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EMERGING TRANSPORTATION PLANNING METHODS

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EMERGING TRANSPORTATION PLANNING METHODS

A Compendium of Papers on Transportation Demand Forecasting Techniques, Transportation Evaluation Methods and Transportation/Land Use Interactions. Based on a Seminar held in Daytona Beach, Florida in December 1976.

Editors: William F. Brown, Principal
Robert B. Dial
David S. Gendell
Edward Weiner

OFFICE OF UNIVERSITY RESEARCH
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at Berkeley, wrote "The Theory and Practice of Disaggregate Demand Forecasting for Various Modes of Urban Transportation," as an introduction to disaggregate behavioral forecasting. The paper outlines the concepts underlying this approach and contrasts behavioral with conventional forecasting methods. It also describes practical applications of disaggregate forecasting and illustrates some early findings.

The second paper by Paul O. Roberts, Professor of Transportation at the Massachusetts Institute of Technology, is entitled, "Disaggregate Demand Modelling: Theoretical Tantalizer or Practical Problemsolver?" The paper describes disaggregate modelling as a pioneering behavioral approach by delineating its points of departure from, and advantages over, the more traditional aggregate approach to transportation demand forecasting. Based on the consumer choices of a person or family, this new, but not untried, method is described as more policy responsive, more flexible, and suitable to more applications than previous models. The paper encompasses the disaggregate nature of travel, the philosophical underpinnings of the disaggregate model, and the prediction framework for using the model.

The scope of the second section is to explore methods for developing and presenting evaluative information to the transportation decisionmaker.

Joseph L. Schofer, Professor of Civil Engineering at Northwestern University, covers transportation evaluation methods in his paper, "Evaluating Transportation Alternatives." Noting a lack of standard approaches, Professor Schofer focuses on achievable improvements in evaluation methodology. He presents the strategic issues that must be considered in developing a strong foundation for specific, successful evaluation tasks. He also prescribes some key steps that should lead the planner to better evaluation. Evaluation is defined as the technical process that links decisionmaking with analysis, planning, and design. Professor Schofer poses several questions that can define and measure the success of this process.

In the second paper on transportation evaluation methods, Thomas B. Deen, Chairman of the Board of Alan M. Voorhees & Associates, discusses "Practical Considerations in Transportation Decisionmaking." He contends that transportation planners face "devilish" problems; the main characteristic is the lack of consensus existing on either the nature of the problem or how to determine whether the problem has been solved. Asserting that transportation planners probably cannot satisfy all the demands of their constituency, he offers several suggestions about how transportation planners can conduct themselves, including: shedding illusions of finding any "best"

solution; continuing to improve methodologies while investing at least as heavily in improving communication with officials and citizens; and refraining from the assumption that planners are more "pure" than politicians or officials.

To complement the coverage of transportation evaluation methods, the summaries of the six workshops are presented. The topics are: treating distributional effects of uncertainty, the evaluation of project plans, evaluation of regional plans and programs, preparation and interpretation of evaluation results, strategic approaches to evaluation, and evaluation and decisionmaking.

The scope of the third section is to explore the integrated forecasting of transportation and land use.

Stephen H. Putman, Associate Professor of City and Regional Planning at the University of Pennsylvania, prepared the paper, "The Integrated Forecasting of Transportation and Land Use." He discusses two closely related advances in operational planning techniques that, when put together, make integrated transportation forecasting and policy analysis a reasonable operational analysis technique. The first of these advances was the demonstration of both the feasibility and superiority of an integrated transportation/land use model package; the second was the development of a more general form of urban land use model along with the procedures necessary for its calibration.

The second paper on transportation/land use interactions was written by Douglass Lee, Jr., Associate Professor at the University of Iowa, and is entitled, "Improving Communications Among Researchers and Planners in the Transportation and Land Use Field." This paper concerns primarily communication between and among professionals and researchers, as well as communication between the technical and political sides of transportation and land use. The report briefly documents discussions at two workshops that were based on case studies illustrative of how political decisionmaking takes place. The actual participants of the two case studies—including politicians—were involved in the workshop discussions. The case studies themselves, which are not presented here, concern the I-66/Metro Corridor and the Mt. Hood Freeway decision.

The third and final paper summarizes six workshop sessions: land use modelling, decisionmaking, and politics; land use/transportation modelling structures; application of land use models in comprehensive planning; short-range forecasting and land use impacts; land use/transportation forecasting at the community scale; and details of the integrated transportation/land use package.

The Seminar on Emerging Transportation Planning Methods, as judged by the participants, was very successful. This success, plus the long term value of the papers, led to the decision to publish this book. The Office of University Research, in order to effectively disseminate research results, plans to hold more seminars of this type in the future.

William F. Brown
Deputy Director
Office of University Research

I. TRANSPORTATION DEMAND FORECASTING TECHNIQUES

Daniel L. McFadden, Professor of Economics
University of California at Berkeley

The Theory and Practice of Disaggregate Demand Forecasting for Various Modes of Urban Transportation

Daniel L. McFadden

Professor of Economics
Massachusetts Institute of Technology

A major responsibility of transportation planners is to forecast those changes in travel demand induced by alternative transportation policies. In recent years, the range of analyzed policy alternatives and the range of considered policy questions have greatly expanded. Emphasis has shifted from long-run planning of highway networks to short-run planning and to management of integrated multimodal transportation systems. These shifts have placed considerable strain on conventional forecasting tools, which were originally designed to address problems of highway network design.

Flexible demand forecasting methods have consequently been sought, particularly those capable of incorporating the behavioral forces linking individual transportation decisions. The resulting behavioral disaggregate methods expand the policy sensitivity of forecasts. Tests and practical experience with these methods indicate that they are comparable or superior to conventional forecasting techniques in terms of data gathering and computational requirements and forecast accuracy. They provide, in short, a useful way of tackling the expanded list of contemporary planning questions.

Most conventional forecasting models were originally developed to address problems of highway design, and were conceived using analogies with physical systems—with traffic flows described in terms of hydraulic or gravity flow models. Different model components in conventional modeling are not developed from a unified framework. For example, a trip generation model may be developed quite independently of a model of modal split. Another deficiency of conventional models is that they often involve costly and time consuming data gathering and computational requirements, and they are not easily adapted to short-run planning and transportation system management. In particular, they are poorly adapted to pencil-and-paper or quick-response policy analyses planners need.

In contrast to conventional methods, disaggregate behavioral forecasting methods are based on a unified conceptual framework. They start from the idea that all travel demand is generated by individual choice behavior, and more specifically (in the current generation of disaggregate behavior models) generated by maximization of preferences or utility. An advantage of disaggregate forecasting is that it is not based on one model; it is an approach or system for building models, and as such it can provide the planner with a method of dealing with a variety of problems as they occur. It is possible to build complex disaggregate behavioral model systems on a scale approaching or exceeding that of conventional models. On the other hand, it is possible to use these techniques to do "quick-and dirty" planning, using "back-of-the-envelope" calculations, without extensive data collection requirements. In general, the use of behavioral models greatly conserves data collection costs relative to conventional models in both the calibration phase and the forecasting phase. A major advantage of disaggregate models is that they allow the planner to address questions, such as the demand for a new mode, which are difficult to answer in a conventional framework. The current generation of disaggregate models have accuracies comparable to or better than that of conventional models. Disaggregate models have proved practical and successful in a number of applications. I emphasize that the state-of-the-art of disaggregate modelling is evolving rapidly; current models are not the final answer, and have some undesirable features. There are many unexpected characteristics of disaggregate models, and many uncharted pitfalls for the user. Disaggregate models are valuable now for solving some planning problems. In the future, as better disaggregate models evolve, the list of effective applications will grow.

