

ticities are valid only for small changes in the explanatory variable.

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Analysis of Predictive Qualities of Disaggregate Modal-Choice Models

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The results of a study that examined the predictive accuracy and ability of a set of disaggregate, behavioral demand models of modal choice are presented. Although other issues such as sample size, value of time, demand elasticity, and policy predictions are discussed, the primary objective was to test the validity of disaggregate logit models in forecasting. The analysis is structured around a carefully designed before-and-after study of individual travel behavior as affected by significant, short-term changes in the transportation system. Various specifications of disaggregate modal-choice models are calibrated by using as input data the actual responses of individuals from the before phase of the travel-behavior surveys. This was followed by a series of prediction and validation phases by using the after data that was generated by changes in the transportation system. Because the actual modal shares are known from the longitudinal data, it is possible to assess accurately the predictive qualities of the calibrated logit models. The results of the empirical analysis indicate that disaggregate models, especially those that include a full range of transportation level-of-service and socioeconomic variables, can be used to predict future behavior with acceptable levels of performance.

Traditionally, disaggregate demand models have been evaluated on the basis of how well they calibrate (or of how well they replicate existing behavior) rather than on their ability to forecast adequately changes in travel demand. Such analyses are severely limited when the sets of data that were used in the model calibration are also used for its validation. As expressed by Pratt (14), "there have been all too few rigorous comparisons of modeled travel demand with actual before-and-after data." Yet, if the primary function of a modal-choice model is to predict the impact of changes in the transportation system on travel behavior, then an essential characteristic of such a model is its ability to predict

accurately. However, because of data restrictions, it is generally not possible to evaluate the accuracy of forecasts obtained from disaggregate demand models.

An opportunity to evaluate and document the capabilities of disaggregate models arose when the University of Massachusetts at Amherst was selected to participate in a demonstration of a free bus service accompanied by increases in parking fees and associated parking restrictions. The demonstration, which was funded by a grant from the Urban Mass Transportation Administration, involved expanding a limited, 3-bus, campus shuttle system by the addition of 10 new buses so that commuter trips could also be served. Later, the fleet was expanded to 16 vehicles by the purchase of 3 more buses.

The purpose of the demonstration was to determine the extent to which the availability of a free, fairly convenient bus service, coupled with the introduction of restrictive parking policies and increased parking prices, might cause a shift away from commuting by automobile to commuting by bus. Later, during the oil embargo and the accompanying energy crisis, it was apparent that further changes in travel patterns and behavior were occurring. Thus, although not part of the original scope of the work, the effect of rapidly increasing gasoline costs was introduced into the study framework. The main focus of the demonstration, however, was on the institution of an attractive and convenient free bus service; extensive data collection and a carefully delineated experimental design centered around changes in the parking policy.

To determine the impact of each change in the transportation system, the demonstration and data-collection phases were divided into four separate events. A before survey of travel patterns was conducted during the semester preceding the demonstration (i.e., survey period 1, the fall 1972 semester). Thereafter, observations of behavior and user characteristics were made: (a) after the introduction of the expanded free bus service (i.e., survey period 2, the spring 1973 semester), (b) after the introduction of changes in parking prices and regulations (i.e., survey period 3, the fall 1973 semester), and (c) during the approximate peak of the energy crisis (i.e., survey period 4, the spring 1974 semester).

To monitor travelers' responses to changes in the transportation system, telephone travel-behavior surveys were conducted that involved reinterviewing of the same sample of individuals over time and collecting information on the characteristics of alternative modes. Only individuals associated with the university (i.e., students, staff, and faculty) were surveyed. The data obtained from these longitudinal or time-series surveys were left in their disaggregate form.

To evaluate the accuracy of model forecasts at least two sets of data are required: one to calibrate the model and the other(s), preferably made after some quantifiable change to the transportation system, to test the prediction. This is seldom possible and the model and the forecasts usually must be tested on the same data set (15). In this study, disaggregate modal-split models were calibrated with data from one time period and validated with data from subsequent time periods. By using a longitudinal data base that was generated by planned transportation changes over time, the calibrated models could be used to forecast changes in modal choice that should result from distinct short-range changes in the transportation system. Because the actual amount of modal shifting was known, the forecasts obtained from the model could be precisely evaluated. A favorable evaluation of the model in prediction implies a properly specified and calibrated model and increases confidence in it.

