研究展望
REVIEW

Proc. of JSCE No. 440/IV-16, pp. 13~29, January 1992

REVIEW

A REVIEW OF DYNAMIC VEHICLE HOLDINGS MODELS AND A PROPOSAL FOR A VEHICLE TRANSACTIONS MODEL

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1. INTRODUCTION

Household vehicle holdings observed at a time point embody many decisions made by the household over a period of time. The set of vehicles the household holds, or "household vehicle fleet", is not acquired instantaneously ; it is the result of a series of transaction decisions to acquire, replace, or dispose of household vehicles. Each of these decisions is conditioned on the current vehicle holdings, and reflects the long-term planning effort of the household.

Most household vehicle holdings models are either "cross-sectional", using data obtained at one point in time, or "pseudo-dynamic", using repeated cross-sectional data or aggregate time-series observations obtained from various sources. Both classes of models are subject to certain limitations. Application of cross-sectional models to forecasting implies "longitudinal extrapolation of cross-sectional variations" (Kitamura, 1990) which is valid only under very restrictive conditions. For example, questions have been raised whether *cross-sectional elasticities* estimated from these models are identical to *longitudinal elasticities* that are associated with changes in behavior (Goodwin, 1987). Cross-sectional models' ability to accurately represent household behavior under changing income, fuel prices, traffic congestion, etc., should be critically re-examined. Aggregate time-series models, on the other hand, are often incapable of capturing causal relationships governing the behavior of individual behavioral units, thus tend to be limited in their accuracy and policy sensitivity.

From this viewpoint, it is most logical to model household vehicle holdings as a dynamic behavioral process that evolves over time. As discussed elsewhere (Kitamura, 1989b), such dynamic models offer many advantages over the conventional cross-sectional models (also see Goodwin, et al., 1990 ; Kitamura, 1990). For example, they possess the ability to forecast the rejuvenation of a national or regional vehicle fleet over time. This is an important advantage when evaluating the introduction of a new type of vehicle which transport policy calls for. Examples include unleaded-gasoline vehicles in European countries, and "clean-fuel" vehicles and "zero-emission" vehicles being proposed in the United States (see Bunch, et al., 1991). Improved predictive accuracy and policy sensitivity can also be expected from the use of dynamic models. In particular, dynamic transactions models allow detailed evaluation of different policy implementation schemes, such as a large one-time increase of gasoline tax versus several increases in small increments.

In this paper, selected dynamic models of household vehicle holdings are reviewed. Based on the review, it is argued that a dynamic vehicle transactions model that depicts a household's decisions to acquire a new vehicle or replace or dispose of the vehicle(s) it owns, offers many advantages and is able to resolve some of the problems of existing dynamic vehicle holdings models.

Most importantly, a dynamic transactions model, combined with a household socio-demographic simulator (e.g., Kitamura and Goulias, 1991), will be capable of producing forecasts which extend ongoing trends while retaining internal consistency among socio-demographic variables. Furthermore, a dynamic transactions model most realistically replicates the household's vehicle holding decision *proess*, and is capable of reflecting more precisely the effects of costs and other factors involved in the acquisition, replacement, maintenance, and disposal of household vehicles. Therefore a transactions model will offer an extended forecasting capability as it will be able to forecast how the evolution in a vehicle fleet is influenced by vehicle and fuel prices and policy actions.

Selected dynamic household vehicle holdings models are reviewed in Section 2. Conclusions emerging from this review are summarized in Section 3. Reasonings and justifications for dynamic vehicle transactions models are presented in Section 4.

2. A REVIEW OF DYNAMIC MODELS OF HOUSEHOLD VEHICLE HOLDINGS

A summary of selected disaggregate, dynamic model systems of household vehicle holdings and utilization is presented in this section. All model systems are based on revealed-preference data, and are constructed while assuming compensatory relationships among vehicle attributes.

(1) Train's Vehicle Holdings, Vehicle Type Choice, and Utilization Model System

The model system developed by Train and his colleague (Train and Lohrer, 1982 ; Train, 1986) is significant because it is the first comprehensive model system that treats all pertinent aspects of household vehicle holdings and use, i.e., the number of vehicles, class (defined in terms of body type and make), age (or "vintage"), and utilization (vehicle-miles traveled). It is one of the early dynamic models that contain "transaction" variables (other examples include Manski and Sherman, 1980), and has strongly influenced subsequent model development efforts (e.g., Mannering and Winston, 1985). Because of its importance in the development of household vehicle holdings and utilization models, Train's model system is reviewed here in detail. Many comments raised in this section apply to other models as well.

The model system consists of nested-logit models for the number of vehicles and vehicle type choice, linear models of vehicle utilization (in terms of vehicle-miles traveled, or VMT), and logit models that assign VMT to different trip types (the focus of this review is on the first components). The system is microeconomically derived with Roy's identity used to relate the vehicle choice and utilization (the exact utilization formula is replaced by a linear formulation as an approximation ; the use of exact formulation can be found in a more recent study by de Jong, 1989).

The "vehicle quantity" submodel predicts the number of vehicles a household will hold. Choices are limited to no vehicle, one vehicle, or exactly two vehicles. The explanatory variables include household income, the number of workers in the household, and the number of household members. In addition, the annual average number of transit trips per capita in the area of residence is used to represent the transit service level. Although this vehicle quantity submodel is not formulated as a dynamic model, dynamics enters into it indirectly through the variables representing the "average utility in class/vintage choice," or so-called "inclusive price" or "logsum" variables representing the expected maximum utility of a vehicle (or a pair of vehicles) chosen. These inclusive price variables are derived from the vehicle "class/vintage" choice submodels (which are dynamic as described below) and reflect the prices and other attributes of vehicles available in the market.

The class/vintage submodels, defined separately for one-vehicle households and two-vehicle households, describe the probability that a particular class/vintage combination will be chosen by a household. The model system assumes 12 classes defined in terms of body type and make (subsubcompact domestic ; subcompact domestic ; etc.) and 10 vintage categories (pre-1970, and the years 1970 through 1978), resulting in 120 class/vintage combinations as the alternatives in the choice set for one-vehicle households. Each combination is characterized in terms of purchase price, operating costs, shoulder room, luggage space, horsepower, and several dummy variables. These characteristics were obtained by calculating their means over all makes and models in each class and vintage. Also included is the logarithm of "the number of makes and models in the class/vintage" to represent the effect of the size of the class/vintage.

The "transaction cost dummy" in Train's model system "takes the value of one for vehicles in a class/vintage that the household did not own in the previous year and zero for a class/vintage of the vehicle that the household did own in the previous year". Therefore, "Assuming that no household sells a vehicle within a class/vintage and buys another one in the same class/vintage, this variable represents the psychic, search, and other transaction costs associated with buying a new vehicle" (Train, 1986, p.155). Defined according to the class/vintage of the previous year, this variable is an endogenous, lagged dependent variable, making the model system dynamic. The endogeneity of the variable, however, creates "econometric questions concerning the consistency and efficiency" of model estimation (op. cit., p.240).