The rich, poor, healthy, and handicapped are rarely homogenous and the aggregate forecasting methods which treat them as such make a specification error. More importantly, these methods preclude the possibility of answering questions such as who benefits and who pays for policy changes. These shortcomings are frequently corrected in part by segmenting the zone population by income class in conventional models. Further segmentation by those socioeconomic characteristics other than income that influence travel patterns would be useful. Conventional calibration of an aggregate model for numerous market segments requires an often unobtainable quantity of data. Pursued to a logical conclusion, each segmented market in an aggregate model should contain a sub-population with identical socioeconomic characteristics and identical transportation environments. This segmentation would amount in practice to distinguishing *each individual* as a "market segment." Aggregate forecasts would then be

regarded as the sum of the travel demand of *individuals*, which is a disaggregate forecasting procedure. Disaggregate demand modelling is, then, essentially market segmentation carried to an extreme and is one end of a continuum, with aggregate demand forecasting at the opposite extreme. Consider for example, the mode split for work trips from an origin zone to a destination zone. The aggregate share of a mode is by definition the sum over market segments of the share of the mode in each market segment, weighted by the proportion of the total origin-zone population contained in this market segment. If the segmentation is complete, then one has the formula shown below, with each homogenous market segment having a share for the particular mode. The aggregate share is the weighted average of the shares in the homogenous market segments.

$$\begin{aligned}\begin{bmatrix}\text{Aggregate}\\ \text{Share of}\\ \text{A Mode}\end{bmatrix} &= \begin{bmatrix}\text{Share of Mode}\\ \text{in First Market}\\ \text{Segment}\end{bmatrix} \times \begin{bmatrix}\text{Proportion of First}\\ \text{Market Segment in}\\ \text{Population}\end{bmatrix}\\ &+ \begin{bmatrix}\text{Share of Mode}\\ \text{in Second}\\ \text{Market Segment}\end{bmatrix} \times \begin{bmatrix}\text{Proportion of Second}\\ \text{Market Segment in}\\ \text{Population}\end{bmatrix} \qquad (1)\\ &+ \ldots + \begin{bmatrix}\text{Share of Mode}\\ \text{in Last Market}\\ \text{Segment}\end{bmatrix} \times \begin{bmatrix}\text{Proportion of Last}\\ \text{Market Segment in}\\ \text{Population}\end{bmatrix}\end{aligned}$$

This formula is one that will recur several times.

An axiom of behavioral disaggregate, choice theory is that the individual is the basic decisionmaking unit, choosing from available alternatives the most desirable. The desirability—or *utility*—of a choice depends upon its attributes and upon the characteristics of the individual. Suitably modified to take account of the psychological phenomena of learning and perception errors, this theory has been used widely and successfully in analyzing and forecasting economic consumer behavior, of which transportation behavior can be viewed a part.

Let us first clarify what transportation behavior is. A complete definition of a transportation alternative for an individual includes the total pattern of travel: location of residence and job; purchases of vehicles; frequency of work, shopping, personal business, recreation and other trips; destination of trips; scheduling of trips; mode choice; and route choice. In practice, travel demand models concentrate on certain dimensions of travel behavior such as mode choice, taking as given other aspects such as scheduling of trips or location of residence. (A great deal of the *behavioral* theory of disaggregate modelling which will not be presented explicitly here deals with how these decisions can be broken apart.)

An alternative's attributes include the transportation level of service variables associated with its pattern of travel. The individual's utility of an alternative is a function of level-of-service variables for the alternative. Utility also depends on the individual's tastes and background—or socioeconomic characteristics. Examples of level-of-service variables are travel time and travel cost. Examples of socioeconomic characteristics are income and family size. An individual chooses among the available alternatives the one which maximizes utility.

Some socioeconomic characteristics and level-of-service variables are observed by the transportation planner. Others are unobserved. For example, income and in-vehicle travel time are usually observed or calculated, while attitudes towards privacy or vehicle noise level are usually not observed.

Consider a group of individuals with similar observed backgrounds and decision environments, characteristics, and observed level-of-service variables for the alternatives. This could be called a *homogeneous market segment*. The frequency of choice for an alternative within a homogeneous market segment is determined by the number of members of this group whose unobserved level-of-service and socioeconomic variables, operating in tandem with the observed variables, give this alternative the highest utility. For example, if an individual's observed travel times on alternative modes, in combination with unobserved attitudes towards privacy, lead him to a higher utility for bus than for auto, then he will choose the bus. Other people with the same observed travel time, and therefore in the same homogeneous market segment, may have different attitudes towards privacy, and as a result may take the auto.

A disaggregate choice model is defined by specifying a probability distribution of the unobserved variables affecting utility, given the values of observed variables in a homogeneous market segment. This probability distribution then determines the *choice probabilities*—the proportions of the group with maximum utility for each alternative.

In summary, a disaggregate behavioral model is specified by forming a concrete individual utility function, a probability distribution of the unobserved variables, and a share of each market segment in the population. Examples of specific utility functions and probability distributions are given below. Using the formula in equation (1), once a

concrete utility function is formed and the distribution of unobserved variables specified, each of the shares in a homogeneous market segment is specified. Knowing the proportions of the population in the various market segments, one can then compute the average share.

I will define the *mean utility* of a homogeneous market segment to be the average of the utilities of all the individuals in this segment. Mean utility depends on the observed level-of-service and socioeconomic variables, and on other determinants of the *distribution* of unobserved variables.

Assuming a concrete probability distribution for the unobserved components of utility leads to a concrete formula for the choice probability. Unfortunately, most distributions of unobserved components yield computationally forbidding choice probability *formulae*, making them difficult to use in practical calibrations and forecasting. One exception is the multinomial logit model, which has choice probabilities of the form shown below. ("Exp" denotes exponentiation.)

$$\begin{bmatrix}\text{Share of}\\ \text{the i-th}\\ \text{Alternative}\end{bmatrix} = \frac{\exp\begin{bmatrix}\text{mean utility of}\\ \text{i-th alternative}\end{bmatrix}}{\exp\begin{bmatrix}\text{mean utility of}\\ \text{the}\\ \text{first alternative}\end{bmatrix} + \ldots + \exp\begin{bmatrix}\text{mean utility of}\\ \text{the}\\ \text{last alternative}\end{bmatrix}} \qquad (2)$$

The multinomial logit model has the following characteristics: first, it can be interpreted as a disaggregate behavioral model with special assumptions on the probability distribution of the unobserved variables which will not be detailed here. Second, a multitude of possible disaggregate travel demand models can be formulated in the multinomial logit framework, with the form of the mean utility function depending on the application. Third, the multinomial logit model has the mathematical form of share models used in conventional travel demand forecasting systems, such as the gravity or intervening opportunity models. For example, consider a singly constrained aggregate gravity model for distribution,

$$N_{kj} = O_k A_j / T_{ki}{}^h \,, \qquad (3)$$

where N_{kj} = number of trips from zone k to zone j;
A_j = attraction of zone j;
T_{kj} = impedance between k and j;
O_k = scale factor to equate trips distributed from zone k to trips originating in zone k.

