Invited Paper

A PANEL ANALYSIS OF HOUSEHOLD CAR OWNERSHIP AND MOBILITY

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1. INTRODUCTION

Past investigations of the relationship between car ownership and travel behavior have consistently indicated the presence of strong statistical association between the two. Car ownership has been considered as one of the key determinants of travel behavior and included virtually in every model of trip generation and mode choice. However, most past analyses are based on cross-sectional data which represent travel behavior at one point in time; inferences have been made without observing changes in travel behavior following changes in car ownership, or changes in car ownership following changes in factors influencing the need to travel.

The usefulness of relationships derived from cross-sectional observation may be limited. For example, it is not obvious whether a relationship established on the basis of statistical variation across behavioral units within a single cross-section applies to change in the behavior of each behavioral unit over time. Furthermore, behavioral relationship cannot be correctly inferred from cross-sectional observation alone on the likely condition that unobserved variables are correlated over time with measured variables (see, e.g., Hsiao, 1986). Davies and Pickles (1985) illustrate this using numerical examples developed from simulation experiments.

The limitation of cross-sectional data in travel behavior analysis is an important factor that motivates the use of panel data sets, i.e., data sets comprising repeated observation of the same behavioral units over time. Many advantages of panel data have been discussed in the literature (e.g. Golob et al. 1986; Hsiao, 1986). For example, panel data make possible a more satisfactory treatment of unobserved elements that vary across behavioral units but remain longitudinally stable for each unit. Panel data also

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making the inference of causal relationship a more amiable task. In addition, some aspects of travel behavior can be most effectively examined using panel data, and some may not be studied at all without panel observation. Such aspects include habit formation and persistence, response lags, and learning (Goodwin, 1977, 1986; Clarke, et al, 1982; Goodwin and Layzell, 1985; Kitamura and van der Hoorn, 1987).

These advantages warrant the development of analytical methods for panel analysis of travel behavior. Established methods exist in econometrics, sociology, and other disciplines (e.g., Goodman, 1973; Wiggins, 1973; Kessler and Greenberg, 1981; Hsiao, 1986). However, some methods are capable of accommodating only a limited number and types of exogenous variables, reducing their usefulness in planning and policy contexts. Others are limited in terms of the type of endogenous variables. This is critical because quite often both categorical and quantitative endogenous variables must be incorporated simultaneously into the analysis of mobility. An example is the number of cars owned by a household (which can be best treated as a categorical variable) and the number of trips made by household members. As a result, suitable model frameworks remain to be developed for certain types of travel behavior analysis.

An analytical framework is developed in this study for panel analysis of travel behavior. The model system involves two endogenous variables; one is discrete and the other continuous. It is assumed that the errors associated with each of the endogenous variables are serially correlated, and that the errors for the two endogenous variables are also correlated. The model components are singly estimated in a sequential manner using correction terms which account for the correlations among the errors. The approach is an extension of the method used to correct for sample selectivity (e.g. Heckman, 1979; Maddala, 1983) and applied previously in the transportation field to examine attrition bias in panel data (Hensher, 1987 a; Kitamura and Bovy, 1987), vehicle acquisition and utilization (Mannering and Winston, 1985), and activity engagement and time allocation (Kitamura, 1984).

The model system is applied to examine the longitudinal relationship between household car ownership and trip generation using empirical data. The household is the behavioral unit used in the analysis. In the present application the model coefficients are assumed to vary over time but not across households. Unobserved effects specific to individual households are represented by serially correlated errors*1.

The applicability of the proposed model system is not limited to the particular aspect of mobility behavior with which the initial empirical effort of this study is concerned. For example, the model system can be modified to include two discrete endogenous variables. Lagged endogenous and exogenous variables can be included. Through such modifications, the model system can be used flexibly to capture many aspects of mobility behavior over time, e.g., car ownership and mode choice for commuting trips. It can also be used to test behavioral hypotheses, e.g., state dependence vs. habit persistence.

The rest of this paper is organized as follows. In the next section, the relations that exist among measurements in panel data are summarized and related to known concepts in the field. The proposed model system is presented together with derivations of the conditional distributions of the error terms in Sections 3 and 4. An estimation procedure which uses correction terms to account for correlated errors is presented in Section 5. The results of an empirical analysis of car ownership and household weekly trip generation are presented next in Section 6. The last section provides a summary and discusses future extension of the effort.

2. RELATIONSHIPS AMONG ELEMENTS OF PANEL OBSERATION

Possible inter-relationships among the levels of car ownership and mobility over time are schematically

^{*1} The error-components appoach, which is frequently used in panel analysis to account for individual- and time-specific effects (e.g., Hensher, 1987b), is not used in this initial effort. Its incorporation into the model system of this study is briefly discussed in the last section of this paper.

represented in Fig. 1. In this section an existing classification scheme (see Golob and Meurs, 1987) is used to categorize the linkages shown in the figure, then applied to relations among endogenous variables, exogenous variables, and error terms. The aspects of travel behavior which these linkages represent are discussed.

Linkages involving car ownership and mobility, both endogenous variables of the proposed model system, are first discussed. It is quite logical to expect that car ownership at time t, D(t), is correlated with that at a previous time point, D(t-s), s=1, $2,\cdots$ This will especially be the case when the time span between observations is short. Similarly, mobility, Y(t), may be correlated over time. These associations can be graphically represented by "inertial links" which are shown by vertical arrows in the figure. As the name suggests, linkages of this type represent behavioral inertia, which may be viewed as a case of history dependence of an endogenous variable.

