

forward as would testing the transferability of the coefficients of Stevens' Law among localities in different geographic areas and with different characteristics. Preliminary psychological research (4) suggests that it may be possible to develop a single equation that captures the relations between reality and perception for all types of travel characteristics.

Another potentially fruitful area for further research would be an integration of the Stevens' Law concept with the concept of cognitive dissonance. The usefulness for transportation choice modeling of the theory of cognitive dissonance, with its implications regarding the interrelation of attitudes and behavior, has been explored by Golob, Horowitz, and Wachs (14), Dumas and Dobson (15), and others. Further application of the insights into human behavior that are available in the literature on psychology and marketing should prove beneficial in improving both knowledge of travel behavior and the ability to forecast future behavior.

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Design and Analysis of Simulated Choice or Allocation Experiments in Travel Choice Modeling

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A new approach for modeling traveler trade-offs and choices is proposed, described, and illustrated. Based on research in psychology, marketing, and economics, a method for developing discrete choice models from controlled laboratory simulation experiments is developed and presented. The method borrows statistical theory from discrete choice theory in econometrics and from the design of statistical experiments to marry work in trade-off analysis with choice analysis. The method is illustrated by means of several travel-choice-related examples that involve choice of mode and destination. Recent evidence of validity in forecasting the actual behavior of real markets is reviewed in support of the approach.

Since the early 1970s, the study of revealed-choice behavior based on the random utility derivations of discrete choice theory in econometrics (1-6) has

gained a following in the analysis and forecasting of travel behavior. If real choice data satisfy the conditions assumed in the statistical choice models, it is possible to derive aggregate-level trade-offs and to simultaneously forecast choice behavior. Hence, methods based on revealed choice have high external validity and practical applicability to strategic policy problems.

Other approaches have recently gained attention-- notably, laboratory simulation methods such as variations of conjoint measurement or trade-off analysis (7-9) and functional measurement (10-15), which are the primary methods of approach for developing quantitative descriptions of multiattribute individual

and group judgments, trade-offs, or utilities. These approaches are based on the responses of travelers to hypothetical travel alternatives and not on their observed behavior. The former type of data is here called "intended choice" and the latter type "revealed choice".

The intended-choice approaches to trade-off analysis have limitations that hamper their applicability, including the following:

1. One is usually forced to make untestable assumptions about the functional form of the trade-offs in practical applications.
2. One must make assumptions about the relation between choice and utility that are untestable and are contrary to most assumptions in practical random utility choice models.
3. It is difficult to incorporate individual constraints on choice effectively except in an ad hoc or post hoc fashion.
4. External validity assessment is less obvious than with revealed-choice methods.

The revealed-choice methods, on the other hand, have major limitations:

1. One must make assumptions about functional form a priori and, in contrast to the intended-behavior methods, one cannot ever guarantee that it will be possible to test these assumptions adequately with real data.
2. One must make assumptions about mean utility parameters or at least segmented mean parameters that are known from evidence to be often false (10,12,13,15,16) and that are used for the sake of tractability rather than empirical reality.
3. Measurement errors and correlations among variables cannot be controlled to any satisfactory degree, or at least have not historically been well controlled (18).
4. The forecasting accuracy of the models has been disappointing, which suggests that external validity of observations of choice is insufficient to guarantee internal validity or forecast accuracy.

Recently, the consequences of failure to satisfy a number of these assumptions have been examined by Horowitz (18,19). Suffice it to say that the intended-choice approach can guarantee satisfaction of many of the assumptions by design while sacrificing immediate external estimation validity, whereas the revealed-choice approach cannot guarantee satisfaction of its assumptions with real choice data but does have immediate external estimation validity.

This paper attempts to partially bridge the gap between the two approaches by developing a method for estimating intended-choice models that satisfies to the extent possible the necessary statistical conditions for a variety of econometric choice models and can be used to make forecasts to test external validity. Evidence in support of external validity is presented later in the paper. In this regard, the approach represents an improvement in the ability to analyze choice behavior with intended-choice data because it actually involves observations on choice or allocation behavior in controlled situations. Because the models derived are estimated from experimentally observed choices, they directly forecast choice behavior rather than judgments, utilities, or rankings. Although it is not explored in this paper, the approach also has the ability through the use of statistical principles in experimental design to rigorously test various assumptions inherent in, or deductions derived from, discrete choice models in econometrics (18,19). This permits one to rigorously test various aspects

of choice models that at best can be tested only weakly with revealed-choice data.

