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An Overview**

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PANEL ANALYSIS IN TRANSPORTATION PLANNING: AN OVERVIEW

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Abstract—The advantages, disadvantages, and issues involved in the panel analysis of travel behavior are discussed. Increased statistical efficiency, possibility of improved prediction, and the ability to observe changes and examine behavioral dynamics, are among the advantages panel data offer. Their disadvantages, on the other hand, stem from the added biases and costs of panel survey, and increased complexity involved in the analysis. Following a discussion of response lags, leads, and other dynamic elements of travel behavior, the paper offers a brief review of statistical methods available for the analysis of panel data. Use of panel data and dynamic models for demand forecasting is then described, followed by sample size, interview frequency, and other considerations in panel survey design and administration.

1. INTRODUCTION

Panel analysis of travel behavior has received increasing attention in recent years.† Dynamic analysis, which is often based on panel data, was the major subject of the 1988 travel behavior conference at Oxford. Several sessions were held also on this subject in the 1989 World Conference on Transport Research in Yokohama, and the Third International Conference on Survey Methods in 1990 hosted a workshop on longitudinal surveys. The same enthusiasm is held by the practitioners as evidenced by the number of panel studies being planned or initiated within the past few years.

This paper offers a review of the advantages, disadvantages, and issues involved in the panel analysis of travel behavior. The intent of the paper is not to cover the subject in technical detail, but to offer a brief overview with emphasis on the practical significance of panel analysis in transportation planning. It is hoped that the paper contributes to a widespread recognition of the usefulness of, and potential difficulties in panel survey and analysis of travel behavior.

The next section contains discussions of the factors that motivate panel analysis. Section 3 is concerned with dynamic aspects of travel behavior, in particular response lags. Classes of analytical methods used in dynamic travel demand analysis are reviewed in Section 4, and Section 5 is concerned with the application of dynamic models to demand forecasting. Issues in panel survey design and administration are discussed in Section 6.

2. WHY PANEL ANALYSIS?

Perhaps the most frequent reason that motivates a panel study is the evaluation of the impact of a change in the transportation system, or a specific transportation planning project, especially when the project involves novel elements. Examples include a panel study of downtown employees in Honolulu conducted in connection with a staggered work hours demonstration project (Giuliano and Golob, 1989; Golob and Giuliano, 1989), a study of freeway commuters to evaluate the impact of new high-occupancy vehicle (HOV) lanes in San Diego (Supernak and Kitamura, 1989), and a study of state employees in Sacramento and San Francisco to measure the impact of telecommuting on household travel patterns (Pendyala *et al.*, 1989; Kitamura, Goulias, and Pendyala, 1990). Public transit fare changes underlie the London panel (Terzis, 1988) and the Dutch National Mobility Panel (Golob *et al.* 1986; van Wissen and Meurs, 1989) which are both consid-

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†"Panel analysis" refers to the statistical analysis of panel data which consist of observations made repeatedly of the same sample.

ered to be general-purpose panels for transportation planning. Monitoring the change in mobility is also among the purposes of such general-purpose panels.

The advantages of a panel are clear in these cases. Panel members are sampled to include individuals (or households) that are influenced by the change in the system (possibly along with individuals that are not influenced as control group members). Repeated observation of the same respondents implies that unobserved contributing factors are well controlled, facilitating more precise measurement of behavioral changes. It also reduces sampling errors, leading to reduced sample size requirements compared with repeated cross-sectional surveys (additional discussions can be found in Section 6).

Another often cited advantage of panel analysis is its ability to identify temporal variation in travel behavior. This is analogous to the case of the analysis of multi-day travel behavior (e.g. Hanson and Huff, 1988; Kitamura, 1988a; Pas, 1988; Pas and Koppelman, 1986). Observing travel patterns of individuals and households over several consecutive days, has offered insights into activity scheduling and travel planning. Variability in travel patterns has important policy implications as well. This is well exemplified in the following hypothetical case which draws on Ben-Porath (1973):

> . . . consider the common finding from a one-day survey that, say, 10 percent of a sample group rode the bus on the survey day. One interpretation is that 10 percent of the population always rides the bus . . . , at the other extreme is the interpretation that everyone in the population rides the bus 10 percent of the time (Hanson and Huff, 1988).

Policy and planning implications of this example is obvious.

In case of panel data, changes in travel behavior is observed with much longer intervals; emphasis here is not on stochastic variations in travel patterns or scheduling behavior, but on long-term changes such as turnovers in mode use. Based on the London panel data, Stokes (1988) notes the "loyalty" shown by frequent public transit users. The ability to identify who tends to be a loyal transit user, a willful solo driver, or an experimenter of new modes, would be crucial for successful transit marketing or carpool promotion. Panel data facilitate such identification.

