

# JOINT-CHOICE MODEL FOR FREQUENCY, DESTINATION, AND TRAVEL MODE FOR SHOPPING TRIPS

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This paper describes the estimation of a disaggregate joint-choice model for frequency, destination, and travel mode for shopping trips. The model builds on earlier research by Ben-Akiva in Transportation Research Record 526 that argued for the replacement of aggregate conditional (or sequential) model systems with disaggregate joint (or simultaneous) models and presented a model for the joint choice of destination and mode for shopping trips. The extension of this general model by use of the same multinomial logit form and a similar specification to include travel-frequency choice is an attempt to provide a more complete version of the joint-model structure. Estimation of the expanded joint-choice model proved to be feasible and resulted in behaviorally and statistically acceptable parameter values. All variables produced coefficients of the expected signs and magnitudes consistent with the behavioral notions on which the model specification was based. In general, the estimation of joint-choice models for travel demand was shown to be a computationally tractable alternative to the less acceptable conditional approaches that have been used in the past. An example of the application of the shopping model (combined with a previously estimated modal-choice model for work trips) to the evaluation of transportation policy options is used to highlight some of the features of both the particular models used and the general modeling approach that they represent.

\*THIS PAPER describes a disaggregate travel demand model based on a joint-choice structure. The development of disaggregate travel demand models has led from initial work on binary modal-choice models to continual expansion of the context of choice in an effort to produce a complete set of models for predicting urban travel patterns. Two recent research projects have set the stage for the results reported in this paper. The first project estimated a disaggregate travel demand model for the choices of frequency, destination, mode, and time of day for shopping trips (4). This model was based on the assumption of a conditional-choice (or sequential-choice) structure. Then Ben-Akiva (2, 3), using theoretical arguments, proposed the joint-choice structure as a more realistic approach for travel demand models. His empirical study centered around the choices of destination and mode for shopping trips. Models were estimated for modal choice followed by destination choice, destination choice followed by modal choice, and the joint (or "simultaneous") choice of destination and mode from the set of alternative combinations of mode and destination. As anticipated, empirical evidence has shown that the coefficient estimates are sensitive to the choice structure on which estimation is performed. This finding, along with theoretical arguments, forms a convincing case for the use of a joint-choice structure for all hierarchical equivalent and interdependent choice dimensions such as frequency, mode, destination, and time of day for shopping trips.

The model described in this paper extends the joint-choice model for destination and travel mode estimated by Ben-Akiva to the inclusion of the third choice dimension that is commonly of interest in travel demand forecasting—frequency choice. Consistent with the previous model, the unit of travel demand that is modeled is a round trip (home-shopping-home). The behavioral unit is the household, which is recognized as the relevant decision-making unit for shopping travel choices. As in most of the previous

disaggregate choice models with multiple alternatives, the multinomial logit model was used because of its many desirable theoretical and computational advantages over other techniques.

The first part of the paper is devoted to the description of the joint-choice shopping travel demand model, its specification, and the estimation results. [A more complete description of the accompanying research and findings is given elsewhere (1).] Following the sections that describe this model, an example of the application of the shopping model (combined with a previously estimated modal-choice model for work trips) is described. This demonstration highlights some of the important features of both the particular models used and the general modeling philosophy that they represent.

## MODEL

This model forecasts the short-term travel choices of a household given predetermined residence location, automobile ownership, and choice of mode to work. By using the multinomial logit form, one can express the joint-choice travel demand model for a given trip purpose as follows:

$$P(f, d, m) = \frac{\exp(V_{f'd'm})}{\sum_{f'd'm' \in \text{FDM}} \exp(V_{f'd'm'})} \quad (1)$$

where

- $P(f, d, m)$  = probability of choice of a given frequency, destination, and modal combination;
- $V_{f'd'm}$  = utility of an alternative fdm combination; and
- FDM = set of available alternatives where an f, d, m combination represents an alternative trip.

$V_{f'd'm}$  is a function of the independent variables as follows:

$$V_{f'd'm} = X'_{f'dm} \theta^{f'dm} + X'_f \theta^f + X'_d \theta^d + X'_m \theta^m + X'_{fd} \theta^{fd} + X'_{fm} \theta^{fm} + X'_{dm} \theta^{dm} \quad (2)$$

The  $\theta$ s in equation 2 are vectors of coefficients to be estimated, and the Xs are vectors of variables defined as follows:

- $X_{f'dm}$  = variables that differ among all alternatives,
- $X_f$  = variables that differ only among frequencies,
- $X_d$  = variables that differ only among destinations,
- $X_m$  = variables that differ only among modes,
- $X_{fd}$  = variables that differ only among frequencies and destinations,
- $X_{fm}$  = variables that differ only among frequencies and modes, and
- $X_{dm}$  = variables that differ only among destinations and modes.

The most important variables that can be strongly justified on deductive grounds, for the shopping joint-choice model, fall into 4 of these classes:

- $X_{f'dm}$  = travel cost (such as time, money, and convenience);
- $X_f$  = socioeconomic characteristics of the household (such as household size, life cycles, occupational status, income, and automobile ownership);

$X_{fd}$  = attractiveness of destination to the given trip purpose (such as retail employment and floor area); and  
 $X_{fm}$  = modal-specific variables (such as availability of the automobile for shopping travel and transit convenience).

