

A BERNOULLI MODEL OF DESTINATION CHOICE

Pat Burnett,* University of Texas at Austin

Many attempts have been made to identify the variables that condition the destination choices of individuals and groups. Diverse models of spatial choice now incorporate many descriptors of the socioeconomic characteristics of decision-makers, of their cognitive and evaluative processes, and of the objective features of destination alternatives. No single model is generally acceptable. This seems to reflect both the complexity of the destination choice decision and the difficulty of developing a single model to predict the choices of a heterogeneous population group. This paper explores an alternative approach. We assume that the individual's destination choices over time, for a given purpose, may appear to be a random process because of the conflicting or interacting effects of many variables. A simple Bernoulli model is developed to describe this process for a heterogeneous population group. A preliminary test of the model is carried out by using data on successive grocery store choices of a sample of 90 households in Uppsala, Sweden. The model fails to fit sections of the data describing the use of particular stores, the use of different classes of store, and the behavior of different population groups. The population groups were differentiated by their degree of store familiarity, by their distance from both the stores they used and from all stores, and by their life-cycle stage. The consistent rejection of the model lends some support to new efforts to isolate variables conditioning destination choice, for example, through the application of learning models and perhaps even the multinomial logit models currently used to study mode choice.

•A VARIETY of models of destination choice have been developed and tested during the past decade (7). They are relevant for the trip distribution phase of urban transportation planning, for they attempt to isolate variables that condition the spatial choices of individuals and groups.

Destination choice involves the selection of a facility at which to conduct a short-duration, recurrent activity (work, shopping, recreation, social visits); it also involves choice of locations or facilities, such as business, industrial, or residential sites, to investigate for future long-duration activities (44).

It is somewhat discouraging, but perhaps not surprising, that no single, generally acceptable model has been found. As Huff suggested in 1960 (30), many variables appear to impinge on destination selection. Thus, models of this kind of spatial behavior now include

1. Gravity, entropy, and central place hypotheses of the effects of distance and benefits of travel to destination alternatives (2, 5, 26, 50);
2. Learning theory, space preference, and subjective utility models of how destinations are cognized and evaluated (1, 3, 8, 17, 19, 20, 21, 22, 24, 30, 38, 41);
3. Hypotheses about the effects of socioeconomic, demographic, personality, and attitudinal variables (6, 28, 33, 36); and
4. Trip linkage studies relating the time sequencing of activities and the individual's successive destination choices (16, 32, 37, 42).

*Ms. Burnett was with Northwestern University and the General Motors Research Laboratories when this paper was prepared.

In addition, recent work on the perception of places, locations, distances, and directions in the city obviously bears on modeling destination decisions (13, 27, 41, 49).

To determine which of the many variables may best be incorporated in models of destination choice is not easy. Moreover, to specify mathematically the ways in which most factors shape this kind of travel decision is difficult. Therefore, continued attempts to develop models to explain or predict destination selections must be justified in terms of variables conditioning the individual's choices. Since, at the moment, there is little indication that any simple set will be influential and measurable for many decision-makers in many destination choice situations, general multivariate models are difficult to derive. Accordingly, we need some evidence as to whether to accept or reject the following hypothesis: Successive destination selections by heterogeneous individuals may better be modeled as the outcome of a random process. (Definitions of heterogeneous and random process are given in later sections.)

Acceptance of this hypothesis would permit at least 2 possible conclusions. First, so many variables might impinge on destination decisions (including variables that would describe alterations in origins and activity combinations over time) that their conflicting and interacting effects make choices appear as if they were random. This kind of argument has been advanced to explain the success of random choice models in predicting complex brand choice behavior (35, p. 121). Second, it is possible that individuals choose destinations at random from a given choice set in some instances. This is likely in cases where destinations are not strongly differentiated, as, for example, supermarkets for convenience food shopping (21, p. 8). Alternatively, rejection of the hypothesis would support the contention that only a few variables may condition destination choice and that these have not yet been successfully identified. This would justify continued work to isolate relevant variables. The rejection of the hypothesis should also hearten policy-makers who urgently require the identification of a few manipulatable factors controlling trip distribution to assist with urban land use and transportation planning.