Panel data also offer a setting for direct observation of changes in contributing factors and changes in behavior. This reduces the possibility of being confounded by the typically strong correlation among possible contributing variables, and facilitates the identification of cause-effect relationship (Golob, 1990; Kitamura, 1989b).

Forecasting is another area where the practical value of panel analysis can be, and should be, realized. The fundamental assumption inherent in a model estimated on a cross-sectional data set (a cross-sectional model) is that a behavioral measure at time t, $Y(t)$, can be expressed as a function of explanatory variables, $X(t)$, and an error term, $\epsilon(t)$, also at time t when the data were taken. Thus, systematic variations in Y are related to variations in X within the same cross section. Applying this relation to forecasting would involve longitudinal extrapolation of cross-sectional variations; changes in behavior over time would be predicted based on differences in behavior across individuals.

Despite the fact that most forecasting models in use are cross sectional and embody this assumption, its validity has not been tested in any rigorous manner. In fact recent findings on cross-sectional and dynamic measures of correlation (Goodwin, 1987; Kitamura and van der Hoorn, 1987) cast doubt on this long-held assumption. There are several conditions that must be satisfied for this assumption to hold (Kitamura, 1986):

1. behavioral changes in instantaneous,
2. behavioral changes are symmetric, or reversible, and
3. behavioral relation is stationary (invariant over time).

If these conditions all hold, then behavior is contemporaneous. Our casual observation as well as recent evidence in the literature, however, are against this notion of contemporaneous behavior. To the contrary, capturing the dynamics in travel behavior may be of funda-

mental importance for the analysis and prediction of travel demand. This leads to the discussion of Section 3 on dynamic characteristics of travel behavior.

Not only being based on a more plausible behavioral foundation, dynamic models also offer the possibility for improved predictive accuracy in forecasting. This is in part due to the fact that longitudinal data contain more information for each behavioral unit than do cross-sectional data. Forecasting with dynamic models is yet a novel concept in transportation planning. Further analysis is needed to determine how much improvement can be expected from the use of longitudinal data and dynamic models. The effort by Wolfe (1989) presents an initial attempt toward this goal.

Finally, panel analysis is the most effective, sometimes the only means through which dynamic aspects of travel behavior can be investigated. Understanding travel behavior dynamics is important in evaluating planning projects and monitoring changes in mobility as well as in formulating predictive models and making forecasts. For example, individuals' adaptation to a change in the supply system is dynamic involving time lags caused by various reasons. Observed behavior and attitudes change not spontaneously but gradually after a system change, sometimes involving over reaction. Giuliano and Golob (1989), for example, note dramatic shifts in attitudes toward staggered work hours before, during, and after a demonstration project in Honolulu. An evaluation of a new system or system improvement may be imprecise or even erroneous if it is not based on an understanding of time lags involved in individuals' responses.

3. TRAVEL BEHAVIOR DYNAMICS

Factors contributing to the travel behavior of a household or an individual change almost continuously. At the macroscopic level, continuing urbanization, evolving consumer technology and products, telecommunications systems, highway and transit improvements, and energy and air quality policies all contribute to urban residents' travel decision. At the microscopic level changes in household attributes such as income, household composition, employment, and license holdings would lead to residential relocation, car acquisition or disposal, and changes in daily travel patterns. The discussion of this section is concerned with the magnitude and timing of the response to changes in such contributing factors.† The discussion is at a conceptual and abstract level, and accumulating empirical evidence is not its intent (Jones *et al.*, 1983, offer a detailed account of household response patterns based on unstructured home-interview survey results).

Useful in this context is the standard conceptualization of the driving task which consists of: *perception* (visual or auditory reception of an external stimulus), *identification* (understanding of the stimulus), *emotion* (decision of what action to take in response to the stimulus) and *reaction* or *volition* (execution of the action). Each step involves a time lag, which accumulates itself as the total response time. Some stimuli may not be perceived at all, leading to nonresponse. The household's response to changes in the travel environment is quite analogous to this characterization of the driving task.

Information is not always acquired immediately, leading to imperfect information or ignorance. This is one of the sources for response lags. A typical example is the time it takes a solo driver to become aware of a new bus line which is suitable for his commute trip and to which he may eventually switch. The process of experimentation and learning results from conscientious effort to acquire information. Some learning almost necessarily involves experimentation (trying out alternative commuting routes) while other may not (checking car prices in the newspaper). Behavioral dynamics exhibited in the process of learning can be found in Chang and Mahmassani (1988).

It is also probable that a change of small magnitude may not prompt any action. This may be due to the presence of a threshold in perception (a "just noticeable difference"; Coombs, Dawes, and Tversky, 1970). However, small changes, each below the perception threshold, may over time accumulate as a large change. Gradually intensifying highway

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†The discussion of this section draws in part on Goodwin, Kitamura and Meurs (1990).

congestion is a good example. The notion of "cumulative effect" applies well in this context; it may be hypothesized that the individual responds when the cumulative effect of small changes exceeds a threshold. The threshold value itself may be a function of the speed of accumulation; slow changes may allow the individual to get used to them (thereby the threshold value is raised), while rapid accumulation may lead to more prompt reaction. Or, it may be the case that "any reaction is delayed until the next 'life-shock' (changing jobs, life-cycle stage, home location, etc.)" (Clarke et al., 1982).