THEORY

It is assumed that the derivations of discrete choice theory based on random utility notions are approximately true--that is, that the random utility version of the Luce (20,21) choice axiom as derived by McFadden (5) and Yellot (22) holds for aggregate choices or allocations:

$$p(a|A, \forall j \in A) = e^{U_a} / \sum_{j \in A} e^{U_j} \quad (1)$$

where

$$p(a|A, \forall j \in A) = \text{probability of selecting alternative } a \text{ from choice set } A, \text{ of which } a \text{ is a member, defined over all } j \text{ members of } A, \text{ including } a;$$

$$U_a, U_j = \text{utilities or scale values of } a \text{ and } j, \text{ respectively; and}$$

$$e = \text{base of the natural logarithms.}$$

One normally assumes that the scale values (utilities) may be expressed as a linear in the parameters and additive function; e.g., for alternative a ,

$$U_a = b_{0a} + b_{1a} X_{1a} + b_{2a} X_{2a} + \dots + b_{na} X_{na} \quad (2)$$

where

$$U_a = \text{scale value of the } a\text{th alternative,}$$

$$b\text{'s} = \text{constants to be estimated from the data, and}$$

$$x\text{'s} = \text{attributes of the } a\text{th alternative.}$$

Equation 1 states that the probability of choosing any particular alternative from a set containing at least one other is expressible strictly as a function of conditional probabilities. Equation 2 imposes a linear in the parameters and additive structure on the conditional probabilities to describe each alternative. In general, the attributes are specific to a particular alternative (e.g., alternative a), but it is possible in some contexts to treat the attributes as generic--i.e., attributes that are common to all or some subset of alternatives. Other problems require mixtures of generic and alternative specific attributes.

If one assumes Equation 1 to be true, it is possible to develop straightforward methods for collecting data and estimating the parameters of the choice models derived therefrom. The results of such choice studies are similar to those of conjoint analysis, trade-off analysis, functional measurement, or the like in that estimates of levels of utility can be derived, various algebraic forms of utility (or decision) models can be tested, and policy-relevant parameters such as elasticities can be obtained (1,7-10,12-17). More important, however, the choice models derived forecast choices directly without the necessity of developing a simulation routine combined with a number of assumptions (such as "highest" ranked equals first choice) that are required to predict choices from rankings or ratings data (16). The approach to this problem is discussed in the next section of this paper.

CONSIDERATIONS ON DESIGN OF CHOICE EXPERIMENTS

Equation 1 implies that any experimental design that ensures the independent estimation of conditional effects (scale values) should suffice as a choice design. Although we readily admit that in theory

random samples of choice sets will satisfy this criterion, in practice it is impossible a priori to know the statistical properties of such designs. Hence, we favor the use of controlled statistical experiments that can be designed a priori to have certain statistical properties of interest. This paper concentrates on two such design properties:

1. The condition that the probability of a choice alternative being in a choice set and the probability of choosing the alternative given that it is in a choice set be independent and balanced across all sets of choice sets so that one can determine whether alternative a has a higher probability of being chosen over b because it is preferred to b or because it is available to be chosen more often than b, and

2. The condition that the attributes of the choice alternatives be as independent of one another as possible (i.e., orthogonal) both within and between alternatives.

In practice, it is possible to guarantee the satisfaction of these two conditions by the appropriate choice of an experimental design plan (9,12,17,23-27). In particular, it is always possible to satisfy these two conditions by treating each attribute as a factor "nested" under the appropriate alternative. By judicious choice of design plan, it is also possible to test for violations of Equation 1 by using some of the ideas contained in Horowitz's various tests for choice model adequacies (18,19). Most such tests require one to be able to estimate certain interactions in addition to main effects; however, one can almost always design such conditions a priori so that they will be satisfied by the data (24-26).

