ALTERNATIVE TRAVEL BEHAVIOR STRUCTURES

STRUCTURE OF PASSENGER TRAVEL DEMAND MODELS

Moshe E. Ben-Akiva, Transportation Systems Division,
Massachusetts Institute of Technology

This study is concerned with the structure of travel demand models. Two alternative structures are defined, simultaneous and recursive, that are based on different hypotheses about the underlying travel decision-making process. The simultaneous structure is very general and does not require any specific assumptions. The recursive structure represents a specific conditional decision structure, i.e., the traveler is assumed to decompose his trip decision into several stages. Thus, simultaneous and recursive structures represent simultaneous and sequential decision-making processes. Theoretical reasoning indicates that the simultaneous structure is more sensible. Moreover, if a sequence assumption is accepted, there are several conceivable sequences, and generally there are no a priori reasons to justify a selection among them. A simultaneous model, however, is very complex because of the large number of alternatives that a traveler faces in making his trip decision. An empirical study is conducted to investigate the feasibility of a simultaneous model and to appraise the sensitivity of predictions made by a travel demand model to the structure of the model. The data set for the study was drawn from conventional urban transportation study data. Included in a trip decision are destination and mode choices. With the same data set, three disaggregate probabilistic models are estimated for the shopping trip purpose: a simultaneous model and two recursive models with two possible sequences. The simultaneous model proved to be feasible in terms of the computational costs and the estimation results. The results of the recursive models showed that estimated model coefficients vary considerably with different model structures. The simultaneous model structure is recommended.

•DECISION-MAKING in transportation planning, as in any other planning activity, requires the prediction of impacts from proposed policies. One of the inputs to the prediction process is the demand function that describes consumers' expected use of transportation services.

The approach most widely used to predict passenger travel demand (6, 12, 13) is the aggregate urban transportation model system (UTMS). [A model can be expressed mathematically in many different ways. The word structure refers to the format of writing a model that has a behavioral interpretation. A model can be used for forecasting in a format that has no behavioral interpretation. The distinction between direct and indirect travel demand model (12) is based on the format used for forecasting and does not necessarily imply a different behavioral interpretation.] It is characterized by a recursive, or sequential, structure that represents a conditional decision-making process; i.e., it is assumed that the traveler makes his trip decision in several stages. A trip decision consists of several travel choices, e.g., mode and destination. In a recursive structure the travel choices are determined one at a time, in sequence.

Two recent developments in modeling travel demand have stimulated the present study. The first was the recognition that the representation of the trip decision as a sequential process is not completely realistic. It has been argued (9) that the trip decision should be modeled simultaneously with no artificial decomposition into sequential stages. Attempts to develop simultaneous models followed the conventional approach of aggregate demand analysis, in which the quantity demanded is taken as a continuous variable (5, 8, 16, 17). The second development was the introduction of disaggregate probabilistic demand models that relied on a more realistic theory of choice among qualitative trip alternatives. However, all the disaggregate models that were developed could be used either for a single stage of the UTMS (18) or, more recently, for all the stages, but again with the assumption of a recursive structure (4).

The common denominator of these two developments is clearly a disaggregate probabilistic simultaneous travel choice model. However, because of the large number of alternative trips that a traveler faces and the large number of attributes that describe each alternative, a simultaneous model can become very complex. This raises some important issues concerning the feasibility of a simultaneous model and the sensitivity of travel predictions to the simplifying assumption of a recursive structure.

The purpose of this research is to investigate these issues and to recommend a strategy for structuring travel demand models. This study explores alternative travel demand model structures and their inherent behavioral assumptions. An empirical study is conducted to calibrate the alternative models and furnish some evidence of the feasibility and desirability of disaggregate simultaneous travel choice models.

MODELS

In general, models are simplified representations of some objects or phenomena. This study deals with econometric models, i.e., mathematical relationships describing economic phenomena of observed variables and unknown but statistically estimable parameters. We use models to better understand real-world phenomena and to make decisions based on this understanding.

Travel demand models are used to aid in the evaluation of alternative policies by predicting the consequences of alternative policies or plans. A model that determines travel consequences independently of the characteristics of various policy options obviously cannot be used to evaluate those options (unless policies are, in fact, irrelevant to consequences).

Specification of a travel demand model involves some assumptions about the relationships among the variables underlying travel behavior. Predictions made by the model are conditional on the accuracy of the behavioral assumptions and, therefore, are no more valid than the assumptions.

A model can duplicate the data perfectly, but may serve no useful purpose for prediction if it represents erroneous behavioral assumptions. For example, consider a policy that will drastically change present conditions. In this case the future may not resemble the present, and simple extrapolation from present data can result in significant errors. However, if the behavioral assumptions of the model are well captured, the model will be valid under radically different conditions. It should be noted that this discussion is very general. Behavioral assumptions are a matter of degree inasmuch as there are many levels of detail at which behavior could be described. (For example, sensitivity to policies could be regarded as a gross level of behavioral assumptions.)

The requirement that models be policy-sensitive is necessary but not sufficient for planning purposes. An additional requirement is that the models be based on valid behavioral assumptions. A model could be policy-sensitive but be useless for policy analysis if it is not based on valid assumptions.

In general, it is impossible to determine the correct specification of a model from data analysis. It should be determined from theory or a priori knowledge based on experience with, and understanding of, the phenomenon to be modeled. Frequently there is no comprehensive theory that will prescribe a specific model. Moreover, important variables are often missing because of lack of data or measurement problems. There are other potential problems that involve the different kinds of data that could be used to estimate the model (e.g., time series versus cross section, attitudinal versus engineering) and the need to use a mathematical form that is amenable to a feasible statistical estimation technique.