Constraints imposed on the household may lead to apparent response lags. For example, the household may not immediately acquire an additional car after its member acquires a driver's license because it has not saved up a down-payment yet. This is a case of resource constraint. The cost of change is another source of response lags. For example, residential relocation involves a considerable amount of monetary cost as well as the time and effort required for searching. If the cost of change is larger than the benefit arising from it, then rational behavior implies no change.

The discussion offers a way of viewing the "habitual" or "routine behavior," "behavioral inertia," or "resistance to change." Namely, the same behavior prevails even after it is no longer optimum due to changes in the environment, because changing the behavior involves monetary, time, and psychological costs. Delaying reaction until the next life-shock may be a way of taking advantage of the economy of scale in behavioral change.

This view is consistent with the notion of the speed of behavioral change or adjustment. Jones et al. (1990) note that tightening constraints force quick reaction while delayed response tends to follow loosening constraints. If the cost of behavioral change implies resistance to change, then prompt change is not likely when constraints loosen, thus forcing no change.

Also important is the notion of "leads" where an action precedes a change in the environment. This may happen due to the decision maker's planning effort in which an action is taken in anticipation of a change. Like lags, leads would imply a mismatch between the behavior and the environment (i.e. the behavior is not fully adjusted to (or has changed ahead of) the environment). This is a case of "disequilibrium" (Goodwin et al., 1987).

Implicit in our discussion has been the assumption that, given enough time, behavior will eventually converge at an equilibrium (unless the magnitude of a change in the environment is too small to react). The next question, then, is where this ultimate equilibrium is located. In particular, whether the point of equilibrium is influenced by the behavioral path taken toward it. Related to this is the question of asymmetry in response (Kitamura, 1989a; Kitamura and van der Hoorn, 1987) (i.e. the magnitude of change in behavior may be different depending on the direction of the change).

Apparent behavioral asymmetry may be due to the differential speed of adjustment. If a behavioral change in response to tightening constraints is more prompt than that following loosening constraints, then the magnitude of change observed after a change in constraints would exhibit asymmetry with the former showing a much larger change. If this asymmetry is indeed due to the difference in the speed of adjustment, then asymmetry should eventually disappear and responses in both directions would exhibit the same magnitude of change.

If changes in travel behavior can be characterized as described so far, and if the speed of adjustment is fast relative to the frequency of changes in the environment, then a majority of the population is in behavioral equilibrium at any time point. Analysis on cross-sectional data would approximate behavior-environment relationship at equilibrium, and an estimated elasticity measure would represent long-term elasticity.

This may not be the case if past experience permanently influences future behavior. This would lead to truly asymmetric response in which the point of equilibrium depends on the direction of change. For example, ultimate behavior would be different between a household whose income has decreased by X from $V + X$ to V and an otherwise identical household whose income has increased by X from $V - X$ to V. Generalizing this, the location of behavioral equilibrium would depend on the entire past behavioral path, and

the behavioral path would exhibit hysteresis (Goodwin, 1977). This is a case of "state dependence" where behavior is "irreversible."

This would also imply "multiple equilibria" (Mahmassani, 1990). If this indeed is the case, then there is no unique behavior corresponding to a given set of conditions observed in the environment. Behavioral relationship identified on cross-sectional observation would not represent behavioral changes over time. This is the case where longitudinal data and analysis are prerequisite for proper identification and prediction of behavior.

4. PANEL ANALYSIS METHODS

This section is a cursory review of analytical methods available for panel analysis of travel behavior. The intent is to present selected classes of models in a unified framework. The reader is referred to the cited references for more fundamental treatment of the subject. In the discussion, we assume that we have panel observation taken at equi-spaced time points. Therefore, the time can be represented by an integer index, and the notion of the elapsed time between events is suppressed in the discussion (duration models therefore lie outside the scope of the discussion here). This discretization of the time dimension is of course an approximation which is subject to certain limitations, some of which are discussed later in Section 6. In addition, several classes of models in panel analysis are not discussed as their applicability to travel demand analysis is not immediately clear. This review is thus not intended to be exhaustive, but is an attempt to briefly summarize discrete-time panel analysis methods that have been applied in dynamic travel behavior analysis.