MODEL

The logit form was chosen as the statistical technique to be used in calibrating the models. Detailed descriptions of this model form are given elsewhere (1, 2, 5). The following equations express the form of the multinomial logit model:

$$P(m: M_t) = \exp G(m, t) / \sum_{m=1}^M \exp G(m', t) \quad (1)$$

where

$P(m: M_t)$ = probability that traveler t , out of the total sample of T travelers, will select mode m from the M set of available modes and
 $G(m, t)$ = utility of mode m to traveler t .

$G(m, t)$ can be expressed more specifically in the following form:

$$G(m, t) = G_m(Z_{m,t}, S_t) - \theta_k X_{mkt} \quad (2)$$

where

$Z_{m,t}$ = vector of variables describing the level-of-service characteristics of mode m for traveler

t (e.g., time and cost),

S_t = vector of socioeconomic characteristics for traveler t (e.g., income, sex, and automobile ownership),

θ_k = $K \times 1$ vector of coefficients ($\theta_1, \theta_2, \dots, \theta_k$), and
 X_{mkt} = $K \times 1$ vector of variables ($X_{m1t}, X_{m2t}, \dots, X_{mkt}$).

Because the primary purpose of the free bus demonstration project was to assess the diversion of travelers from automobile to bus that would result from the implementation of free bus service and increased parking fees (and later increased gasoline costs), only the automobile and bus modes are considered here. For this two-mode situation, the model can be rewritten as

$$P(a) = \exp \theta_k X_{atk} / (\exp \theta_k X_{atk} + \exp \theta_k X_{btk}) \\ = 1 / [1 + \exp -\theta_k (X_{atk} - X_{btk})] \quad (3)$$

or

$$\ln [P(a)/P(b)] = \theta_k (X_{atk} - X_{btk}) \quad (4)$$

Variables Considered in the Model

The selection of variables was based on a combined analysis of those typically considered in previous modal-choice models [Parody (12)] and those that were included in the telephone-survey questionnaires conducted during the free bus demonstration. They are described in Table 1.

Data Selection

The first task in selecting the sample population for use in the analysis was the identification and eventual discarding of improper data. For example, the main purpose of this study was to evaluate the choices travelers will make when there are changes in the transportation system. Therefore, all captive mode users were eliminated from the sample. The individuals eliminated included those for whom bus service was not available (as determined by their proximity to the nearest bus stop) and those who responded negatively to the automobile-availability question. By using these criteria, about 70 percent of the total sample population were considered to be choice automobile or bus users.

Telephone survey 2, taken toward the end of the first semester of the free bus operation (i.e., spring 1973), was chosen as the initial data base for calibration, from which all forecasts and predictions were to be made. Thus, for calibration purposes, survey 2 was the before time period, and survey 3 (after the introduction of higher parking fees) was the forecasted time period. Consequently, in selecting the individuals to be included in the sample, it was important to ensure that the respondents answered at least surveys 2 and 3 and that they could be considered choice travelers in terms of the automobile or bus modes.

Initially, it was intended that only the reported responses of the individuals would be used as inputs to the model. However, it soon became apparent that some individuals did not record some data (usually travel times) for the alternative mode. This was almost exclusively limited to those for whom the bus was the alternative mode: Very few bus users did not estimate automobile-drive time. Of the approximately 400 individuals surveyed in each time period, 91 responded completely to all of the appropriate questions. These individuals comprise data set 1-1.

To enlarge the sample size, estimates were made for those automobile users who did not report bus travel-time information during the survey. Because a large

fraction of the sample population lived in approximately 15 apartment complexes surrounding the university, the automobile and bus travel times reported by those individuals who resided in the largest of the apartment complexes were analyzed, and the results of this analysis were used as a guide in estimating omitted bus travel-time data. Then, the data on the individuals residing in apartment complexes, for whom it had been necessary to estimate missing responses to the bus travel-time question, were combined with the previous data set to form data set 1-2. The use of this procedure increased the sample size to 128 individuals.