In general, main-effects plans that treat each attribute of each alternative as a factor will suffice for model estimation if Equation 1 is approximately true. Louviere and Woodworth (25) have shown these design plans to be near optimal for parameter estimation in terms of efficiency. The next section of this paper outlines parameter estimation for aggregated choice data. We concentrate on aggregated data for the sake of exposition of ideas; future papers will explore individual-level models, repeated-measures designs, and covariance analyses.

PARAMETER ESTIMATION FOR AGGREGATED CHOICE DATA

For many applications, such as sketch planning, aggregated choice data are sufficient to derive policy implications. If sample sizes permit, the choice data may be disaggregated into various policy categories of interest (assumed to be mutually exclusive) and aggregates of choices may be developed for analysis. So there is some limited flexibility for market segmentation with this approach. If disaggregated results are desired, the data must be treated as a series of discrete choices at the individual-respondent level and maximum likelihood estimation used to derive parameter estimates. Such methods are now well-known in travel analysis and need not be pursued here (1-6). However, because the problem of repeated measures on individuals has yet to be treated, caution should be used in any applications of traditional logit choice algorithms to the types of data described in this paper.

It is important to note that each individual is asked to make choices (or allocate choices, money, time, etc.) from a series of choice sets. The experimental designs briefly outlined in the previous section generate the appropriate choice sets to be administered to each individual, and each individual makes a sufficient number of choices to permit esti-

mation of a separate, individual-specific choice model. Unfortunately, the theory of maximum likelihood estimation developed for multinomial logit choice models (4,5) only holds for large-sample problems, and the properties of the estimates for individual-level choice models are currently unknown. However, because each individual makes a series of discrete choices from statistically designed sets of choice sets, there is likely to be more than enough choice data in the aggregate across a typical sample (say, 400 individuals) to satisfy the large sample requirements. By "aggregate" we mean both (a) the total of discrete choices available (the number of individuals times the number of choices in all choice sets) and (b) the aggregated choice frequencies obtained by calculating the total number of choices made by individuals for all alternatives in all choice sets.

We now illustrate the method of estimation for aggregated choice data; Louviere and Woodworth (25) have demonstrated its asymptotic efficiency for large samples, as have others (4,28,29). The estimation method involves weighted least-squares regression in which Equation 1 is put in linear form as follows.

The relative frequency with which alternative j (= 1,2,...,J) is chosen in choice set i (= 1,2,...,I) is denoted as Rf_{ij} . This relative frequency is taken as an estimate of the unknown choice probability, and Equation 1 is rewritten as follows:

$$Rf_{ij}(a|A, \forall j \in A) = e^{U_{ia}/K_i} \tag{3}$$

where κ_i is $\sum_{j \in A} e^{U_{ij}}$ and all other terms are as previously defined. That is, for the ith choice set, the denominator is a constant for all j alternatives. Taking logarithms to the base e of both sides yields

$$\ln[Rf_{ij}(a|A, \forall j \in A)] = U_a - \ln(\kappa_i) \tag{4}$$

Equation 4 implies that the U_a can be estimated by creating dummy variables for each j and for each i--in particular, a weighted multiple linear regression analysis in which each choice response (relative or absolute choice frequency) is associated with a design matrix of (1,0) dummy coded indices so that, if the choice observation (Rf_{ij}) pertains to choice alternative a, the dummy index for alternative a is coded one, otherwise zero. Similarly, if the choice observation appears in choice set i, the dummy index for choice set i is coded one, otherwise zero. In practice, of course, only (J - 1) and (I - 1) dummy indices can be used in estimation unless one "centers" the regression about the origin. Another estimation method (29) permits one to dispense with choice set constants by using the log odds with respect to some base alternative as the dependent variable. It is easy to demonstrate that the denominators or choice set effects cancel out for this case. As in disaggregate multinomial logit estimation, one choice alternative serves as a base alternative--the "origin" of the scale values.

Weighted least squares is used because the dependent variable is a proportion (the relative frequency of choices in choice set i), which does not conform to classical homoscedasticity assumptions in multiple linear regression. Louviere and Woodworth (25) and Grizzle, Starmer, and Koch (28) discuss weighting for this condition. The method yields modified minimum chi-square estimates that are asymptotically efficient and consistent in large samples.