This decomposition of the joint utility function is useful for the interpretation of conditional probabilities. For example, the conditional probability of modal choice for given frequency and destination derived from the joint-choice model is:

$$P(m|f, d) = \frac{\exp(V_{m|fd})}{\sum_{m' \in M_{fd}} \exp(V_{m'|fd})} \quad (3)$$

The choice set  $M_{fd}$  includes all alternative modes available for the given frequency and destination, and the conditional modal-choice utility is

$$V_{m|fd} = X'_{fdm}\theta^{fdm} + X'_m\theta^m + X'_{fm}\theta^{fm} + X'_{dm}\theta^{dm} \quad (4)$$

The variables  $X_f$ ,  $X_d$ , and  $X_{fd}$  have no effect on the conditional modal-choice probability. Similarly,  $X_d$ ,  $X_m$ , and  $X_{dm}$  have no effect on the conditional frequency choice, and  $X_f$ ,  $X_m$ , and  $X_{fm}$  have no effect on the conditional destination choice. It should be noted, however, that all the variables in the joint utility function affect the marginal choice probabilities for all the 3 dimensions of choice. For example, the marginal probability of frequency choice could be expressed as:

$$P(f) = \frac{\exp(X'_f\theta^f + \theta_n P_1^0)}{\sum_{i \in F} \exp(X'_i\theta^i + \theta_n P_1^0)} \quad (5)$$

where

$$P_1^0 = \sum_{j \in D_1} \exp(X'_j\theta^d + X'_{i,j}\theta^{fd} + \theta_n P_{1,j}^M), \text{ and}$$

$$P_{1,j}^M = \sum_{k \in M_{j,f}} \exp(X'_{f,j,k}\theta^{fdm} + X'_k\theta^m + X'_{r,k}\theta^{fm} + X'_{j,k}\theta^{dm})$$

Thus a change in the value of any variable in the joint-choice model will affect all of the marginal choice probabilities.

The logit formulation not only allows specifications of models, including all of these types of variables, but also permits considerable freedom in the composition of alternative sets (FDM) so that the definition and number of alternatives made available to each individual observation in the sample can be varied. The specification of the model consists of the formulation of the utility functions and the definition of the alternatives in the choice set.



## DATA

The data used for model estimation were derived from the Metropolitan Washington (D.C.) Council of Governments (WCOG) 1968 home-interview survey and from additional information compiled by WCOG and R. H. Pratt and Associates. The travel information in the home-interview survey consists of household questionnaire responses detailing the travel activity for a 24-hour period of all household members 5 years old or older. For this modeling effort, the surveyed households first were reduced to 25 percent of the original sample, and then the remaining observations were screened for missing or poorly coded information. This left 4,097 households in the working sample. However, of the households in which some shopping travel was reported over the survey period, not all exhibited the simple home-shop-home behavior that was to be modeled. Of the 1,259 households that reported 1 or more shopping sojourns, 501 had traveled in the simple pattern to be modeled, and 403 of these had used either automobile or bus (the 2 modes to be modeled). Because of the systematic reduction of the sample of households that had made shopping trips, the sample of households reporting no shopping travel also had to be reduced to maintain correct proportions of the 2 types of household. (Sensitivity runs were performed to determine the bias in alternative-specific variables due to incorrect proportions in the estimation sample. Although the bias was significant for extremely nonrandom proportions, it became negligible within 10 to 20 percent of the true proportions.) Thus these were reduced to 910 leaving a total estimation sample size of 1,313 households. [The sample of households making shopping trips was reduced to 32 percent of the original (from 1,259 to 403); therefore, the sample of households not making shopping trips was similarly reduced to 32 percent (2,838 to 910).] The relation of this final estimation sample to the original survey sample of households is shown in Figure 1.

In addition to the travel observations, a major data item to be prepared was level-of-service information not only for the observed travel but also for all alternative shopping trips. These data for highway and transit networks had been compiled previously for the Washington, D.C., area.

## ALTERNATIVES AND VARIABLES

The frequency alternatives, as represented in the model, were a choice between a simple home-to-shopping-to-home round trip and the no-travel option. However, one aspect of the no-travel alternative deserves specific note. The original home-interview survey from which the estimation samples were derived included travel information for vehicular trips only (except for the first journey to work for which walk trips were recorded). Thus, the no-travel alternative for the shopping model implicitly includes a walk-to-shopping option. This was a factor that had to be accounted for directly in the derivation of the utility functions for the frequency alternatives.

In modeling frequency choice, it was assumed that 3 sets of effects influenced a household's probability of making a shopping trip. The first set is called here the generating effects, which are those characteristics of the household that would make that household more likely to reach the threshold of need for a shopping sojourn on a given day. One such effect is household size, which would account for the rate of growth of a need for shopping activity as well as for the availability of household members to devote time to the activity. Additional variables to measure the structure of the household, such as the ratio of workers to nonworkers and the life cycle of the household, also were considered to be household generating effects. Similarly, income was hypothesized to represent the ability of a household to stock large quantities of goods and thus avoid the general disutility of travel.

A second group of attributes that is seen to affect frequency of shopping travel is the set of variables that measure the impedances of travel to shopping destinations and the attractiveness, for shopping purposes, of these destinations. The notion that the threshold level of need for shopping travel varies with the costs of travel and with the probability of finding the desired goods (7) corresponds behaviorally with the inclusion of this set of

effects. Measurement of the levels of service to the various destinations is relatively straightforward, but determination of attractiveness to the household is less apparent.

The third factor included in frequency choice is a measure to account for the accessibility of shopping destinations by walking trips. This is necessary compensation for the fact that the no-travel alternative includes possible walking trips (these were not recorded in the survey). However, because most travel-forecasting applications deal with vehicle-transportation options, the ability to separate walking trips (which, in the home-interview survey, were defined to include bicycle, motorcycle, and other "miscellaneous" modes) from no travel was not considered important for this model.