The approach taken here, i.e., to describe household vehicle holding behavior as discrete choice of alternative vehicle fleets, leads to several difficulties. For example, two-vehicle households are assumed to choose from among pairs of class/vintage combinations. This, however, is a very unrealistic assumption ; in most cases a household replaces one of the vehicles it holds at a time (or over a relatively short period of, say, one year). There are two likely reasons for this :

- a household's decision process is so structured as to update its vehicle fleet by replacing one vehicle at a time, possibly because of the complexity of simultaneous replacement of the entire fleet as a decision to make (the number of alternatives in the two-vehicle class/vintage choice in Train's system can be as large as 14,400 ($=120^2$)) ; and
- the transaction cost involved in replacing the entire fleet at once is so excessive as to make it practically impossible.

Form the first viewpoint, a vehicle is chosen given the set of vehicles the household continues to hold. The choice, then, is a conditional optimization, which may not lead to the same household fleet as would be chosen if the household replaced the entire fleet simultaneously. The former may present an optimal solution, which is suboptimal in the latter unconditional, simultaneous choice problem. One could argue that the transaction variable, included also in the two-vehicle class/vintage choice submodel, would account for this apparent discrepancy (the transaction variable is now defined as the number of transactions involved between the previous year's pair and the alternative class/vintage pair). The above suboptimal fleet may in fact be optimal due to the large transaction cost involved in replacing the entire fleet. Unfortunately, the representation of transaction costs here is rather problematic. This is shown using examples.

Consider a household with a 1978 annual income of less than $12,000. This households has two pre-1972 vehicles whose "purchase prices" would be $1,200 and $800. The contribution of the purchase price to the utility is $-0.000531\times(1200+800)=-1.062$, where -0.000531 is the coefficient of the "purchase price of both vehicles, summed in dollars" (op. cit., Table 8.4). Suppose this household intends to replace one of the vehicles (valued at $800) with a vintage 1976-1978 vehicle, whose characteristics are exactly the same as the one being replaced, except for the purchase price and vintage. Suppose the purchase price is $3,000. In Train's model system, a household's transaction decision is viewed as a choice from among a set of vehicle pairs ; one of the pairs coincides with the pair the household currently owns, and all the other pairs have appropriately defined transaction costs assigned to them. Then the difference in the utility value between the new pair and the old pair is

$$[-0.000531\times(3000+1200)-4.48 +0.155]-[-0.000531\times(1200+800) =-5.49$$

where -4.48 is the transaction cost coefficient and 0.155 is added due to the vintage 1976-1978 vehicle. The decline in utility is phenomenal*1. The utility difference, -5.49, is equivalent to a purchase price of $10,340 ($= 5.49/0.000531$) for this household. In other words, the expected utility of the new vehicle pair would not be greater than that of the pre-1972 vehicles the household currently holds, *unless* the purchase price of the new vehicle is −$7,340 (=$3,000−$10,340), i.e., the household receives $7,340 for acquiring the new vehicle!

Likely improvements in vehicle operating costs offered by the new vehicle would offset the reduction in utility only partially (the operating cost variable in the model system apparently represents fuel costs only). Suppose that gasoline is 80 cents per gallon ; the pre-1972 vehicles get 10 miles per gallon ; and the vintage 1976-1978 vehicle is twice as fuel efficient with 20 miles per gallon. The unit operating cost is 8 cents per mile for the older vehicles and 4 cents per mile for the new vehicle. Therefore the utility difference between the vehicle pairs is

$$[-0.000531\times(3000+1200)-4.48$$

*1 In the example here, the only difference in the pairs of vehicles is the purchase price and vintage. The behavioral reasoning for transacting one of the pre-72 vehicles for a 76-78 vehicle can then only be the preference for a newer vintage which exceeds the disutility of transaction. If a model uses annualized fixed costs instead of the purchase price, the reason for transaction might also be a positive cost difference (for instance because an old vehicle is likely to require high repair costs). Should the model somehow incorporate the household production concept, a newer vehicle might also mean lower variable costs (e.g., lower fuel costs) which could be separated from the other reasons for preferring a newer vehicle (e.g., prestige and reliability). Such a model would then be able to entertain reasons for transaction such as :
- lower (expected) annualized fixed costs,
- lower variable costs, and
- other differences in preference to vehicles of different vintages.

$+0.155-0.441\ (4+8)]-[-0.000531$
$\times(1200+800)-0.441\ (8+8)]=-3.73$

where -0.441 is the coefficient of operating costs of both vehicles summed in cents per mile. The difference in expected utility is equivalent to a purchase price of $7,020.

These rather unrealistic results are partly due to the "transaction" coefficient of 4.48. This value implies that the cost per transaction is equivalent to a purchase price of $8,440 (= 4.48/0.000531) for this household! In 1978, this was perhaps greater than the prices of many brand-new vehicles that were in the market. Using the purchase price coefficient of 0.000383 for households of with incomes between $12,001 and $20,000, the cost per transaction is equivalent to the purchase price of $11,700, and for households in the highest income category (greater than $20,000), transaction cost is estimated at $26,150 per transaction! (The last figure, however, involves a large standard error.) Using the estimated coefficients of the class/vintage submodel for one-vehicle households, transaction costs are estimated at $9,600 for households with incomes less than or equal to $12,000, and $12,800 for those with incomes exceeding $12,000.

Underlying these results is the fact that, although a transaction variable is included in the utility function, the submodel is not a transactions model and does not necessarily capture households' transaction behavior properly. The class/vintage submodels attempt to capture both transaction decision and vehicle type decision within one model structure. The models' emphasis is clearly on the latter decision and the former is treated only tenuously. For example, the information on the current household vehicle fleet (or, the one from the last period) does not properly enter the model system, despite that the remaining life of the vehicle and how long it has been held by the household are likely determinants of vehicle transaction decision.*2

This tenuous treatment possibly leads to another problem, i.e., brand loyalty or switching between body types may not be properly represented by the class/vintage submodels ; the transaction dummy signifies the particular class/vintage the household holds, but does not indicate those alternative class/vintage combinations that are of the same body type or make (domestic vs. foreign). Vehicle transaction behavior as depicted by these submodels is essentially memoryless, except that the current class/vintage combination has a much higher chance of being chosen again (no transaction) because of the heavy penalty for transaction in the model. Although these submodels may replicate the frequency of transactions, they do not explain transaction behavior. Their validity in forecasting is questionable.

The working of Train's model system can be visualized as follows (it is not clear how the class/vintage submodels apply when the number of vehicles held by a household changes. The following discussions assume that the vehicle quantity stays the same). At the end of each time interval, say a year, every household considers replacing its fleet, comparing its utility against those of available class/vintage combinations. If the household chooses not to transact, the utility difference is zero, assuming no depreciation for simplicity. The purchase price is not differentiated between the fleet the household holds and an alternative fleet. This works nicely when utility difference is evaluated ; the "purchase price" of the vehicles currently held acts as their re-sale price, which applies toward the purchase of a new fleet (the linear utility formulation in the model implicitly assumes that the marginal utility of the net profit from a transaction is constant and is identical in its absolute value to the marginal disutility of purchase price. It is also assumed that the resale price of a vehicle of a given class/vintage equals its purchase price).