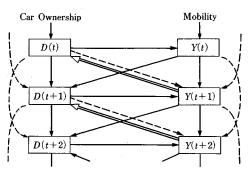


Fig. 1 Relationships Among Elements of Panel
Observation

It has been conventional to assume that the mobility level

at time t is influedced by the car ownership level at that time point. This relation is represented by the solid horizontal arrows, which are called "synchronous links", These links represent contemporaneous causal relationships. One-directional relationship is assumed in the figure between D(t) and Y(t) with D(t) being the causal factor. This reflects the viewpoint that the mobility level, Y(t), in the short run is conditioned on the level of car ownership, D(t).

"Cross-lagged links", which are shown by diagonal arrows, represent lagged effects of car ownership upon mobility or of mobility upon car ownership. This is history depedence of an endogenous variable upon another endogenous variable. For example, a high mobility level at time t may lead to a decision to acquire a car, and thereby leading to an increase in car ownership in the following time period. This relation is shown by the solid cross-lagged links in the figure. It is also possible that the car ownership level in the previous period is associated with the current mobility level due to habit persistence. This is shown by the links in dashed lines in the figure. Furthermore, it may be the case that the current car ownership is influenced by future mobility levels; a household may choose to acquire an additional car in anticipation of increased mobility needs in the future. This effect may be represented by the cross-lagged links with double-lined arrows.

Various degrees of time lags are conceivable for inertial and cross-lagged linkages. It is plausible that the level of car ownership at time point t, D(t), depends on that of t-1, D(t-1), but is conditionally independent of the car ownership levels prior to t-1, given D(t-1). This Markovian first-order history dependence can be represented by the solid inertial links shown in the figure. It is also conceivable that D(t) is influenced by D(t-2), D(t-3), and so on, because of higher-order history dependence. The inertial links shown by dashed lines represent such relations. Similar relations are shown in the figure for the mobility measure, Y(t).

The above discussion and the figure are concerned with the two endogenous variables, car ownership and mobility. Inertial, synchronous, and cross-lagged linkages can also be postulated within the same framework to represent relationships among exogenous variables, among endogenous variables, among endogenous variables, and among error terms. The resulting linkages capture various dynamic aspects of mobility behavior. Table 1 summarizes these relations.

For example, inertial links among error terms represent serial correlation, which arises when unobserved elements exist that uniquely influence the behavior of each behavioral unit over time. Cross-lagged links between an endogenous variables and a vector of exogenous variables represent

	Synchronous	Inertial	Cross-Lagged
Exogenous ←→ Exogenous	Cross-Sectional Correlation $X(t) \longleftrightarrow Z(t)$		Cross-Lagged Correlation $X(t) \longleftrightarrow Z(t-\delta)$ $Z(t) \longleftrightarrow X(t-\delta)$
Endogenous ←→ Exogenous	Contemporaneous Causal Relation $Y(t) \longleftarrow X(t)$ $D(t) \longleftarrow Z(t)$		Lagged Causal Relation (Response Lag) $Y(t) \longleftarrow X(t-\delta)$ $D(t) \longleftarrow Z(t-\delta)$
Endogenous ←→ Endogenous	Contemporaneous State Dependence $Y(t) \longleftarrow D(t)$ $D(t) \longleftarrow Y(t)$	History (State) Dependence $Y(t) \longleftarrow Y(t-\delta)$ $D(t) \longleftarrow D(t-\delta)$	Cross-Lagged History (State) Dependence $Y(t) \longleftarrow D(t - \delta)$ $D(t) \longleftarrow Y(t - \delta)$
Error Terms	Correlated Errors $U(t) \longleftrightarrow V(t)$	Serial Correlation $U(t) \longleftrightarrow U(t-\delta)$ $V(t) \longleftrightarrow V(t-\delta)$	

Table 1 Synchronous, Intertial, and Cross-Lagged Linkages Among Endogenous and Exogenous Variables,

response lags. Inertial links connecting the same exogenous variables measure the stability of the travel environment.

A general model system that is capable of incorporating these linkages among observed and unobserved elements will permit flexible analysis of travel behavior over time. The model system proposed in this paper aims at this goal. Although the discussions contained in this paper assume a specific linkage pattern, the model framework presented can be easily modified to adapt to other patterns. In the present formulation, correction terms are developed to account for correlations among up to three error terms simultaneously. This implies that conditional independence must be assumed when more than three error terms need to be considered in model estimation. Introduction of endogenous variables as explanatory factors also requires care in this case. Other than this limitation, however, the model system is flexible and can be estimated using readily available statistical software packages.

MODEL SYSTEM

The model system consists of a discrete choice model of household car ownership and a model of mobility. In the discussion of this paper it is assumed that mobility can be represented using a linear regression model. The ordered-response probit model is used to represent household car ownership.

Car Ownership Model: For household i and observation time point t, let D(i, t) be an indicator of car ownership, W(i, t) be a latent variable, and Y(i, t) be a measure of household travel behavior, and let $W(i, t) = a_t Q(i, t) + \tau_t A(i, t-1) + \theta_t Y(i, t-1) + U(i, t)$

$$D(i, t) \begin{cases} = \alpha_t' X(i, t) + U(i, t) \\ = 0 \text{ if } W(i, t) \le q_t \\ = 1 \text{ if } q_t < W(i, t) \le r_t \end{cases}$$

$$= 2 \text{ if } r_t < W(i, t)$$
(1)

for $t=1, 2, \dots, T$, where a_t , a_t , and τ_t are coefficient vectors, θ_t is a scalar coefficient, Q(i, t-1) is a vector of exogenous variables, A(i, t-1) is a vector of dummy variables representing the car ownership

Y(t) and D(t) are endogenous variables and X(t) and Z(t) are exogenous variables. U(t) is the error term associated with Y(t), and V(t) is associated with D(t).

level at t-1. X(i,t) is a vector of all explanatory variables, U(i,t) is a random error term, q_t and r_t are threshold values associated with the car ownership level, and T is the number of observation points. In this formulation, car ownership is represented by three categories, (0 car, 1 car, 2 or more cars), and car ownership at period t is assumed to be dependent on the car ownership and the mobility level of the previous period. The inclusion of A(i, t-1) implies the assumption of Markovian first-order history dependence in car ownership.