The objective of our analysis is to gain stochastic characterization of the observed behavior at t, $Y(t)$, as a function of the history of contributing factors, $\mathbf{X}(t) = (X(t), (X(t-1), \ldots, X(0))$, and past behavior, $\mathbf{Y}(t-1) = (Y(t-1), \ldots, Y(0))$ (i.e. to determine the function F) such that,

$$Pr[Y(t) \leq y | \mathbf{X}(t), \mathbf{Y}(t-1)] = F(y, \mathbf{X}(t), \mathbf{Y}(t-1))$$

where bold-faced letters represent vectors. If Y is continuous, we have a class of regression models:

$$Y(t) = G(\mathbf{X}(t), \mathbf{Y}(t-1), \epsilon(t))$$

where $\epsilon(t)$ is a random error term from a distribution. Similarly, if Y is discrete,

$$Pr[Y(t) = j | \mathbf{X}(t), \mathbf{Y}(t-1)] = H_j(A_1, \ldots, A_K), j = 1, \ldots, J$$
$$A_k = A_k(\mathbf{X}(t), \mathbf{Y}(t-1), \epsilon_k(t)), k = 1, \ldots, K$$

where J is the number of discrete states Y may assume, and A_k may be termed a "latent variable." The well-known multinomial logit and probit models (for which $J = K$) fall in this class of models.

The Markovian model represents a purely state dependent process,

$$Pr[Y(t) = j | \mathbf{X}(t), \mathbf{Y}(t-1)] = Pr[Y(t) = j | \mathbf{Y}(t-1)] = H_j(\mathbf{Y}(t-1))$$

where $\mathbf{X}$ has no bearing on Y. As a special case, consider a Markov chain model of the first order, i.e.,

$$Pr[Y(t) = j | \mathbf{Y}(t-1)] = Pr[Y(t) = j | Y(t-1) = i] = p(i,j)$$

where $p(i,j)$ is the "transition probability." This process can be studied by tabulating observed transition frequencies as a two-way classification table where the (i,j) cell represents the observed frequency of transitions from i to j. Similarly, higher-order Markov chain processes can be examined empirically using multi-way classification tables. Statistical tests for the assumptions of stationarity (that the transition probability is invariant over time) and kth order history dependence (that $Y(t)$ depends only on $Y(t-1)$ through $Y(t-k)$) are discussed in Anderson and Goodman (1953). The log-linear model of classification table analysis can be conveniently utilized in hypothesis testing in this context.

Analysis using these Markovian models is critically limited because it offers no explanation but replication. One would wish to explain the transition probability (or, the probability of behavioral change) as a function of $X(t)$ as well as the past history of the behavior itself, $Y(t)$. This has led to the use of various discrete choice models as functional specifications of the transition probabilities (e.g. Lerman, 1979; Kitamura and Kermanshah, 1983; van der Hoorn, 1983). In particular, choice models have been applied to longitudinal analysis of household car ownership with a variety of assumptions about the history dependence and inter-temporal correlation of the error terms (e.g. Hocherman *et al.*, 1983; Mannering and Winston, 1985; see Kitamura and Bunch, 1990, for a review). The state-of-the-art of the estimation of discrete choice models with lag terms ($Y(t)$) and inter-temporally correlated errors is not well advanced, limiting the types of dynamic models (and model systems) that can be conveniently and appropriately estimated to depict discrete choices observed over time.

The beta-logistic model (Heckman and Willis, 1977) is a notable exception in this context which may be viewed as an *approximate* discrete choice model with individual-specific error components. In its original form, however, the model is limited because of the assumption that the series of choices made over time by each individual forms a Bernoulli process consisting of repeated independent binary choices with identical choice probabilities (its application to travel behavior can be found in Uncle, 1987). Extensions of the original beta-logistic model can be found in Davies (1984) and Dunn and Wrigley (1985), and an empirical application in Smith *et al.* (1986). The extensions, however, are at the cost of losing the computational tractability that the original model offers. More recently, Kitamura and Bunch (1990) have proposed ordered-response probit models with individual specific random error components to examine the question of heterogeneity (unobserved individual specific effects) versus state dependence (see Heckman, 1981b). Their model formulation and estimation, while computationally tractable, is exact involving no approximation.

Extensive results are available on the formulation and estimation of dynamic models that are linear in their parameters, i.e.

$$Y(t) = \mathbf{Q}'\mathbf{Y}(t - 1) + \mathbf{B}'\mathbf{X}(t) + \epsilon(t)$$

where $\mathbf{Q}$ and $\mathbf{B}$ are coefficient vectors. A special case that deserves attention is

$$Y(t) = qY(t - 1) + \mathbf{B}'\mathbf{X}(t) + \epsilon(t),$$

where q and $Y(t - 1)$ are scalar and $\mathbf{X}(t)$ contains measurements at t alone. The model assumes that the observed behavior at time t is a function of the behavior observed at time $t - 1$. This may be viewed as a model of "partial adjustment." Let the equilibrium behavior, Y^*, which would be reached when X remains unchanged at $X(t)$, be given as $Y^* = \mathbf{B}'\mathbf{X}(t)$. Assuming that behavioral adjustment is proportional to the difference between the behavior in the previous period, $Y(t - 1)$, and the equilibrium behavior, Y^*, and with the proportionality constant, $(1 - q)$,

$$Y(t) = (1 - q)(Y^* - Y(t - 1)) + Y(t - 1) + \epsilon(t)$$
$$= qY(t - 1) + (1 - q)\mathbf{B}'\mathbf{X}(t) + \epsilon(t).$$