This depiction without distinguishing between a vehicle being held (which is an asset) and a vehicle to be purchased (as an expenditure item), however, produces somewhat counterintuitive behavior whose empirical validity does not appear to have been examined. To illustrate the point, consider the following utility difference :

(Utility of alternative fleet)
 −(Utility of current fleet)
$=b_p$ (purchase price of alternative fleet)$+\cdots$
 $+b_t$ (number of transactions needed)$+\cdots$
 $-[b_p$ (purchase price of current fleet)$+\cdots]$

Because coefficient b_p is negative, this utility difference increases as the purchase price of the currently held vehicles increases. The difference is positive when a net monetary gain is achieved by "trading down" the vehicles a household holds ; therefore the incentive to trade down increases as the value of the household's fleet increases. According to the model, then, the more expensive the vehicles the household holds, the more attractive other fleets become, *ceteris paribus*. This implies that the probability of transaction, or trading down in this case, increases as the purch-

*2 The information about the household's current fleet enters the class/vintage submodel only indirectly and partially through the inclusion of the class/vintage combination corresponding to the current fleet *without* transaction cost, and all other possible pairs combinations transaction costs.

ase price of the currently held vehicles increases; households with more expensive vehicles are more likely to trade them down! It is not clear whether this is in agreement with observed vehicle transaction behavior.*3

These counterintuitive examples appear to have their roots in the difficulty of representing household vehicle holding behavior as a series of choices from a choice set of the currently held vehicle fleet and alternative fleets. Had the class/vintage submodels been specified without the transaction dummy variable or "prestigious vehicle" dummy variable, they would have depicted household vehicle holding behavior as independent multinomial choices repeated over time (note that the ownership of a vintage-1978 vehicle, which is classified as a "prestigious vehicle", would imply that a transaction was made in the preceding period). A choice of a fleet in one period would be conditionally independent of the fleet the household owned in the previous period, given the explanatory variable values. Consequently the household fleet would tend to change randomly from period to period. This would not be realistic. The transaction and prestigious vehicle variables avoid this depiction of vehicle holding behavior as a highly transient process, by anchoring a household's future fleet to its current fleet. This, however, has resulted in rather questionable estimates of transaction costs as pointed out above.

More logical, behaviorally consistent formulations may be obtained by modeling vehicle holding decisions as a transaction process. Indeed Train's class/vintage submodels would work well if they are applied conditionally given that the household engages in a transaction (therefore the current class/vintage combination does *not* enter the choice set and the transaction dummy is no longer needed). The difficulty of incorporating the ownership of more than two vehicles would no longer be overwhelming, and the task of differentiating among the cost of vehicle acquisition, fixed costs of vehicle ownership, and variable costs of maintenance and operation, would become more amiable in such a transactions model system.

During the period of about a decade since Train's then entirely novel model system was introduced, advances were made in both data collection and model estimation methods that enable the development of dynamic model systems. With statistical hurdles in the formulation of dynamic models removed, a dynamic transactions model system of household vehicle holdings emerges as a feasible alternative that promises enhanced behavioral realism and predictive accuracy.

(2) Mannering and Winston's Vehicle Holdings, Vehicle Type, and Utilization Model System

The model system developed by Mannering and Winston is similar to Train's system. It comprises submodels for vehicle quantity, vehicle type choice, and utilization. Mannering and Winston (1985) note that Train and Lohrer (1982), like Manski and Sherman (1980), used "transaction dummy variables without attempting...to provide a theoretical basis for the specification of a dynamic model". Indeed dynamics in vehicle holdings is one focus of this model development effort, with the discussions encompassing the question of stationarity and state dependence (Mannering and Winston, 1985, p.216), "brand preference" and "brand loyalty". It is noted that the study represents "taste changes" through "a state variable...which we assume summarizes all past utilization relevant to a given vehicle i at time t" (op. cit., p.217). The derivation of a utilization function using the notions of the "accumulated value of the state variable over time interval" and a "corresponding costate variable", is quite interesting (op. cit., pp.217-218). Roy's identity is used to derive an indirect utility function in a manner similar to Hausman (1981).

Like Train's system, the model system by Mannering and Winston consists of a nested-logit model of vehicle quantities (number of vehicles) and vehicle type choice (make, model and vintage), combined with linear utilization models. The vehicle quantity model is in itself static, but dynamics is introduced through the "log-sum"

*3 In reality many factors are collinear and the condition *ceteris paribus* is unlikely; a vehicle with a high purchase price tends to be "prestigious" and of recent vintage. For example, consider a two-vehicle household with an annual income exceeding $12,000 whose fleet includes a domestic vintage 1978 vehicle (all vintage 1978 vehicles—the latest vintage included in the study—are classified as "prestigious" in Train's study). The vintage 1978 vehicle contributes to the utility funciton by 2.705 units (1.20 due to the "dummy (variable) indicating at least one class/vintage in the pair is 'prestigious'" and 0.155 for the "number of vintage 1976-78 vehicles in pair", plus 1.35 for the "number of vintage 1976-78 vehicles in pair, for households with income greater than $12,000"). Because of this contribution, this household is less likely to trade down its vintage 1978 vehicle. The utility contribution also depicts indifference prices in which newer vintage vehicles are valued very high. For example, the purchase price of a vintage 1978 domestic subcompact (which is automatically regarded as "prestigious") can be higher than that of an otherwise identical vintage 1977 domestic subcompact by as much as $3,100 (=1.20/0.000383, assuming that the household's income is between $12,000 and $20,000). The value seems to be much higher than the typical first-year depreciation of a brand-new domestic subcompact in 1978.

terms representing the expected maximum utility gained from vehicle type choice. This is also similar to the structure of Train's model system. The set of explanatory variables used is also quite similar to that of Train. The type choice and utilization models are dynamic, involving up to two-period lag terms. These lag terms capture brand loyalty in vehicle type choice.

The possibility of "statistical correlation between vehicle-specific attributes and additive error terms in the dynamic utilization equations" is noted in the study by Mannering and Winston (1985, p.220). They use the predicted probability of make-model-year choice as an instrument in the vehicle utilization equation (op. cit., p.220). The approach is attributed to Dubin and McFadden (1984). Note that this approach does not utilize the information contained in the observed choice ; it is of interest to examine its efficiency relative to the "conditional expectation correction method" (Dubin and McFadden, 1984, p.355 ; also see Amemiya, 1978 ; Heckman, 1976, 1978, 1979 ; and Maddala, 1983) and full-information maximum likelihood estimation of the entire equations system (Nelson, 1984).

Mannering and Winston state that "we are forced to assume that the remaining error term is serially independent" in the vehicle type choice model (Mannering and Winston, 1985, footnote 19, p.220). This is unfortunate in light of the prominence of lagged dependent variables in the model system (for instance the authors note, "We find very strong brand loyalty effects as the coefficients for all lagged utilization variables are significant"; op. cit., p.225). For example, the type-choice models, specified for single-vehicle and two-vehicle households separately (as in Train, households with three or more vehicles are omitted from the analysis), contain up to two-period lagged utilization variables for the *same vehicle*, and *vehicles of the same make* as those that the household may have owned. The same lagged variables are present in the vehicle utilization models also. Evidently the authors chose to treat these lagged endogenous variables as fixed, exogenous variables ; or to treat these variables to constitute non-stochastic initial conditions. This would lead to inconsistent estimates in the likely case of serial correlation. In a subsequent paper Mannering acknowledges the "endogenous variable problem" (Mannering, 1986, p.3) : "Due to the large number of vehicle type alternatives and the difficulty in accounting for serial correlation in the presence of lagged endogenous variables in discrete choice models [see Heckman (1981a)] , it is necessary to assume that the disturbances are serially independent."