If we assume that U(i,t) has a normal distribution, then the model structure for D(i,t) is the ordered-response probit model. It has been shown (see Maddala, 1983) that the log-likelihood function for this model is concave everywhere. This formulation is chosen here because household car ownership can be reasonably considered as an ordered response. It is preferred over a multinomial probit model because it involves only one error term, making possible more parsimonious representation of unobserved elements.

Mobility Model: Let the mobility level of household i at time t, Y(i, t), be expressed as

$$Y(i, t) = b_t' R(i, t) + \mu_t' A(i, t) + \Omega_t' A(i, t-1) + V(i, t)$$

= \beta_t' Z(i, t) + V(i, t) \cdots \qquad (2)

for $t=1, 2, \dots, T$, where b_t, μ_t, Ω_t , and β_t are coefficient vectors, R(i, t) is a vector of exogenous variables, Z(i, t) is a vector of all explanatory variables, and V(i, t) is a random error term. In this formulation, the mobility level is assumed to be a function of the car ownership level of period t-1 as well as that of period t.

STRUCTURE OF THE ERROR TERMS

Suppose the linkages among the error terms of the car ownership model and mobility model can be expressed as shown in Fig. 2. The inertial linkages in this case imply that the errors are serially correlated. It is assumed that the error of the mobility model, V(i, t), depends on the error of the car ownership model in the same time point, U(i, t), and that U(i, t) depends on the error of the mobility model in the previous time point, V(i, t-1).

The conditional expectations of the error terms are developed in this section using this linkage scheme and assuming that, given U(i, t-1) and V(i, t-1), U(i, t) is conditionally independent of the error terms prior to t-1, i.e.,

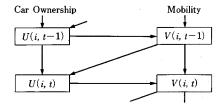


Fig. 2 Correlative Structure of the Error Terms

$$\Pr[U(i, t) \le x \mid U(i, t-1), \ V(i, t-1), \ U(i, t-2), \ V(i, t-2), \cdots] = \Pr[U(i, t) \le x \mid U(i, t-1), \ V(i, t-1)], \ -\infty < x < \infty \cdots \cdots \cdots \cdots \cdots (3 \cdot a)$$
 and similarly.

$$\Pr[V(i, t) \le x | U(i, t), V(i, t-1), U(i, t-1), V(i, t-2), \cdots] = \Pr[V(i, t) \le x | U(i, t), V(i, t-1)], -\infty < x < \infty \cdots (3 \cdot b)$$

This assumption is similar to the assumption of the first-order serial correlation in regression analysis and does not imply that U(i, t) and U(i, t-s), $s=2, 3, \dots$, are uncorrelated.

In deriving the conditional expectations, we use the following results (Johnson and Kotz, 1972). Consider the trivariate standard normal random variables,

$$(U_1, U_2, U_3) \sim MVN(O, \Sigma) \cdots (4 \cdot a)$$
 where O is a vector of zeros, and

$$\sum = \begin{pmatrix} 1 & \sigma_{12} & \sigma_{13} \\ & 1 & \sigma_{23} \\ & & 1 \end{pmatrix} \cdots (4 \cdot b)$$

Then U_2 and U_3 given U_1 are bivariate normal with $\mu_{23-1} = (\sigma_{12}U_1, \ \sigma_{13}U_1) \cdots (5 \cdot a)$

$$\sum_{23\cdot 1} = \begin{pmatrix} 1 - \sigma_{12}^2 & \sigma_{23} - \sigma_{12}\sigma_{13} \\ & 1 - \sigma_{13}^2 \end{pmatrix} \dots (5 \cdot b)$$

Then, applying the known results for truncated bivariate normal distributions (see Johnson and Kotz, 1970, 1972; Maddala, 1983),

$$E[U_3 | U_1, U_2 > h] = \sigma_{13} U_1 + \sigma_{23-1} \sqrt{1 - \sigma_{13}^2} \frac{\phi(h)}{\phi(-h)}$$
 (6)

where $\phi(\cdot)$ and $\Phi(\cdot)$ are respectively the standard normal density and distribution functions, and

$$\sigma_{23-1} = \frac{\sigma_{23} - \sigma_{12}\sigma_{13}}{\sqrt{(1 - \sigma_{12}^2)(1 - \sigma_{13}^2)}}$$

The expectations with different truncations of U2 can be obtained similarly.