The modal-choice alternatives were limited, for this model, to automobile (driver and passengers from the same household) and transit. Other modes and modal combinations accounted for 71 of the original 501 observations of simple shopping trips. Although automobile passengers (with drivers not from the same household) accounted for the largest number of these (42), these were not explicitly modeled because they were interhousehold shared rides for which no information was collected on the number of persons in the automobile or sharing of costs. (All intrahousehold shared rides were explicitly identified and modeled as single shopping trips; transit fares were multiplied by the number of persons making the trip together.) The next largest category was taxicab passenger; however, there were only 7 observations for this category.

The automobile alternative was given only to those households that owned at least 1 automobile; automobile ownership was assumed here to be a predetermined choice for shopping travel choices. The bus transit alternative was given only to those households for which a station was accessible within 0.5 mile (0.8 km) of the residence location (the household's location also was assumed as a predetermined choice). For those households that did have transit accessible, the alternative was allowed only to those destinations that also were served by transit.

The types of variables used to model the modal choice include, of course, generic level-of-service variables and additional variables to account for modal-specific effects. The level-of-service variables in this model are in-vehicle travel time (IVTT), out-of-vehicle travel time (OVTT), and out-of-pocket cost (OPTC). IVTTs for both automobile and bus were taken from networks and computer over the shortest path. OVTTs, however, were measured differently for the 2 modes. For bus, the measured OVTT includes an average walk time to the station, wait time for the bus (a varying percentage of the headway), and additional wait times if transfers are necessary. For automobile, OVTTs were taken from zone vectors supplied by WCOG, which set origin terminal times at an average of 2 min (to allow start-up time and the like) and computed destination terminal times depending on the expected difficulty of finding a parking place near the actual destination.

OPTCs for bus trips were the designated fares (multiplied by the number of persons in the same household making the trip). For automobile trips, costs were in 2 portions. The first was expected parking costs (taken from zone vectors); the second was calculated based on origin-destination (O-D) highway distances and travel times. The travel times were used to compute a cost per mile (kilometer) (which varied according to the computed average speed) for fuel and maintenance costs. This was then multiplied by the travel distances to provide an O-D travel cost.

The only other useful piece of modal information available was the number of bus transfers required, but, because transfer time was included in the computation of OVTTs for the bus, the number-of-transfers variable proved to be insignificant for explanation in models that also included OVTTs.

The selection of an alternative set for destination choice was much less straightforward than for frequency and modal choices. To begin with, all of the available information that was to be used for model estimation was based on the WCOG Transportation Planning Board zone and district boundaries. These data included levels of service to zone destinations as well as figures on zone-based retail employment. Although an attempt might have been made to identify specific activity sites, as has been done elsewhere (6), the time and money required for this task were not available. Therefore, an alternative scheme was developed to use the zone-based data.

The selection of a candidate set of destination alternatives for each household was



based on district-level trip matrices for the shopping purpose (134 districts in the metropolitan area). All districts for which at least 1 shopping trip was recorded from the household's residence district were allowed as destination alternatives to that household. The idea for using the trip matrix for this initial assignment of alternatives was to ensure that all destinations with positive probabilities (at least in the estimation sample) were given as alternatives. The district level was chosen both because it was convenient to use with the available level-of-service and attraction data and because it seemed to correspond most closely with a perceptual breakdown of the urban area into shopping opportunities. For example, almost all districts (each of which is composed of several zones) were found to have a single zone (or small cluster of adjacent zones) that had a large retail employment relative to the others. This concentration of retail activity (which was easily distinguished from corner stores or other predominantly local retail outlets) could be seen as the general attractor that forms the basis of comparison for the destination alternatives. Thus the level of service for each destination alternative was computed to this "shopping zone."

Beyond the allocation of destination alternatives by the trip matrix, however, additional alternatives were given to all households, based on deductive notions of the perception of alternatives. Specifically, "local" alternatives (intrazone and intradistrict) and the central business district (CBD) were allowed as destination alternatives to all households. Because of the household's almost certain familiarity with these alternatives, they were singled out to be included as part of the perceived set of alternatives for all households. In fact, as would be expected by their more favorable levels of service, intrazone and intradistrict travel were observed quite frequently in the sample (almost 40 percent of all shopping trips). The CBD alternative was defined by an aggregate of 6 downtown districts that are all small in area but represent a dense retail area that would be perceived as a single alternative. For households without an automobile, the set of destinations was reduced to those for which bus access was possible.

The final representations of destination alternatives thus were based primarily on a zone system but were adjusted to a more appropriate set corresponding to the more perceptual notion of activity sites by adding specific alternatives that were assumed to be highly attractive alternatives for all households. The inclusion of intrazone and intradistrict alternatives is justified further by the expanding web of perception notion that describes an individual's spatial perceptions as being most detailed in the region immediately surrounding his or her residence and progressively less complete and more aggregate as distance from the home increases.

## SPECIFICATION OF UTILITY FUNCTIONS

Table 1 gives the variables and their codes and definitions that were used in the utility functions to describe the 3 choice dimensions. [Annual household income data were coded according to the following classes (in 1968 dollars): (a) 0 to 2,999, (b) 3,000 to 3,999, (c) 4,000 to 5,999, (d) 6,000 to 7,999, (e) 8,000 to 9,999, (f) 10,000 to 11,999, (g) 12,000 to 14,999, (h) 15,000 to 19,999, (i) 20,000 to 24,999, and (j) more than 25,000.] This specification of the joint-choice model for frequency, destination, and mode initially was based in its destination-modal components on a specification developed by Ben-Akiva (2). Several changes were made from that specification, however, to arrive at a form that seemed to better fit the expanded set of choice dimensions being modeled. As a first step, 2 of the level-of-service variables, those representing excess and in-vehicle times, were restructured. The disutility perceived from excess time was seen to be affected by the length of the trip being made. For example, a waiting time of 20 min would seem more onerous on a 1-mile (1.6-km) trip than on a 10-mile (16-km) trip. This was represented by a variable that is formulated as excess time divided by distance for the trip. The other level-of-service variable that was changed for this specification was IVTT, which had been included directly as a measure of disutility. This was restructured, however, as a total travel time (excess plus in-vehicle time) to be included in a logarithmic form in the utility function. Behaviorally, this corresponds to the hypothesis that the sensitivity to absolute changes in total travel time decreases for longer trips.