EXAMPLE APPLICATIONS

This section illustrates the application of the approach to three travel-choice-related examples and also provides evidence from three validity tests that suggests the approach is predictive of the actual behavior of people in real markets.

Simple Destination Choice Problem: Choosing a Fast-Food Restaurant for Lunch

Example A involved 99 upper-class undergraduates in marketing at the University of Iowa, who were shown 10 different choice sets consisting of various combinations of the five major hamburger chains in Iowa City: Wendy's, Burger King, Hardee's, McDonald's, and Burger Palace. The choice sets were developed by treating each restaurant as a factor with two levels: available or unavailable. All possible sets of choice sets would be the 2⁵ combinations of availability of each restaurant. This is a factorial design. We selected 8 choice sets from the 32 possible according to an orthogonal main-effects plan (24). One of the 8 sets selected is the null set (all unavailable); hence, there is a target group of 7 sets for analysis. Subjects were shown 3 preliminary sets of no analytic interest to acquaint them with the task.

Subjects indicated which restaurant they would be most likely to choose for lunch given that only the ones listed in a particular set were available. Subjects were informed that some restaurants could fail or others enter the market, and we wished to know what they would do if some now present were closed. The discrete choice data were aggregated to relative frequencies for analysis by weighted least-squares regression:

$$Rf_{\kappa} = \beta_0 + \beta_1 \text{Wendy's}_{\kappa} + \beta_2 \text{Burger King}_{\kappa} + \beta_3 \text{Hardee's}_{\kappa} + \beta_4 \text{McDonald's}_{\kappa} + \beta_5 \text{Set 1}_{\kappa} + \beta_6 \text{Set 2}_{\kappa} + \beta_7 \text{Set 3}_{\kappa} + \beta_8 \text{Set 4}_{\kappa} + \beta_9 \text{Set 5}_{\kappa} + \beta_{10} \text{Set 6}_{\kappa} \quad (5)$$

where

- Rf_κ = observed relative frequency for the κth (κ = 1, 2, ..., K = 40) choice possible in the task;
- Wendy's, Burger King, etc. = (1, 0) dummy variables to represent (J - 1) alternatives (restaurants) (each choice observation is coded one if it is the alternative in question, zero otherwise);
- Set 1, Set 2, etc. = (1, 0) dummy variables to represent the (I - 1) different denominators or "choice set effects" (each choice observation is coded one if it was observed in the ith set, zero otherwise); and
- β₀, β₁, etc. = empirical regression parameters to be estimated from the data.

The statistical results are as follows:

Restaurant	Estimated Scale Value	Standard Error
Burger Palace	0.00	--
Wendy's	2.56	0.11
Burger King	1.82	0.11
Hardee's	1.08	0.11
McDonald's	2.39	0.11

The F (14, 26) = 48.36, which has a probability of occurring by chance of less than 0.0001. The R² value is 0.98. The model appears to give a good account of the aggregated choice data.

Only the scale values are of interest in the examples; the choice set parameters are needed merely to ensure that the probabilities sum to one in each choice set and because they are algebraically necessary in the model form to be estimated. One could recover the original choice proportion data (the relative frequencies) by using the scale values estimated in the regression. Thus, the degrees of freedom necessary to account for the choice data are always much less than indicated in the regression analyses. Nonetheless, it should be noted that Equation 1 implies a constant cross elasticity for all attributes of all alternatives and the choice set constants contain all cross-elasticity effects. If one suspects that this hypothesis is not true, more detailed analysis of each choice alternative will be necessary.