For notational simplicity, let W(i, t) and Y(i, t) be expressed as

$$W(i, t) = \alpha_t' X(i, t) + U(i, t)$$

$$Y(i, t) = \beta_t Z(i, t) + V(i, t)$$

and let the error terms of the model system be

$$(U(i, t), U(i, t-1), V(i, t-1)) \sim MVN(0, \sum_{v}), t=1, 2, \cdots, T \cdots (7)$$

$$\sum_{v} = \left(egin{array}{cccc} 1 & \sigma_{vvr} & \sigma_{vvr} \ & 1 & \sigma_{vr} \end{array}
ight) \ & \sigma_{vr}^2 \ \end{array}$$

Using the observation at t-1, we can obtain an estimate of V(i, t-1). However, only observation of trucation (or a range) is available for U(i, t-1), i.e.,

$$U(i, t-1) \le q_{t-1} - \alpha_{t-1} X(i, t-1)$$
 if $D(i, t-1) = 0$

$$q_{t-1}-\alpha_{t-1}'X(i, t-1) < U(i, t-1)$$

$$\leq r_{t-1} - \alpha_{t-1} X(i, t-1)$$
 if $D(i, t-1) = 1$

$$r_{t-1} - \alpha_{t-1} X(i, t-1) < U(i, t-1)$$
 if $D(i, t-1) = 2 \cdots (8)$

Now given V(i, t-1) = V, U(i, t) and U(i, t-1) are bivariate normal with the following mean vector and covariance matrix:

$$\mu_{UUT \cdot VT} = (\sigma_{UVT} V / \sigma_{VT}, \ \sigma_{UTVT} V / \sigma_{VT})$$

$$\mu_{UUT \cdot VT} = \begin{pmatrix} 1 - \sigma_{UUT}^2 & \sigma_{UVT} - \sigma_{UVT} \sigma_{UTVT} \\ & 1 - \sigma_{UTVT}^2 \end{pmatrix} \dots (9)$$

and

$$E[U(i, t)|U(i, t-1) \le q_{t-1} - \alpha_{t-1} X(i, t-1), V(i, t-1) = V]$$

$$= \sigma_{uvr} V / \sigma_{vr} + \sigma_{uvr \cdot vr} \sqrt{1 - \sigma_{uvr}^2} \frac{-\phi(h)}{\phi(h)}$$
(10 · a)

where

$$\sigma_{\mathit{UU^T}\ .\ \mathit{VT}} \! = \! \frac{\sigma_{\mathit{UU^T}} \! - \sigma_{\mathit{UV^T}} \sigma_{\mathit{U^T}\mathit{V^T}}}{\sqrt{(1 - \sigma_{\mathit{U^T}\mathit{V^T}}^2)(1 - \sigma_{\mathit{U^T}\mathit{V^T}}^2)}}$$

$$h = q_{t-1} - \alpha_{t-1} X(i, t-1)$$

Similarly,

$$E[U(i, t) | r_{t-1} - \alpha_{t-1} X(i, t-1) < U(i, t-1), V(i, t-1) = V]$$

$$= \sigma_{UV} V / \sigma_{V} + \sigma_{UU} v_{V} \sqrt{1 - \sigma_{UV}^{2}} \frac{\phi(k)}{1 - \phi(k)}$$
(10·b)

$$E[U(i, t)|q_{t-1}-\alpha_{t-1}]X(i, t-1) < U(i, t-1)$$

$$\leq r_{t-1} - \alpha_{t-1} X(i, t-1), V(i, t-1) = V$$

$$= \sigma_{uvr} V / \sigma_{vr} + \sigma_{uur} \cdot vr \sqrt{1 - \sigma_{uvr}^2} \frac{\phi(h) - \phi(k)}{\phi(k) - \phi(h)}$$
(10·c)

where

$$k = r_{t-1} - \alpha_{t-1} X(i, t-1).$$

The expressions for the conditional mean of V(i, t) given U(i, t) and V(i, t-1) can be defined in the same manner.

5. ESTIMATION PROCEDURE

Using the results of the previous section, U(i, t) given the error terms from the previous periods can be expressed as

$$[U(i, t) \text{ given } U(i, t-1) \le q_{t-1} - \alpha_{t-1} X(i, t-1), \text{ and } V(i, t-1) = V]$$

$$= aV + b(-\phi(h)/\phi(h)) + \varepsilon(i, t) - \cdots$$
(11)

where

$$a = \sigma_{UVT} / \sigma_{VT}$$

$$b = \sigma_{UUT \cdot VT} \sqrt{1 - \sigma_{UVT}^2}$$

and

$$E[\varepsilon(i, t)] = 0.$$

Using this result, correction terms can be developed to account for the correlations among the error terms and to obtain consistent estimators of the model parameters.

Let the model system be

$$W(i, t) = \alpha_{t} X(i, t) + U(i, t)$$

$$Y(i, t) = \beta_{t} Z(i, t) + V(i, t)$$

$$= 0 \quad \text{if} \quad W(i, t) \le q_{t}$$

$$= 1 \quad \text{if} \quad q_{t} < W(i, t) \le r_{t}$$

$$= 2 \quad \text{if} \quad r_{t} < W(i, t)$$
(12)

for $t=1, 2, \dots, T$. Suppose estimates of model coeffeients from the previous period (t-1) are available. Using these, define

$$\hat{V}(i, t-1) = Y(i, t-1) - \hat{\beta}_{t-1} Z(i, t-1)
\hat{h} = \hat{q}_{t-1} - \hat{\alpha}_{t-1} X(i, t-1)
\hat{k} = \hat{r}_{t-1} - \hat{\alpha}_{t-1} X(i, t-1)$$
(13)

where "a" denotes an estimate of the parameter. Noting the conditional expectations of the error terms, rewrite the model system as

$$W(i, t) = \alpha_{t} X(i, t) + a_{1} \hat{V}(i, t-1) + b_{1} Q[D(i, t-1)] + \varepsilon_{1}(i, t)$$

$$Y(i, t) = \beta_{t} Z(i, t) + a_{2} \hat{V}(i, t-1) + b_{2} Q[D(i, t)] + \varepsilon_{2}(i, t)$$