Figure 1. Creating the estimation sample.

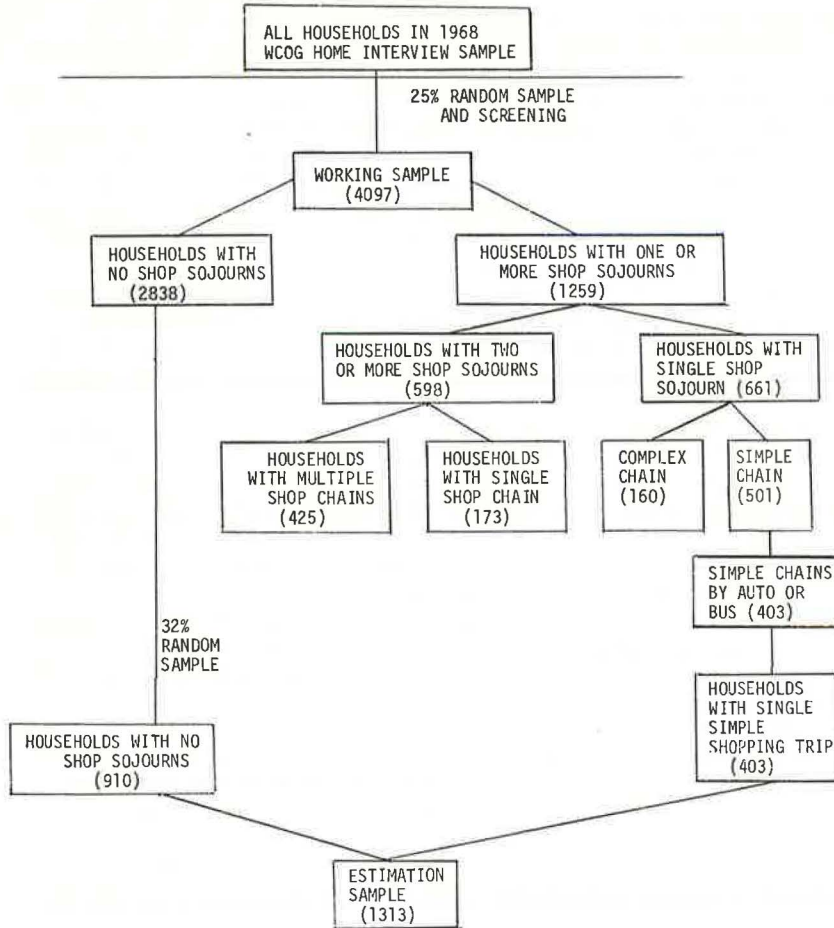


Table 1. Definitions of variables and constants.

Number	Code	Definition
1	DC	1 for car, 0 otherwise
2	OVTT/DIST	Round-trip out-of-vehicle travel time in minutes/1-way distance in miles (kilometers)
3	IVTT + OVTT	Round-trip in-vehicle travel time in minutes + round-trip out-of-vehicle travel time in minutes
4	OPTC/INC	Round-trip out-of-pocket travel cost in cents/annual household income
5	AAC	Number of automobiles available to household - number of automobiles used for work trips by workers in household for car, 0 otherwise
6	1/DIST	1/1-way distance in miles (kilometers)
7	REMP	Retail employment of shopping destination in number of employees
8	DCBD	1 for CBD shopping destination, 0 otherwise
9	DF	1 for 0 frequency, 0 otherwise
10	HHSF	Number of persons in household for 0 frequency, 0 otherwise
11	DENF	Retail employment density in residence zone in employees per acre (hectometer <sup>2</sup> ) for 0 frequency, 0 otherwise
12	INCF	Annual household income for 0 frequency, 0 otherwise

Note: Alternatives are no trip = 0 frequency; items 1 through 8 = 0; trip to shopping destination d and by mode m is for all relevant shopping destinations including the CBD and for car and transit modes.

Table 2. Utility functions for choice alternatives.

Alternative	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\theta_5$	$\theta_6$	$\theta_7$	$\theta_8$	$\theta_9$	$\theta_{10}$	$\theta_{11}$	$\theta_{12}$
f = 0	0	0	0	0	0	0	0	0	1	HHSF	DENF	INCF
f = 1, m = auto, d = CBD	1	OVTT/DIST	$\theta_3(OVTT + IVTT)$	OPTC/INC	ACC	1/DIST	$\theta_7(REMP)$	1	0	0	0	0
f = 1, m = auto, d = nonCBD	1	OVTT/DIST	$\theta_3(OVTT + IVTT)$	OPTC/INC	ACC	1/DIST	$\theta_7(REMP)$	0	0	0	0	0
f = 1, m = bus, d = CBD	0	OVTT/DIST	$\theta_3(OVTT + IVTT)$	OPTC/INC	ACC	1/DIST	$\theta_7(REMP)$	1	0	0	0	0
f = 1, m = bus, d = nonCBD	0	OVTT/DIST	$\theta_3(OVTT + IVTT)$	OPTC/INC	ACC	1/DIST	$\theta_7(REMP)$	0	0	0	0	0

The second major modification to the model form used by Ben-Akiva (2) was the inclusion of a variable representing automobile availability for daytime shopping trips (AAC). This variable is used to explain both frequency and modal choice (more cars available should mean increased likelihood of going shopping and of using a car). This represents one of the areas of complementarity in household decisions that is important to their travel choices: the allocation of automobiles in a household among the variety of household activities. The behavioral hypothesis that leads to inclusion of this form of the variable in the shopping model is that the allocation of automobiles among activities begins with work trips (which are more regular and more important to the household than discretionary purposes) and that the number of automobiles available for daytime shopping is conditional on this choice of mode to work.