The result is that we may have several alternative models to evaluate. Unfortunately, "in statistical inference proper, the model is never questioned.... The methods of mathematical statistics do not provide us with a means of specifying the model" (11). In other words, given several alternative models and a data set, statistical inference will not be conclusive on which model represents the "true" process. This does not say, however, that the data do not play a role in the selection among models. At various stages of an empirical analysis, some aspects of assumptions that do not agree sufficiently with the findings may be revised. More generally, accumulated past evidence from empirical studies influences the formulation of the assumptions of new efforts.

Suppose that we are faced with a choice among some alternative models that were not discarded in the course of data analysis. If these alternative models are based on different sets of assumptions, we should decide which set makes the most sense according to a priori knowledge about behavior, along with goodness-of-fit measures and statistical significance tests.

In modeling passenger travel demand, we are concerned with the trip-making behavior of individuals or households. Hence, a prerequisite to travel demand modeling is a set of assumptions that describe the process of trip-making decisions of these individuals or households. The basis for comparing different travel demand models should be the reasonableness (or the correspondence with a priori knowledge) of the behavioral assumptions of each model.

In this study we consider two travel demand model structures: simultaneous and recursive, each representing a different travel behavior assumption. We assume a priori that a simultaneous structure is appropriate. However, we also consider recursive models, in order to evaluate the significant differences between the two.

Disaggregate Models

The behavioral assumptions of a demand model take the perspective of an individual as he weighs the alternatives and makes a choice. An aggregate model based on consumers aggregated by location or socioeconomic category could be constructed. However, aggregation during the model construction phase will only cloud the actual relationships and can cause a significant loss of information (7, 14). An aggregate model that is based on averages of observations of socioeconomic types and geographic location would not necessarily represent an individual consumer's behavior, and the same relationships may not hold in another instance or another location. For planning purposes, we are concerned with the prediction of the behavior of aggregates of people. However, in principle, aggregation to a level required for forecasting can always be performed after estimation.

In urban transportation planning (UTP) studies the data are collected on the disaggregate level and aggregated to a zonal level for use in the conventional UTMS (13). Using this disaggregate data directly in disaggregate travel demand models can bring about large savings in data collection and processing costs. Because the data are used in the original disaggregate form and are not aggregated to the zonal level, a comprehensive home interview survey is not essential as is the case of conventional aggregate models. Previous work with disaggregate travel demand models (4, 18) indicates that it is a feasible modeling approach. Thus, disaggregate travel demand models have several practical advantages over aggregate models:

1. Possible reduction in data collection costs,
2. Transferability of the models from one area to another, and
3. Possibility of using the same set of models for various levels of planning.

The problem of aggregating a disaggregate model for forecasting requires more research. However, some simplified methods, such as the use of homogeneous market segments (1, 12), are available and can be used.

Choice Theory

In general, models that describe consumer behavior are based on the principle of utility maximization subject to resource constraints. Conventional consumer theory, however, is not suitable for deriving models that describe a probabilistic choice from a qualitative or discrete set of alternatives. Therefore, the travel demand models developed in this study rely on probabilistic choice theories (2, 3, 4, 10).

It is assumed that the consumer selects the alternative that maximizes his utility. The probabilistic behavior mechanism is a result of the assumption that the utilities of the alternatives are not certain but are random variables determined by a specific distribution.

The choice probability of alternative i is

$$P(i:A_t) = \text{Prob}[U_{it} \geq U_{jt}, \forall j \in A_t]$$

where

A_t = set of alternative choices available to consumer t and
U_{it} = utility of alternative i to consumer t.

The utilities are essentially indirect utility functions that are defined in theory as the maximum level of utility for given prices and income. In other words, U_{it} is a function of the variables that characterize alternative i, denoted as X_i, and of the socioeconomic variables describing consumer t, denoted as S_t. Thus, we can write

$$U_{it} = U_i(X_i, S_t)$$

The set of alternatives A_t is mutually exclusive and exhaustive such that only one alternative is chosen. The deterministic equivalent of this theory is simply a comparison of all alternatives available and selection of the alternative with the highest utility.

The mathematical form of the choice model is determined from the assumption about the distribution of the utility values. The coefficients of the utility functions are estimated with a cross section of consumers and by observations of actual choices. Therefore, the observed dependent variable has a value of zero or one. The forecast of the model is a set of probabilities for the set of alternatives.

The Multinomial Logit Model

There are a number of probabilistic choice models that are available; two of the most popular and most useful are the probit and logit models. The multinomial logit model, as described below, appears to be superior to probit because of the computational time requirements.

The logit model (2, 4) is written as follows:

$$P(i:A_t) = \frac{e^{U_i(X_i,S_t)}}{\sum_{j \in A_t} e^{U_j(X_j,S_t)}}$$

With disaggregate cross-sectional data, the logit model is estimated by using the maximum likelihood method (15).

The Travel Choices

A trip decision for a given trip purpose consists of several choices: trip frequency, destination, time of day, mode, and route. In a probabilistic choice approach we are interested in predicting the joint probability $P(f,d,h,m,r{:}FDHMR_t)$, which is defined as the probability that individual or household t will make a trip with frequency f to destination d during time of day h via mode m along route r. The set of alternatives $FDHMR_t$ consists of all possible combinations of frequencies, destinations, times of day, modes, and routes available to individual t.