$$= 0 \quad \text{if} \quad W(i, t) \leq q_{t}$$

$$= 1 \quad \text{if} \quad q_{t} < W(i, t) \leq r_{t}$$

$$= 2 \quad \text{if} \quad r_{t} < W(i, t) \qquad (14)$$

where

$$Q[D(i, t-1)] = \begin{cases} -\phi(\hat{h})/\Phi(\hat{h}) & \text{if } D(i, t-1) = 0\\ |\phi(\hat{h}) - \phi(\hat{k})|/|\Phi(\hat{k}) - \Phi(\hat{h})| & \text{if } D(i, t-1) = 1\\ |\phi(\hat{k})/|1 - \Phi(\hat{k})| & \text{if } D(i, t-1) = 2 \end{cases}$$

and \hat{h} and \hat{k} are as defined above. The error terms now have means of 0 and are independently distributed. Consistent estimators of α and β can be obtained by applying the maximum likelihood method individually to the equations for W(i, t) and Y(i, t) of Eqn 14.

The parameters, a_j and b_j , j=1, 2, correspond to:

$$a_1 : \sigma_{uvr}/\sigma_{vr}$$

$$b_1 : \sigma_{uvr} \cdot vr \sqrt{1 - \sigma_{uvr}^2}$$

$$a_2 : \sigma_{vvr}/\sigma_{vr}$$

$$b_2 : \sigma_{uvr} \cdot vr \sqrt{1 - \sigma_{vvr}^2}$$

Therefore, the estimates of the parameters on the left are consistent estimates of the quantity on the right.

The variances of $\varepsilon_j(i, t)$, j=1, 2, can be evaluated similar to Kitamura and Bovy (1987). The variances are no longer homoscedastic and estimates of the standard errors of the model parameters are biased. However, estimated t-statistics can still be used to test the null hypothesis that there is no correlation among the error terms (Heckman, 1979).

EMPIRICAL ANALYSIS: HOUSEHOLD CAR OWNERSHIP AND TRIP GENERA-6. TION

This section presents the results of an initial application of the model system described above to a panel data set in order to examine the relationship between household car ownership and trip generation. The sample of the study is obtained from the Dutch National Mobility Panel data set (see Golob, et al., 1986). In addition to the typical set of demographic and socioeconomic attributes of households and individuals, the data set contains information on weekly travel behavior obtained from 7-day travel diaries kept by household members of at least 12 years old. The characteristics of weekly trip generation in the data set are presented in Golob and Meurs (1986), and Kitamura and van der Hoorn (1987).

The sample of this study consists of 1031 households that are in all of the first three waves of the panel survey, conducted in March, 1984, September, 1984, and March, 1985 (the number of households used in model estimation varies from model to model due to missing variable values). The total number of trips recorded by household members in weekly travel diaries is used as a measure of household trip generation. Household car ownership is represented by three categories: no car, one car, and two or more cars.

An Overview of the Data Set: Table 2 shows the transition of car ownership levels across the three waves. During the period spanning 12 months, 87 % of the panel households stayed in the same levels of car ownership: 199 households (19.5%) had no car, 607 households (59.6%) had one car, and 84 (8.3%) had two or more cars, respectively, in all of the three survey weeks*2. The sample-wide fraction of no-car households remained stable at 22 %.

Table 2 Transition in Car Ownership in the First Three Waves of the Dutch Mobility Panel Data Set.

						Transition between Wave 1 and Wave 2				
Wave 1 Car Ownership Wave 2 Car Ownership	Wave 3 Car Ownership			Wave 1 Car	Wave 2 Car Ownership					
	Ownership	No Car	One Car	≥ 2 Cars	Total	Ownership	No Car	One Car	≥ 2 Cars	Total
	No Car	199	10	0	209	No Car	209	119	1	229
~	One Car	1	17	1	19	One Car	10	626	47	683
No Car	≥ 2 Cars	0	0	1	1	≥ 2 Cars	.0	13	93	106
Tota	Total	200	27	2	229	Total	219	658	141	1 018
	No Car	7	3	0	10					
	One Car	11	607	8	626	Transition between Wave 2 and Wave 3				
One Car	≥ 2 Cars	2	11	34	47	Wave 2 Car Wave 3 Car Ownership				
	Total	20	621	42	683	Ownership	No Car	One Car	≥ 2 Cars	Total
	No Car	0	0	0	0	No Car	206	13	0	219
	One Car	0	12	1	13	One Car	12	636	10	658
≥ 2 Cars	≥ 2 Cars	1	8	84	93	≥ 2 Cars	3	19	119	141
	Total	1	20	85	106	Total	221	668	129	1 018
			I			Note: The san	nple consists	of all 1 01	B households	which

three waves.

participated in all of the three waves of home interview survey and for which car ownership levels are known for the

^{*2} This tabulation and that in Table 3 in particular are susceptible to attrition bias (see Kitamura and Bovy, 1987, for a discussion of attrition behavior in the Dutch Panel data set). No attempt is made in this study to account for attrition biases because the objective of this empirical analysis is to explore inter-linkages in observed and unobserved elements across waves and between car ownership and mobility for a given set of households, but not to infer population characteristics in car ownership and mobility,

The level of car ownership changed at least once for the remaining 12.6 % of the sample households. The number of multi-car households increased from 106 (10.4%) in wave 1 to 141 (13.9%) in wave 2, then decreased to 129 (12.7%) in wave 3. The increase can be seen in the transition matrix between wave 1 and wave 2 in which 47 households show transitions from one-car to multi-car ownership while only 13 households show the reverse transitions from multi-car to one-car ownership. The transition matrix from wave 2 to wave 3 shows a reverse trend, but to a much lesser extent.