(3) Hensher, Barnard, Smith and Milthorpe's Dynamic Model System of Vehicle Holdings, Vehicle Type and Utilization

Hensher, et al. (1989), developed a nested logit model of "automobile holdings bundles" characterized in terms of the fleet size, body type and model/vintage combination (op. cit., p.146). The model system is similar to the ones by Train and by Mannering and Winston. Unlike these two systems, however, Hensher, et al., base the model development on the results of a panel survey conducted for dynamic analysis of household vehicle holdings. The panel data were collected in the Sydney metropolitan area from 1981 through 1985. The number of households in the four survey waves are 1434, 1291, 1245 and 1197, respectively. Information was gathered on each vehicle the sample households held (type, use, financial data, etc.), socio-demographics on household members, and work trip characteristics.

The model formulation attempts to capture "expectations" and "experience" effects (op. cit.) that are at work in a household's vehicle decisions made over time. These effects are both represented using geometric lag formulations. The utility associated with each "holding bundle" (called "conditional intertemporal indirect utility") is specified as a function of the expectations effect, experience effect, initial conditions, and an error term.*4 As for initial conditions, they note the unavailability of "a satisfactory method of including initial conditions in the vehicle model/vintage model" (op. cit.). "Initial conditions variables are, however, included in the body-mix/fleet-size choice sub-model and lagged indices are applicable to all models" (op. cit)., The models are thus highly dynamic with numerous lagged variables representing different effects.

Hensher, et al. note the problem of including lagged dependent variables as in Mannering and Winston (1985) : "Those past studies that have recognised the influence of state variables have done so by including a dummy variable, or set of dummy variables, for the observed choice in a previous period." The approach taken in this study is the use of instrument variables : "We avoid serial correlation due to this source by substituting the exogenous choice-determining variables in previous periods for the previous period

*4 Although it is desirable that each explanatory variable be included in both expectations and experience form, this did not prove possible because of multicollinearity. The approach taken was to, "in general, include the financial and socio-economic variables in expectations form and the vehicle attribute quality variables in experience form" (Hensher, et al., 1989).

endogenous choice variables" (op. cit.).

The estimation results of the type-mix choice model (the definition of the alternatives is not presented in the paper) led to a very small estimate of a parameter of the distributed lag formulation, "which suggests that the response reaction in automobile type choice holdings to a change in type choice determinants is predominantly instantaneous with a small additional one lag reaction" (op. cit., p.163).*5

Unlike the models by Train and by Mannering and Winston, no transaction cost variable is introduced into the model. However, the uniformly negative coefficients of "experience effects" represent general resistance to change.

Like the model by Train, the utility formulation in this study leads to questions on the treatment of vehicle costs (the model system does *not* involve a transactions model as its component): Should "vehicle capital cost" variables enter the "indirect utility equation" each year, even when there's no transaction?

Another problem is the endogeneity of the explanatory variables used to experss "experience" effects, which are the attributes of the alternatives chosen in the past. Although Hensher, et al., note the problem created by the inclusion of lagged endogenous variables, no measure is apparently taken to account for the endogenous experience effects. Consistency of the coefficient estimates, then, rests on the absence of serial correlation among the error terms.

The vehicle use model is linear, formulated with a lagged endogenous variable (lagged by one period), and a household specific error component. The model is estimated using the method of Anderson and Hsiao (1981, 1982). The initial condition is specified using exogenous variables measured during the panel period. This formulation is presumably due to Bhargava and Sargan (1983). Hensher, et al. note : "The results ... represent the first known effort to estimate a dynamic vehicle use model in which explicit allowance is made for unobserved heterogeneity within the panel period and prior to the panel (i.e., initial conditions) as well as true state dependence..." (Hensher, et al., 1989, p.167). Similar estimation results using dynamic linear models are presented later in Hensher and Simth (1990). Trip generation analysis using a similar dynamic model formulation but a different estimation method can be found in Meurs (1990).

*5 No documentation is offered on the method used to estimate this distributed lag parameter, which makes the utility function non-linear in parameters.

(4) Kitamura's Dynamic Model Systems of Vehicle Holdings and Trip Generation

Kitamura proposed several model systems of household vehicle quantity, trip generation and modal split (Kitamura, 1987, 1988, 1989a). They are all based on data from the Dutch National Mobility Panel survey, a large scale, nation-wide, general purpose panel survey initiated in 1984 and ended in 1990 (see Golob, et al., 1986 ; and van Wissen and Meurs, 1989). The emphasis of the model development is on the exploration of dynamic characteristics in household vehicle holding behavior. Vehicle type choice is outside the scope of these studies.

The number of vehicles held by a household is modeled in these studies using ordered-response probit models, with the vehicle quantity observed in the previous period represented by a set of lagged dependent variables (Kitamura, 1988). The error terms are assumed to be serially correlated in all these studies (Kitamura, 1987, 1988, 1989a). To account for the estimation problem resulting from serially correlated errors, especially when lagged dependent variables are present, Kitamura develops correction terms for his ordered-response probit models using conditional expectations of multivariate normal random variables (Heckman, 1979 ; Maddala, 1983). This appears to be the first effort where the assumption of serial correlation is explicitly introduced into a dynamic household vehicle quantity model.

Similar correction terms are used to estimate dynamic trip generation models whose errors are assumed to be correlated with those of the vehicle quantity model as well as being serially correlated. Use of correction terms enables the estimation of the model system equation by equation using readily available estimation software packages. This approach, however, is not efficient. In fact Nelson (1984) offers results that cast serious doubt on the usefulness of such sequential estimation because of their gross inefficiency. Initial results obtained by Kitamura, de Jong and Tuinenga (1991), however, indicate that these correction terms offer estimates with reasonably small standard errors, and are effective in estimating Kitamura's model systems.

The main driving force of household vehicle holdings in Kitamura's models is socio-demographic characteristics of the household, in particular the number of licensed drivers. The model in Kitamura (1987), estimated for three time points separately, contains only contemporaneous exogenous variables. Its error term is assumed to be serially correlated, however. In addition, the error is assumed to be cross-correlated with the error term of the utilization model for the previous time period $(t-1)$. Through an extensive examination of alternative model formulations, Kitamura concludes that weekly person trip generation by a household is primarily determined by socio-demographic characteristics of the household and is independent of the vehicle availability in this Dutch data set (Kitamura, 1987, p.24)

The model in Kitamura (1989a) contains exogenous variables from time t and $t-1$. The intent of the analysis is to identify the asymmetric nature of changes in household vehicle ownership. For example, an increase and a decrease in the number of drivers may influence the number of vehicles with different magnitudes as well as in different directions. By estimating a cross-sectional model, a symmetric-effect model, and an asymmetric-effect model, Kitamura reports the asymmetric effect of income, in which a decrease in income has no immediate impact on the number of vehicles while an increase in income does have positive effects.