Then, the *share* of trips from zone k to zone i satisfies

$$P(i|T_{ki}, \ldots, T_{kj}, A_j) = \frac{A_i/T_{ki}{}^h}{\sum_{j=1}^{J} A_j/T_{kj}{}^h}. \quad (4)$$

This is a multinomial logit functional form in equation (2) with mean utility = log A_i − h log T_{ki}. Hence, the multinomial logit form is not new to planners, but has been widely used in one form or the other, although perhaps not widely recognized. As the example makes clear, the multinomial logit form can be used in ways which are quite different in motivation than the principles of disaggregate behavioral theory. In the special case of two alternative modes, the multinomial logit model is termed the (binomial) logit mode split model. This case gives a response curve to a type familiar to every planner in which the share of a particular mode is plotted against the relative desirability of the modes, as in Figure 1. If desirability is measured in terms of relative impedance or more generally relative disutility, standard mode split models can be interpreted as behavioral models.

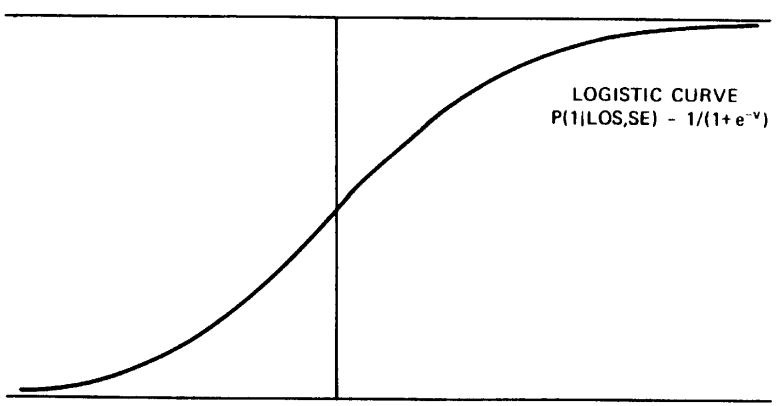


Figure 1.—Binary logit response curve.

What then are the primary differences between traditional aggregate share models and the multinomial logit disaggregate models? First, the structure of the mean utility function in the multinomial logit model is based on economic and psychological regularities in individual behavior. As a consequence it will have a similar form in models of different aspects of transportation choice such as generation, scheduling, distribution, and mode split. For example, if one can determine the variables that matter in mode split, it should be the case that similar variables matter in trip distribution. Second, the calibration and utilization of the model are carried out at the disaggregate level for homogeneous market segments rather than applied to aggregate data.

A successful forecasting model, behavior disaggregate or otherwise, must assess correctly the impact of level-of-service changes on demand. This requires in calibration that the effects on demand of variations in level-of-service be sorted out from the effects of non-transportation variables. For example, suppose large families with small children locate disproportionately in the suburbs where walk time to transit is high, and workers in large families are disposed to transit because of competing needs of household automobiles. Then a mode split model which fails to control family size and attributes the pattern of transit usage to variations in walk time will understate the onerousness of walk time and yield faulty predictions of the impact on transit patronage of policies influencing transit walk time. The problem is corrected by including family size as an explanatory variable in the model.

Disaggregate calibration methods allow inclusion of a more extensive list of level-of-service and socioeconomic variables than do most aggregate methods, improving the possibility of untangling the effects of level-of-service and other variables. It should be noted, however, that it is possible to develop simple disaggregate models using only conventional variables familiar to planners, such as travel time and travel cost. Empirical tests suggest that the introduction of variables other than conventional components of impedance in a disaggregate mode choice model may improve only marginally the ability of the model to "explain" observed choices in a calibration data base, but may significantly improve forecasting accuracy.

It should be emphasized that the disaggregate behavioral approach is a systems approach to modelling, not a specific model. Disaggregate models can be developed to meet the specific needs of the individual planner. In particular, one can build disaggregate models which are completely analogous to conventional models in terms of data used and types of variables employed, such as travel time and cost. Alternately, one can expand on these models by expanding the description of level-of-service attributes, thereby increasing the ability of the models to be responsive to expanded policy questions. Or, one can expand the socioeconomic description of these models to take into account correlations between level-of-service variables and socioeconomic variables which may have been leading planners to spuriously impute impacts to level-of-service variables. Finally, even though when one thinks of forecasting models, one usually thinks in terms of concrete and well-defined variables such as travel time and travel cost which can themselves be forecast from networks under alternative policy scenarios, it is also possible to develop models which depend on survey data on perceptions or attitudes. Although a distinction is sometimes made between attitudinal models and behavioral models, the disaggregate systems approach to building models incorporates both.

Disaggregate models are relatively parsimonious in terms of data requirements. A typical mode choice model, for example, can be calibrated on a sample size of 300 to 3,000 individuals with quite tolerable levels of accuracy. Socioeconomic variables are normally available at an individual level from household surveys. Transportation level-of-service variables are much harder to provide at the level of the individual traveler. Typically these data are obtained from transportation networks, which can provide data only at a traffic analysis zone level. Studies have shown that it is usually reasonable to approximate level-of-service variables for the individual by zonal averages. One exception is walk time to transit, where significant improvements in forecast accuracy can be obtained by segmenting zones geographically and recording individual walking distances. A final point is that the accuracy of any model, conventional or disaggregate, which uses network data is limited in forecasting accuracy by the accuracy of the network. There are many subjective elements and assumptions that go into coding of networks, and one has to be careful in applying forecasting models to understand how these assumptions interact with model calibration.

In principle, the mean utility function in a disaggregate behavioral multinomial logit model can be a very complex function of personal characteristics and level-of-service variables. In existing practical models, however, these variables have appeared in a simple form, usually linearly, with an "importance weight" attached to each variable. For example, mean utility might equal the negative of the sum of travel time and travel cost deflated by wage, each weighted by an importance weight. It may be useful to describe how such a specification can be related to an underlying theory of individual behavior. I will outline a very simple model which provides this special structure. Let us assume that the utility or desirability of an alternative depends on the amount of goods an individual consumes; the amount of leisure he

has available; the hours spent traveling (a "bad" rather than a "good" for most people); amenities of various travel destinations; and unobserved factors. The alternatives available to the individual in this model are destination and mode choice, so this is a joint destination and mode choice model. The option of no trip is included as an alternative, so that the model includes trip generation as well.

Each individual is assumed to be constrained by a budget which requires his total expenditures, equal to expenditure on goods plus expenditure on travel, be equal to his total income, which in turn equals wage income plus other income. Time is allocated between leisure, labor, and travel in a way to maximize utility. First, for any travel alternative a mix of labor and leisure is chosen to maximize utility. If the individual considers the alternative of taking the bus to a particular shopping destination, then the optimal amount of time worked, adjusted to take into account the choice of this alternative, will be determined. At this optimal mix, the marginal utility of goods (defined to be the amount of additional utility obtained from one additional unit of goods) multiplied by the wage rate equals the margin utility of leisure. Second, the travel alternative actually chosen is the one maximizing utility, taking into account the labor-leisure adjustment above for each alternative. The features of this model are summarized in Table 1.

The preceding argument provides a justification—from the economic theory of utility maximizing behavior—for the entry of travel time and travel cost divided by wage as linear variables in the mean utility function. Generalization of this model is possible in several directions.

