and dynamic influences on both endogenous variables; and the dynamic influences involve both lags and leads (Tables 8a and 8b). 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 total effects on travel time by **public transport** at time t_2 are graphed in Figure 10. The two most important explanators are the number of adults and the number

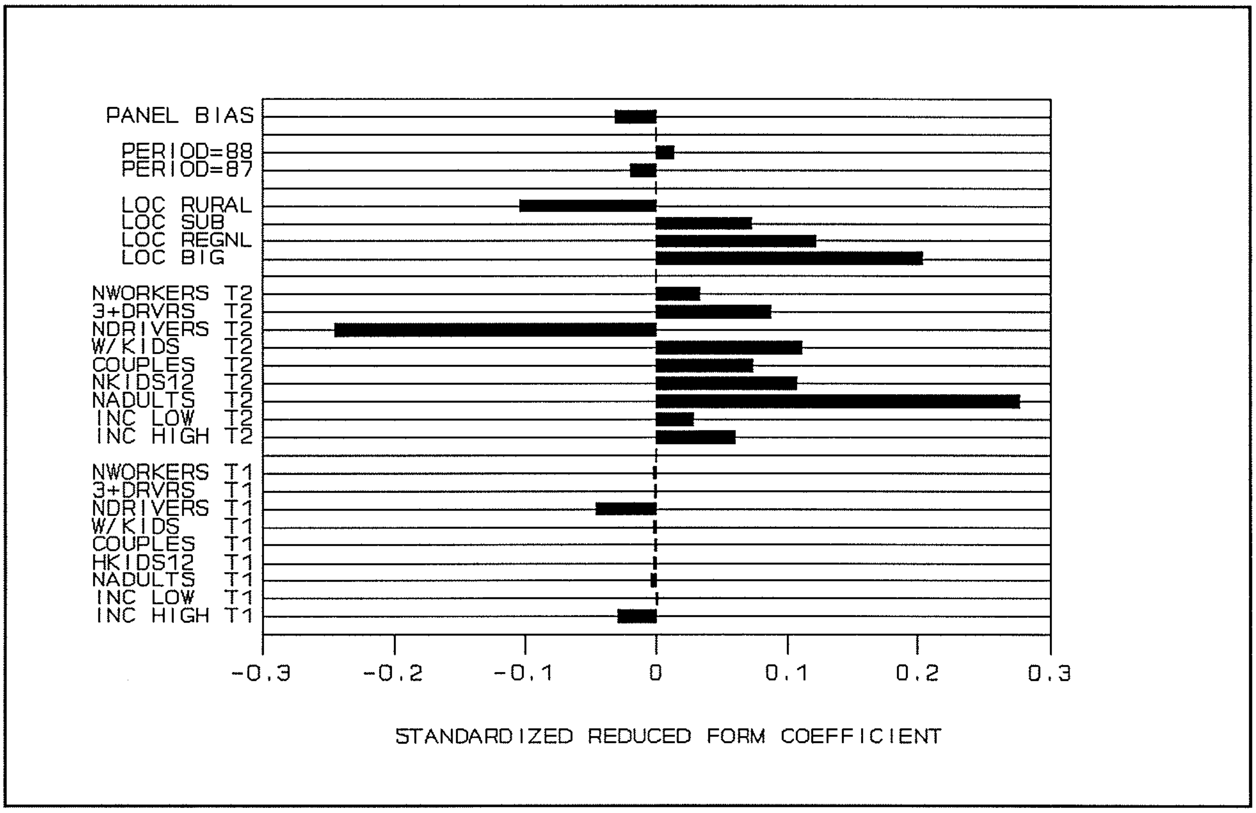

FIGURE 10

STANDARDIZED TOTAL EFFECTS FOR
PUBLIC TRANSPORT TRAVEL AT TIME t_2

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, the total effects on **nonmotorized mode** time are graphed in Figure 11. 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; Golob, 1989; 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.

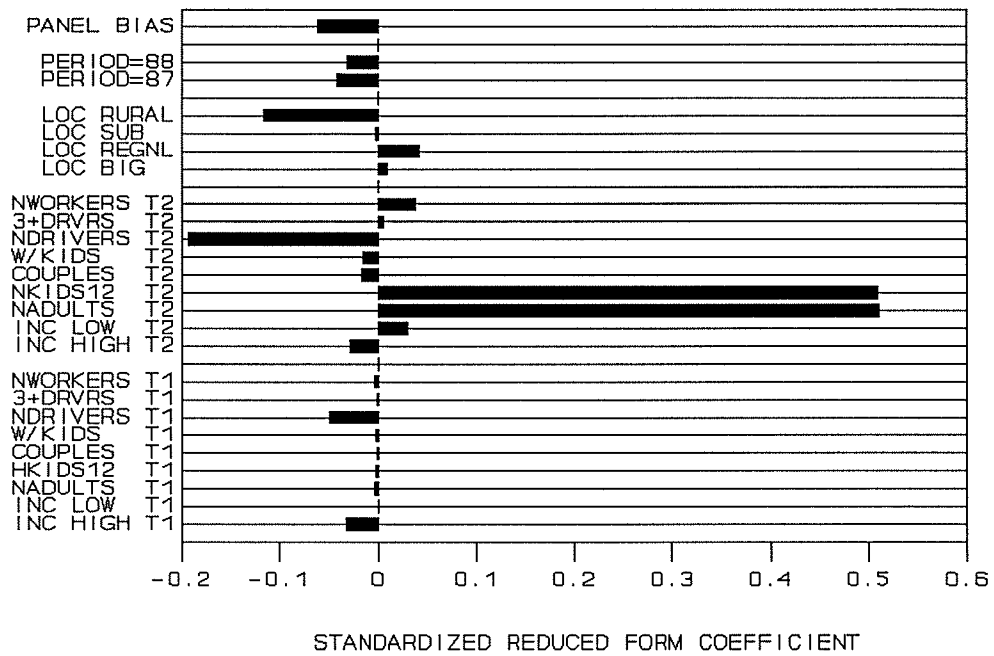

FIGURE 11

STANDARDIZED TOTAL EFFECTS FOR
NONMOTORIZED TRAVEL TIME AT TIME t_2

CONCLUSIONS AND A DIRECTION FOR FURTHER RESEARCH

One main 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.

Another main 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 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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