The vehicle quantity model in Kitamura (1988) is dynamic with the vehicle quantity, trip rate and modal split from $t-1$ introduced as lagged and crosslagged dependent variables, with correction terms derived from an analysis of the tri-variate normal distribution (see Kitamura and Bovy, 1987). Also introduced into the model is a set of dummy variables representing the number of drivers in period $t-1$, and the change in the number of drivers between $t-1$ and t. The dynamic model system is applied in a simulation experiment to forecast future vehicle ownership and use under different scenarios (Kitamura and Goulias, 1991).

These model systems take advantage of the rich information contained in the large panel data. Most notable in the series of model development efforts is the attempt to obtain consistent estimates of model coefficients for ordered-response probit models with serially correlated errors and lagged dependent variables. Previous studies ignored the estimation problem (Mannering and Winston, 1985), assumed that serial correlation is not present (Hocherman, et al., 1983 ; Train, 1986), or used instrument variables instead of lagged dependent variables (Hensher, et al., 1989). This emphasis has led to the subsequent development of dynamic ordered-response probit vehicle quantity models with individual-specific error components and lagged dependent variables (Kitamura and Bunch, 1990 ; reviewed later in this paper). Incorporation of vehicle attributes such as purchase prices and fuel efficiency, remains as a part of a future extension of the model systems.

(5) Structural Equations Model Systems by Golob

Golob and his colleagues developed dynamic model systems of vehicle quantity, utilization, trip generation, mode choice, and fuel choice using structural equations models (Golob, 1989 ; Golob and van Wissen, 1989 ; Golob, 1990). The series of studies are also based on the Dutch National Mobility Panel data set.

Golob (1989) attempts to explain household vehicle quantity and trip generation by mode using household income as an exogenous explanatory factor. The structural equations models examined in this study are all cross-sectional, and the emphasis of the study is on the stability of causal relationships over time. Golob notes that "income effects on vehicle demand are channeled exclusively through vehicle ownership, and that vehicle ownership and vehicle travel explain a significant portion of public transport and bicycle demand. However, there are also direct links from income to public transport and bicycle demand." Golob also observes the stability in the relationship between vehicle quantity and vehicle trip generation. The relation between income and public transit trips is noted to be least stable.

One of the advantages of the structural equations modeling approach is its ability to identify causal relationships among many endogenous variables. This is particularly the case when the relationship to be identified is dynamic. Golob and van Wissen (1989) extends the above study to explore relationships among income, vehicle quantity and mode use at two time points. Using an estimation package (LISCOMP ; Muthen, 1987) which is capable of incorporating categorical and censored dependent variables, Golob and van Wissen represent vehicle quantity and income class as discrete variables and travel distances by mode as censored (non-negative) continuous variables. The analysis identifies "inertial", "synchronous" and "cross lag" effects that exist among these variables and reveals intricate competitive relationship among modes.[*6]

A substantially extended range of exogenous variables are included in a subsequent analysis by Golob (1990), who postulates a set of relationships among four endogenous variables. The

＊6 The effect between measurements of the same variable taken at different time points is called an "inertial" effect. "Synchronous" effects refer to those that exist among variables within one corss-section. A "cross lag" effects is one between two variables measured at different time points. For further discussions see Golob and Meurs (1987) and Kitamura (1987).

number of vehicles available to a household is assumed to affect travel times by vehicle, by public transport and by non-motorized modes. A recursive effect is assumed between travel time by vehicle and travel time by public transport. Travel time by non-motorized modes is influenced by travel times both by vehicle and by public transit, but no effect is assumed in the opposite direction. Dynamic effects are represented by cross-lagged effects from travel time by vehicle and travel time by public transport to the number of vehicles in the subsequent time period (apparently no inertial link is postulated for the number of vehicles observed over time).

The treatment of the panel data in this study is quite comprehensive. The number of vehicles in the household is treated as a discrete ordered-response variable, and travel time by mode as a truncated, non-negative continuous variable. The model system assumes serial correlation and non-zero covariances for the errors associated with the four endogenous variables. Additional variables are introduced to account for panel conditioning and period effects. The capability offered by the structural equations approach in estimating such highly involved model systems has enabled Golob to conclude that "the three household travel demand variables...are mutually interdependent. A demand model that specified any one of these variables as a function of one or more of the others (say, vehicle usage as a function of vehicle ownership) without additional 'feedback' equations is subject to endogeneity bias."

The series of studies by Golob and his colleagues have shown that structural equations modeling is effective in identifying dynamic causal relationships in panel observation. Initial limitations in the type of endogenous variables and the number of variables that can be incorporated into the model system are apparently less restrictive in more recent estimation software packages. As a tool for explorative analysis, this is by far more effective than the conventional econometric approach.

This effectiveness arises from the fact that the structural equations approach adopts an entirely different estimation principle than the econometric approach : instead of maximizing the likelihood of the observations in the data as in the econometric approach, the likelihood of the covariance matrix of the variables in the model system is maximized in the structural equations approach. How these two approaches are related is a subject for future research. In particular, whether structural equations modeling yields unbiased forecasting models, needs to be carefully determined. The problem of initial conditions is another unresolved issue here as in the econometric approach (see the reviews below of Smith, et al. and Kitamura and Bunch).

(6) Hocherman, Prashker and Ben-Akiva's Transactions Model System

The model system developed by Hocherman, et al. (1983), is formulated as a transactions model. The system consists of transaction models (specified for no-vehicle households and one-vehicle households separately), and a vehicle type choice model. The latter is nested with the transactions model in the form of a nested logit model. The model development is motivated by the recognition of the need to incorporate dynamic elements into vehicle holdings modeling, such as transaction costs (Hocherman, et al., note search costs and information costs), brand loyalty, and income effect.

Multi-vehicle households are excluded from the analysis on the grounds that only 5% of the households in Israel fell into that category. Furthermore, the possibility of disposing of a vehicle is not considered for one-vehicle households. Therefore transaction options considered are to purchase a vehicle or do nothing for a no-vehicle household, and to replace the vehicle it owns or do nothing for a one-vehicle household.

The alternatives of the vehicle type choice model are defined according to the make, model, body type, and vintage of the vehicles, resulting in a choice set of 950 alternatives (op. cit., p.138). The logarithm of the "number of elemental alternatives" is introduced for each combination of make, model, body type, and year, to account for the effect of the size of the combination as an alternative (how the "number of elemental alternatives" is exactly defined and measured is not documented in Hocherman, et al.). These measures are entered into the model as "a group of age-specific variables" because "as vehicles get older, the heterogeneity among them increases" (op. cit., p.137).

As noted earlier, the vehicle transactions models and the vehicle type choice model are nested such that the latter is applied only when a household decides to acquire (or replace) a vehicle. Some of the problems in Train's model system are thus avoided. The authors note the extreme significance of the "brand loyalty dummy" variable in the vehicle type choice model (note that this variable is endogenous). The measures of alternative size and vehicle age are also very significant. The only variable used to indicate the origin of a vehicle is a dummy veriable for vehicles made in Israel.