For individuals not residing in apartment complexes, estimates of bus travel times were based on residential location and, to the extent possible, on data generated from nearby apartment complexes. The sample size of this third data set (i.e., data set 1-3) was 164.

These three data sets were used to evaluate the stability and statistical reliability of the model variables as a function of increasing sample size. The three data sets also were used to test the predicting capability of models, each drawn from the same population, but based on various levels of formulated data because the first data set was based entirely on the responses of the surveyed individuals, the second data set contained the best manual estimation of some sample points, and the third data set contained additional estimates of travel time values.

Model Calibration

The first specification of model variables was limited to the time and cost differences between automobile and bus. By using this model specification as a starting point, other combinations of variables were then used to test a number of models. The coefficients (estimated on the basis of maximum likelihood techniques), t-statistics, and levels of significance (LOS) for each variable are given in Table 2 for the three-variable model specification and in Table 3 for the seven-variable model specification. Other summary statistics are given in Table 4.

From a priori knowledge of travel behavior, it appears at first that all of the variables except sex have the correct sign. Past studies have usually indicated either that stratifications by sex cannot be used to differentiate modal preference (10) or that females, on a relative basis, select the bus mode more often than do males (5, 16). However, the sex-variable sign given in Table 3 indicates that males select the bus more frequently than do females. A closer examination of data set 1-3, for example, shows that males are split 58 percent automobile users and 42 percent bus users, and females are split 79 percent automobile users and 21 percent bus users. Thus, in the Amherst-University of Massachusetts area, males, on a relative basis, are about twice as likely to choose the bus mode than are females. (All females included in the sample must have responded affirmatively to the question on automobile availability.)

Statistical Reliability

An initial comparison of the magnitudes of the estimated coefficients for the three models in Table 3 shows a high degree of stability. A more exact way to examine both the stability and statistical reliability is to compare the relative magnitudes of the standard error terms for the various coefficients. As expected, this comparison (12) shows that the standard errors decrease and that all variables, except possibly the sex variable, approach a fairly stable condition as the sample size increases. As

in other studies (3), travel time is the most stable coefficient.

From this analysis, it can be inferred that there will be relatively high standard errors if the sample size is too small, even if it is based entirely on the responses of individuals. But what can be said about the size of the sample necessary for calibration? Watson (16) has reported, for example, that 100 data records should be the absolute minimum required for calibration. Ben-Akiva and Richards (3) concluded that a desirable sample size is between 300 and 400 observations and that at least 600 observations are desirable if comparisons are to be made between two independent random samples. From the changes in standard error as a function of increasing sample size given here, it appears that most coefficients (except sex) appear to stabilize at sample sizes of 175 to 200 observations. [Additional details have been given by Parody (12).]

MODEL PREDICTION AND VALIDATION

Test 1

Possibly the best way to examine the efficacy of a model is to evaluate its ability to predict changes in travel behavior that occur as a result of actual changes in the transportation system. To make such an evaluation, all three data sets and the three- and seven-variable specifications of the models were used for the first before- and after prediction analysis. The before case was represented by the period of the expanded free bus service and regular parking charges (i.e., survey period 2). The after case was represented by the time period following the introduction of significantly higher parking fees (i.e., survey period 3).

In the before period, a flat \$5/year parking fee was charged for all lots. In the next time period, a convenience fee based on the approximate location of the desired lot with respect to the center of the campus was charged in addition to the \$5 base fee. Three categories of convenience fees were established: (a) core lots at \$36.00/year (except \$50.00 for one lot adjacent to the administration building), (b) edge lots at \$12.00/year and (c) peripheral lots at \$0.00/year. (Shuttle bus service was provided to these outlying parking lots.) It was proposed originally that parking fees be increased up to \$75.00, with reserved parking spaces priced at \$125.00 but, because of strong, adverse, and vocal reactions by students and union employees, the rates of increase were scaled down.