Simple Modal-Choice Problem: Bus Versus Automobile Versus Other

A modal-choice task was developed by manipulating three attributes of bus systems and three attributes of automobiles in an experimental design. The attributes of bus (and their levels) were fare (25¢ and 50¢), travel time (15 and 40 min), and walking distance (1 and 5 blocks); the attributes of automobile were gasoline cost per gallon (\$1.35 and \$1.75), travel time (10 and 20 min), and parking costs per hour (20¢ and 50¢). In other words, the experimental design was created by treating each attribute as a factor with two levels and selecting a fraction of the 2⁶ complete factorial design. The orthogonal fraction selected from Hahn and Shapiro (24) has 16 treatment combinations, each of which is a choice set. That is, a choice set consists of a description of the levels of the three bus attributes and the levels of the three automobile attributes; subjects were requested to indicate whether, given their present circumstances, they would choose to travel to the University of Iowa for regular morning classes by the described automobile, bus, or other (left unspecified). Subjects were the same 99 undergraduates involved in example A.

The discrete choice data were aggregated to relative frequencies for analysis by weighted least-squares regression. The following model was estimated:

$$Rf_{\kappa} = \beta_0 + \beta_1 \text{bus}_{\kappa} + \beta_2 \text{auto}_{\kappa} + \beta_3 \text{fare} (\$) \text{ if bus}_{\kappa} + \beta_4 \text{time} (\text{min}) \text{ if bus}_{\kappa} + \beta_5 \text{walk} (\text{blocks}) \text{ if bus}_{\kappa} + \beta_6 \text{gasoline} (\$/\text{gal}) \text{ if auto}_{\kappa} + \beta_7 \text{parking} (\$/\text{h}) \text{ if auto}_{\kappa} + \beta_8 \text{time} (\text{min}) \text{ if auto}_{\kappa} + \sum_{i=1}^{15} \alpha_i C_i \quad (6)$$

where

- Rf_κ = κth relative frequency of choice observation (κ = 1, 2, ..., K; K is I x J);
- bus, auto = alternative specific constants, derived by treating each as a (1, 0) dummy variable;
- fare, time, etc. = alternative specific attributes that have their numerical values if the choice observation pertains to the mode in question or are zero otherwise;
- C₁ = 15(I - 1) (1, 0) dummy variables used to represent choice sets; and
- α₁, β₀, β₁, β₂ = empirical constants to be estimated from the data.

The results of the analysis are as follows (choice set results suppressed):

Variable	Parameter	Standard
	Estimate	Error
Bus	1.26	0.55
Auto	-1.30	1.07
Other	-2.31	0.57
Bus time	-0.07	0.01
Bus fare	-2.58	0.85
Bus walk	-0.17	0.05
Auto gas (\$)	-0.10	0.48
Auto parking (\$)	-0.57	0.64
Auto time	-0.01	0.02

The F (24,24) was 36.97; the probability of an F-value that large occurring by chance is less than 0.0001. The R² is 0.95, so this model also gives a reasonably adequate account of the logs of the relative frequencies of choice data. Results indicate that, whereas University of Iowa students in marketing prefer buses to other modes, they are particularly sensitive to bus attributes in comparison with automobile attributes. It is notable that the travel-time coefficient for bus is almost nine times larger than that for automobile, which clearly indicates that time is not the same via either mode. With the bus equation, the implied value of travel time is about \$1.65/h; however, these are student subjects.

Intraurban Modal-Choice Example: Bus Versus Air

An intraurban modal-choice task was developed by asking Iowa City individuals to make choices between the regular air service operating from Cedar Rapids, Iowa, to Chicago, Illinois (which requires Iowa City residents to drive approximately 26 miles to the Cedar Rapids Airport) and several different bus services proposed to operate directly from Iowa City to Chicago. At the time this paper was written, regular air service was offered by Ozark, Midstate Air, and Mississippi Valley Airlines. All operate non-stop services with flying times that range from 54 min to an hour and 45 min. All airlines had beverage but no in-flight food service.

Individuals were asked to choose among six alternatives: (a) regular air service at a particular price, (b) a bus service with drink and food service at a particular price, (c) a bus service with drink service but no food at a particular price, (d) a bus service with food service but no drink at a particular price, (e) the current bus service with no food or drink service at a particular price, and (f) some other method of travel, such as private vehicle. Respondents were asked to make choices in 16 different choice sets, which were developed by considering the air and four bus modes as factors with four levels of price; other was not given a price because it would vary from respondent to respondent.