The first part of this paper accordingly presents a Bernoulli model of a random destination choice process for a heterogeneous population. Because of limitations of space, a knowledge of probability theory and elementary stochastic process theory has to be assumed (14). However, the present model closely follows Massey, Montgomery, and Morrison's application of Bernoulli process theory to brand selection (34, chap. 3), and a simplified description of the theory and its testing may be found in their work.

The present model's predictions are tested by using 1971 travel diary information on the successive store choices of a random sample of 90 households in Uppsala, Sweden. An analysis was made of data showing all stores used for grocery purchases by each household during 39 days. These kinds of data were chosen for 2 reasons. First, most work has been done on shopping trips, which conform clearly with the general characteristics of the individual's destination choice problem for an activity [formally specified by the author in another paper (7) and in a later section in this paper]. Second, longitudinal data for the most frequently purchased convenience goods are obviously the least expensive to collect. These data also provide the greatest number of observations of destination choices during any given period.

The results of the tests support the rejection of the hypothesis of random destination choices by individuals and groups. This paper, therefore, provides impetus for further work to isolate the socioeconomic, attitudinal, learning, or other variables that condition individual and group destination choice.

SPECIFICATION OF THE BERNOULLI MODEL

Destination Choice as a Stochastic Process

Formally, stochastic process models of destination choice deal with the following problem. An alternative characterization of the destination choice problem, which is shown to apply to current work, is given in another paper (7).

If the following are given

1. A constant set of k destinations that represent alternatives for the conduct of an activity (for example, a set of shopping places for the purchase of a good),

$$D = \{D_1, \dots, D_i, \dots, D_k\}$$

2. A group of m individuals in given locations (for example, their place of residence), every one of whom is aware of and accessible to each destination,

$$I = \{I_1, \dots, I_j, \dots, I_m\}$$

3. That the set of destinations D constitutes the "state space" for each of the individuals, that is, each decision-maker can choose one of the destinations on any selection (be in one of k mutually exclusive and exhaustive states);

4. That the m individuals differ in their probability of selecting any destination on any choice, but have identical decision-making criteria (for example, all individuals may decide to select destinations at random or according to what they subjectively decide is best); and

5. That the m individuals have made n past destination selections for the conduct of the activity,

then derive a probability for each of the k destination alternatives that it will be selected by the group of m decision-makers on their next $(n + 1)$ th choice; that is, derive

$$P_{D, n+1} = \{P_{1, n+1}, \dots, P_{i, n+1}, \dots, P_{k, n+1}\}$$

A mathematical solution to this kind of problem has been demonstrated to exist and to yield testable results only for the simplified case in which the number of states is reduced from k to 2 by some prior classification procedure (34). In other words, D , the destination set, must be reduced to $D^* = \{D_0^*, D_1^*\}$, where D_0^* and D_1^* are mutually exclusive and exhaustive subsets of D , neither of which is empty. The problems that arise from classifying or aggregating states (here, destinations) in this way are discussed in Bush and Mosteller (9, sect. 1.8): Aggregation remains a recommended, though dubious, procedure for constructing operational stochastic models. Moreover, the purpose of this paper is not to produce a new model of destination choice but to test a hypothesis of random destination selection and, ideally, to reject it and further the development of multivariate models. In this context, a high degree of simplification of real-world choice states may be acceptable, although admittedly undesirable.

Bernoulli Hypothesis

The Bernoulli hypothesis involves the following definitions and assumptions:

1. Define X as a variable whose values represent the outcome of an individual's random selections between a 0 (destination class 0) and a 1 (destination class 1) on each of n successive choices. For example, let $n = 3$, so that 001 is a possible trip history or sequence of values for X on the individual's third last choice, second last choice, and last choice (for X_{t-2} , X_{t-1} , X_t).