From the revenues and capacity figures for each lot, it was determined that parking fees increased an average of \$21.00. If it is assumed that most spaces are purchased on a 9-month basis, this represents an average daily increase of 11 cents. Thus, for the after analysis, data were generated by adding 11 cents to each individual's automobile cost. The calibrated model coefficients, which were assumed to remain constant, were applied to the vector of forecasted variables for each traveler to generate new probabilities of modal selection. Finally, modal shares were developed by summing choice probabilities across all individuals in the data set. The use of this forecasting procedure makes the analysis free from aggregation bias.

Table 5 gives the actual and predicted modal shares and the percentages by which the predicted values differed from the actual ones for both the three- and seven-variable models for the three data sets. For example, the percentage error associated with data set 1-1 with the three-variable specification is $(34.7 - 28.6)/28.6$, or an overestimation in the change of automobile use of 21.5 percent.

Table 5 shows that the seven-variable model speci-

ation performs better in prediction than does the three-variable model. Similarly, models calibrated with data set 1-3 perform better than models calibrated with data sets 1-1 and 1-2 in terms of their accuracy in forecasting modal switching. This conclusion is consistent with the statistical stability results given above.

Test 2

The data sets for the first prediction test were compiled on the basis of surveys of travel behavior before and after the parking-fee increase. The second prediction test extended the time-series analysis by one more period to analyze, by using the disaggregate logit model, those changes in modal split that resulted from the in-

Table 1. Description of variables.

Variable	Description
Const	Modal constant (automobile = 1, bus = 0)
BusW	Walk time at origin to nearest bus stop (min); automobile walk time at origin assumed to be 0
FOS	Level-of-service variable representing frequency of bus service [low service frequency (headways of about 20 min) = 1, high service frequency (headways of about 10 min) = 0]
TimeDif	Total travel time by automobile minus total travel time by bus (min)
CostDif	Total travel cost by automobile minus total travel cost by bus ($\$$); in general terms can be expressed as $A_1 \times$ automobile fixed cost + $A_2 \times$ automobile operating cost + $A_3 \times$ (parking + toll) - transit fare*
Sex	Binary variable (male = -1, female = 0)
SEcon	Occupation status of traveler (graduate student = 1, undergraduate student = 2, nonprofessional staff = 3, professional staff = 4, faculty = 5) ^b

* In this application, A_1 is assumed to be 0, which is common to most analyses [except Wigner (16)]; operating cost is based on link trip distance \times 3 $\$/\text{km}$ (5 $\$/\text{mile}$) and A_2 is assumed to be 1; A_3 is also assumed to be 1 (5), but drops out in calibration because parking cost was 0 [Wigner (16) assigns A_3 a value of 0.5; limited empirical evidence (6) suggests that travelers are more responsive to a unit change in parking cost than to a unit change in operating cost; equivalent observation for in-vehicle and out-of-vehicle times is given by Kraft and Domencich (8)].
^b Variable may also be regarded as a surrogate for income.

Table 2. Coefficients and levels of significance for three-variable model specification.

Variable	Data Set 1-1			Data Set 1-2			Data Set 1-3		
	Coefficient	t-Statistic	LOS	Coefficient	t-Statistic	LOS	Coefficient	t-Statistic	LOS
Const	-1.215 7	-2.246	0.03	-0.187 19	-0.469 67	NS	-0.007 252	-0.018 052	NS
TimeDif	-0.478 65	-4.875	0.01	-0.463 71	-5.365 3	0.01	-0.505 10	-6.019 7	0.01
CostDif	-0.060 25	-1.89	0.06	-0.063 08	-2.433 9	0.02	-0.070 68	-2.797 20	0.01

Note: N = 91, 128, and 164 for data sets 1-1, 1-2, and 1-3 respectively.

Table 3. Coefficients and levels of significance for seven-variable model specification.