Respondents consisted of a sample of 99 individuals chosen for convenience and willingness to participate and were drawn from three groups: (a) 33 Iowa City air travelers interviewed in the departure areas of the Cedar Rapids Airport; (b) 33 bus travelers interviewed at the Iowa City Bus Terminal, and (c) 33 students chosen because they declared that they made at least occasional trips to Chicago from Iowa City. All respondents participated in all choice sets. Data were aggregated to relative frequencies of choice for analysis by weighted multiple linear regression. The following model was estimated from the data:

$$Rf_k = \beta_0 + \beta_1 air_k + \beta_2 bus_k + \beta_3 other_k + \beta_4 air\ cost_k + \beta_5 bus\ cost_k + \beta_6 bus\ food_k + \beta_7 bus\ drink_k + \beta_8 bus\ food \times drink_k + \beta_9 choice\ set\ 1_k + \beta_{10} choice\ set\ 2_k + \dots + \beta_{23} choice\ set\ 15_k \quad (7)$$

where all terms are as previously defined or self-evident.

This model implies that there are different effects for dollar costs depending on whether the mode is bus or air and that food and drink have (potentially) nonadditive effects within bus. The results are as follows:

Variable	Parameter	Standard
	Estimate	Error
Air	0.344	0.403
Bus	1.208	0.254
Other	-1.464	0.169
Air cost	-0.019	0.004
Bus cost	-0.127	0.010
Food	0.140	0.057
Drink	0.043	0.056
Food x drink	0.135	0.057

These results indicate that bus is preferred to air, which is probably the result of the preponderance of the sample of bus travelers and students and the larger number of different bus choices. In this respect, it is important to note that the sample is six times more sensitive to bus cost than to air cost and is much more influenced by the provision of a food service than a drink service. The (food x drink) interaction implies that having both is better than having either separately but having neither is considerably less preferred. If the sample were representative, it would imply that considerable leverage on patronage could be gained by the food-drink option and by offering air or bus travel cost specials.

SELECTED EVIDENCE OF EXTERNAL VALIDITY

This section briefly outlines the results of three recent tests of intended-choice-based models derived from controlled experimental manipulations of choice alternatives as described in previous sections of this paper. Other evidence of validity is reviewed by Levin, Louviere, Norman, and Schepanski (13) and elsewhere (8,11,12,14,15,25,30) and is therefore omitted in the interests of brevity. Suffice it to say that since 1975 intended-choice-based methods have compiled a consistent record of empirical successes in validity trials in the United States, Australia, and The Netherlands. The results reported here are representative of these other findings.

The first choice study to use the methods described above was conducted on behalf of a major pet food manufacturer. Because the results are proprietary, we provide only sufficient description to assess the outcome.

Random samples of pet food users were selected from several major markets in the United States in such a way as to be representative of the market. Subjects interviewed were shown 16 different choice sets consisting of combinations of 13 target pet food products based on a main-effects plan (23,24,26,27) drawn from the 2¹³ factorial. Subjects were asked to allocate 11 points across the alternatives in each choice set so that the allocations reflected the proportion of each product that they would be likely to purchase in a typical month. Allocation data were aggregated to develop relative frequencies of choice, and a choice model similar to that represented by Equation 5 was estimated by weighted least-squares regression.

Market share forecasts were then made by using

the scale values of the products derived from the regression. Data on U.S. national inventory withdrawal shares were obtained from a commercial company for the validity test. These data reflect distribution outlet withdrawals from inventory sources, which is not the same as aggregate sales share data but should be closely related. The results of this test revealed an obvious linear relation between observed and forecast national shares. The correlation was 0.83; some calibration (linear adjustment) would be necessary to apply the choice model developed in the interviews directly to the share data.

The second test involves a similar type of experimental design administered to a sample of 100 residents of Iowa City. The eight major supermarkets in Iowa City were treated as factors with two levels (available and unavailable), and 12 choice sets were constructed by developing a main-effects plan from the 2⁸ factorial (23,24,26,27) to generate choice sets. First, those interviewed were asked to estimate how much of their grocery shopping budget they had spent in each of the eight stores over the preceding month. They were then shown the 12 choice sets and asked to indicate in which store they would be most likely to spend most of their budget if they could choose only from those listed in each choice set.