The sample means of demographic and socioeconomic variables show little change at the aggregate level (Table 3). Notable is the slight but

Table 3 Changes in Sample Means of Demographic, Socioeconomic and Mobility Variables Across the Three Waves

	Wave 1	Wave 2	Wave 3
No. of Diary-Keepers	2.29	2.30	2.30
No. of Workers	0.95	0.97	0.99
No. of Drivers	1.49	1.49	1.50
Household Income	30.63	31.06	31.71
Household Size	2.94	2.96	3.00
No. of Children	1.17	1.17	1.19
No. of Cars	0.89	0.94	0.94
Weekly Household Trip Generation			
Total Person Trips	55.12	52.65	51.51
Home Trips	22.39	21.53	21.71
Work Trips	5.90	5.81	5.78
Shopping and Personal Business	7.60	6.99	6.68
Social-Visit Trips	9.04	8.56	7.83
School Trips	2.92	2.62	2.71
Serve Passenger Trips	2.71	2.83	2.81
Other Trips	4.57	4.31	3.98
No. of Trip Segments by Mode			
Total No. of Trip Segments	63.90	59.98	58.47
Total Car Trip Segments	17.94	17.07	16.72
Total Walk Trip Segments	13.79	11.42	12.40
Total Driver Trip Time in Min.	316.7	329.0	294.3

steady increasing trend found for the number of workers, household size, and household income. As suggested by the above results in car ownership transition, the average number of cars per household shows an increase between wave 1 and wave 2.

Such stability, however, is not observed for the mobility indicators shown in the table. Weekly household trip generation shows a steady decline for all purposes except serving passengers. This trend cannot be attributed to seasonal variation since the first and third surveys both took place in September. A possible reason underlying the decline is increasing under-reporting of trips in later waves due to the "fatigue" of panel households (reporting errors across diary days in the wave-1 survey are summarized in Golob and Meurs, 1986).

In the model system of this study, unexplained variations in mobility and trip reporting errors are both represented by the serially correlated error terms of mobility equations. The intercepts of trip generation models, which are estimated by wave, vary over time reflecting both genuine period effects and mean reporting errors of the respective waves. Possible systematic tendencies in reporting errors undoubtedly influence the coefficient estimates when a reported number of trips is used, which unfortunately is the case in practically every trip generation analysis. This must be borne in mind when interpreting the empirical results presented below*3.

Linkage Structure: The same linkage pattern of error terms assumed in the model development (Fig. 2) is used in this empirical effort. As noted earlier, serial correlation is assumed in the errors of car ownership models and those of trip generation models. The model system thus assumes heterogeneity in unobserved elements including reporting errors. Syncronous correlation assumed between the error terms of the car ownership model and trip generation model in the same wave, can be used to test the presence of common unobserved propensity to own cars and to make trips. A cross-lagged linkage is assumed between

^{*3} This is the case of measurement error. It is not possible from the available observation to separate the effect of an exogenous variable upon mobility and that upon reporting error. Accordingly the estimated coefficients presented later in this paper do not extract the former effect by itself when the latter effect is significant. For further discussion, see Kitamura and Bovy (1985).

Table 4 Definition of the Variables Considered in the Model Development.

Variable	Definition
NRECORDS	No. of diary-keepers in the household
HHSIZE	No. of persons in the household
CHILD06	No. of children living in the household between 0 and 6 years old
CHILD11	No. of children living in the household between 7 and 11 years old
CHILD17	No. of children living in the household between 12 and 17 years old
CHILD18	No. of children living in the household of at least 18 years old
CHILDTTL	Total number of children living in the household
MARRIED	1 if the nucleus of the household is a married couple; 0 otherwise
SGLPRNT	1 if single-parent household; 0 otherwise
SINGLE	1 if single-person household; 0 otherwise
WORKERS	No. of workers in the household
NOWORKER	1 if no household member is employed; 0 otherwise
MTWORKER	1 if more than one household member are employed; 0 otherwise
√HHINCOME	Square-root of household income in 1 000 Guilders
√MXINCOME	Square-root of the personal income of the principal wage earner
HHEDUC	1 if the person with highest education in the household has a college degree; 0 otherwise
DRIVERS	No. of licensed drivers in the household
ONECAR	1 if the household has one car available; 0 otherwise
MULTICAR	1 if the household has two or more cars available; 0 otherwise
ONECARP	NRECORDS if the household has one car available; 0 otherwise
MULTICARP	NRECORDS if the household has two or more cars available; 0 otherwise
ONECARD	DRIVERS if the household has one car available; 0 otherwise
MULTICARD	DRIVERS if the household has two or more cars available; 0 otherwise
GMTGROUP	${f 1}$ if the respondent reside in a metropolitan area with highly developed public transit services

the error term of the car ownership model for period t and that of the trip generation model for period t-1. This linkage can be used to test the hypothesis that a higher-than-expected level of mobility at a time period is likely to cause acquisition of a car in a later period. No lagged endogenous or exogenous variables are considered in this initial exploration.

Variables Considered in Model Development: A wide range of variables are considered in the model development. As Table 4 shows, the group of variables includes demographic variables (number of diary-keepers, household size, number of children by age group, dummy variables for single-parent, single-person, and nuclear households), number of workers (with dummy variables for no- and multi-worker households to account for possible non-linear effect), income, education, metropolitan size, and car ownership. Household car ownership is represented by a set of dummy variables, again to account for possible non-linear effect. Two additional sets of car ownership dummy variables are also considered when developing trip generation models. These variables take on values 0 or X, rather than 0 or 1, where X is a household attribute variable. For example, ONECARP is set equal to the number of diary-keepers (NRECORDS) if one car is available to the household, and is set to 0 otherwise. Using the mnemonics of Table 4, these dummy varibles can be defined as ONECARP (ONECAR) (NRECORDS), ONECARD (ONECAR) (DRIVERS), etc.