The household size, income, head's occupation and head's age are among the significant explanatory variables in the purchase decision model for zero-vehicle households. The travel time variables by auto and by transit are mostly significant with expected signs. The replacement decision model for one-vehicle households includes variables representing the characteristics of the vehicle owned in the previous period. In particular, the model year is a significant factor. The authors note, "An unexpected finding was that high income reduces the probability of replacing a vehicle" (op. cit., p.139). The result is contrary to the indication from Train's class/vintage choice submodel discussed earlier that owners of more expensive vehicles will replace their vehicles more frequently. "The coefficient of the expected maximum utility in this model is negative but small" (op. cit., p.140) ; apparently vehicle replacement decision is independent of the characteristics of the vehicles available in the market.

The modeling effort by Hocherman, et al. is significant because it represents the first attempt to develop a vehicle transactions model. As such, it is subject to the limitations discussed above, i.e., it does not incorporate multi-vehicle households and does not allow for vehicle disposal for one-vehicle households. In addition, no theoretical underpinning of such transactions models has been developed. These remain as the challenge of future modeling effort.

(7) Smith, Hensher and Wrigley's Beta-Logistic Transaction Model

Smith, et al. (1989) propose a binary transactions model for the replacement decision by one-vehicle households using a beta-logistic model. Beta-logistic models (Heckman and Willis, 1977) belong to a class of discrete choice models in which it is assumed that the probability that an alternative is chosen varies across individuals, even when the explanatory variables are identical, because of "unobserved heterogeneity," i.e., differences across individuals due to unmeasured, or omitted, effects. A binary logit formulation is used together with a beta distribution which accounts for this heterogeneity.

A beta-logistic model is used in Uncles (1987) for the analysis of mode choice. This application, however, inherits the limitations in the original model formulation (Heckman and Willis, 1977) that choices made over time are assumed to be independent ; that no explanatory variables change their values over the observation period ; and that choices are binary. The original beta-logistic model has been extended to represent multinomial choice (Dunn and Wrigley, 1985) and to incorporate time-varying explanatory variables (Davies, 1984). Smith, et al. (1989) adopt Davies' model in their binary analysis of household vehicle transaction. They emphasize the "separation of real intertemporal relationships from the effects of persistent inter-individual differences" (op. cit., p.2) and "allow for time varying effects and initialization of the dynamic choice process" (op. cit., p.3).

Accounting for initial conditions in dynamic models is difficult with short panel data that involve at most several observation periods. The problem stems from the fact that complete observation of behavior is unavailable before the survey period, unless accurate measurement is possible through retrospective questioning (the literature on survey research indicates accurate retrospective recollection is unlikely ; see, e.g., Kasprzyk, et al., 1989). Consequently no lagged dependent variables are available for a model formulated to describe the behavior in the initial survey period (or more periods if the model contains lagged dependent variables that are lagged by more than one period). The available knowledge on the behavior of coefficient estimates with improper treatment of initial conditions seems limited and no accepted method appears to exist (Heckman, 1981c).

The approach taken by Smith, et al. (1989) is to eliminate the correlation between "the error terms associated with an initial conditions model" and "the error terms of the within-panel model." This is done by using the lifecycle stage observed at the beginning of the panel survey as a proxy for "the experience of the household in transacting vehicles in the pre-sample period..." (op. cit., p.11).*7 Smith, et al. then proceed by expressing the parameters of their beta distributions as functions of "initial conditions dummies" defined by the initial lifecycle stage (op. cit., p.8).

The approach by Smith, et al. extends the scope of beta-logistic models. It must be noted, however, that the correlation in errors across time preiods will nonetheless persist if there exist unobserved effects that govern behavior prior to, and during, the panel period which are unaccounted for by the lifecycle measure. In other words, although Smith, et al. accounted for the heterogeneity attributable to lifecycle, this may not entirely eliminate unobserved heterogeneity. The approach, therefore, addresses only limited

*7 Preceding this is a step where "unobserved household-specific effects" are additively decomposed into two, one representing the period of observation, the other the period prior to observation, or initial conditions (Smith, et al., 1989, p.4).

aspects of the problem of initial conditions.

Another issue for further examination is the accuracy of the Maclaurin expansion used to evaluate choice probabilities (op. cit., p.7). This is due to the computational difficulties introduced when the original beta-logistic model is extended to incorporate time-varying explanatory variables. The questionable accuracy of the Maclaurin expansion when the first two terms alone are used, casts doubt on the quality of the estimates obtained in the empirical analysis.

The empirical analysis of the study uses a self-selected sample of 373 households from the Australian panel data set used in Hensher, et al. (1989). Each of these households had exactly one vehicle during four consecutive survey waves. The transaction choice examined in the study is limited to whether to replace or not to replace the vehicle the household holds. The major factors influencing replacement decision include: "activity constraints" defined as the percentage of "dedicated" or mandatory trips in the total, "locational constratints" represented by the number of workers in the central business district, "financial avoidance" which is the percent of vehicle costs that are deducted, and the age of the vehicle. Note that the age variable is endogenous.

The contribution of this work lies in its explicit treatment of unobserved heterogeneity in vehicle transaction behavior. The results offer strong evidence that heterogeneity does exist. This pioneer work, however, contains several problems, i.e., its treatment of initial conditions, endogeneity of some of the explanatory variables, and numerical approximation used in the estimation. In addition, the model is applicable only to replacement decisions made by one-vehicle households. Some of the problems are overcome in the work by Kitamura and Bunch reviewed next.

(8) Kitamura and Bunch's Ordered-Response Probit Models of Vehicle Holdings with Individual-Specific Error Components

Kitamura and Bunch (1990) examine the issue of heterogeneity versus state dependence in household vehicle holdings. This issue arises because the temporal correlation among unobserved elements may be the source of apparent state dependence. In other words, differences across individuals due to unobserved effects ("heterogeneity") that persist over time, may lead to observations in which the behavior at a time point is apparently dependent upon those at previous time points (false "state dependence"). However true state dependence is also possible (see Heckman, 1981b, for discussions on the heterogeneity versus state dependence issue).

Kitamura and Bunch note that the issue of heterogeneity versus state dependence has not been addressed in the transportation literature. This, however, does not imply that the issue is of no practical significance. In fact the issue can be crucial for tranportation planning and policy development as the following example (prepared in this review) illustrates.

> It is not uncommon in the analysis of commuters' mode choice that a large fraction of the variation in individuals' choices cannot be explained by the model using available explanatory variables. This unexplained variation is partly due to the stochastic variation inherent in the choice behavior. At the same time, it is likely that a larger fraction of the variation is due to heterogeneity which in this case would arise from unexplained preferences for travel modes, unobserved constraints in mode use, unmeasured variations in level-of-service attributes, etc.
>
> Now suppose a dynamic model of mode choice is developed using a panel data set, and suppose the model shows a strong effect of the mode choice at the previous period ($t-1$, say) upon the mode choice of the current period (t). Mode choice behavior is apparently state dependent. However, this state dependence may be false; it may be due to unobserved heterogeneity which persists over time. For example, the actual distance to the nearest bus stop can be half a mile for a commuter, whereas a zonal average of a quarter mile is used in the model estimation. This generates heterogeneity due to measurement error, leading to apparent state dependence.
>
> If mode choice behavior is state dependent, future mode choice would be a function of the current mode choice. The transit agency in charge, then, might issue free tickets or adopt other promotional schemes to temporarily increase transit use because, if mode choice is state dependent, then this change would generate changes in mode choice behavior in the future, hopefully in the direction of increased transit patronage. On the other hand, if this apparent state dependence is an artifact of heterogeneity, then such attempts to temporarily change mode choice would be of no use as it would produce no permanent effect.