For the purpose of presentation we consider only two travel choices: destination and mode. The set of all alternative combinations of destinations and modes is denoted as DM. (For simplicity we drop the subscript t.) We can partition this set according to destination to get the sets of alternative modes to a given destination M_d. If modes and destinations have no common attributes and the two choices are independent, then M_d is independent of d and can be written as M. However, this is an unrealistic assumption because there are many attributes, such as travel time, that are in fact characterized by all the travel choices. Therefore, it is assumed that $M_d \neq M_{d'}$. We are interested here in predicting the joint probability P(d, m:DM).

The Alternative Structures

If we assume that the two choices are independent, we write the following independent structure:

$$P(d{:}D) = \mathrm{Prob}[U_d \geq U_{d'},\ \forall\, d' \epsilon D]$$

$$P(m{:}M) = \mathrm{Prob}[U_m \geq U_{m'},\ \forall\, m' \epsilon M]$$

and

$$P(d, m{:}DM) = P(d{:}D) \times P(m{:}M)$$

where

D = set of alternative destinations,
M = set of alternative modes,
U_d = utility from destination d, and
U_m = utility from mode m.

(This is an unrealistic structure for travel demand, but it is presented for the purpose of comparison with other structures.)

Consider a conditional decision-making process in which, for example, destination is chosen first and then, conditional on the choice of destination, a mode is chosen. For this assumption we write the following recursive structure:

$$P(d{:}D) = \mathrm{Prob}[U_d \geq U_{d'},\ \forall\, d' \epsilon D]$$

$$P(m{:}M_d) = \mathrm{Prob}[U_{m|d} \geq U_{m'|d},\ \forall\, m' \epsilon M_d]$$

and

$$P(d, m{:}DM) = P(d{:}D) \times P(m{:}M_d)$$

where

M_d = set of alternative modes to destination d and
$U_{m|d}$ = utility from mode m given that destination d is chosen.

Assuming that the choice of mode is dependent on the choice of destination and vice versa, we can write the following simultaneous structure:

$$P(d{:}D_m) = \mathrm{Prob}[U_{d|m} \geq U_{d'|m},\ \forall\, d' \epsilon D_m]$$

$$P(m{:}M_d) = \mathrm{Prob}[U_{m|d} \geq U_{m'|d},\ \forall\, m' \epsilon M_d]$$

where D_m = the set of alternative destinations by mode m.

In the independent and recursive structures we predict the joint probability by multiplying the structural probabilities. However, in a simultaneous structure, the two conditional probabilities are insufficient information to predict the joint probability. Therefore, we need to estimate either a marginal probability, say P(d:D), or, directly, the joint probability. The problem with the first approach is that we need to define a

U_d where we originally specified $U_{d|m}$. The second approach requires a specification of the joint utility U_{dm}, in which the combination dm is considered as a single alternative. This approach is more logical because it corresponds with the notion of a simultaneous choice. Hence, in the simultaneous structure, we need to estimate the following choice probability:

$$P(d, m:DM) = \text{Prob}[U_{dm} \geq U_{d'm'}, \forall\, d'm' \epsilon DM]$$

Given the joint probability we can derive any desired marginal or conditional probability. For example,

$$P(m:M) = \sum_{d \epsilon D_m} P(d, m:DM)$$

and

$$P(d:D_m) = \frac{P(d, m:DM)}{P(m:M)}$$

<u>Alternative Models</u>

For simplicity, we write the probabilities in this section without the notation for the set of alternatives. In other words, we will write $P(d, m:DM_t)$ as $P_t(d, m)$, and $P(m:M_{dt})$ as $P_t(m\,|\,d)$.

In the prediction of joint probability $P_t(f, d, m, h, r)$, the set of alternatives consists of all possible trips or all possible combinations of frequencies, destinations, modes, times of day, and routes available to individual t. In a simultaneous structure of the logit model, this will be the definition of the set of alternatives, and the choice probability will be for an alternative f, d, m, h, r combination.

The joint probability can be written as a product of marginal and conditional probabilities:

$$P_t(f) \times P_t(d\,|\,f) \times P_t(m\,|\,f, d) \times P_t(h\,|\,f, d, m) \times P_t(r\,|\,f, d, m, h)$$

and can be written in many ways:

$$P_t(f) \times P_t(h\,|\,f) \times P_t(m\,|\,f, h) \times P_t(d\,|\,f, h, m) \times P_t(r\,|\,f, h, m, d)$$

In a recursive structure we will use a logit model for each probability separately and arrange the set of alternatives for each choice according to the sequence implied by the way we write the product. For example, the probability $P_t(m\,|\,f, d)$ is the probability of choosing mode m, when the set of alternatives consists of the modes available to individual t, to destination d at trip frequency f.

Calibrating a sequential model requires assumptions beyond the definitions of the relevant sets of alternatives for each choice. Consider, for example, the choice model for the probability $P_t(m\,|\,f, h)$. The problem is how to include in the model all the variables that for a given mode vary across destinations. Clearly, we cannot use all these variables as separate variables with their own coefficients. Therefore, we need to construct composite variables. There are many possible composition schemes. In addition there is the possibility of constructing the composite variables from several original variables together such that the trade-off among them is kept constant in all choices. For example, for an alternative destination we can define a generalized price by each mode that is a function of travel time and travel cost; then we aggregate across destinations to create a composite generalized price that is specific only to mode.

THE EMPIRICAL STUDY

The data for this study were taken from a data set prepared for the Metropolitan

Washington Council of Governments (WCOG). The data set was combined from a home interview survey conducted in 1968 by WCOG and a network (i.e., level of service) data set assembled by WCOG and R. H. Pratt Associates.