A third change from the initial specification was a reformulation of the destination-attraction variables. A logarithmic form of the attraction variable represented by retail employment was chosen because of the large relative value of CBD employment, which caused a high negative value on the CBD dummy variable. Also, instead of using only the retail employment of alternative sites to indicate preferences for larger and more diverse shopping areas over smaller areas, a second destination-specific factor was added to explain destination choice. This was in the form of a variable that is the inverse of 1-way distance from the home zone to the shopping area. The attraction of alternative shopping destinations now is expressed (by the destination-specific factors) as arising from both its relative size and its proximity to the household. This is justified by the hypothesis that a household's knowledge of alternative shopping areas depends on how close it is to them; closer shopping opportunities are more attractive (even beyond the fact that levels of service to them are better) because the household more likely will have better information about the nature of shopping opportunities available and generally will be more likely to actively consider them in its choice set.

One final detail of the specification was that 4 frequency-specific variables were included (along with the level-of-service and attraction variables) to explain frequency choice. These correspond closely to the general classes of variables recommended earlier. They represent household size, ability to stock larger quantities of goods (income), and walking accessibility to shopping alternatives.

The utility functions for the choice alternatives given this specification are given in Table 2. As can be seen, the 3 level-of-service variables enter at positive levels for all alternatives except for 0 frequency when they are also 0. The alternative-specific variables such as automobile availability enter only for the given alternative (in this case, automobile). The dummy variables are 0 or 1 for the specified alternatives.

## ESTIMATION RESULTS

Coefficients and other information for this specification of the model are given in Table 3. All of the important policy variables are significant at the 99 percent confidence level. The coefficients of the level-of-service variables (time and cost) have the expected negative signs and result in reasonable values of time. For a typical shopping trip of 2.5 miles (4 km) and a total round-trip travel time of 40 min, OVTT has a disutility that is about twice that of IVTT. Of the attraction factors, 1/DIST has the expected positive sign, indicating that closer destinations are, overall, preferred to those that are more remote. The AAC variable has a relatively large positive parameter, showing that the greater the number of automobiles available is the more likely the household is to make a shopping trip and use the automobile for it.

Of the frequency variables, HHSF has a negative sign, indicating (as expected) that, for a larger household, the probability of not making a shopping trip on a given day becomes less. The variable formulated as DENF is an attempt to account for walk trips to shop, which are not recorded in the home-interview survey. This variable is a proxy for the availability of suitable shopping destinations within walking distance of the home. The expected positive sign of the coefficient of this variable means that a household living in a zone with dense retail employment is more likely not to embark on a vehicle-shopping trip (but is likely to choose a walk-shopping trip instead). The



positive sign on the INCF variable, consistent with results obtained elsewhere (4), indicates that higher income households are able to maintain larger stocks of goods and thus will shop with lower frequency.

By using this model specification, we estimated 2 of the important conditional-choice models. Table 5 gives for the conditions in Table 4 the number of observations, number of alternatives, log likelihood for coefficients of 0  $L^*(0)$ , log likelihood for estimated coefficients  $L^*(\theta)$ , and explained log likelihood/total log likelihood  $\rho^2$ . In Table 4, parameter estimates for the conditionals of mode given frequency and destination, destination given mode and frequency, and the joint choice of frequency, destination, and mode are compared. As expected and as previously demonstrated by Ben-Akiva (2), the estimated coefficients show great variability depending on the structure used for estimation. The 2 conditionals use less information than the joint estimation uses, and they can be expected to be generally less reliable, theoretically as well as statistically, than the parameters from the joint estimation.

#### EMPIRICAL APPLICATION OF SHOPPING JOINT-CHOICE MODEL TO EVALUATION OF TRANSPORTATION POLICY OPTIONS

The purpose of this section is to demonstrate how the disaggregate choice models developed in this research can be used to illustrate the behavioral effects of various transportation options on the demand for travel. The emphasis in this analysis was on highlighting the varying effects that several transportation alternatives would have on 3 different types of households. The types of households were represented by 3 of the samples taken in the 1968 Washington, D.C., home-interview survey. A similar analysis could be performed by using a random sampling of all households in the area or by constructing segments on which the effects could be compared. A larger scale case study, which also is being conducted in this research project, is using a set of disaggregate models, including this one, in a full network equilibration framework. The use of 3 typical households (for which frequency, mode, and destination, but not route choice, were forecast) was chosen for this study primarily for reasons of simplicity of presentation and ease of computation.

#### Policy Alternatives

Five policy alternatives were chosen to be compared to the base case. These alternatives are representative of the range of options currently being considered in response to, among other issues, air-quality and energy-conservation programs. The alternatives can be summarized as follows:

1. Base case—conditions existing in Washington, D.C., in 1968;
2. Case 1—gasoline prices 3 times greater than those of 1968;
3. Case 2—parking costs 3 times greater than those of 1968;
4. Case 3—employer-based car-pool incentives and special car-pool lanes to decrease travel time to work to 70 percent of 1968 base times;
5. Case 4—transit available for all trips [IVTT as good as for automobile and OVTT = 20 min + (10 min × number of transfers) but no more than existing conditions]; and
6. Case 5—combination of cases 1 through 4.