Estimation Results: Alternative model formulations were examined using observations from the three waves, both separately by wave and together after pooling. This process did not yield an entirely identical set of explanatory variables across the waves. However, it was apparent that the variations in estimation results were due to sample fluctuations combined with high degrees of correlations among many of the variables under consideration. Accordingly, it was decided to apply the same model formulation to all waves. The resulting models are shown in Table 5.

The variables included in the final car ownership models are number of drivers, number of children between 11 and 17 years old, square-root of household income, metropolitan size, and education*4. Number of drivers is by far the most significant variable. As expected, households in larger, public transit-oriented metropolitan areas tend to have fewer cars, as indicated by the negative coefficients of GMTGROUP. Also as expected, household income positively contributes to car ownership. The presence of high-school age children is associated with higher levels of car ownership. Household education (defined in terms of the education level of the person with the highest education in the household) has a negative coefficient; ceteris paribus, households with higher education tend to own fewer cars.

Demographic variables play dominant roles in the trip generation models. The variables included are number of diary-keepers, number of children by age group (0 through 6, 7 through 11, and 12 through 17 years old), number of drivers, household education, and marital status of the adult members. The last two dummy variables are multiplied by the number of diary-keepers. Therefore their coefficients represent the differences in the number of trips per diary-keeper by marital status or education.

Table 5 Household Car Ownership and Trip Generation Model System: Estimation Results.

Household Car Ownership

	WAVI	E 1	WAV	Æ 2	WAVE 3		
	Coef.	t	Coef.	t	Coef.	t	
DRIVERS (t)	1.152	16.72	1.470	17.29	1.311	16.53	
CHILD17 (t)	0.194	3.01	0.274	3.37	0.189	2.69	
$\sqrt{\text{HHINCOME}}$ (t)	0.135	4.87	0.185	5.14	0.134	4.41	
GMTGROUP(t)	-0.308	-3.00	-0.597	-4.52	-0.404	-3.61	
HHEDUC (t)	- 0.265	-3.01	-0.248	- 2.24	- 0,.205	-2.16	
Q[D(i,t-1)]			1 .482	20.91	1.059	13.47	
\hat{V} $(t-1)$			-0.004	-1.26	0.001	0.36	
q (t)	1.221	8.00	1.327	6.98	1.237	7.31	
r(t)	4.021	2.07	5.049	19.89	4.375	19.80	
L (0)	-1 419.2		-1 377.2		-1 372.5		
$L(\hat{C})$	-87	77.8	- 90	07.0	-882.2		
$L(\hat{oldsymbol{eta}})$	-60	14.7	-353.8		-506.9		
$-2[L(0)-L(\hat{\beta})]$	1 628.9 (7)		2 046.9 (9)		1 731.2 (9)		
$-2[L(\hat{C})-L(\hat{\beta})]$	546.2 (5)		1 106.4 (7)		750.5 (7)		
N No Car	228		211		211		
1 Car	68	30	64	44	649		
≥ 2 Cars	118		153		139		
N Total	1 026		1 00	08	999		

Note: L(0) is the log-likelihood with all coefficients set to 0, $L(\hat{C})$ is the log-likelihood with Q(t) and Q(t) alone taking non-zero values, and Q(t) is the log-likelihood with all coefficients unconstrained. Q(t) and Q(t) and Q(t) and Q(t) are as defined in Eqn 13 and Eqn 14, respectively.

^{*4} The model development effort in this study takes on the approach of accouting for the variation in car ownership on the basis of demographic and socioeconomic characteristics of households. This is based on the brief that the major factors influencing the acquisition of a car are socio-demographic in nature, e.g., young household members forming a separate household, a member of the household gaining employment, having a new baby, etc. (see Town, 1983; Onnen and Knippenberg, 1986). Consequently, the car ownership models of this study do not include variables representing model competition (especially for work trips) and car acquisition and maintenance costs that were considered in previous analyses of car ownership with different emphases (e.g. Ben-Akiva and Lerman, 1974; Train and Lohrer, 1983; Mannering and Winston, 1985). Also note that the measure of transit development used in this study, GMTGROUP, is a very crude measure of transit accessibility. The car ownership model can be improved by introducing variables characterizing transportation supply system that can be obtained from supplementary data sources

Table 5 (Continued)

Weekly Household Trip Generation

	WAVE 1		WAVE 2		WAVE 3	
	Coef.	t	Coef.	t	Coef.	t
Constant	2.311	:	5.272		8.128	
NRECORDS (t)	14.720	11.15	12.861	11.35	11.264	8.88
DRIVERS (t)	4.519	5.54	3.660	5.35	2.962	3.79
HHEDUC *NRECORDS (t)	3.413	7.42	3.658	9.47	3.233	7.53
CHILD06 (t)	1.910	2.40	3.530	5.44	3.585	4.97
CHILD11 (t)	3.286	3.50	2.866	3.55	3.298	3.83
CHILD17 (t)	7.034	5.75	6.307	5.44	8.526	6.60
MARRIED *NRECORDS (t)	2.967	3.55	2.665	3.84	2.831	3.64
Q[D(i,t)]	-0.392	- 0.58	-0.721	-1.01	0.246	0.36
$\hat{V}(t-1)$			0.618	23.82	0.522	14.80
R^2	0.694		0.764		0.687	
F	287.6 (8,1017)		358.1 (9,998)		227.8 (9,989)	
N	1 026		1 008		999	

^{():} Degrees of freedom

The models were estimated using weighted least squares to account for possible heteroscedasticity. The weight was developed assuming that the error variance is proportional to the expected number of trips.