The choice data were aggregated to relative frequencies for analysis, and a model similar to Equation 5 was estimated from the data. The estimated scale values for each store were used to forecast their market share, and this was compared with the reported share data for the previous month's shopping obtained in the interview. The relation was again linear and the correlation was substantial (0.96). Again, a linear adjustment would be required to calibrate the laboratory model to the actual reported choice data.

The final example involves a transportation modal-choice problem in Australia. For policy reasons, it was desired to assess the sensitivity of choice for travelers to and from Tasmania and mainland Australia to changes in costs and types of service by sea and air. A sample of Tasmania and mainland residents completed a choice experiment that elicited (among other things) respondents' choices among an air service at a particular price, three different sea services (overnight with berth, overnight with chair, and fast daylight) at various prices, or "no travel". Respondents were shown 12 choice sets consisting of the four modal alternatives at different costs and the no-travel option. Three different questionnaires were created to permit all possible two-way interactions among the cost components of each mode to be estimated. Respondents were randomly assigned to the different questionnaires, and their choices were aggregated for a multiple linear regression analysis somewhat similar to Equation 6.

The model derived from the choice data was then used to predict the current known shares by air and sea (0.82 and 0.18, respectively). The derived model forecast the shares to be 0.78 and 0.22, respectively. This result suggests that the model requires minimum calibration and produces results consistent with actual observation.

DISCUSSION AND CONCLUSIONS

Many strategic research questions involve behavior for which either there are no current observational data or there is insufficient range and/or variation in independent variables of interest. Forecasting the response to introductions of new technology is but one of many examples of such research questions; others involve changes in existing transportation

systems for which there is no historical precedent, such as a bus system that has historically operated all lines on a 30-min headway changing some to 15- or 60-min headways. In such instances, one usually tries to transfer knowledge from cognate problems or sites. It is well-known that such transfers have usually been disappointing. This paper proposes a new approach to the problem that involves observations of behavior under hypothetical, controlled simulation conditions.

The approach proposed in this paper produces models that are compatible with existing methods and technology; hence, no new educational or technical developments are required to implement the analysis. Of course, training would be required in the design of experiments and in the theoretical backgrounds in psychology and economics. The approach, however, has the advantages of being very flexible and inexpensive and providing quick response compared with more traditional methods. Cost savings accrue because so much more data can be obtained per individual. Moreover, experience with the procedures in academic and commercial applications has shown that the tasks for respondents are relatively straightforward and can be completed rapidly. Furthermore, analysis of the data is easy and inexpensive.

Based on external validity tests conducted with the proposed method and similar approaches developed in psychology and marketing, it is now clear that judgment and choice simulation methods can and do predict external behavior well. Indeed, it would be possible to argue, based on the evidence discussed in this paper and elsewhere (8,11,12,14,15,25,30), that judgment and choice models do no worse than econometric or other revealed-behavior models and most often perform considerably better. The additional advantages of being able to consider policy variables not now in place and to forecast responses to new innovations are also noteworthy. It now appears that judgment and choice models have matured to the point where they deserve the serious attention of practicing planners and others interested in strategic policy analysis and behavioral simulation modeling. At least one major planning group, the Wisconsin Department of Transportation, has adopted the approach in concert with its statewide road planning efforts, and the Australian Bureau of Transport Economics of the Australian Department of Transportation is now completing its third major study involving these techniques. In addition, we have conducted several dozen major commercial studies involving the methods discussed here, and there have been hundreds of other studies that have used trade-off methods.

This paper calls further attention to the complementarity of the judgment and choice approaches and more traditional revealed-behavior-based methods of data collection and analysis in transportation. Planners in the 1980s will require new and innovative solutions at low cost to solve problems effectively. The judgment and choice methods offer significant advantages that should not be ignored. The old argument that judgmental methods or methods based on behavioral intentions are less valid than methods based on observations of real behavior is now known to be false. Hence, validity arguments should no longer serve as a barrier to application of judgment and choice methods in travel choice modeling. Rather, it is time for researchers in both areas to begin to work together on common and complementary problems in travel choice behavior.

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