Another interpretation is possible by substituting the above expression into itself to obtain the following geometric-lag model

$$Y(t) = \mathbf{B}'\mathbf{X}(t) + q\mathbf{B}'\mathbf{X}(t - 1) + q^2\mathbf{B}'\mathbf{X}(t - 2) + \ldots$$
$$+ \epsilon(t) + q\epsilon(t - 1) + q^2\epsilon(t - 2) + \ldots$$

This is the most parsimonious version of the model which carries the effect of the entire past history. This formulation is used in Meurs (1990) and Hensher and Smith (1990) for the analysis of trip generation and vehicle utilization, respectively. Alternative estimation procedures are also described in these papers. Griliches (1967) offers further discussions on this class of models.

Alternative formulations of the error term have been proposed to capture the effects of unobserved elements more appropriately. Because an error term represents the effects of unobserved factors, some of which may remain unchanged over time, it is reasonable to assume that errors are temporally correlated. This leads to the assumption of serial correlation.

Alternative approach is the use of error components. For example, let

$$\epsilon(i,t) = u(i) + v(t) + w(i,t)$$

where *i* refers to the individual observation, $u(i)$ is a random error term representing the effect that is specific to individual *i* and invariant over time, $v(t)$ is a time-specific effect that affect all individuals equally, and $w(i,t)$ is a purely random error term. This error formulation is used in the analysis of multi-day travel patterns by Pas and Koppelman (1986). Both Hensher and Smith (1990) and Meurs (1990) adopt the random term, $u(i)$, to represent unobserved individual-specific random effect.

Another specification issue involved in the formulation of dynamic models concerns the structure of lagged variables. Questions include: whether lagged *X* variables should be included as well as, or in place of, lagged *Y*, and what the extent of the lag should be. Although the identification of the structure of lags is said to be difficult (Griliches, 1967), further investigation is due in this area to determine the characteristics of response lags in travel behavior.

Structural equations models are a powerful tool in this context. The estimation principle adopted by this class of models is different; instead of maximizing the joint probability that the measurements in the sample will occur, model parameters are determined so as to best replicate the covariance matrix of the variables in the model system. This approach facilitates the estimation of complex model systems with relative ease. Computer codes have been developed to estimate such model systems and determine causal relationships among a set of variables, which may include ordinal response variables as well as continuous measurements.

A series of work by Golob and his colleagues (Golob, 1989, 1990; Golob and Meurs, 1987; Golob and van Wissen, 1988) offers an excellent overview of the available methods and demonstrates their capabilities in dynamic travel behavior analysis. Quite important is the ability these codes offer to estimate model systems simultaneously involving several behavioral measures of interest (e.g. car ownership, trip generation, and travel expenditure). A similar, perhaps less versatile, approach is the log-linear model of cross-classification tables. Examples include Kitamura (1989b) and Supernak and Kitamura (1989). How the structural equations approach, the log-linear model, and the traditional econometric approach compare with each other, and whether they arrive at comparable model specifications and behavioral interpretations, remain as a challenging research subject.

Several unresolved issues exist in the estimation of dynamic models using panel data. These center around the estimation of dynamic discrete choice models:

1. *Representation of the initial condition:* No information is usually available from a panel data set on variable values prior to the survey. Several approaches have been proposed to represent initial conditions for the linear model; the method in Hensher and Smith (1990) is to express the initial conditions using observed variables (Bhargava and Sargan, 1983), while Meurs (1990) uses instrument variables. Methods are not well established for nonlinear models including the discrete choice model; see Heckman (1981a).
2. *Estimation of multi-period, multi-alternative discrete choice models:* Although it is evident that multi-period, multi-alternative discrete choice can be represented by a multinomial probit model (Daganzo and Sheffi, 1982), application of the multinomial probit model is limited due to the computational difficulty it poses and the model identification issues involved (Dansie, 1985; Bunch and Kitamura, 1990). The only published empirical example of probit panel analysis that the author is aware of in-

volves only two alternatives at two time points (Johnson and Hensher, 1982). An alternative is a single-equation approach where a model is estimated for each period separately with correction terms to account for longitudinal correlation in the error term (Kitamura, 1987). The statistical efficiency of this approach, however, needs to be determined. The recent developments in beta-logistic models and error-component ordered-response probit models discussed above indicate that certain types of multiperiod, multi-alternative discrete choice models can be practically estimated.