2. Assume that each individual has a constant probability over time, p , of a destination class 1 choice on any occasion and, consequently, a constant probability $1 - p$ of a destination class 0 on any occasion (the implications of this will be discussed later).

Then these assumptions and definitions constitute a hypothesis of destination choice as a Bernoulli process. This is formally denoted as a process such that

$$\{X_t, t \in T\}, X_t \in R$$

$$P[X_t = 1 | X_{t-1}, X_{t-2}, \dots, X_{t-n}] = p$$

for all $(X_{t-1}, \dots, X_{t-n}) \in R^n$. $n = 1, 2, 3, \dots$. Here $R = \{0, 1\}$, and $T = \{1, 2, \dots\}$.

To allow for differences among individuals, we may make the further assumption that any individual is a random sample from a heterogeneous population who choose destinations according to H_b , but who have different p values. Thus, any individual's p may be regarded as a random sample from the distribution of p values over the population, described by the density function $f(p)$.

The assumption of a constant p value for all individuals over time may seem questionable. However, it considerably simplifies the derivation of predictions to test H_b . The assumption also has a well-documented behavioral interpretation. It implies that most individuals have stable patterns of behavior with respect to each destination class; that is, that a decision-maker will generate the same relative frequency of trips to any class in each time period over the long run. This seems to be the case in reality, except in newly established neighborhoods or where facilities are rapidly changing. For example, Cunningham (10, 11) early identified "store loyal" segments with stable shopping behaviors, while Golledge (20, p. 418) and Stone (45) also discuss store choice behavior of this kind. In addition, the assumption of a constant yet different p value for different individuals implies that, although each individual may have a stable pattern of behavior, the pattern of any 2 individuals need not necessarily be the same. This also seems realistic.

Predictions of the Bernoulli Model

x_1 is a trip history for a randomly sampled decision-maker who has n past trips to either destination 1 or destination 0.

$l(x_1 | p)$ is the likelihood of this history, given that the individual's behavior can be described by a Bernoulli process with probability p of a destination 1 choice next after any single past choice.

$f(p)$ is the prior distribution of p for the randomly sampled decision-maker, that is, the distribution of the probability that the individual will choose destination 1.

$b(p | x_1)$ is the posterior distribution of p for the randomly sampled decision-maker, that is, the distribution of the probability that the individual will choose destination 1 next after the particular sequence of past choices given by x_1 .

$P(1 | x_1)$ is the probability under H_b that the individual who has history x_1 will visit destination 1 next.

N_{x_1} is the number of decision-makers in a hypothetical random sample who have history x_1 .

R_{x_1} is the number of decision-makers in N_{x_1} who visit destination 1 next, under H_b .

$\bar{p}_{x_1} = R_{x_1} / N_{x_1}$ is the probability (relative frequency) under H_b of a destination 1 choice next by a randomly selected group of individuals who have the same history x_1 but different p values.

By the use of the rules of conditional probability for the individual

$$b(p | x_1) = l(x_1 | p) \cdot f(p) \tag{1}$$

(Bayes Theorem) and

$$P(1 | x_1) = \int_0^1 p \cdot b(p | x_1) \cdot dp = \text{mean of } b(p | x_1) \tag{2}$$

(34, p. 63, Eq. 3.1, and pp. 64-66). It can now be shown that

$$N_{x_1} \xrightarrow{\text{lim}} \frac{R_{x_1}}{N_{x_1}} = N_{x_1} \xrightarrow{\text{lim}} \bar{p}_{x_1} = P(1 | x_1) \tag{3}$$

This means that, in the limit, as the size of the group of individuals who have history x_1 and different p values becomes large, the relative frequency with which the decision-makers choose destination 1 next, \bar{p}_{x_1} , is equal to the posterior expectation of p . This

is the expected probability that any individual with history x_1 will travel to destination 1 next, $P[1|x_1]$. [One proof of this Bernoulli law of large numbers is given by Massey, Montgomery, and Morrison (34, pp. 66-67).]