Time, cost, and other attributes of alternatives may have subcomponents. Time, for example, can be partitioned into on-vehicle time under congested or non-congested conditions, walk time, and wait time. Costs can be divided into overhead, indirectly charged per-trip costs such as fuel and maintenance, and daily out-of-pocket costs such as tolls. These components can be given separate coefficients in equation (*) of the preceding table; the relative weights of components can then be determined as part of the calibration of the model, which is preferable to assigning traditional weights.

The coefficients b_T, b_C, and b_A may depend on observed socioeconomic variables. For example, the weight b_T associated with the walk time component of travel time may be a function of an individual's age and health status, or of those neighborhood characteristics correlated with safety. If this association is expressed in a linear-in-parameters form, then the mean utility function (*) is linear

TABLE 1. A Simple Behavioral Utility Model

- Utility depends on goods, leisure, hours spent traveling, amenities at various travel destinations, unobserved factors
- Alternatives describe destination and mode choice, including the no trip option
- Each individual is constrained by a budget:

$$\begin{matrix}\text{Expenditure}\\ \text{On Goods}\end{matrix} + \begin{matrix}\text{Travel}\\ \text{Cost}\end{matrix} = \begin{matrix}\text{Wage}\\ \text{Income}\end{matrix} + \begin{matrix}\text{Other}\\ \text{Income}\end{matrix} \qquad (5)$$

- Time is allocated between leisure, labor, and travel
- For any travel alternative, the mix of labor and leisure is chosen to maximize utility. At this mix, the marginal utility of goods, multiplied by the wage rate, equals the marginal utility of leisure
- The chosen alternative maximizes utility

$$\begin{bmatrix}\text{UTILITY}\\ \text{OF } i^{th}\\ \text{ALTERNATIVE}\end{bmatrix} = -\left[\begin{bmatrix}\text{TRAVEL}\\ \text{TIME}\end{bmatrix} + \frac{[\text{TRAVEL COST}]}{[\text{WAGE}]}\right] \times \begin{bmatrix}\text{MARGINAL}\\ \text{UTILITY}\\ \text{OF LEISURE}\end{bmatrix}$$

$$+ \begin{bmatrix}\text{TRAVEL}\\ \text{TIME}\end{bmatrix} \times \begin{bmatrix}\text{MARGINAL UTILITY}\\ \text{OF TRAVEL TIME}\end{bmatrix}$$

$$+ [\text{AMENITIES}] \times \begin{bmatrix}\text{MARGINAL UTILITY}\\ \text{OF AMENITIES}\end{bmatrix}$$

$$+ \begin{bmatrix}\text{UNOBSERVED}\\ \text{ATTRIBUTES}\end{bmatrix} \times \begin{bmatrix}\text{MARGINAL UTILITY OF}\\ \text{UNOBSERVED ATTRIBUTES}\end{bmatrix}$$

$$\begin{bmatrix}\text{MEAN UTILITY}\\ \text{OF THE } i^{th}\\ \text{ALTERNATIVE}\end{bmatrix} = -b_T \times \begin{bmatrix}\text{TRAVEL}\\ \text{TIME}\end{bmatrix} - b_C \times \frac{[\text{TRAVEL COST}]}{[\text{WAGE}]} \qquad (*)$$

$$+ b_A \times [\text{AMENITIES}]$$

b_T, b_C, AND b_A ARE PARAMETERS

in these parameters, and the calibrated model will describe both the importance weight attached to walk time and the variation of this weight with socioeconomic factors.

There are a number of methods available to calibrate disaggregated behavioral multinomial logit models. The technique which is most commonly used is maximum likelihood estimation. From the user's point of view, this method is comparable to regression analysis—the inputs and outputs of computer programs which carry out this calibration resemble closely the inputs and outputs of regression programs, and require the same skills from the user as do regression analyses. Therefore, any planning organization which currently has the capacity to do regression analyses also has the potential ability to calibrate multinomial logit models.

There are good statistical computer programs available for multinomial logit analyses using the maximum likelihood method. One available to many planners is the ULOGIT programs in the UTPS package. There are several other stand alone logit programs available with options not included in ULOGIT. QUAIL, a flexible data management and multinomial program developed by McFadden and his colleagues, is available in versions suitable for use on CDC or IBM machines. Multinomial logit programs for IBM machines are also available from Cambridge Systematics, Inc. and from Charles Manski at Hebrew University. All these programs are available at the cost of reproducing tapes and manuals.

In addition to maximum likelihood estimation, there are several other techniques for fitting multinomial logit models. One technique, currently available only on QUAIL, is non-linear least squares. This method has an advantage relative to maximum likelihood estimation in that it is less sensitive to data measurement errors, an important consideration given the nature of transportation data. Finally, there is an estimation technique called the Berkson-Theil method which requires grouped data rather than individual observations. If data is collected by individual, it must be grouped to use this method. On the other hand, the method requires only a standard regression program, and hence is readily available to most planners. When data can be grouped easily, the Berkson-Theil procedure is recommended. It has good statistical properties, and is considerably less expensive than maximum likelihood estimation.

Let us next consider a simple calibrated disaggregate multinomial logit model with work trip mode choice. The model in Table 2 was calibrated by the maximum likelihood technique on a sample of 771 commuters in the San Francisco Bay Area in 1973, before the inauguration of BART Trans-Bay service. The explanatory variables in this model are the level-of-service attributes commonly used to define impedance in conventional models, on-vehicle travel time, excess or out-of-vehicle time, and cost divided by wage. The model contains four alternatives: auto drive alone, auto shared with someone else (either family or non-family carpool), and bus, subdivided by access mode. Auto access to bus includes "kiss-ride" and "park-ride." Alternative-specific dummy variables are introduced to capture the average influence of unobserved attributes of each mode. The number of dummy variables is one less than the number of alternatives, as the coefficient of the bus-with-walk-access dummy is normalized to zero. One such arbitrary normalization is necessary.

A negative coefficient for a variable indicates that an increase in this variable for a mode will lower the mode's choice probability. For example, the coefficient of excess time is negative. If excess time rises for a particular mode—say, bus-with-walk-access—then the mean utility of this mode will fall, and as a consequence the choice probability for this mode in a homogeneous market segment will fall. The T-statistics on the right-hand-side are indicators of the precision of the parameters. Values less than two indicate that the parameters cannot be reliably distinguished between zero. This particular model indicates that individuals react strongly to transportation level-of-service variables. The average effects of unobserved variables, reflected in the coefficients of the alternative-specific dummy variables, are important.

TABLE 2. A Simple Work Trip Mode Choice Model, Estimated Pre-BART

(Mode 1—Auto Alone; Mode 2—Bus, Walk Access; Mode 3—Bus, Auto Access; Mode 4—Carpool)

Model: Multinomial Logit, Fitted by the Maximum Likelihood Method

(The Variable takes the described value in the alternatives listed in parentheses and zero in non-listed alternatives)

Independent Variable	*Estimated Coefficient*	*T-Statistic*
Generic		
Cost divided by post-tax wage, in cents divided by cents per minute (1–4)	−.0412	7.63
On-vehicle time, in minutes (1–4)	−.0201	2.78
Excess time, in minutes (1–4)	−.0531	7.54

TABLE 2. A Simple Work Trip Mode Choice Model, Estimated Pre-BART—*(Continued)*

Specific		
Auto alone dummy (1)	−.892	3.38
Bus with auto access dummy (3)	−1.78	7.52
Carpool alternative dummy (4)	−2.15	8.56

Likelihood ratio index	.1499
Log likelihood at zero	−1069.0
Log likelihood at convergence	−717.7
Percent correctly predicted (by maximum probability)	58.50 (compared with 39.42 by chance)

Value of time saved as a percent of wage (t-statistics in parentheses):

On vehicle time	49 (2.68)
Excess time	129 (5.16)

All cost and time variables are calculated round-trip. Excess time is defined as the sum of walk time, transfer wait time, and half of initial headways. Dependent variable is alternative choice (one for chosen alternative, zero otherwise).