3. *Correlated errors in a dynamic model system:* Again, estimation theory is well advanced for the system of linear dynamic models. It is frequent in transportation planning that a model system must involve both discrete and continuous dependent variables, requiring nonlinear models as components. Car type choice and utilization (Hensher, 1986; Mannering and Winston, 1985) and car ownership and trip generation (Golob, 1990; Kitamura, 1988b) are good examples. These studies use varying degrees of assumptions about the longitudinal correlation of the error terms involved, with some completely ignoring the possibility of correlation. A few studies that account for such correlation use correction terms to account for possible biases due to correlated errors. The same comments raised above for the case of discrete-time panel analysis apply here. As noted earlier, comparative analysis of the conventional maximum likelihood estimation and the structured equations approach is another subject for future investigation.

4. *Model identifiability and data requirements:* An empirical question is the estimability of a given model when the explanatory variables are "slow moving," or behavioral changes of interest are infrequent. In the extreme case where the explanatory variables do not change at all, then the information content in the data is similar to that in the analysis of variance with repeated measurements. The data would not support the analysis of behavioral dynamics except for the variation in behavior across observational occasions. The issue is more complex when the dependent variable is discrete, and requires further investigation.

5. DEMAND FORECASTING WITH DYNAMIC MODELS

The application of cross-sectional models to forecasting necessarily involves the assumption that the model coefficients obtained based on cross-sectional variation in behavior can be used to predict behavioral changes over time. The use of dynamic models in forecasting, on the other hand, is an attempt to extrapolate longitudinal trends in the data into the future.

The procedure of forecasting is fundamentally different between cross-sectional and dynamic models. In the case of cross-sectional models, the values of the explanatory variables, X, for the horizon year, T, are (usually externally) forecast, then a forecast, $Y(T)$, is obtained simply by plugging in $X(T)$ into the model equation. For a linear model, this is

$$\hat{Y}(T) = \hat{B}'X(T)$$

where $\hat{B}$ is a coefficient vector estimated on a cross-sectional data observed at, say, t. For the linear model, the procedure applies to disaggregate households or individuals in the study area, or to aggregate averages.

Application of a dynamic model to forecasting is fundamentally different. For one thing, the coefficients of a dynamic model reflect the observational time span in the longitudinal data used for estimation. Forecasting, therefore, must be performed using the same time span; if the panel data used for model estimation were collected with one-year intervals, then one-year intervals must also be used for prediction.

Forecasting with a dynamic model is not a single shot into a distant future. It consists of a series of forecasts obtained using appropriate time intervals. For a linear model, noting that a sum of errors has an expectation of 0, and assuming that the standard error of q is negligibly small,

$$\hat{Y}(t + 1) = q Y(t) + \hat{\mathbf{A}}' \mathbf{X}(t + 1)$$
$$\hat{Y}(t + 2) = q \hat{Y}(t + 1) + \hat{\mathbf{A}}' \mathbf{X}(t + 2)$$

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$$\hat{Y}(T) = q \hat{Y}(T - 1) + \hat{\mathbf{A}}' \mathbf{X}(T)$$

where q and $\hat{\mathbf{A}}$ are obtained using panel data, and the $\mathbf{X}$'s are forecast (externally) for all the interim time points. (This procedure can be used with aggregate averages of $\mathbf{X}$ and Y if the model is linear. For discrete-choice models which are difficult to aggregate, the procedure applies only at the disaggregate level. This is discussed later.) Other possible use of dynamic data and models for forecasting can be found in van der Hoorn and Kitamura (1987) and Wolfe (1989).

As is evident in the above discussion, dynamic forecasting requires more input (although this may not impose any burden because many input variables such as demographic variables, are forecast by extrapolating observed trends using small time increments). This added cost, however, produces the following advantages:

1. Changes in demand that may take place over time after a change in the environment can be forecast.
2. A planning scenario can be represented as a sequence of events, allowing more versatile and strategic evaluation of alternative planning options.
3. Dynamic forecasting is not longitudinal extrapolation of cross-sectional variations.

The advantage extends beyond these when future behavior is microscopically simulated using dynamic models and panel observation.

Given a system of dynamic models formulated at the household or individual level, evolution of households and changes in their behavior can be simulated through stochastic simulation. Such simulation is most meaningful when models are available to simulate all salient household and personable attributes, such as car ownership, employment, and driver's license holdings. When a simulation model system represents the evolution of the household in its demographic, socioeconomic, and mobility characteristics, it may be called a "microanalytic simulation."