Equations 1 and 3 may now be used to derive the testable model prediction: that groups of decision-makers will have equal probabilities of a destination 1 choice next (that is, the same \bar{p}_{x_1}) if they have histories with proportional likelihoods of occurrence. Consider any 2 past histories of length n , labeled x_1 and x_2 , such that $\ell(x_1|p) = \text{constant } \ell(x_2|p)$. Then, from Eq. 1,

$$\begin{aligned} b(p|x_1) \ell(x_1|p) \cdot f(p) &= \frac{\ell(x_1|p) \cdot f(p)}{\int_0^1 \ell(x_1|p) \cdot f(p) \cdot dp} \\ &= \frac{\not\ell \ell(x_2|p) \cdot f(p)}{\int_0^1 \not\ell \ell(x_2|p) \cdot f(p) \cdot dp} \\ &= b(p|x_2) \end{aligned} \quad (4)$$

and from Eqs. 2 and 3

$$N_{x_1} \xrightarrow{1/n} \frac{R_{x_1}}{N_{x_1}} = N_{x_2} \xrightarrow{1/n} \frac{R_{x_2}}{N_{x_2}}, \text{ i.e., } \bar{p}_{x_1} = \bar{p}_{x_2} \quad (5)$$

The converse should also hold. Groups will have unequal probabilities of a destination 1 choice next (e.g., $\bar{p}_{x_3} \neq \bar{p}_{x_4}$) where their last trip histories are such that their likelihoods of occurrence are not proportional [i.e., $\ell(x_3|p) \neq \text{constant } \ell(x_4|p)$].

Which histories of length n should have proportional likelihoods of occurrence under H_0 and which should not remain to be found. We may then use data to see whether randomly sampled groups of individuals with each of these past histories display the expected similarities and differences in the proportions of decision-makers choosing destination 1 next.

First, consider the group of histories of length n with r visits to destination 1, where each history is generated by a Bernoulli process. Then the likelihood of any past sequence of length n with r ones is equal to the binomial probability $\binom{n}{r} p^r (1-p)^{n-r}$, and the likelihood of each past sequence of length n with r ones is equal to $p^r (1-p)^{n-r}$. That is, under H_0 , all past histories of the same length and with the same number of ones will have not only proportional but equal likelihoods of occurrence. Similarly, it may be shown that all histories of the same length, but a different number of ones, have different and disproportionate likelihoods of occurrence. Accordingly, under H_0 , groups with past histories of the same length and number of ones should have the same proportions making a destination 1 choice next. Also, groups with past histories of the same length but different numbers of ones should have different proportions choosing destination 1 next.

It is only necessary now to choose an appropriate value of n to test H_0 . If n is not small, then large, costly samples of individuals and their travel diary data will be necessary, since there must be a reasonable number of persons in each of 2^n possible past destination choice histories. On the other hand, if n is relatively small, then any individual's observed destination sequence may be broken into nonoverlapping subsequences of the given length, and this will increase the number of observed histories of the correct length without increasing the sample of decision-makers. (Where subsequences are used, observations will not be independent. This will introduce unknown biases into any standard statistical test of the model; they may be counteracted by selecting a 0.01 instead of 0.05 confidence interval for the rejection of a hypothesis.) Accordingly, a small value for n is preferred here for practical reasons.

To yield sufficient observations from a data base for initial tests of the model, we let $n = 3$. Table 1 then gives the model's predictions for each of the 8 possible histories of 3 successive destination choices. From the information given in column 3 of Table 1, H_0 and the Bernoulli model can be rendered unacceptable by the rejection of any one of the following hypotheses; conversely, at least all three of the hypotheses have to be upheld before H_0 can be accepted.

Table 1. Predictions of Bernoulli model.