Kitamura and Bunch (1990) develop an ordered-response probit model of vehicle quantity which has household-specific error components that account for unobserved heterogeneity. The model also includes variables representing the vehicle holdings of the previous time period to account for state dependence. The error term of the ordered-response probit model is defined as a sum of this household-specific component and an independent random variable. The former is assumed to be invariant over time, leading to serially correlated error terms.

The model is applied to household vehicle holdings observed at three time points, obtained from the Dutch National Mobility Panel data set (observations taken over four time points are actually involved, with the observation from the first period used as the initial condition terms for the second period). A set of three-period dynamic models is estimated in Kitamura and Bunch (1990) using the full-information maximum likelihood method with the assumption that the household-specific error components have a normal distribution, and for two different structural schemes of the error term. Two treatments of initial conditions, non-stochastic representation and the use of a predicted probability of the observed initial condition, are also examined in the study.

In the most general formulation with lagged dependent variables and "one-factor" error terms (in which period-specific constants are applied to the error components), significant exogenous variables are the square-root of household income, number of drivers, an indicator of transit service levels, and education. The lagged dependent variables representing the vehicle quantity of the previous period, are also highly significant.

The examination of alternative hypotheses on heterogeneity and true state dependence indicates that heterogeneity and true state dependence are both present in household vehicle holding behavior. However, the effect of state dependence is shown to be much more significant than that of heterogeneity. The study also shows that estimation results are sensitive to the formulation of the error term and the treatment of initial conditions, although "the coefficient estimates themselves may be robust." Kitamura and Bunch further note, "we caution against jumping to the conclusion that simply including lagged dummies is an adequate solution to the dynamic modeling problem. This may lead to erroneous conclusions about true state dependence and heterogeneity, which in turn may result in inaccurate forecasts using dynamic models" (op. cit., p.494).

3. FINDINGS OF THE REVIEW

Two major conclusions have emerged from this review :

- Many "dynamic" vehicle holdings models are formulated from the premise that, at any point in time, a household holds an optimal fleet of the most desirable size and composition. These "vehicle holdings" and "type choice" models assume that the household maximizes "utility" at all time points. However, most models make no reference to the time-frame in which such utility may be defined*8. Household vehicle ownership is not viewed as a process that evolves over time.
- Behavioral principles that may govern transaction decisions made over time have not been established, and no rigorous model has been formulated for the *process* of household vehicle holdings (note that transaction decisions pertain to vehicle acquisition, replacement, and disposal, which in turn determine the size and composition of the household vehicle fleet). Little is known on the time horizon in the household's transaction behavior and planning, or on the decision mechanism which determines the duration a vehicle will be held by a household.

Implied by the first conclusion is the possibility that many existing household vehicle holdings models may be fundamentally mis-specified with inadequate structural representations. This would lead to incorrect elasticities and forecasts.

The second conclusion points to the need for further research in theoretical formulation of household vehicle transaction behavior and quantitative model development. In addition, in light of the limited knowledge on household vehicle transaction behavior, further explorative survey research is most definitely required. Indeed many questions remain unanswered. For example, why do some households purchase brand-new vehicles and hold them until their usable life depletes, while others replace their vehicles every two years or so? When and how does a household decide to replace a vehicle? Why do some households purchase brand-new vehicles, while others purchase used vehicles that are equally expensive? How does a household decides whether to purchase a durable vehicle and hold it for a long period, or to purchase a few, less durable vehicles within the same period? In particular, how much of vehicle transaction behavior is pre-plan-

*8 Although vehicle choice is formulated to be conditional on the household's current vehicle holdings (as indicated by the inclusion of "transaction dummy" and other lagged endogenous variables), the characteristics of the vehicles owned are not fully incorporated in the model as descriptors of decisions to replace them.

ned by the household and what is the planning horizon? Well designed surveys should offer valuable information that will fill the many voids in the currently available knowledge on vehicle transaction and holdings.

Additional conclusions are obtained in the assessment of the current state-of-the-art in dynamic household vehicle holdings modeling :

- The statistical methods used to estimate previous "dynamic" models are in most cases inadequate. Only a few studies properly account for the presence of both serially correlated errors and lagged dependent variables.
- Transaction dummy variables used in many "dynamic" vehicle holdings models are of questionable nature.
- The endogenous nature of the fixed costs of vehicle acquisition and holdings is not well represented.
- No full-fledged household vehicle transactions models exist. Only two transactions models are identified in the literature, and they are fromulated only for one-vehicle households or no-vehicle households. Acquisition, replacement and disposal decisions made by multi-vehicle households have never been modeled.
- The alternatives of a vehicle type choice model for multi-vehicle households may not be mutually independent because some of the alternatives may share the same make and model with the vehicles currently owned by the household. This may require complex nesting of the alternatives that is not incorporated in the existing models.
- Practically all vehicle-holdings and type-choice models assume that a household holds at most two vehicles. Although this may be a reasonable assumption today in many countries, basing long-term forecasts on this assumption may be a dangerous proposition (in fact a significant number of households own three or more vehicles in California).

The last two limitaions are presumably due to the aforementioned fact that these models treat household vehicle holding decision as a simultaneous choice that concerns the entire household fleet. When the number of vehicles exceeds two, the number of alternatives to be considered in these models becomes astronomical. For example, as noted earlier Train's model system has 120 vehicle class/vintage combinations. There are, therefore, potentially 14,400 ($=120^2$) alternatives to be considered by two-vehicle households, and 1,728,000 ($=120^3$) by three-vehicle households! And these alternatives are not independent!

4. TOWARD THE DEVELOPMENT OF DYNAMIC VEHICLE TRANSACTION MODELS

Disaggergate dynamic models are applied to forecasting through procedures that are fundamentally different from those for cross-sectional models. Little is known about forecasting with dynamic models, simply because the concept is new, with only a few dynamic models of household vehicle holdings and mobility developed so far. It is nevertheless believed that forecasts obtained from a dynamic model will offer rich information about future vehicle holdings and use.

(1) Reasons for Dynamic Modeling

There are many behavioral, as well as statistical, reasons to favor dynamic models (Heckman, 1981a ; Goodwin, Dix and Layzell, 1987 ; Goodwin, Kitamura and Meurs, 1990 ; Kitamura, 1990). Goodwin and Mogridge (1981) note the "resistance to change" as one of the dynamic aspects of vehicle ownership behavior that previous cross-sectional models have failed to capture. Factors that motivate the use of dynamic models include :

- asymmetry in the magnitude of response, i.e., elasticity may be different depending on the direction of change (between income incerase and income decrease, say),
- asymmetry in the speed of response — the time lag since the time when a change takes place in the travel environment and the time a response takes place—may be different depending on the direction of change,
- past experience or future expectation may influence behavior (e.g., brand loyalty),
- effects of temporal changes and trends need to be represented (e.g., national economy, increasing population of licensed drivers), and
- changes in the composition of a national or regional vehicle fleet over time are desired to be forecast.