Number of people in sample who chose

Auto alone	429
Bus with walk access	134
Bus with auto access	30
Carpool	178
Total sample size	771

I will expand further on the nature of the variables entering this model, and specifically on the alternative-specific dummy variables. Socioeconomic variables which influence the mean utility of every alternative in exactly the same way have no influence on choice probabilities. They change both the numerator and the denominator of the multinomial logit formulae by a factor which cancels out. Hence, there is interest only in those socioeconomic variables which interact with level-of-service variables to affect the mean utility of different alternatives differently. For example, income can matter only if, when income changes, it increases the attractiveness of one of the alternatives relative to a second. Travel cost divided by wage is one example of interaction. A second example is a variable which takes the value of one for an alternative which requires driving a vehicle when the individual has a driver's license, and is zero otherwise. The variable in this example is the product of a socioeconomic variable which is one if the individual can drive and zero otherwise, and a level-of-service variable which is one if the alternative requires driving and zero otherwise. In the model in Table 2, an alternative-specific dummy variable for an alternative is one for this alternative and zero for all other alternatives. Mean utility may be included in alternative-specific dummy variables appearing alone, or in interaction with other variables. The coefficient of an alternative-specific dummy variable can be interpreted as reflecting the impacts of an alternative's unmeasured level-of-service attributes that are not captured in the remaining variables. For example, the auto-alone dummy variable is one for the auto-alone mode and zero otherwise. (The number following the name of the variable indicates for which alternatives it is non-zero.) The coefficient −.892 can be interpreted as representing the average impact of unmeasured characteristics of the auto alternative relative to the bus-with-walk-access alternative.

A variable which is the result of interaction between an alternative-specific dummy variable and another variable is termed an alternative-specific variable. An example of an alternative-specific variable would be one which gives the value of out-of-vehicle travel time for the bus with auto access alternative and zero for all other alternatives. The coefficient of this variable compared with the coefficients of other alternative-specific travel times would reflect the impact of specific attributes of auto-accessed transit on the onerousness of transit travel time. A generic, or homogeneous-effect, variable is one which does not incorporate interaction with alternative-specific dummy variables. An example is a variable which gives out-of-vehicle travel time for each alternative, uninfluenced by the name of the alternative; i.e., an out-of-vehicle time of fifteen minutes is treated the same whether it is auto access time or transit wait time. In this model the level-of-service variable—cost, on-vehicle travel time, and access time—were all generic or homogeneous-effect. Each of these variables has values for each of the four alternatives. For example, travel time in auto has the same importance weight as travel time in transit.

Individual utility, expressed as a function of observed and unobserved variables, should depend on only generic variables. The reason for this is behavioral—individual utility depends on the constellation of physical experience associated with an alternative, and cannot depend on labels such as "auto," "transit," or "CBD"—attached to alternatives by the planner. Mean utility on the other hand may depend on alternative-specific variables which mimic or act as proxies for the influence of unobserved generic variables. For example, suppose individual utility depends on generic on-vehicle travel time weighted by

a generic index of comfort. Suppose the comfort index is unobserved, but varies between alternatives. Then the mean utility for an alternative will have a coefficient of on-vehicle time which reflects the average comfort index on this alternative. It will then appear to the planner that mean utility depends on alternative-specific travel times. Alternative-specific variables in a multinomial logit model are evidence of failure to observe generic variables which are influencing behavior. A long-run objective of behavioral demand analyses is to improve model specification and data collection to the point where alternative-specific variables are not needed. Models based solely on generic variables are also desirable from the point of view of forecasting. Coefficients of alternative-specific variables do not isolate behavioral sources of variation across alternatives, or establish that alternative-specific effects will be stable or extendable to new situations when forecasting. In the current state-of-the-art of disaggregate demand analyses, alternative-specific effects do capture the impacts of variables not observed in standard transportation data sets; their omission would bias the importance weights associated with other variables.

In the lower half of Table 2 are several summary statistics which give some notion of the goodness-of-fit of this model to the calibration data base. The likelihood ratio index is an analog of the multiple correlation coefficient in regression analysis. Empirically, its values run lower than typical values for a multiple correlation coefficient. A value of .2 to .3 indicates a good fit. A second measure of goodness-of-fit is the ability of the model to forecast accurately. In this particular sample, 39% of the choices of individuals would be predicted correctly by change, whereas the model predicts 58% correctly. A third method commonly used to assess the merit of models is to compute the implicit values of time implied by the model. This is a potentially misleading measure of goodness-of-fit, both because these statistics tend to be very unreliable and because there is some tendency to accept or reject models on the basis of consistency with earlier result in the literature, which could perpetuate errors in the assessment of time evaluations. On the other hand, the critical role of value of time tradeoffs in policy applications makes it necessary to compute these values. Value of time calculations in the multinomial logit model are determined from the ratio of time and cost coefficients. These calculations assume that within a homogeneous market segment, the value of time is uniform. Note that this is not necessarily a good assumption. For the model in Table 2, on-vehicle time is valued at half the wage rate and access time at 130% of the wage rate. Table 3 describes a more complex multinomial logit modal split model.

TABLE 3. Work Trip Mode Choice Model, Estimated Pre-BART

(Mode 1—Auto Alone; Mode 2—Bus, Walk Access; Mode 3—Bus, Auto Access; Mode 4—Carpool)

Model: Multinomial Logit, Fitted by the Maximum Likelihood Method

(The Variable takes the described value in the alternatives listed in parentheses and zero in non-listed alternatives)

Independent Variable	*Estimated Coefficient*	*T-Statistic*
Cost divided by post-tax wage, in cents divided by cents per minute (1–4)	− .0284	4.31
Auto-on-vehicle time, in minutes (1,3,4)	− .0644	5.65
Transit on-vehicle time, in minutes (2,3)	− .0259	2.94
Walk time, in minutes (2,3)	− .0689	5.28
Transfer wait time, in minutes (2,3)	− .0538	2.30
Number of transfers (2,3)	− .105	0.776
Headway of first bus, in minutes (2,3)	− .0318	3.18
Family income with ceiling of $7,500, in $ per year (1)	− .00000454	0.0511
Family income minus $7,500 with floor of $0 and ceiling of $3,000, in $ per year (1)	− .0000572	0.430
Family income minus $10,500 with floor of $0 and ceiling of $5,000, in $ per year (1)	− .0000543	0.907
Number of persons in household who can drive (1)	−1.02	4.81
Number of persons in household who can drive (3)	− .990	3.29
Number of persons in household who can drive (4)	− .872	4.25
Dummy if person is head of household (1)	− .627	3.37
Employment density at work location (1)	− .00160	2.27
Home location in or near CBD (2 = in CBD, 1 = near CBD, 0 otherwise) (1)	− .502	4.18
Autos per driver with a ceiling of one (1)	5.00	9.65
Autos per driver with a ceiling of one (3)	2.33	2.74
Autos per driver with a ceiling of one (4)	2.38	5.28
Auto alone alternative dummy (1)	−5.26	5.93
Bus with auto access dummy (3)	−5.49	5.33
Carpool alternative dummy (4)	−3.84	6.36