The scale and the objectives of this empirical study dictated that we use only a small subsample of the original data set for a single trip purpose, shopping. The data were kept in the disaggregate form where the observation unit is a household. This follows the assumption that the behavioral unit for a shopping trip is also a household.

Hence, the disaggregate data were exclusively drawn from conventional urban transportation study data. Specifically, trip and socioeconomic data from a home interview survey, level-of-service data from coded networks, and other user cost data customarily collected by transportation planning agencies were used.

Because our purpose is to evaluate the sensitivity of the predictions to the structure of the model, we consider in the empirical work only the joint probability of destination and mode (given that a trip is taken)—$P_t(m, d)$. We model this joint probability with three alternative structures: a simultaneous logit model that estimates this probability directly and the following two possible recursive model sequences:

$$P_t(d) \times P_t(m \mid d)$$

and

$$P_t(m) \times P_t(d \mid m)$$

where a logit model is applied to each probability separately. We also investigate alternative ways of constructing composite variables for the marginal probability.

The justification for separating destination and mode choices from other choices is as follows: The choice of time of day is assumed to be insignificant because the sample included only off-peak shopping trips. Route choice is not reported in the available data. The actual frequency is also not reported. Trips are reported for a 24-hour period. Therefore, the observed daily frequency is either 0 or 1 (and in a few cases 2). If we use an aggregate of households, this is sufficient information to compute an average frequency. For a disaggregate model the actual frequency is not available. We are forced to assume that the choices of mode and destination are independent of the actual frequency and, therefore, can be modeled separately. Note that with 0, 1 daily frequencies, $P_t(f = 1 \mid d, m) = 1$ and $P_t(f = 0 \mid d, m) = 0$.

The sample used for estimation consists of 123 household home-shop-home round trips that were selected randomly from a home interview sample in the northern corridor of Metropolitan Washington. Each household has a choice between two modes, the family car and bus, and several shopping destinations, ranging from one to eight according to the location of the household residence. It is important to note that we need to consider only alternatives that have positive choice probabilities. Therefore, a shopping location that is too far or a mode that is unsafe and consequently not feasible, or assumed to have negligible choice probability, need not be included in the set of alternatives.

The data consist of level-of-service variables by mode and destination, shopping opportunities by destination, and socioeconomic characteristics of the household. Each observation included the value of the variables for all the relevant alternatives for this household and the observed choice.

Specification of the Variables

The following list gives the definitions of the variables:

TO_{dm} = out-of-vehicle travel time to destination d by mode m (in minutes)
TI_{dm} = in-vehicle travel time to destination d by mode m (in minutes)
$\frac{C_{dm}}{INC}$ = out-of-pocket cost to destination d by mode m (in cents), divided by household income
E_d = wholesale-retail employment (number of jobs)
$DCBD_d$ = CBD specific dummy variable for destination d

$$= \begin{cases} 1 \text{ for } d = \text{CBD} \\ 0 \text{ otherwise} \end{cases}$$

DA_m = automobile-specific dummy variable for mode m

$$= \begin{cases} 1 \text{ for } m = \text{automobile} \\ 0 \text{ for } m = \text{bus} \end{cases}$$

$DINC_m$ = automobile-specific income variable for mode m

$$= \begin{cases} \text{INC for } m = \text{automobile} \\ 0 \text{ for } m = \text{bus} \end{cases}$$

The level-of-service variables are generic rather than mode-specific. (This would increase the number of level-of-service variables from three to six.) In this case, the marginal rates of substitution among level-of-service variables will differ for alternative modes. From a theoretical point of view it makes more sense to have equal marginal rates of substitution. The differences among modes that are not explained by the level-of-service variables included, such as differences in comfort and safety, are accounted for by the mode-specific dummy variables. This assumption has been tested (4) from an empirical point of view. A mode choice model was calibrated with mode-specific level-of-service variables, and it was found that the modal coefficients were not significantly different. This supports the a priori assumption of equal marginal rates of substitution.

The alternative models estimated are presented in terms of the log of the odds of choosing one alternative over another. That is, the models are expressed as

$$\text{Log}\,\frac{P(i)}{P(j)} = \sum_{k=1}^{K} (X_{ik} - X_{jk})\,\hat{\theta}_k$$

where

$P(i)$ = choice probability of alternative i,
X_{ik} = k th explanatory variable for alternative i, and
$\hat{\theta}_k$ = coefficient estimate of the k th explanatory variable.

The Simultaneous Model

In the simultaneous model presented below, the joint probability of destination and mode (given that a trip is made) was directly estimated. The sets of alternatives consist of combinations of mode and destination. There are from two to 16 alternatives for each observation. The results that were obtained are as follows:

$$\begin{aligned}\text{Log}\,\frac{P(d,m)}{P(d',m')} = {} & \underset{(0.970)}{-1.36}\ (DA_m - DA_{m'}) \underset{(0.0202)}{- 0.0633}\ (TO_{dm} - TO_{d'm'}) \\ & \underset{(0.0116)}{- 0.0164}\ (TI_{dm} - TI_{d'm'}) \underset{(0.0216)}{- 0.0757}\ (C_{dm}/INC - C_{d'm'}/INC) \\ & \underset{(0.158)}{+ 0.114}\ (DINC_m - DINC_{m'}) \underset{(0.0000875)}{+ 0.000171}\ (EMP_d - EMP_{d'}) \\ & \underset{(0.554)}{+ 0.316}\ (DCBD_d - DCBD_{d'}) \end{aligned} \tag{1}$$

$L^*(0) = -277.678$
$L^*(\hat{\theta}) = -207.380$
$\rho^2 = 0.25$
$\bar{\rho}^2 = 0.25$

where

$P(d, m)$ = joint probability of choosing destination d and mode m,
$L^*(0)$ = log likelihood for 0 coefficients,
$L^*(\hat{\theta})$ = log likelihood for the estimated coefficients,
ρ^2 = coefficient of determination
$= 1 - \dfrac{L^*(\hat{\theta})}{L^*(0)}$, and
$\bar{\rho}^2$ = ρ^2 adjusted for degrees of freedom,

and the numbers in parentheses below the model coefficients are standard errors.