History x_i (sequence of last 3 destination choices) ^a	Likelihood of x_i for the Individual ^b	Proportion of Individuals Choosing Destination 1 Next, Given History $(x_i)_{\bar{p}_{x_i}}$
000 (n = 3, r = 0)	$(1 - p)^3$	Different from all other histories
100 } (n = 3, r = 1)	$p(1 - p)^2$	Same within this group; different from \bar{p}_{x_i} for histories not in group
010 }	$p(1 - p)^2$	
110 }	$p(1 - p)^2$	
110 } (n = 3, r = 2)	$p^2(1 - p)$	Same within this group; different from \bar{p}_{x_i} for histories not in group
101 }	$p^2(1 - p)$	
011 }	$p^2(1 - p)$	
111 (n = 3, r = 3)	p^3	Different from all other histories

^an is the trip history length, or number of past destination choices; r is the number of destination 1 choices.

^bUnder the Bernoulli model, the likelihood of an individual making a destination 1 choice on any trip is p and a destination 0 choice is $(1 - p)$.

$$H_1: \bar{p}_{100} = \bar{p}_{010} = \bar{p}_{001}$$

$$H_2: \bar{p}_{110} = \bar{p}_{101} = \bar{p}_{011}$$

$$H_3: \{\bar{p}_{100}, \bar{p}_{010}, \bar{p}_{001}\} \neq \{\bar{p}_{100}, \bar{p}_{101}, \bar{p}_{011}\} \quad (6)$$

In these hypotheses, the subscripts of \bar{p}_{x_i} , that is, the relevant trip histories x_i of length 3, have been written out in full. (For example, H_1 states that the probabilities of a destination 1 choice next should be the same for groups of individuals with past histories 100, 010, and 001. In other words, the relative frequencies with which individuals go on to make a destination 1 choice next should all be the same for each history.) The 3 hypotheses are each verifiable by the chi-square test of homogeneity (12, pp. 224-226). The approach differs only from the well-known chi-square test of the independence of classifications in that "the totals for columns are given in advance . . . [and] we are actually testing that the various columns have the same (or different) proportions of individuals in various categories" (12, p. 225). The results of tests of hypotheses H_1 , H_2 , and H_3 constitute the substance of Tables 3 and 4 and of the concluding section of this paper.

TESTS OF THE BERNOULLI MODEL

Data Base

The data that were used were the grocery shopping records of 90 households randomly sampled from 6 life-cycle groups. [A detailed description of the field survey design and questionnaires that supplied these data is given in other reports (51, 52).] The record for each household consisted of every store in which a grocery purchase was made during a 39-day period and each store's location, land use activity, size (square meters of gross floor area), and chain affiliation. The stores were listed in each household's record in the sequence in which they were visited. The data were analyzed to see whether there was any evidence of

1. Random use of a given destination;
2. Random use of destinations classed by activity, scale, and organizational affiliation; and
3. Random destination choice by different population groups.

Random Use of a Given Destination

The patronage of each of 3 stores was examined in turn; only those stores generated during the 39-day period a large enough sample of trip histories for analysis. All those households using a given store were first isolated. The successive destinations in each household's trip record were then coded so that a destination scored 1 if the

designated store were visited and 0 otherwise. This produced a binary matrix of the type given in Table 2. Each row represents a household's sequence of visits to either the designated store or to any other.

Each household's binary destination choice sequence was broken into subsequences of length 3, as indicated by the columns of Table 2; incomplete subsequences of 2 choices or fewer at the ends of records were ignored. The length 3 subsequences constitute the histories of each kind, x_1 , which are given in Table 1, and which are required to test the Bernoulli model. For a given store, the number of histories of each kind was totaled for all households, and then the proportions of each kind that were followed by a destination 1 choice were added. These observed proportions were then compared to see whether they were as expected according to the model's 3 hypotheses (Eq. 6 and Table 1). Chi-square tests of the hypotheses and of the Bernoulli model were performed for each store.