#### Typical Households

Three households were chosen from the Washington, D.C., area to represent a range of characteristics, from low-income, captive-transit inner-city residents to high-income, automobile-captive suburban residents. The specific characteristics of these households that are relevant as inputs to the model are given in Table 6. Not given (but used

**Table 3. Model coefficient values.**

Variable	Coefficient	t-Statistic	Variable	Coefficient	t-Statistic
DC	-0.555	-2.13	$\phi_1$ (REMP)	0.161	3.29
OVTT/DIST	-0.100	-3.38	DCBD	0.562	2.07
$\phi_1$ (IVTT + OVTT)	-2.24	-11.85	DF	-3.78	-4.51
OPTC/INC	-0.0242	-4.20	HHSF, 0 frequency only	-0.186	-4.57
AAC, car only	0.557	5.61	DENF, 0 frequency only	0.383	1.38
1/DIST	0.0686	1.66	INCF, 0 frequency only	0.0414	1.18

Note: Number of observations = 1,313; number of alternatives = 44,718; log likelihood for coefficients of 0 = -3,830; log likelihood for estimated coefficients = -2,511; and explained log likelihood/total log likelihood = 0.36.

**Table 4. Comparison of conditionals and joint estimation.**

Variable or Constant	(m   f, d)		(d   f, m)		(f, d, m)	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
DC	-1.35	0.732			-0.555	0.260
OVTT/DIST	-0.116	0.623	-0.0399	0.0277	-0.100	0.0296
$\phi_1$ (OVTT + IVTT)	-2.21	0.367	-2.60	0.240	-2.24	0.189
OPTC/INC	-0.0243	0.0151	-0.0237	0.00726	-0.024	0.00576
AAC	1.63	0.667			0.557	0.0992
1/DIST			0.0344	0.0634	0.0686	0.0414
$\phi_1$ (REMP)			0.370	0.0533	0.161	0.0489
DCBD			0.354	0.284	0.562	0.271
DF					-3.78	0.839
HHSF					-0.186	0.0404
DENF					0.383	0.276
INCF					0.0414	0.0350

**Table 5. Log functions and other data for conditionals and joint estimation of Table 4.**

Condition	Number of Observations	Number of Alternatives	L*(0)	L*( $\theta$ )	$\rho^2$
(m   f, d)	225	450	-156	-62	0.60
(d   f, m)	403	8,732	-1,210	-988	0.19
(f, d, m)	1,313	44,718	-3,830	-2,511	0.36

**Table 6. Typical households.**

Characteristic	Household 1	Household 2	Household 3
Income per year, dollars	5,000	13,500	22,500
Number of automobiles owned	0	1	2
Household size	4	4	5
Distance to CBD, miles	3	6	9.5
Retail employment density at residential zone	High	Medium	Low
Transit availability	Good	Medium	None
Distance to work, miles	2.5	4	6.5

Note: 1 mile = 1.6 km.

**Table 7. Model forecasts for households 1, 2, and 3.**

Household	Alternative	Mode to Work (percentage of individuals)			Mode to Shop (household trips/day)		
		Drive Alone	Car Pool	Transit	Car	Transit	Total
1	Base case	0	13.8	86.2	0	0.010	0.010
	Case 1	0	12.0	88.0	0	0.010	0.010
	Case 2	0	13.8	86.2	0	0.010	0.010
	Case 3	0	42.2	57.8	0	0.010	0.010
	Case 4	0	7.6	92.4	0	0.072	0.072
	Case 5	0	37.6	62.4	0	0.072	0.072
2	Base case	89.4	2.9	7.7	0.482	0.012	0.494
	Case 1	89.1	1.4	9.5	0.420	0.013	0.433
	Case 2	89.4	2.9	7.7	0.454	0.013	0.467
	Case 3	81.2	11.9	6.9	0.494	0.012	0.506
	Case 4	76.7	2.6	20.7	0.463	0.083	0.546
	Case 5	65.8	11.9	22.3	0.389	0.094	0.483
3	Base case	96.2	3.8	0	0.499	0	0.499
	Case 1	95.7	4.3	0	0.441	0	0.441
	Case 2	95.4	4.6	0	0.478	0	0.478
	Case 3	83.2	16.8	0	0.517	0	0.517
	Case 4	82.4	3.3	14.7	0.468	0.096	0.564
	Case 5	63.7	17.7	18.6	0.418	0.105	0.523



in the model calculations) are the residence locations of the households, which affect the set of relevant shopping destination and modal alternatives. Also not given are the work locations, which, however, are notable only in that household 3 alone has a worker who commutes to a downtown location that requires a parking fee.

### Use of Models to Forecast Effects of Transportation Options

The 2 models that are used for this application are the joint model of choice of mode to shop previously described and model of choice of mode to work (also multinomial logit) developed in related research that forecasts the probability of choice among the automobile-driven-alone, car-pool, and bus modes (5). The choice-of-mode-to-work model takes as inputs level-of-service and modal-specific variables similar to those used in the shopping model. To distinguish the effects of car-pool incentives on the use of car-pools, we included a variable indicating the presence of employer-based car-pool incentives (as they existed in 1968 for government workers) in the model.