There are several reasons to believe that this approach to demand forecasting is worthy to pursue. The most important are:

1. *Endogenous generation of explanatory variables:* Many advances have been made in the formulation and estimation of disaggregate travel demand models in the past 15 years or so. However, forecasts of the explanatory variables used in these models are typically unavailable at a comparable disaggregate level. Using microanalytic simulation, these explanatory variables can be internally determined instead of being imported from external forecasting sources, thus fully support disaggregate behavioral models.
2. *Cohesive forecasts of interactive variables:* Many household and personable attributes are interrelated. Accordingly, a household's "long-term response may, in fact, be much more complex involving changes of home and job location, car ownership changes, and so on" (Mackett, 1990). In microanalytic simulation, these variables are forecast in a cohesive manner using model components replicating decisions by the household and individual.

These advantages, in turn, would lead to

3. *More realistic and consistent forecasting:* Microanalytic simulation is capable of capturing the repercussions of a change by simulating a chain of changes that follows the

initial change, thus representing complex cause-effect relationships, and capturing full consequences of a change in the environment.

Use of simulation to generate explanatory variables for demand forecasting with disaggregate models is not new. Examples can be found in a corridor planning model developed for the San Francisco Bay Area (Talvitie *et al.*, 1976) and a nationwide demand forecasting models system based on synthetic sample households (Daly and Gunn, 1986). But dynamic simulation, while often used in demography, is a concept new in travel demand forecasting. Examples include Goodwin *et al.* (1987), Kitamura and Goulias (1988), Mackett (1990), and Miller *et al.* (1987). The system by Mackett (1988) is developed based largely on cross-sectional data, while Kitamura and Goulias construct their dynamic model components using a panel data set. The simulation system by Miller *et al.* (1987), developed for the analysis of housing demand, and that by Kitamura and Goulias (1988) both have detailed demographic and employment components. The latter includes models of household car ownership and trip generation by mode. These two models are, however, still in their developmental stages; microanalytic simulation is a new concept in the field of transportation planning whose feasibility and value need to be further examined.

6. PANEL SURVEY

The models and forecasting procedures discussed above require longitudinal data obtained through a panel survey. The discussion of this section is concerned with the advantages and disadvantages of panel surveys.†

From a statistical viewpoint, a panel survey has the definite advantage that it offers more accurate estimates of *changes* than would repeated cross-sectional surveys of the same sample size (Cochran, 1977). For example, suppose one wishes to monitor changes in bus use that may follow an introduction of a new line, and a sample of 1,000 households is drawn for a survey prior to the introduction of the line. If estimating change is the primary concern, then it is best to survey the same 1,000 households again after the new line opens. This increased accuracy offered by the panel survey implies that its sample size is smaller than the one required for a cross-sectional survey to attain the same level of accuracy in the estimates of changes. It is also important to note that sampling cost may be substantially reduced in a panel survey when the same set of respondents is repeatedly interviewed.

There are many additional advantages of panel surveys, some of which have been discussed in Section 2. A panel survey allows the analyst to observe changes in contributing factors and changes in travel behavior, which, in turn, allows more precise determination of causal relationships and model development. A panel survey also facilitates the observation of changes over time in travel behavior. For example, it will facilitate the examination of how new suburban residents adapt to the new travel environment and form their travel patterns. Such an analysis will shed light on the issue of suburban congestion and the question of improving transit services in the suburb. Panel analysis will be an indispensable tool in many planning and policy contexts as urban areas continue to unfold with changing demographic, socioeconomic, land use, level-of-service, and travel behavior characteristics.

These advantages of panel analysis, however, are accompanied by certain difficulties. Extreme care must be exercised in order to obtain survey responses that support the intended analysis. Consideration must be given to:

1. possible increase in nonresponses due to the fact that respondents are required to participate in more than one survey,
2. problem of attrition (i.e. dropping out of respondents between waves of surveys)
3. problem of locating respondents in multiple survey waves due to residential relocation and dissolution of households,
4. possible decline in reporting accuracy due to "panel fatigue," and

†Kasprzyk *et al.* (1989) offer an excellent treatment of this subject.

5. problem of "panel conditioning" where the behavior and responses in later surveys are influenced by the fact of participating in the panel, and also by the responses to earlier surveys.

Additional effort is due in panel surveys to maintain desired sample properties (e.g. population representativeness):

6. increased sampling effort due to the need to introduce new respondents to augment drop-out panel households and "refresh" the panel,
7. need to represent changing populations by sampling new households, and
8. need to sample in-migrating and other new households in the study area.

And the fact that

9. data collection effort inevitably takes longer,

may preclude the use of panel analysis in some instances.

Examples of these problems can be found in the Dutch National Mobility Panel survey (Golob et al., 1986; van Wissen and Meurs, 1989). It is a general purpose transportation survey whose instruments included a weekly trip diary. In an initial screening survey conducted to establish the panel, addresses in 20 municipalities were randomly sampled and 6,128 households were contacted by phone, or at home if no telephone number was available (Golob et al., 1986). Of these, only 2,886 households (47.1%) indicated that they were willing to participate in the panel survey. Out of the 2,886 households, a stratified random sample of 2,185 households was selected as the initial panel and home interviews were administered. Usable responses were obtained only from 1,764 households (80.7%) of the households interviewed.