TABLE 3. Work Trip Mode Choice Model, Estimated Pre-BART— *(Continued)*

Likelihood ratio index	.294
Log likelihood at zero	−1069.0
Log likelihood at convergence	− 595.8
Percent correctly predicted (by maximum probability)	67.83 (compared with 39.42 by chance)

Values of time saved as a percent of wage (t-statistics in parentheses):

Auto on-vehicle time	227 (3.20)
Transit on-vehicle time	91 (2.43)
Walk time	243 (3.10)
Transfer wait time	190 (2.01)

Value of initial headways as a percent of wage: 112 (2.49)

All cost and time variables are calculated round-trip. Dependent variable is alternative choice (one for chosen alternative, zero otherwise).

Number of people in sample who chose

Auto alone	429
Bus with walk access	134
Bus with auto access	30
Carpool	178
Total sample size	771

One way of judging the effectiveness or the accuracy of a disaggregate demand model is to compute what is called a prediction success table. Table 4 is a prediction success table for the model in Table 3. Each column corresponds to a predicted alternative and each row corresponds to an actual choice. The number 296.6, for example, is the number of persons who were predicted to take auto alone who did in fact choose this alternative, and 29.0—the next number below it—is the number predicted to take auto alone who in fact took bus with walk access. Predictions in this table are based on the choice probabilities of individuals. For example, the entry 29.0 is the sum of the predicted choice probabilities of auto alone, taken over the set of all individuals who actually chose bus-with-walk-access. This prediction success table summarizes goodness-of-fit of the model to its calibration data base. This table has the property that the average observed shares (56% auto, 17% bus/walk, 4% bus/auto, and 23% carpool in this sample) coincide with the predicted values. This is a consequence of calibration, and says nothing about the accuracy of the model. A notion of how well the model fits is obtained by looking at the percent correctly predicted

TABLE 4. Prediction Success Table for Pre-BART Model and Calibration Data Base

Actual Alternatives	(1) Auto Alone	(2) Bus/ Walk	(3) Bus/ Auto	(4) Carpool	Row Total	Observed Share (%)
	Predicted Alternatives					
(1) Auto alone	296.6	29.4	10.0	93.1	429.0	56
(2) Bus/Walk	29.0	75.1	6.6	23.3	134.0	17
(3) Bus/Auto	9.8	5.9	6.7	7.6	30.0	4
(4) Carpool	93.6	23.7	6.7	54.0	178.0	23
Column Total	429.0	134.0	30.0	178.0	771	100
Predicted Share (%)	56	17	4	23	100	
Percent Correct	69.1	56.1	22.3	30.4	56.0	
Success Index	1.23	3.30	5.58	1.32		

The equality of predicted and observed shares is a conseqence of the calibration process.

in aggregate for each alternative. For auto alone, 69% of our predictions are correct, while for the bus with auto alternative, only 22% are predicted correctly. These figures illustrate that it is much easier to be successful when you are predicting demand for a highly used mode than when you are predicting demand for a little used mode. This observation applies throughout travel demand modeling, including conventional models. An index of prediction accuracy for an alternative can be obtained by dividing the percent correctly predicted by the percent correct you could achieve by chance. The higher this prediction success index, the better the model. In terms of the prediction success index, the model in Table 3 has the most difficulty distinguishing between auto alone and carpool, and does reasonably well in predicting transit usage.

A more interesting test of the accuracy or validity of a disaggregate model is to examine its ability to predict on a data set different than the calibration data set. Recall that the model in Table 3 was fitted to 1973 data, prior to the inauguration of Trans-Bay BART service. To test the validity of the model, we used it to forecast mode split in 1975, including full BART service. This was done by comparing the actual mode choices of a 1975 sample with the choices predicted by the model

in Table 3 when the 1975 set of alternatives and level of explanatory variables were substituted for each individual. The prediction success table for these forecasts is given in Table 5. The columns correspond to predictions using the 1973 calibrated model. Recall that the 1973 model

TABLE 5. Prediction Success Table for Pre-BART Model and Post-BART Data

Actual Alternatives	(1) Auto Alone	(2) Bus/ Walk	(3) Bus/ Auto	(4) BART/ Bus	(5) BART/ Auto	(6) Carpool
	Predicted Alternatives					
(1) Auto alone	255.1	22.21	6.362	1.513	13.72	79.07
(2) Bus/Walk	11.56	36.43	2.988	1.679	1.421	13.92
(3) Bus/Auto	1.249	2.811	.687	.0066	1.625	2.622
(4) BART/Bus	.858	1.934	.120	1.391	.258	1.440
(5) BART/Auto	8.898	3.149	1.756	.695	8.828	9.674
(6) Carpool	74.68	12.43	3.305	1.357	7.497	37.73
Column Total	352.4	78.97	15.22	6.642	35.35	144.4
Predicted Share (%) (standard error)	55.8 (11.4)	12.5 (3.4)	2.4 (1.4)	1.0 (.5)	5.3 (2.4)	22.9 (10.7)
Percent Correct	72.4	46.1	4.5	21.0	26.5	26.1
Success Index	1.30	3.69	1.88	21.0	5.0	1.14
Predicted Share less observed share	−4.1	1.7	1.0	0.05	0.1	1.2
Actual Share (%)	59.9	10.8	1.4	.95	5.2	21.7

Totals

Sample Size	631	
Percent Correct	53.9	(42.0 by chance)
Success Index	1.28	

has no BART alternatives, only auto-alone or shared-or bus-with-walk or auto access. From these alternatives we wish to predict the patronage on two new models, BART with auto access and BART with walk access. The model in Table 3 contains some alternative-specific variables, and it was necessary to make judgments about what form those alternative-specific variables would have in the post-BART situation. We assumed that BART with auto access has the same unobserved characteristics as bus with auto access, so that their alternative-specific variables would enter with the same coefficients. Analogously, we assumed that BART with bus access has the same characteristics as bus-with-walk-access, with alternative-specific variables entering with the same coefficient. An overall judgment from Table 5 is the disaggregate model in Table 3 is relatively successful in predicting demand for a major new transportation mode. The model forecast a BART mode share of 6.3 percent, compared with an observed share of 6.2 percent. A caveat is necessary, however. The statistical imprecision of the calibrated coefficient of the pre-BART model would lead one to expect forecasts for modes with low aggregate shares, such as BART, to have relatively large percentage errors. The actual prediction accuracy here is better than one could expect by change, given the size of these standard errors of the forecasts. Further, disaggregate models in the form in Table 3 tend to be quite sensitive to the selection of variables entering the mean utility function, and to the definition and measurement of explanatory variables. For example, one of the problems which appears in this table is an overforecast of bus usage. An explanation can be found in the network calculation of bus access time. To construct these times, we used a 1980 Bay Area network which was constructed assuming 1980 bus service levels. The network was scaled back to 1975 by dropping bus links which did not exist in 1975, but the 1980 walk times which were shortened because the assumed 1980 transit service remained at the 1980 levels. As a result, walk time from our network calculations under-estimate true bus access time. This data measurement problem seems to be the major source of prediction error in Table 5. However, disaggregate models such as the one in Table 3 exhibit some anomalies when calibration samples are partitioned by location, family composition, or choice-alternative definition, suggesting that there are factors influencing travel demand which the current models do not capture adequately.