Variable	Data Set 1-1			Data Set 1-2			Data Set 1-3		
	Coefficient	t-Statistic	LOS	Coefficient	t-Statistic	LOS	Coefficient	t-Statistic	LOS
Const	-4.169 7	-2.6475	0.01	-2.970 7	-2.6309	0.01	-2.606 5	-2.4905	0.02
TimeDif	-0.544 32	-3.9813	0.01	-0.521 06	-4.5335	0.01	-0.556 43	-4.9055	0.01
CostDif	-0.121 87	-2.1518	0.04	-0.126 93	-2.9958	0.01	-0.141 73	-3.4131	0.01
BusW	0.473 57	1.5034	0.14	0.550 86	2.1263	0.03	0.462 71	2.0422	0.05
Sex	0.921 40	1.1907	NS	0.788 41	1.3813	0.16	0.942 25	1.6875	0.10
FOS	2.096 3	1.932	0.06	1.820 2	2.337	0.02	1.958 7	2.586	0.01
SEcon	0.640 19	1.9725	0.06	0.571 03	2.5648	0.01	0.579 17	2.6290	0.01

Note: N = 91, 128, and 164 for data sets 1-1, 1-2, and 1-3 respectively.

Table 4. Summary statistics for three- and seven-variable model specifications.

Variable	Three-Variable Model			Seven-Variable Model		
	Data Set 1-1	Data Set 1-2	Data Set 1-3	Data Set 1-1	Data Set 1-2	Data Set 1-3
-2log λ	53.1637	59.4995	97.3101	72.4601	87.7606	131.6842
LOS	0.01	0.01	0.01	0.01	0.01	0.01
$L^*(0)$	-63.076	-88.723	-113.676	-63.076	-88.723	-113.676
$L^*(\hat{\theta})$	-36.495	-58.973	-65.021	-26.841	-44.842	-47.834
ρ^2	0.42	0.34	0.43	0.57	0.49	0.58
$\hat{\rho}^2$	0.40	0.32	0.42	0.53	0.47	0.56

Note: N = 91, 128, and 164 for data sets 1-1, 1-2, and 1-3 respectively.

Table 5. Disaggregate predictions for the three and seven-variable model specifications.

Data Set	Survey Period	Actual		Three-Variable Model				Seven-Variable Model			
		Automobile ($\$$)	Bus ($\$$)	Automobile		Bus		Automobile		Bus	
				$\$$	Difference* ($\$$)	$\$$	Difference* ($\$$)	$\$$	Difference* ($\$$)	$\$$	Difference* ($\$$)
1-1	2	42.9	57.1	42.9	—	57.1	—	42.9	—	57.1	—
	3	28.6	71.4	34.7	21.5	65.3	8.6	31.5	10.40	68.5	4.2
1-2	2	57.8	42.2	57.8	—	42.2	—	57.8	—	42.2	—
	3	37.5	62.5	47.2	25.8	52.8	15.5	42.0	12.1	58.0	7.2
1-3	2	65.9	34.1	65.9	—	34.1	—	65.9	—	34.1	—
	3	48.8	51.2	55.6	13.9	44.4	13.2	50.9	4.2	49.1	4.0

* Based on actual modal shares.

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Table 6. Coefficients and levels of significance for data set 2 and six-variable model specification.

Variable	Coefficient	t-Statistic	LOS
Const	-3.845 5	-3.0566	0.01
TimeDif	-0.578 48	-3.9406	0.01
CostDif	-0.150 97	-2.5985	0.01
BusW	0.676 72	2.7409	0.01
FOS	2.163 3	2.0849	0.05
SEcon	0.632 39	2.3275	0.03

Table 7. Disaggregate predictions for the six-variable model specification and data set 2.

Survey Period	Actual		Predicted			
	Automobile (%)	Bus (%)	Automobile		Bus	
			%	Difference* (%)	%	Difference* (%)
2	68.3	31.7	68.3	—	31.7	—
3	52.9	47.1	53.1	0.4	46.9	-0.4
4	48.3	51.7	46.0	-4.8	54.0	+4.5

* Based on actual modal shares.

crease in gasoline prices after the embargo of oil by the Organization of Petroleum Exporting Countries.

The before time period was identical to that used in the first prediction test. The two after cases were represented by the periods following increases in parking fees and in gasoline costs respectively. In selecting the sample for data set 2, the procedures that were used to establish the data sets in the first prediction tests were followed with the exception that individuals had to respond to at least surveys 2, 3, and 4 to be included in this new data set. With this procedure, a sample (containing both actual and estimated responses) of 104 individuals was selected for the second prediction analysis. About one-third of the individuals who had responded to surveys 2 and 3 could not be reached at the time of survey 4 or had made modal choices other than automobile or bus.