Not surprisingly, the most significant exogenous variable of the trip generation models is number of diary-keepers in the household (NRECORDS). This variable alone accounts for 56 % of the variation in weekly household trip genration in the wave-2 and wave-3 models. It is believed that the positive contribution of education is at least in part due to its association with trip reporting (see Kitamura and Bovy, 1987).

Effect of the Car Ownership Level on Trip Generation: As the list of variables shown in Table 4 indicates, the synchronous effect of car ownership on trip generation was carefully examined in the model development effort. The examination offered a strong indication that weekly trip generation by diary-keepers in the Dutch Mobility Panel is statistically independent of household car ownership. Note that all reported trips are included in the analysis, regardless of the travel mode used. The finding is against the common wisdom in trip generation analysis that household car ownership is a major determinant of trip generation*5. On the other hand, it supports the notion that household members have mobility levels, or out-of-home activity levels, that are determined independent of car ownership.

Serial and Cross-Lagged Correlations: The significant coefficients of Q[D(i, t-1)] in the car ownership models and $\hat{V}(i, t-1)$ in the trip generation models indicate the presence of strong serial correlation. A household's unexplained propensity to travel (and unaccounted reporting errors) and unexplained propensity to own cars are each significantly correlated over time.

On the other hand, the coefficients of $\hat{V}(i, t-1)$ in the car ownership models and Q[D(i, t)] in the trip generation models are insignificant. There is no statistical indication that cross-lagged linkages exist between unobserved elements influencing car ownership and those influencing trip generation. Neither the level of car ownership nor unobserved elements associated with it significantly influence trip generation. This analysis of car ownership and trip generation thus offers a strong indication that these two aspects of mobility behavior are statistically independent and therefore can be analyzed and predicted separately.

^{*5} The result offers an additional piece of evidence supporting the hypothesis that the effect of car ownership on trip generation becomes less significant as motorization progresses, pustulated and supported in the analysis by Kitamura and Kostyniuk (1986) and Kostyniuk and Kitamura (1986) using repeated cross-sectional observations.

Recall, however, that the measure of trip generation used in this analysis includes trips made by all modes. It is probable that different conclusions will be drawn if other aspects, such as car trip generation or vehicle utilization, are studied.

Initial Conditions: The models for wave 1, which lack the correction terms, may be viewed as instruments to provide initial conditions for the models of subsequent waves. The problem of initial conditions in panel analysis is a significant one whose investigation is still in an early stage (Heckman, 1981 b; Hensher, 1987 b). The lack of initial conditions does not impose serious problem in the present model system since its model components do not involve lagged variables and the cross-lagged correlations among the error terms are insignificant as the above analysis indicated. Serial correlation is found to be significant, but the ordinary estimator based on a single cross-sectional observation is consistent under serial correlation. Consequently, the estimation results exhibit a certain degree of similarity in the coefficient vectors across the three waves, despite the lack of correction terms in the wave-1 models. This would not be the case if the models involved lagged endogenous or exogenous variables.

7. CONCLUSION

This paper presented an analytical framework for panel analysis of mobility behavior. The model system is a simultaneous equations system involving discrete and continuous endogenous variables, and allows for the presence of serial correlations among the errors associated with each of the endogenous variables, and synchronous and cross-lagged correlations between the errors for the two endogenous variables. The discussion showed how components of the model system can be singly estimated using correction terms developed to account for correlated errors.

The model system is applied to study longitudinal relationship between household car ownership and weekly person trip generation using a panel data set. An important finding of this empirical analysis is that car ownership and trip generation are statistically independent of each other; cross-lagged and synchronous correlations in the error terms are not significant and, most importantly, the level of car ownership does not significantly affect trip generation by household members. Note, however, that the total number of trips made by household members by all modes is used as the mobility indicator in the analysis of this study. Different conclusions may be drawn if other aspects of travel behavior are investigated.

The empirical exercise has shown that the model system can be effectively applied to panel analysis of travel behavior. Being an initial attempt, however, the particular application shown here leaves room for improvement and extension, including:

Treatment of the Unobserved: The use of error components to represent unobserved individual-specific effects in panel data is perhaps a profitable modification. Achieving this with the linear regression models of the proposed model system does not impose any problem provided that the error components are not correlated with other error terms, i.e., the error term of the linear regression model can be decomposed into error components and an additional error term with the correlatives structure as assumed in the present study. Adopting the one-factor random effect model (Heckman, 1981 a) in place of serial correlation for the series of discrete choice models is also a possibility, although the existing approach (Heckman and Willis, 1977) may not apply to the model system here.

Heterogeneity: The apparent serial correlation may be caused by variation in model coefficients across households within each observation point. Testing a system comprising random coefficient models as an alternative formulation may offer insights into the strong longitudinal correlation in unobserved elements found in this study.

Linkage Structure: This study examined only one set of inertial, synchronous, and cross-lagged linkages. Many other linkage structures with different degrees of lags are possible. Examination of alternative linkage structures will allow rigorous analysis of the degrees of longitudinal dependence in

mobility behavior.

Incorporation of Lagged Variables: The test of state dependence in mobility behavior is an important future subject. This will serve as a test of habit persistence or response lags. Response lags can also be expressed through the use of lagged exogenous variables. The use of lagged dependent variables in modeling car ownership is an important alternative approach that assumes Markovian transition in car ownership. Through the effort of such model formulation and estimation, it is possible to address behavioral questions such as: Does past car ownership leave a permanent imprint on a household's travel behavior?

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