The forecasting procedure that was used for each policy alternative is as follows: First, the independent variables were introduced in the choice-of-mode-to-work model to produce forecasts of modal-choice probabilities; then, the shopping model was applied with the independent variables including the residual automobile-availability variable that resulted from the forecast probabilities of choice of mode to work. This procedure was repeated for each household.

The forecasts of the models for all the policy alternatives for each household are given in Table 7. The 3 modal probabilities for mode to work reflect the availability as well as the characteristics of the alternatives: Car pool was allowed for everyone, drive alone was allowed only for those owning automobiles, and transit was allowed only where it was available. The number of household shopping trips per day is given directly by the model, and this is multiplied by the modal probabilities (also taken directly from the model output) to give trips per day by automobile and bus (car pool is not a relevant mode for shopping).

### Results of Comparisons

Tables 8, 9, and 10 give a summary of the important results of the analysis. The data given in Table 8 show how the number of shopping trips made by each household varies for the 6 alternatives (trip frequency for the work trip, of course, remains constant). The first household, which is captive to transit, makes more shopping trips only when transit improvements are implemented (increases more than 6 times over base levels). For the second household, decreases are observed, as expected with price disincentives on automobile use. However, the introduction of car-pool incentives shifts use of the household's automobile away from the work trip and leaves it available for daytime shopping by other household members. Thus, car-pool incentives increase the amount of shopping travel by automobile. Transit improvements increase shopping travel by transit, as expected, for all households. The data given in Table 9 translate the shopping and work travel into daily vehicle miles of travel (VMT) (vehicle kilometers of travel) for each household (based on forecast probabilities and known distances to alternative destinations). As expected, the 2 price increases on automobile travel reduce VMT (vehicle kilometers of travel) for all households for both work and shopping travel. Car-pool incentives, however, increase VMT (vehicle kilometers of travel) for shopping in those households that own automobiles and increase work-trip VMT (vehicle kilometers of travel) for households that previously had no direct access to an automobile for travel to work, but now are encouraged to use car pools. The total VMT (vehicle kilometers of travel) over all 3 households and across the 2 trip purposes of work and shopping is less than for the base case; however, inclusion of other travel purposes, such as recreation and personal business, which also are affected by automobile availability, easily could make the total VMT (vehicle kilometers of travel) for the car-pool-incentives option greater than that for the base case.

**Table 8. Effect of policy alternatives on household shopping trips.**

Alternative	Household 1		Household 2		Household 3	
	Household Shopping Trips/Day	Change From Base (percent)	Household Shopping Trips/Day	Change From Base (percent)	Household Shopping Trips/Day	Change From Base (percent)
Base case	0.010	0	0.494	0	0.499	0
Case 1	0.010	0	0.433	-12	0.441	-12
Case 2	0.010	0	0.467	-5	0.478	-4
Case 3	0.010	0	0.506	+3	0.517	+4
Case 4	0.072	+620	0.546	+10	0.564	+13
Case 5	0.072	+620	0.483	-2	0.523	+5

**Table 9. Effect of policy alternatives on vehicle miles (kilometers) of travel.**

Household	Alternative	Work		Shop		Total	
		VMT	Change From Base (percent)	VMT	Change From Base (percent)	VMT	Change From Base (percent)
1	Base case	0.276	0	0	0	0.276	0
	Case 1	0.240	-13	0	0	0.240	0
	Case 2	0.276	0	0	0	0.276	0
	Case 3	0.844	+206	0	0	0.844	+206
	Case 4	0.152	-45	0	0	0.152	-45
	Case 5	0.752	+172	0	0	0.752	+172
2	Base case	7.245	0	4.020	0	11.265	0
	Case 1	7.173	-1	3.327	-17	10.500	-7
	Case 2	7.245	0	3.844	-4	11.089	-2
	Case 3	6.877	-5	4.127	+3	11.004	-2
	Case 4	6.219	-14	3.870	-4	10.089	-10
	Case 5	5.645	-22	3.127	-22	8.772	-22
3	Base case	12.70	0	4.48	0	17.18	0
	Case 1	12.66	-0.3	3.62	-19	16.28	-5
	Case 2	12.64	-0.5	4.26	-5	16.90	-2
	Case 3	11.69	-8	4.64	+4	16.33	-5
	Case 4	10.88	-14	4.21	-6	15.09	-12
	Case 5	9.20	-28	3.41	-24	12.61	-27
1, 2, and 3	Base case	20.22	0	8.50	0	28.72	0
	Case 1	20.07	-1	8.95	-18	27.02	-6
	Case 2	20.16	0	8.10	-5	28.26	-2
	Case 3	19.41	-4	8.77	+3	28.18	-2
	Case 4	17.25	-15	8.08	-5	25.33	-12
	Case 5	15.60	-23	6.54	-23	22.14	-23

Note: 1 vehicle mile of travel = 1.6 vehicle km of travel.

**Table 10. Bias from assuming no effect of level-of-service changes on frequency of household shopping trips.**

Alternative	Household 1			Household 2			Household 3		
	Actual VMT	VMT Given Base-Trip Generation	Bias (percent)	Actual VMT	VMT Given Base-Trip Generation	Bias (percent)	Actual VMT	VMT Given Base-Trip Generation	Bias (percent)
Base case	0	0	0	4.020	4.020	0	4.480	4.480	0
Case 1	0	0	0	3.327	3.729	+12	3.623	4.095	+13
Case 2	0	0	0	3.844	4.065	+6	4.263	4.445	+4
Case 3	0	0	0	4.127	4.025	-2	4.642	4.480	-3
Case 4	0	0	0	3.870	3.500	-10	4.205	3.716	-12
Case 5	0	0	0	3.127	3.197	+2	3.407	3.249	-5

Note: 1 vehicle mile of travel = 1.6 vehicle km of travel.