Attrition was also substantial in the Dutch panel survey, especially between the first wave and the second wave which was conducted six months later. Of the 1,764 households in the first wave, only 1,196 (67.8%) responded to the second-wave survey. This high attrition rate is perhaps due in part to a change in survey administration; those households that were in the first wave were contacted only by mail (Kitamura and Bovy, 1985).

Attrition in the Dutch panel survey was clearly selective, with low-income households, smaller households, households without cars, and those with lower education dropping out at higher rates (Golob et al., 1986; Kitamura and Bovy, 1985, 1987). Of the 1,764 households that were in the first wave, 1031 (58.4%), 853 (48.4%), 668 (37.9%), and 629 (35.7%) remained in the panel in waves 3, 5, 7, and 9, respectively (spaced with one-year intervals; van Wissen and Meurs, 1989).

The issue of reporting accuracy in the Dutch panel survey is addressed in Meurs et al. (1989). As in Golob and Meurs (1986), they found trip reporting decline gradually within each diary period.† Using the average number of trips reported on the first diary day as a reference, Meurs et al., estimate that trip under-reporting amounted to an average of 2.27 trips per week per person in the first survey that a respondent participated. This increased to 4.44 trips in a second survey, and up to 8.35 trips by the time a respondent stayed in the panel to participate in a seventh survey (Meurs et al., 1989).

Careful and well planned survey design and administration will help minimize nonresponse, attrition, and response errors. Some of the problems cited above can be resolved during the tabulation and analysis of survey results. Hensher (1987) lists as factors influencing panel participation: (i) duration of the interview, (ii) interviewer, (iii) household and individual (contact respondent) characteristics, and (iv) household and individual mobility. The results of Kitamura and Bovy (1987) offer evidence on the last two factors.

Nonresponse and attrition caused by these factors tend to be selective (as opposed to

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†Bailar (1989) reports similar declining tendencies in reporting in a consumer expenditure diary survey.

random) as shown above. This will lead to biased estimates of means and proportions. Although the selection on exogenous variables by itself does not bias regression and other model estimation results, likely selection on unobserved elements may. It is desirable that these problems be resolved by recontacting and (in case of attrition) tracing nonrespondents. When this is not done or not complete, the sample should be weighted to account for nonresponse or attrition biases. Such weights may be developed using auxiliary variables that well predict "target statistics," or behavioral measures of concern, as well as the response rate (van de Pol, 1987). In the case of attrition, a probabilistic model of attrition, constructed using measurement from the earlier survey wave(s), can be used to formulate a more efficient weight that takes advantage of mobility and other available information (Kitamura and Bovy, 1987). For discussions on panel conditioning and reporting accuracy, see Golob (1990), Golob and Meurs (1986), Meurs *et al.* (1989), and van de Pol (1987).

Sample size requirements for a panel survey can be derived from the available sampling theory. Attention should be paid to the fact that the analyst is often interested in measuring differences or estimating the probability of changes. Another dimension in sample design, then, is the rate of behavioral change in respective population subgroups. Stratified sampling schemes may be developed to account for the rate of change in the target measure as well as its mean and standard deviation within each population stratum. Important in this context is the finding that households in earlier stages of life-cycle tend to undergo many life-shocks and changes (Clarke *et al.* 1982; Goodwin, 1987).

The duration of a survey and the frequency of interviews are additional elements of panel survey design. The duration of a survey is determined by the characteristics of the behavioral aspect under investigation. For example, 2 years may be long enough to study ride-share behavior among households with cars, while 5 to 10 years may be needed for residential location. Note that variability in both behavioral measures and explanatory variables needs to be considered in selecting the duration of a panel survey. Consideration should also be given to panel conditioning, attrition, initial participation rate, and the practicality of following the respondents over a long span of time.

The variability in the behavior and the contributing factors is a principal factor that determines the frequency of interviews. Frequent interviews would produce data containing fewer changes in each wave, while some changes would be overlooked (Bailar, 1989). The need to maintain a desirable panel leads to additional considerations. Frequent interviews would reduce the chance of loosing respondents due to relocation and lead to more accurate responses if retrospective questions are involved. At the same time, they may lead to increased nonresponse and attrition as they require an increased level of commitment on the part of the panel members, and the results may be more susceptible to panel conditioning.

Panel analysis is a new approach in transportation planning. This paper has shown that panel analysis offers many advantages over the conventional cross-sectional approaches. It has also identified many difficulties and issues that are yet to be resolved. It is believed that further investigation in the near future will offer solutions to many of the problems, and the panel analysis will become a standard tool for travel behavior analysis and demand forecasting.

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