All the signs and the relative values of the coefficient estimates are as expected. The pure automobile effect, θ_{DA}, gave a minus sign; however, it should be interpreted as a transit bias only together with the coefficient of the automobile-specific income variable, which is positive. Out-of-vehicle travel time is on the order of four times more onerous than in-vehicle travel time. The standard errors of the coefficients of the automobile specific income and the CBD dummy variables are relatively large; however, they have the expected signs.

Alternative Recursive Models

Three alternative composition rules were used: weighted prices, weighted generalized price, and log of the denominator. The composite variables are defined when the estimation results are presented. In addition, there are two possible sequences:

1. $d \rightarrow m$:d followed by m, and
2. $m \rightarrow d$:m followed by d.

Hence, we estimated a total of six recursive models, three for each sequence. The estimation starts with the conditional probability, i.e., $P(m|d)$ in the first sequence and $P(d|m)$ in the second sequence. Then, the marginal probability is estimated by using the composite variables that are calculated with results from the conditional probabilities. Note that for each sequence there are one conditional probability and three marginal probabilities for the alternative composition rules.

Sequence $d \rightarrow m$: The Conditional Probability

The conditional probability presented below is the equivalent of a trip interchange modal-split model (20). The model predicts the probability of mode choice for a given destination (and given that a trip is made). The sets of alternatives consist of the bus and automobile modes for the chosen destination. The estimation results are as follows:

$$
\begin{aligned}
\text{Log}\,\frac{P(m|d)}{P(m'|d)} = &\underset{(1.33)}{-0.639}\,(DA_m - DA_{m'}) \underset{(0.0237)}{- 0.0515}\,(TO_{dm} - TO)_{dm'} \\
&\underset{(0.0261)}{- 0.0108}\,(TI_{dm} - TI)_{dm'} \underset{(0.0530)}{- 0.137}\,(C_{dm}/INC - C_{dm'}/INC) \\
&\underset{(0.199)}{+ 0.0490}\,(DINC_m - DINC_{m'})
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
L^*(0) &= -85.257 \\
L^*(DA) &= -56.216 \\
L^*(\hat{\theta}) &= -23.033 \\
\rho^2 &= 0.73 \\
\bar{\rho}^2 &= 0.72 \\
\rho^2_{DA} &= 0.59 \\
\bar{\rho}^2_{DA} &= 0.58
\end{aligned}
$$

where

$P(m|d)$ = conditional probability of choosing mode m given that destination d is chosen,

$L^*(DA)$ = log likelihood for 0 coefficients except for pure automobile effect DA, and
ρ^2_{DA} = coefficient of determination in addition to the pure automobile effect.

It can be seen that all the coefficients have their expected signs. Out-of-vehicle travel time is almost five times more onerous than in-vehicle travel time. The standard errors of the coefficients of in-vehicle travel time and income are relatively large; however, the coefficients have their expected signs.

Sequence d → m: The Marginal Probability

The marginal probability of destination choice is the equivalent of a pre-modal-split distribution model. This model predicts the probability of destination choice with the mode choice indeterminate. The sets of alternatives consist of the alternative shopping destinations. Three models with the alternative composition rules were estimated for this probability, and the results are presented below for weighted prices.

$$\text{Log}\,\frac{P(d)}{P(d')} = \underset{(0.0523)}{-0.0227}\,(TO^M_d - TO^M_{d'}) - \underset{(0.0173)}{0.0374}\,(TI^M_d - TI^M_{d'})$$
$$- \underset{(0.0327)}{0.0269}\,(C^M_d/INC - C^M_{d'}/INC) + \underset{(0.0000910)}{0.000130}\,(EMP_d - EMP_{d'})$$
$$+ \underset{(0.595)}{0.638}\,(DCBD_d - DCBD_{d'}) \qquad (3)$$

$L^*(0) = -192.421$
$L^*(\hat{\theta}) = -182.485$
$L^*_{dm}(\hat{\theta}) = -205.518$
$\rho^2 = 0.05$
$\bar{\rho}^2 = 0.04$
$\rho^2_{dm} = 0.26$

where

$P(d)$ = marginal probability of choosing destination d,

$TO^M_d = \sum_m TO_{dm} \times P(m|d)$,

$TI^M_d = \sum_m TI_{dm} \times P(m|d)$,

$C^M_d = \sum_m C_{dm} \times P(m|d)$,

$L^*_{dm}(\hat{\theta})$ = log likelihood for the joint probability, and
ρ^2_{dm} = coefficient of determination for the joint probability.