The data given in Table 10 show the bias that results from assuming that level-of-service changes have no effect on the frequency with which households make shopping trips. Actual VMT (vehicle kilometers of travel) given base-trip data are as predicted by the full joint-choice model; the VMT (vehicle kilometers of travel) given base-trip data are as computed by the conditional model  $P(d, m | f_{base})$ , which assumes frequency to be unaffected by the transportation options. The bias percentages are those that result in this application of the model. Although the biases from not including price effects on travel frequency are not overwhelming in magnitude, they are consistent in under-



estimating the effectiveness of disincentives to decrease automobile use and of transit improvements to increase public transit patronage. Thus, to accurately model these policy alternatives, which often have impacts on demand only on the order of magnitude of the observed biases, it would seem extremely important to consider, in the model structure, the effects of level-of-service changes on frequency of travel.

## CONCLUSIONS AND IMPLICATIONS OF RESULTS

The estimation of this joint-choice model provides what is an encouraging, though not final, step in the development of a full set of disaggregate choice models of travel demand. The relative ease of estimating the single joint-choice model compared to calibrating 3 separate models by using arbitrary sequence assumptions is a clear advantage (even beyond the general acceptability of joint over conditional models). All the estimated coefficients have reasonable signs and magnitudes and relatively small standard errors that primarily are due to the full use of the data by joint estimation. The joint model was estimated by using a maximum likelihood procedure that consumed less than 1 min of central processing unit time in 80,000 bytes of core on an IBM 370/165.

Several important properties of the disaggregate choice model set were demonstrated in the example application of the models. It was shown how the models can be used directly to compute the quantitative effects of transportation policy options on the travel demand of either specific types of households or of more generally constructed market segments. The inclusion of a large set of policy-relevant variables in the model specification allows for the testing of a wide range of options, and the model forecasts can be computed directly for many types of impacts—from the effect on CBD shopping frequency of parking cost increases to the effect of car-pool incentives on areawide VMT (vehicle kilometers of travel).

Another set of properties that were demonstrated in the case study were some of the effects of model structure on the resulting forecasts. One feature of the model set used here is the explicit linking of household decisions in choosing among travel alternatives. The choice situation that is represented in these models is the automobile-allocation decision: whether the automobile will be used for the work trip and how this affects household choices for other types of trips. That an automobile left at home will stimulate automobile travel for discretionary purposes (shopping) is an extremely important effect in evaluating car-pool incentive programs. Other household travel choices that involve complementarity among trip purposes (such as the consolidation of travel through trip chaining) can and should be similarly represented to present a more complete behavioral picture of travel demand.

Another structural property of the shopping joint-choice model that has been shown to be important is the representation of level-of-service effects on travel frequency. The bias from not including this effect is significant in that it is consistent in underestimating the effectiveness of some of the currently relevant transportation options. Thus use of a model structure that represents effects of levels of service on all choices (in this case, a joint-choice structure) is necessary to realistically appraise policy options.

Two areas of further work are logical continuations of the effort documented here. The first is in the development of improved specifications to increase the sensitivity of the model toward a larger variety of policy options. This might include extension of the model to treatment of additional modes or simply inclusion of additional variables to either strengthen the behavioral representation or allow an expanded set of policy variables. A group of alternative specifications for which estimation already has been performed is documented by Adler (1).

A more fundamental gap between current travel demand models and existing theories of travel behavior still exists. All modeling efforts to date have stratified trips by trip purpose and used a single link as the unit of travel demand. The most recent choice models such as the one reported in this paper have assumed simple round trips as the relevant unit. It is becoming increasingly obvious, however, that estimation of these

models is not adequate to describe the large numbers of more complex trip patterns that are observed in urban travel. In the 1968 Washington, D.C., home-interview survey, patterns of travel that integrated shopping trips with other trip purposes (shopping on the way home from work) are observed in greater numbers than the simple patterns in which a household makes a single 2-link round trip for shopping. The recent trend, which largely is due to rising fuel prices, has been toward increased traveler tendencies to consolidate their needs for transportation by linking several purposes in a single, expanded round trip from home. There are several trade-offs involved in the households' comparisons among travel patterns. One is the desire to satisfy needs for travel as they accumulate to a threshold level against the attempt to unite them temporally to allow for a single, more efficient round trip. Clearly, there are behavioral issues here that have potentially great impact on energy-conservation programs as well as on other modally oriented incentives (relative advantages of the various modes in servicing these more complex patterns of travel) but remain unaddressed in any current travel demand models.

The problem with the most recent efforts in addressing the issues posed by complex patterns of travel seems to be their orientation around single trip purposes as a means of stratification of behavioral responses. A more integrated approach would be in the use, as a unit of demand, of complete patterns of household travel and in the identification of the general classes of travel that can be decomposed from those patterns. For example, a useful classification might distinguish among fixed patterns of travel (such as travel to work or school where the destination is generally static in the short term), discretionary travel (where mode, destination, and frequency are active choices), and patterns where fixed and discretionary travel purposes are combined (as in a shopping trip on the way home from work). Such a scheme would allow for behavioral comparisons among all patterns of household travel rather than exclude the more complex patterns that are of increasingly greater interest to transportation planners as the more restrictive travel-purpose-based stratifications do.

This expansion of the scope of disaggregate behavioral models will, of course, benefit from the research of the past few years. In particular, the general format of the joint-choice model is seen as being a key to the modeling of dimensions of choice (for example, among morphologically different multipurpose round trips) that are even less subject to the imposition of a sequence assumption than the frequency, mode, and destination choices now being modeled.

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