For empirical examples of dynamic aspects of travel behavior, see Golob and Meurs (1987), Goodwin (1987), Hensher, et al. (1989), Kitamura (1987), and Kitamura and van der Hoorn (1987).

As noted earlier, aggregate time-series models, although dynamic, do not capture the causal relations that govern the behavior of individual households. This limits their accuracy, versatility, and policy sensitivity. Problems associated with disaggregate, cross-sectional choice models have also been pointed out. Daly and Gunn note that models based on cross-sectional data fail to "incorporate significant time-dependent changes, e.g. in tastes, attitudes, etc." (Daly and Gunn, 1985, p.7). In addition, cross-sectional discrete choice models may be flawed because :

- cross-sectional elasticities evaluated using a cross-sectional model may not be identical to longitudinal elasticities associated with behavioral changes of individual households, thus may not offer accurate forecasts,
- the presence of unobserved variables influencing vehicle holdings which are correlated with observed variables, will lead to biased coefficient estimates, which in turn will produce false elasticities and forecasts, and
- the "utility maximization" principle in which these models find their behavioral basis, assumes that each household at the time of observation is in equilibrium with an optimum number and types of vehicles.

The last assumption that a household, at any randomly selected point in time, maintains an optimum fleet, is quite restrictive in light of behavioral inertia, incomplete information, and asymmetric behavior. It is also questionable in light of the sequential and dynamic nature of household decision making (one could also argue that, if a household "optimizes" its vehicle holdings over a certain span of time, then that optimal holdings pattern may not imply that cross-sectional optimality is maintained all the time).

Another argument against optimality in household vehicle holdings can be developed by studying the sequential nature of decision making among multi-vehicle households. As noted earlier, it is not likely that a household acquires or replaces more than one vehicle at one time ; more often an older vehicle a multi-vehicle household owns is replaced while the other, newer vehicles continue to be maintained. It can be conjectured that *a multi-vehicle household does not simultaneously choose its fleet* ; a set of vehicles a household holds is not chosen as a set, but chosen one at a time, sequentially over time. If this choice is an optimization process at all, then it is more likely to be a *conditional optimization process, given the rest of the vehicles in a household's fleet.* The formulation of existing vehicle type choice models is not consistent with this depiction of household decision making. If this depiction is in fact correct, then most existing vehicle holdings models cannot be called causal models.

(2) Reasons for Vehicle Transaction Models

Form the viewpoint that observed household vehicle holdings represent the cumulative outcome of the process of acquiring, replacing and disposing of household vehicles, it is natural to model household vehicle holdings through dynamic transactions models. These models offer a more realistic representation of household decision making by replicating the decision process over time ; with a dynamic transactions model it is no longer necessary that a household at one time point selects and acquires an optimum fleet of vehicles to hold.

In several respects, a dynamic transactions model is similar to a dynamic, state dependent vehicle holdings model (e.g., Hensher and Wrigley, 1986 ; Kitamura, 1988). For example, both models depict vehicle quantity at time t as dependent on that of time $t-1$; they are similar in the way they explain the decision to acquire an additional vehicle or to dispose of a vehicle currently owned. The former, however, offers several advantages that the latter does not. The advantages are :

- a fully developed transactions model, which predicts demand for purchase, resale, and scrappage, can serve as a component of a vehicle market model,
- transaction costs can be meaningfully incorporated,
- asymmetry in transaction costs can be represented (disposing of a vehicle involves much less transaction costs than acquiring one), and those costs can be compared with those of no transaction (maintaining a vehicle, once acquired, requiers a relatively small amount of cost),
- a transactions model treats the vehicle holding duration as a endogenous variable. This offers the opportunity to model a household's long-term decision on vehicle holdings, and allows to treat fixed costs as an endogenous variable, and
- a dynamic transactions model allows a meaningful incorporation of vehicle utilization as a factor influencing vehicle transaction decision.

A fully-developed transactions model system, with added dimensions of vehicle type choice and scrappage choice, is applicable to forecast new vehicle sales and predict aging and rejuvenation of a national or regional vehicle fleet. As noted earlier, this extends the model's applicability to the estimation of the market penetration of alternative-fuel vehicles or electric vehicles.

(3) Research Areas

Unlike models of vehicle quantity, vehicle type choice and utilization, household vehicle transactions models are few and far apart, presumably reflecting the difficulty in obtaining suitable data. As reviewed above, the few examples available in the literature adopt binary choice models, capturing only limited aspects of household transaction behavior.

The development of a full-fledged vehicle transactions model system requires a considerable amount of theoretical development. In fact consideration of household vehicle holding behavior as a transaction process reveals the weakness of the economic foundation of many "utility maximizing" vehicle quantity and vehicle type choice models. Of particular importance is the determination of vehicle holding costs. Questions that need to be addressed include : What cost should be used as the fixed cost (per year, say) of a vehicle when a household considers to acquire the vehicle? How would this cost be different from the fixed cost of the same vehicle if a household which already owns it considers to replace it? As discussed earlier, the issue is further complicated due to the endogenous nature of fixed costs, i.e., a household's choice of holding duration influences fixed costs. Much research is needed for the formulation of acquisition, disposal, and replacement decision models.

Heterogeneity is another important issue. As noted earlier, it is likely that vehicle transaction behavior varies greatly from household to household. If behavioral differences are due to heterogeneity, and if unobserved factors are invariant over time and correlated with measured variables, then estimates of model coefficients are likely to be biased. Identification of heterogeneity effect in discrete choice models, however, requires elaborate models and estimation procedures. A few examples that are currently available (Kitamura and Bunch, 1990 ; Smith, et al., 1989) offer a starting point.

Another issue to be addressed in the development of a full transactions model system concerns the structure of transaction decision. The three types of transaction—acquisition, disposal and replacement—involve two dimensions that are qualitatively different : vehicle quantity (acquisition and disposal) and vehicle quality (replacement). These two aspects are most probably governed by two different decision mechanisms, thus a transitions model system should be structured to reflect them. Empirical studies exist that suggest the causal factors underlying vehicle acquisition (Town, 1983) and scrappage (Ghering, Teulings and Cramer, 1989 ; Manski and Goldin, 1983). Vehicle replacement, on the other hand, is an aspect not well explored in the transportation planning field, and empirical evidence must be sought in economics, consumer behavior, and other related fields.

The proposed effort toward a dynamic vehicle transactions model system is a novel and undoubtedly challenging effort. Its economic foundation must be laid out, a model structure formulated, and estimation procedures developed. Yet it is believed that the advantages it offers more than warrant such a developmental effort. Integrated into a dynamic simulator, a transactions model would offer many forecasting capabilities that are not offered by currently available vehicle holdings models.

Acknowledgments

The author benefited from comments made on earlier versions of this paper by David S. Bunch, Andrew Daly, Gerard C. de Jong, (who contributed Footnote 1), Thomas F. Golob, and Jereon Klooster. Most of the work was done in September, 1990, while the author was at Hague Consulting Group, the Hague, the Netherlands. Funding was provided by Rijkswaterstaat, Dienst Verkeerskunde, the Netherlands Ministry of Transport.

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(Received November 11. 1991)