A statistical test of whether the post-BART data was in fact explained by the pre-BART model failed. That is to say, from a statistical point of view there are post-BART factors which are not explained adequately by the 1973 model despite the fact that it does a reasonably good job of forecasting aggregate BART patronage. In short, disaggregate demand forecasting has the flexibility and the potential accuracy to meet current planning needs, but the field of disaggregate demand forecasting is relatively uncharted, offering many potential pitfalls to the planner.

One property of the multinomial logit model which has gained some notoriety is called the *independence from irrelevant alternatives* (IIA) condition. This is a feature of the model which occurs when the mean utility of an alternative depends only on the attributes of that alternative and on the characteristics of the decisionmaker, and not on the attributes of other alternatives. In this case, the IIA property requires that the relative share of any two alternatives is independent of the

attributes of the remaining alternatives. The terminology is due to the psychologist Duncan Luce, who first proposed the IIA property as an axiom for behavior in psychological choice.

The IIA property is a blessing and a curse for the multinomial logit model. It has some significant advantages. First, it allows calibration without having to consider all possible alternatives. For example, if one wants to carry out a study of destination choice, it is possible to calibrate the model with data on a selected number of destinations rather than having to consider the full set of destinations. This can substantially reduce data collection requirements. Second, IIA permits quick determination of the effects of introducing a new alternative, because the forecast of mode share for a new alternative mode can be obtained by including one additional term in the denominator of the multinomial logit formula.

The IIA property also has some major disadvantages. It fails to allow for different degrees of competition or similarity between alternatives. Consider the following example. Suppose that individuals initially have a shopping choice between the central business district (CBD) and a shopping mall—call it East Mall; and suppose that they initially split 50–50 between these two destinations. For simplicity, assume all individuals have exactly the same observed explanatory variables; i.e., they represent a homogeneous market segment. Suppose now that a new situation is introduced in which a North Mall is constructed. Suppose the North Mall and East Mall are equally far away for these individuals, with equal amenities. Then one would expect individuals who previously chose to shop in the CBD to continue to do so, and individuals who previously went to the East Mall to now split evenly between the East and North Malls. Hence, one would expect in this situation to observe a split of 50% CBD, and 25% for each of the two Malls. On the other hand, a multinomial logit model will predict a one-third split for each of the alternatives. The reason it does so is that it assumes that the relative odds of choosing between CBD and East Mall will be unchanged when an additional alternative is introduced—the North Mall. In other words, the multinomial logit model is unable to take account of the fact that the new North Mall will be more competitive with the East Mall than it will be with CBD shopping.

Let us pursue this example one step further. Suppose that we could break down the "homogeneous" market segment further, into, say, males and females, and that there were very strong differentials in shopping characteristics for these two socioeconomic groups. Suppose before the construction of North Mall the female segment divides 95–5 in favor of shopping at East Mall, while the male segment divides 95–5 in favor of CBD destinations. The aggregate share for the two segments is 50–50. Suppose now one applies the multinomial logit model to forecast destinations after North Mall is built, with separate forecasts for males and females. Then, the predicted splits for the female segment will be 48.7% for each Mall and 2.6% for CBD destinations; for the male segment, 4.8% for each Mall and 90.5% for CBD destinations; and finally an aggregate mode split of 46.5% for CBD destinations and 27% for each of the two Malls. Compare this to the observed split which is 50% for CBD destinations and 25% for each Mall. Then, the error introduced by the failure of IIA is small when market segmentation is effective in dividing the market.

In summary, the IIA property is extremely useful for practical planning. Its limitations are a more serious problem in aggregate modelling than in disaggregate modelling, where refining market segments can minimize errors. Although much of the discussion of the IIA property in the literature is concentrated on its logical possibility, a much more important consideration for the practicing planner is its empirical validity. If the disaggregate multinomial logit model having the IIA property can be shown to fit calibration data sets well and to forecast accurately in a particular application, then it is a useful tool for the planner.

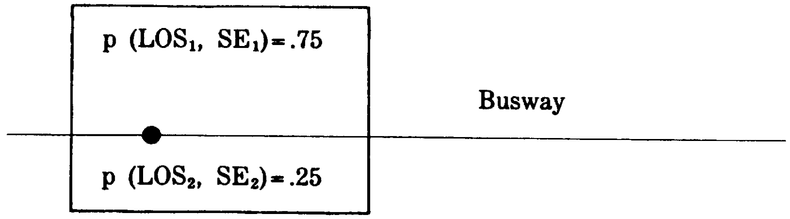
Specific statistical tests for the IIA property applicable to transportation data sets have been developed by McFadden, Tye, and Train. These tests can be used to investigate various specific sources of failure of IIA. Tests of IIA have been applied to a seven-alternative work trip data set for the San Francisco Bay Area. Because of the multiple transit alternatives (we have three BART, two bus, auto alone, and carpool alternatives) with common main-mode characteristics for alternative access modes, one would expect this data set to provide a rather stringent test of the IIA property. The multinomial logit model tested was of the same general form as the model in Table 3. The hypothesis that the model satisfied the IIA property was accepted for all the tests performed, with two exceptions which tended to point to data specification problems rather than IIA problems. Hence, this empirical study suggests that although IIA is an unpalatable logical restriction from the standpoint of the general theorist, it may be inconsequential from the standpoint of practical planning. At the very least, satisfaction of IIA is an empirical question, not a question of doctrine.

What should a planner do about the IIA property, given that its validity is a matter of concern in the profession? First, carry out diagnostic tests of the validity of the property for the specific data set you are using. If you reject the IIA property, try to refine the specification of your model by a more detailed market segmentation, improving data definition, or by adding variables to the models. If necessary, replace the multinomial logit model with one allowing patterns of substitution between alternatives.

The multinomial logit model is a special case of a disaggregate model, and not in any sense the end of the line in terms of realism and accuracy. However, it is the only disaggregate model which I believe is of current widespread practical useability.

I have described the process of defining and calibrating disaggregate behavioral models. Now I will discuss how these models are applied in forecasting. First, one must translate policy questions into specific technological features of the proposed transportation service. For example, suppose the policy question posed is "How much more transit service can we provide with a $1,000,000 block grant?" The question must be first translated into specific operating proposals for headways, route density, and so forth. Then, network or manual calculations, or an idealized supply model, must be used to provide the level-of-service variables resulting from a proposal. These variables must be provided for each homogeneous market segment for the level of segmentation at which the analysis is being carried out. Next, the size of each homogeneous market segment must be determined. In the short-run, one can normally assume population demographics continue to hold. For long-run forecasting, one must make projections of land use and demographic trends, and factor these forecasts into the segmentation. Finally, one must use the basic aggregation formula in equation (1) to predict changes in aggregate shares. Information on homogeneous market segments can be used to calculate the distributional consequence of proposals if this information is needed. Patronage and revenue calculations for the homogeneous market segments can be carried out, and aggregated to give totals. These figures, along with the capital and operating costs of alternative proposals, determine their feasibility. Among those proposals forecast to be feasible, a selection can be made using the evaluation criterion employed by the planning agency.