Note that $\bar{\rho}^2_{dm}$ is not computed. The reason is that the two separate models have different numbers of degrees of freedom. The results for weighted generalized prices are as follows:

$$\text{Log}\,\frac{P(d)}{P(d')} = \underset{(0.0000867)}{0.000149}\,(EMP_d - EMP_{d'}) + \underset{(0.510)}{0.353}\,(DCBD_d - DCBD_{d'})$$
$$+ \underset{(0.141)}{0.507}\,(GP^M_d - GP^M_{d'}) \qquad (4)$$

$L^*(0) = -192.421$
$L^*(\hat{\theta}) = -184.866$
$L^*_{dm}(\hat{\theta}) = -207.899$

$$\rho^2 = 0.04$$
$$\bar{\rho}^2 = 0.04$$
$$\rho^2_{dm} = 0.25$$

where

$$GP^M_d = \sum_m (-0.0515 \times TO_{dm} - 0.0108 \times TI_{dm} - 0.137 \times C_{dm}/INC)\ P(m|d)$$

The results for the log of the denominator are as follows:

$$\text{Log}\ \frac{P(d)}{P(d')} = \underset{(0.0000862)}{0.000149}\ (EMP_d - EMP_{d'}) + \underset{(0.510)}{0.295}\ (DCBD_d - DCBD_{d'}) + \underset{(0.147)}{0.549}\ (\log P^{M*}_d - \log P^M_{d'}) \qquad (5)$$

$$L^*(0) = -192.421$$
$$L^*(\hat{\theta}) = -184.068$$
$$L^*_{dm}(\hat{\theta}) = -207.101$$
$$\rho^2 = 0.04$$
$$\bar{\rho}^2 = 0.04$$
$$\rho^2_{dm} = 0.25$$

where

$$P^M_d = \sum_m \exp(-0.639DA_m - 0.0515TO_{dm} - 0.0108TI_{dm} - 0.137C_{dm}/INC + 0.0490DINC_m)$$

All the models have relatively low coefficients of determination, which is attributed to the lack of more descriptive attraction data. All three models gave coefficient estimates with the expected signs. However, in Eq. 3, the coefficient of out-of-vehicle travel time is smaller than the coefficient of in-vehicle travel time, in contrast to what we would expect. The standard errors in Eq. 3 are relatively large; however, it fits the data as well as the two other models.

The model with weighted prices represents the assumption that the marginal rates of substitution among level-of-service attributes are different for different choices. The two other models assume equal rates for different choices. From a theoretical point of view, the latter assumption seems more reasonable. It is more likely that a traveler will have an identical trade-off between travel time and money cost for different travel choices rather than several of them, each being used for a different choice. The poor results from the weighted prices model support this assumption. It appears that all previous travel demand models reported in the literature have made the assumption of equal marginal rates of substitution for different choices.

Comparison of Eqs. 4 and 5 shows that there are no significant differences (2). The coefficient estimates of the CBD dummy variable have relatively large standard errors in the two models. However, the coefficients have the expected signs. The model shown in Eq. 4 is equivalent to the model developed by Charles River Associates (4).

Sequence m → d: The Conditional Probability

The conditional probability in this sequence is the equivalent of a post-modal-split trip distribution model. The model predicts the probability of destination choice for a given mode. The sects of alternatives consist of the alternative shopping destinations for the chosen mode. The estimation results of this model are as follows:

$$\text{Log}\ \frac{P(d|m)}{P(d'|m)} = \underset{(0.0380)}{-0.0610}\ (TO_{dm} - TO_{d'm}) - \underset{(0.0136)}{0.0287}\ (TI_{dm} - TI_{d'm})$$
$$- \underset{(0.0263)}{0.0470}\ (C_{dm}/INC - C_{d'm}/INC) + \underset{(0.0000899)}{0.000148}\ (EMP_d - EMP_{d'})$$
$$+ \underset{(0.548)}{0.330}\ (DCBD_d - DCBD_{d'}) \qquad (6)$$

$$L^*(0) = -192.421$$
$$L^*(\hat{\theta}) = -179.680$$
$$\rho^2 = 0.07$$
$$\bar{\rho}^2 = 0.06$$

where $P(d|m)$ = conditional probability of choosing destination d given that mode m is chosen.

The signs of the coefficient estimates are as expected. Out-of-vehicle travel time is more than two times more onerous than in-vehicle travel time. The coefficient of the CBD dummy variable has the expected sign but a relatively large standard error. The goodness of fit of this model is relatively low because of the large number of alternatives and the lack of better attraction description.

Sequence m → d: The Marginal Probability

The marginal probability of mode choice is the equivalent of a trip-end modal-split model (20). This model predicts the probability of mode choice with indeterminate destination choice. The sets of alternatives include the bus and automobile modes. Again, we model this probability with the three alternative composition rules. The results that were obtained for weighted prices are as follows:

$$\text{Log}\ \frac{P(m)}{P(m')} = \underset{(1.27)}{-0.952}\ (DA_m - DA_{m'}) - \underset{(0.0204)}{0.0509}\ (TO_m^D - TO_{m'}^D)$$
$$+ \underset{(0.0429)}{0.109}\ (TI_m^D - TI_{m'}^D) - \underset{(0.0725)}{0.183}\ (C_m^D/INC - C_{m'}^D/INC)$$
$$+ \underset{(0.225)}{0.293}\ (DINC_m - DINC_{m'}) \qquad (7)$$

$$L^*(0) = -85.257$$
$$L^*(DA) = -56.216$$
$$L^*(\hat{\theta}) = -24.596$$
$$L^*_{dm}(\hat{\theta}) = -204.276$$
$$\rho^2 = 0.71$$
$$\bar{\rho}^2 = 0.70$$
$$\rho^2_{dm} = 0.26$$
$$\rho^2_{DA} = 0.56$$
$$\bar{\rho}^2_{DA} = 0.55$$