In every case for the 3 stores, H_1 and H_2 were accepted, but H_3 was not (Table 3); thus, these limited tests offered no support for the hypothesis that the selection of particular destinations is a random process of the kind specified by the Bernoulli model. Individuals may switch destinations for a given activity in a simple purposive fashion, as described, for example, in learning theory explanations of consumer use of a given store (19). Alternatively, some simple set of variables, as yet unidentified, may determine the sequence of destination choices over time by a heterogeneous population group.

Random Use of Classes of Destination

A similar procedure was followed to ascertain whether different classes of destination are used at random. Stores were classified by product range (large grocery store, specialist food stores, grocery sections in department stores), size (above or below the median gross floor area), and chain affiliation (KONSUM, ICA, VIVO, and others).

The Bernoulli model was tested for each class of store; data matrices with a similar format to that given in Table 2 were used. In a matrix for a class of store, the rows comprised the trip records for every household using that class of store during the 39-day observation period; a 1 represented a visit to a designated store class, and a 0 represented a visit elsewhere. The Bernoulli model fit the destination choice behavior of households using 3 classes of store, but did not fit the data for 5 classes (Table 3).

Random Destination Choice by Population Groups

The question was also addressed as to whether the destination choices of some population groups might be modeled as a random process. The Uppsala households were classified in turn by store familiarity (3 groups), by mean distance from all grocery stores (2 groups), and by stage in life cycle (3 groups). Ten arbitrarily defined groups were thus examined altogether (Table 4).

It seemed likely that the groups with least information might switch destinations in an apparently random manner as they learned about alternatives, and that the more experienced groups might fluctuate randomly among "destination states" while in an effort-minimizing equilibrium choice pattern (19, 20, 22, 44). Moreover, it seemed plausible that groups at greater distances from shopping place alternatives, on trade-area margins, might select destinations in an apparently random fashion, and closer groups might develop simple stable trade-off functions between distance to store and other costs and benefits of travel (21, pp. 12-13). Finally, groups with different demographic characteristics seemed likely to have distinctive destination selection behaviors. Households with the least time and money constraints (the well-endowed, older Swedish households without children) especially might appear random in destination selection (33).

The Bernoulli model was tested for each group in turn; again data matrices similar in format to that given in Table 2 were used. Each data matrix comprised the trip records for all the households belonging to a group. The household's successive

Table 2. Example of binary data matrix for test of Bernoulli model.

Household Using Store Y at Least Once During 39 Days	Destination for Grocery Purchase ^a								
	1st	2nd	3rd	4th	5th	6th	...	q th	
1	1	0	1	0	0	1	...	1	
2	0	1	0	1	1	0	...	0	
3	1	1	1	0	1	1	...	1	
4	1	0	0	0	0	0	...	0	
5	1	0	1	0	0	1	...	1	
.	
.	
.	
y	0	1	1	0	1	0	...	0	

^a1 = store Y visited; 0 = another store visited.

Table 3. Results of tests of Bernoulli model: random use of selected destinations.

Destination Store	Sample Size ^a	Accept or Reject at 0.01 level			Acceptance of Bernoulli Model
		H ₁	H ₂	H ₃	
Store 1	93	A	A	R	Reject
Store 2	40	A ^b	A ^b	R ^b	Reject
Store 3	57	A ^b	A ^b	R ^b	Reject
Product range					
Large	200	A	A	A	Accept
Small	53	A ^b	A ^b	R ^b	Reject
Groceries in department stores	162	A	A	A	Accept
Gross floor area					
<200 m ²	113	A	A	R	Reject
>200 m ²	158	A	A	R	Reject
Affiliation					
KONSUM	137	A	A	A	Accept
ICA	99	A ^b	A ^b	R	Reject
VIVO and others	56	A ^b	— ^c	R ^b	

^aTotal number of length 3 histories over all households.

^bA fourth to a half of expected frequencies in chi-square tests were less than 5. In these instances, Yates' correction for continuity was used. This correction is described for the case of a 2 x 2 contingency table by Dixon and Massey (12, pp. 225-226).

^cNot estimated (small sample).

Table 4. Results of tests of Bernoulli model: random destination selection by population groups.