Consider the following example of the use of this procedure. Assume in Figure 2 that the square box at the top represents a traffic zone. Assume that the traffic zone is bisected by an express busway, and that one busway station denoted by the black dot serves the zone. The population densities within the zone are such that 75% of the people live north of the busway, and the remaining 25% live south of it. Suppose there is no parking provided at the busway station; hence, the people either walk, take feeder bus, or are driven to the station. Suppose current feeder-bus headways are twenty minutes on both the north and the south side and that the modal shares to the busway station are as follows: on the north side 52% walked; 18% take the bus; 30% are driven. On the south side 10% walk; 10% take the bus; 80% are driven and in total in this zone 41% walk; 16% take the feeder bus; 43% are driven.



Current Modal Shares

	Walk	*Bus*	*Driven*	*Proportion in Population*
North	.52	.18	.30	.75
South	.10	.10	.80	.25
Total	.41	.16	.43	1.0

Figure 2.—An example: The impact of improved feeder bus service.

The Planning Commission is contemplating improving the feeder bus service on the north side by reducing the headway from twenty minutes to five minutes, but leaving it unchanged in the low density area south of the busway. The consequences of this policy are calculated using a multinomial logit model with mean utility function at the bottom of Table 6. The mean utility is 3.11 times a variable which is 1 if the person walks and 0 otherwise, plus .495 times a variable which is 1 if the individual takes the bus, zero otherwise, minus .11 times travel time, minus .08 times headway, minus .2 time cost, plus .672 times the number of drivers (if the person is driven) and 0 otherwise. Here are the changes in mode shares calculated from the multinomial logit model when north-side feeder bus headways are reduced: North of the segment, the walk share goes down by .15, the bus share rises by .24, the number driven goes down by .09. Summed over the zone, the impact then is a .18 increase in the feeder bus share, a .11 decrease in the walk share, and a .07 decrease in the share of persons driven.

So far I have discussed the calculation of the effects of policy change on a homogeneous market segment. It is necessary to in general combine results for homogeneous market segments into an aggregate prediction for the population as a whole. If the segmentation is extremely detailed, then it may not be practical to carry through the aggregation by summing over all homogeneous market segments. There are a number of short-cuts or approximations to the aggregation process which can be used. I will mention four. First, one can approximate the empirical distribution of homogeneous market segments in

TABLE 6. Change in Mode Shares when North Side Feeder Headway is Cut from 20 Minutes to 5 Minutes

Segment	*Walk*	*Bus*	*Driven*	*Proportion in Population*
North	−.15	+.24	−.09	.75
South	0	0	0	.25
Total	−.11	+.18	−.07	

Mean Utility = 3.110 (if walk) + 4.950 (if bus) − .110 (traveling time) − .080 (headway) − .200 (cost) + .672 (no. of drivers, if driven)

the population with a mathematical distribution for which the expectation, or average, can be calculated analytically, possibly after a transformation of variables. Second, one can approximate the empirical distribution of socioeconomic variables and level-of-service variables in the population by a histogram, with each cell in the histogram corresponding to a fairly homogeneous market segment. Then the aggregate forecast is approximately equal to a sum over these market segments. This segmentation can be as coarse or as fine as desired; the finer the structure, the more accurate the segmentation. If a very coarse segmentation is used, then the method is close to an aggregate procedure. Third, one can approximate the empirical distribution of attributes of homogeneous market segments by using series expansions in terms of statistical moments, so that aggregate shares are written as functions of choice probabilities at average arguments and moments of the distribution of explanatory variables. Fourth, one can sample randomly from the empirical distribution of characteristics of homogeneous market segments, and form the sample expectation as an approximation to the population expectation. The first and third methods require information on moments of the distribution of explanatory variables. The second requires data on the size of market segments, and the fourth requires a representative sample from the population. The first method is not feasible except in special cases. Segmentation method two is feasible, and simple to apply for quick, rough answers when the number of explanatory variables is not too large. The third method does not converge rapidly, or perhaps not even at all, unless the distribution of explanatory variables is relatively concentrated. The fourth method is the most flexible. The required data for this method can be supplied from a calibration data base provided that the base is representative of the population, or from other data sources such as U.S. Census data, provided these sources contain the variables used in the forecasting model. In contrast to calibration, forecasting requires no data on actual transportation choices. Those are predicted by the model. Hence one can utilize socioeconomic data sets which are not specifically transportation-oriented to provide explanatory variables. A method of synthesizing socioeconomic data from Census data has been developed by Cosslett, Duguay, Jung, and McFadden (1977).

In summary, the sampling method of approximating statistical expectations is the most flexible tool for aggregate forecasting from disaggregate models. The method can be combined with survey or synthesized data to provide aggregate forecasts at reasonable cost.

The basic principles of behavioral disaggregate modelling, in summary, are that aggregate travel demand can be expressed as the sum of the demands of homogeneous market segments, and that the demand within a homogeneous market segment has a structure determined by behavioral regularities that are stable over time and space. How different are disaggregate and aggregate models in concept? They differ primarily in degree. Disaggregation carries market segmentation to the extreme. It emphasizes the regularity of individual choice behavior, in contrast to conventional modelling which emphasizes the physical regularity of aggregate flows. Aggregate and disaggregate models differ significantly in the number and form of explanatory variables, consistency across different aspects of travel behavior, calibration methods, and forecasting techniques. These differences are, however, primarily technical; the result of historical development and the practical limitations of data compilation and computation. Behind every good aggregate model stands a disaggregate model, and vice versa. The discovery of empirically valid regularities which simplify and extend forecasting methodology, and the relaxation of empirically invalid restrictions, should be a goal of every transportation analyst. From this point of view, disaggregate behavioral forecasting is a natural evolution of traditional aggregate demand analysis.

Calibration of behavioral disaggregate models requires less data than aggregate model calibrations. In forecasting, disaggregate models need to consider both the explanatory variables for each homogeneous market segment, and the computation of each segment's mode split. Fortunately, a variety of analytic or statistical methods, or a coarse market segmentation, can provide forecasts of aggregate mode shares. The range of answerable policy questions is limited by the extent of level-of-service variables affecting the choice probability. The planner's ability to translate policy changes into level-of-service changes is another potential limitation.

Aggregation predictions in disaggregate models can be adapted to comprehensive analysis of large-scale transportation system changes, or to "quick and dirty" analysis of limited aspects of travel behavior and incremental policy changes. In short, the behavioral disaggregate forecasting methodology can provide a multi-channel forecasting system. The theory of individual behavior provides a blueprint for the construction of disaggregate models. The methodology has the flexibility to meet the varied policy analysis needs of the planner.

It must be stressed that disaggregate behavioral analysis is neither a model nor model system; it is an approach to the development of model systems. There will never be "best" or "final" disaggregate models. Model systems will continue to evolve as experience accumulates. Not all model systems developed from behavioral principles will be "good." The method is open to abuse and misuse, as are aggregate model systems. Given that the analytic and statistical methods employed in disaggregate behavioral modelling will be new to many planners, and given that many planners are not well-grounded in the "folk theory" of behavioral modeling from economics and psychology, one can predict the unsuccessful disaggregate models will outnumber the successful ones. On the other hand, there is now a track record of success with these models. They have proved that they can provide accurate and flexible forecasts, and that used with judgment, they can provide a useful tool for organizing and systematizing policy analysis.