where

$P(m)$ = marginal probability of choosing mode m,

$$TO_m^D = \sum_d TO_{dm} \times P(d|m),$$

$$TI_m^D = \sum_d TI_{dm} \times P(d|m), \text{ and}$$

$$C_m^D = \sum_d C_{dm} \times P(d|m).$$

For weighted generalized price, the results are as follows:

$$\text{Log} \frac{P(m)}{P(m')} = \underset{(0.959)}{-2.07} \; (DA_m - DA_{m'}) + \underset{(0.157)}{0.117} \; (DINC_m - DINC_{m'})$$

$$+ \underset{(0.371)}{1.62} \; (GP_m^D - GP_{m'}^D) \qquad (8)$$

$$\begin{aligned} L^*(0) &= -85.257 \\ L^*(DA) &= -56.216 \\ L^*(\hat{\theta}) &= -31.039 \\ L^*_{dm}(\hat{\theta}) &= -210.719 \\ \rho^2 &= 0.64 \\ \bar{\rho}^2 &= 0.63 \\ \rho^2_{dm} &= 0.24 \\ \rho^2_{DA} &= 0.45 \\ \bar{\rho}^2_{DA} &= 0.44 \end{aligned}$$

where

$$GP_m^D = \sum_d (-0.0610TO_{dm} - 0.0287TI_{dm} - 0.0470C_{dm}/INC)P(d|m)$$

For the log of the denominator, the results are as follows:

$$\text{Log} \frac{P(m)}{P(m')} = \underset{(0.955)}{-1.74} \; (DA_m - DA_{m'}) + \underset{(0.168)}{0.0489} \; (DINC_m - DINC_{m'})$$

$$+ \underset{(0.303)}{1.42} \; (\log P_m^D - \log P_{m'}^D) \qquad (9)$$

$$\begin{aligned} L^*(0) &= -85.257 \\ L^*(DA) &= -56.216 \\ L^*(\hat{\theta}) &= -27.832 \\ L^*_{dm}(\hat{\theta}) &= -207.512 \\ \rho^2 &= 0.67 \\ \bar{\rho}^2 &= 0.67 \\ \rho^2_{dm} &= 0.25 \\ \rho^2_{DA} &= 0.50 \\ \bar{\rho}^2_{DA} &= 0.50 \end{aligned}$$

where

$$P_m^D = \sum_d \exp(-0.0610TO_{dm} - 0.0287TI_{dm} - 0.0470C_{dm}/INC$$

$$+ 0.000148EMP_d + 0.330DCBD_d)$$

Again, Eq. 7, the weighted prices model, gave unreasonable coefficient estimates, similar to those in Eq. 3. The two other models, Eqs. 8 and 9, gave better results. The coefficients of the income variable have the expected signs but relatively large standard errors. The model of Eq. 8 uses the same composition scheme as the model developed by CRA (4); however, this model assumes a different sequence.

Comparison of Alternative Models

The alternative models that gave reasonable coefficient estimates are given below.

Model	Method	Equation
Simultaneous	Direct estimation	1
Recursive d → m	Weighted generalized price	2, 4
	Log of the denominator	2, 5
Recursive m → d	Weighted generalized price	6, 8
	Log of the denominator	6, 9

It was not the purpose of this study to accept or reject the a priori assumption of a simultaneous decision-making process. As expected, the empirical evidence does not show which of the alternative structures, one simultaneous and two recursive, is more likely to be correct. All the models gave reasonable coefficient estimates. Furthermore, all the models gave essentially equal goodness of fit: $\rho^2 = 0.25$. The simultaneous model includes seven coefficients, whereas the recursive models included eight. This implies that the simultaneous model has a slight edge in this category, but it is certainly not a conclusive difference.

The simultaneous model that included observations with up to 16 alternatives and seven variables gave reasonable coefficient estimates. The computer cost was only slightly higher (≃20 percent) than the cost of a binary mode choice model with five variables. This indicates that a simultaneous model is feasible for the two choices of destination and mode. It also indicates that expanding the set of choices and therefore increasing the number of alternatives and variables may not be an unrealistic objective.

Comparison of the coefficient estimates of the simultaneous model with those of the estimated recursive models suggests that the predictions are sensitive to the structure of the model. This sensitivity can be demonstrated by showing some examples of the important trade-offs and elasticities. Table 1 gives the values of time implied by the different models.

Although the standard errors are relatively large, this is not atypical for estimates of value of time (19). (The estimated model coefficients that were used to compute the values of time were significantly different from zero.)

Estimated values of time from the simultaneous model are greater than those estimated from a mode choice model (given destination) and smaller than those estimated from a destination choice model (given mode).

Table 2 gives some direct elasticities of the mode choice probability. The figures in Table 2 are based on the following case:

1. Annual household income is between \$10,000 and \$12,000,
2. The probabilities of choosing bus and automobile are 0.2 and 0.8 respectively,
3. Out-of-vehicle travel times are 20 minutes by bus and 10 minutes by automobile,
4. In-vehicle travel times are 30 minutes by bus and 15 minutes by automobile, and
5. Out-of-pocket costs are 50 cents by both bus and automobile.

Table 1. Value of travel time in dollars per hour.

Variable	P(m, d)	P(m|d)	P(d|m)
Out-of-vehicle travel time	3.02 (1.44)	1.36 (0.98)	4.67 (4.36)
In-vehicle travel time	0.78 (0.68)	0.28 (0.66)	2.21 (2.01)

Note: The figures are for a household with annual income between \$10,000 and \$12,000. Numbers in parentheses are standard errors.