Population Group	Sample Size	Accept or Reject at 0.01 Level			Bernoulli Model
		H ₁	H ₂	H ₃	
Familiarity: visits to favorite store					
<15	69	A ^c	A ^c	R ^c	Reject
<25	138	A	A	R	Reject
>25	96	A	A	R	Reject
Distance ^a : avg kilometers from stores used					
<1.07	144	A	A	R	Reject
>1.07	159	R	A	A	Reject
<2.24	132	A	A	R	Reject
>2.24	171	A	A	R	Reject
Stage in life cycle ^b : age of main income source					
<50, no children	134	A	A	A	Accept
18 to 49, no children	67	A	A	R	Reject
18 to 49, children	102	A	A	R	Reject

^aFor each household, the average distance from the grocery stores the household used and all grocery stores was calculated. The median household value for each distance measure was used to separate households into the 4-distance groups.

^bLife-cycle groups as defined for the purposes of the Uppsala field survey (52, 53).

^cA fourth to a half of expected frequencies for chi-square tests were less than 5; Yates' correction for continuity was used.

destination choices across a matrix row were now coded 1 if the store used were that household's most frequently visited (most preferred) store and 0 if otherwise. Thus, the data matrix for a group described the switching behavior of component households between the nearest store in their psychological space and other stores. The Bernoulli model holds that switching behavior should appear to be random for all population groups.

The test results given in Table 4 show that the Bernoulli model holds in only one case: that of older households with no children. In other instances, H_1 and H_2 are accepted, but H_3 is rejected. The consistency of this pattern of rejection suggests that the lack of verification of the model is more than the artificial product of arbitrary group definitions. Some underlying, simple, purposive destination selection process may be common. Since the same conclusion was indicated by the tests for random selection of particular destinations and of classes of destination, we tentatively explore the results of the data analysis for indications of an appropriate general model of destination choice.

Conclusions

From Eq. 6, the acceptance of H_1 and H_2 and the rejection of H_3 implies that households with trip histories 001, 100, and 010 have the same probability of a destination 1 choice next as households with trip histories 110, 101, and 011. This in turn means that households with the relatively larger number of destination 1 choices are generating a relatively higher proportion of destination 1 choices in their records than households with fewer destination 1 choices. Since in each set of tests a 1 choice designated a particular destination, or a particular destination class, or a most preferred store, the data seem to indicate 2 possibilities:

1. Households tend to converge toward "loyalty" to a single shopping place or set of shopping places, or
2. Households tend to be "loyal" to the most frequently used place in an immediate past period.

Either possibility points to some kind of adaptive learning behavior on the part of households in which experience with destinations as the outcome of trip-making influences next destination choice. The results support the specification and application of Markov or linear learning models to destination choice behavior, as has, of course, often been suggested by Brown (4), Golledge (20), and Ginsberg (18). The results are also consistent with findings from studies of choice between complex objects (stores, brands) in marketing, where Markov and linear learning models for both heterogeneous and homogeneous population groups have met with some success (1, 15, 29, 31, 39, 40, 43).

An alternative approach to destination choice modeling also seems both plausible and operational. If destination choice is adaptive, the process may be conditioned by the individual's socioeconomic characteristics and attitudes. Huff (30) provides a theoretical rationalization for this point of view. Hence, methodologies now employed to probe the effects of attitudinal and demographic variables on mode and route choice (23, 25, 28, 48) may be extended to destination choice. The extension of multinomial logit models to destination selection and the development of multivariate models of "destination demand" that incorporate attitudinal variables seem especially promising.

SUMMARY

This paper examines the hypothesis that destination choice by a heterogeneous population group may appear to be a random process because of the conflicting and interacting effects of many variables on the choice decision. A formal model of random destination choice was specified, and its predictions were tested by using data for 3 particular destinations, 8 classes of destinations, and 10 population groups. The model was rejected in 17 out of the 21 tests. The findings support the development of Markov, linear learning, multinomial logit and other multivariate models of destination choice.

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