Table 2. Direct elasticities of the mode choice probability.

	Bus		Automobile	
Variable	P(m, d)	P(m|d)	P(m, d)	P(m|d)
Out-of-vehicle travel time	-1.01	-0.82	-0.13	-0.10
In-vehicle travel time	-0.31	-0.26	-0.05	-0.03
Out-of-pocket cost	-0.40	-0.91	-0.13	-0.23

The most striking variation in Table 2 is in the cost elasticity. The mode choice model derived from an estimated joint probability gives cost elasticities that are about half the elasticities computed from a recursive mode choice model.

The differences among the models could be attributed to specification errors, which affect a mode choice model and a destination choice model differently. The effects could be in the opposite directions, and therefore the joint probability model gave estimates that are in some way between the estimates of the two other models.

The marginal probabilities of the recursive models, which were formulated with composite variables, also demonstrated significant differences from the corresponding probabilities derived from the simultaneous models.

Thus, the chosen structure can make a big difference in terms of the values of the estimated coefficients. Inasmuch as there are a priori reasons to assume a simultaneous rather than a recursive structure, we should estimate the joint probabilities directly. Then, if necessary, we can derive any conditional probability.

CONCLUSIONS

Models based on disaggregate data and choice theory were estimated in the past either for a single travel choice, primarily mode choice, or for several choices but in a recursive structure. The empirical study that was conducted in this research demonstrated the estimation of a disaggregate simultaneous model. The results from the estimation of a simultaneous destination and mode choice model indicate that this approach is feasible within reasonable computation cost. Moreover, the estimation results of models with recursive structures for the same two choices show that important coefficient estimates vary considerably with the different model structures.

This empirical study was limited in scale, and it is recommended that the evidence should be extended to include alternative data sets, different trip purpose categories, a complete set of travel choices, and a more extensive set of explanatory variables (in particular, attraction description).

The empirical evidence taken together with the theoretical assumptions of a simultaneous structure and the advantages of disaggregate models suggests that future efforts in travel demand modeling should be in the direction of simultaneous disaggregate probabilistic models. Given the joint probability (from the simultaneous model), one can derive conditional probabilities and use the model for forecasting in sequential stages, corresponding with the UTMS procedure.

One of the important problems in using disaggregate models for forecasting is the aggregation problem. Future research efforts should investigate this problem. However, for the short run, simplified aggregation procedures, such as market segmentation, are available and can be used.

The use of disaggregate models suggests new emphasis in data collection efforts for transportation planning. The amount of data needed for disaggregate models has not yet been determined, but it is clear that a change in the general method of collecting travel data is appropriate. The comprehensive home interview survey covering an entire planning region might be replaced by several more descriptive small samples, in selected areas of the region. Thus, the emphasis should be to represent the full range of socioeconomic characteristics affecting travel behavior, rather than to sample all parts of the region at a uniform rate. Smaller scale surveys will make possible the collection of the detailed information (not conventionally collected) important for disaggregate demand models. For example, information on car pooling, how often a trip is made (instead of reporting only the trips made during the last 24 hours), institutional constraints such as preferred arrival time, and so forth, would be obtained. In addition to the travel data requirements, better information is also needed with respect to the attributes of alternative trips. In particular, the attraction data available from conventional data sources used in urban transportation planning are not very descriptive. More detailed attraction data are needed to achieve better predictions of destination choice.

In-depth studies of travel behavior based on detailed interviews and attitudinal data could be fruitful. However, it appears that the most beneficial directions for research toward improvements of transportation planning capabilities are the aggregation problem, behavioral modeling of round trips with non-home-based links, and experimental application of simultaneous disaggregate models to case studies of important transportation issues at different levels of planning.

In conclusion, this research has indicated the desirability and the feasibility of a simultaneous disaggregate travel choice model.

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DISAGGREGATE ACCESS MODE AND STATION CHOICE MODELS FOR RAIL TRIPS

Peter S. Liou, New York State Department of Transportation; and
Antti P. Talvitie, University of Oklahoma

In this study disaggregate probability choice models are developed for access mode and for access station selection. In each of the models, there are at least two alternatives available to the individual traveler. A multinomial logit model that is based on the axiom of the "independence of irrelevant alternatives" is used. Two methods of approach concerning travelers' decision-making processes are used. The first is the simultaneous approach, which assumes that the traveler may make the access mode and station choice decisions in one of two sequences: station choice preceding mode choice or mode choice preceding station choice. In the sequential approach, the choices of access mode and access station are modeled separately. Results suggest that the traveler's decision-making process for the access mode and station choices is behaviorally separate, the sequence being station choice followed by access mode choice. The study also shows that travelers do not assign the same weights to the set of transportation system attributes when making these decisions and that the pedestrian and bus modes are preferred to the automobile mode. For the station choice, the accessibility of the train station has the greatest effect on the traveler's decision.

•A PERSON planning any type of an intraurban trip makes a number of choices including those on destination, mode, and travel route. These decisions have an important bearing on transportation planning, and therefore the knowledge of how travelers go about making their decisions is essential to transportation planners.

This research discusses the access part of the rail journey. It is assumed of course that decisions on trip origin, trip destination, rail line, and so on have already been made; consequently, travelers are faced with two access choices: access mode and access station.

The main purpose of this study is to develop disaggregate choice models of the access mode and station selection for rail work trips. At the same time, this study investigates whether travelers make the two choices simultaneously or in a sequence and, if the latter, which specific sequence? Another objective of this study is to determine the types of transportation and socioeconomic attributes that affect travelers' choice decisions and how much.