To keep the evaluation as independent as possible from the first prediction analysis, logit models were again calibrated for data set 2 [a cross-prediction test in which models were not recalibrated can be found in Parody (12)] using the same seven-variable model specification. For this model, all variables (except sex) were significant at appropriate confidence levels. Therefore, a model was calibrated without the sex variable; its coefficients are shown in Table 6. All six variables are significantly different from zero at the 0.05 level or better. Summary statistics for the entire model are given below.

Term	Value
-2 log λ	86.972
LOS	0.01
$L^*(0)$	-72.087
$L^*(\hat{\theta})$	-28.602
ρ^2	0.60
$\hat{\rho}^2$	0.58

Forecasts were then made with this calibrated model for two different time periods. The first forecast, to the period represented by increased parking fees, followed the procedures outlined for the first prediction test. For forecasts into the second period, it was first necessary to compute the amount that gasoline prices (and thus automobile costs) had increased over the base time period. In the Amherst area, the pre-embargo price of gasoline was about 10.6 cents/L (40 cents/gal). During the embargo, it increased to approximately 14.5 cents/L (55 cents/gal), an increase of 37.5 percent.

[A study of the embargo period in the Chicago area calculated that gasoline prices there increased more than 40 percent (13) and, in the New York-New Jersey region, gasoline prices increased 35 to 40 percent (11).] On the assumption that most drivers consider only the operating cost of traveling, the 3.1 cents/km (5 cents/mile) driving cost used in calibration was increased by 37.5 percent to 4.3 cents/km (6.9 cents/mile). This new operating cost, in addition to the increased parking cost, was used to determine the automobile traveling cost for the second prediction period. This new vector of data for each individual was used with the calibration coefficients to give a second set of new probabilities and their resulting modal splits. Table 7 gives the actual and forecasted modal shares and the percentage by which they differed from each other for the before and the two after time periods.

For the period representing increased parking fees, the predictions obtained from the logit model were exceptionally accurate. For the period representing increased gasoline prices, the model overpredicted the amount of switching away from the automobile mode by about 5 percent. Given the large changes that occurred in modal splits from the base time period, the errors associated with these predictions were considered to be very reasonable.

In terms of the way in which modal use changed over time, two points deserve note. First, as was also shown by the first prediction test, a fairly significant number of automobile users switched to the bus mode after the introduction of higher parking fees. Second, the higher gasoline and driving costs caused by the oil embargo caused only a minimal amount of modal switching. For example, for data set 2, automobile users were 68.3 percent of the sample population during the base period; this decreased to 52.9 percent after the parking fee was increased, and to 48.3 percent during the embargo.

Other studies have arrived at comparable results with regard to changes in travel behavior during the embargo. For example, a Northwestern University study showed that the increased price of gasoline had little effect on the work-trip traveling habits of individuals (13). A more important factor was the availability of gasoline.

ADDITIONAL ANALYSIS

Value of Time

For the model calibrated with data set 1-3, the implied price of time was \$2.36/hour. The use of the identity given by Kendall and Stuart (8) for the ratio of two random variables gives a standard error of estimate of \$1.05/hour. Consequently, the value reported is significantly different from zero at the 95 percent confidence level.

Elasticity

To make comparisons with other studies or to examine the sensitivity of model variables, it is useful to consider the elasticity of demand with respect to price and time.

Direct and cross elasticities of demand were computed based on the aggregate elasticity identities derived for logit models by using data set 1-3 [see Parody (12)]. The automobile time and cost elasticities given below compare favorably with elasticities reported elsewhere.

Aggregate Elasticity	Value
Direct	
Automobile cost	-0.2772
Automobile time	-0.8622
Bus time	-2.0679
Bus walk	-0.322
Cross	
Bus with respect to automobile time	1.6993
Bus with respect to automobile cost	0.5346
Automobile with respect to bus time	1.0722
Automobile with respect to bus walk	0.1670

For example, in a study by Charles River Associates (CRA) on free transit (9) the automobile-cost (line-haul) direct elasticity for work trips was found to be -0.49, and the automobile-cost elasticity determined here is -0.28; CRA found an automobile-in-vehicle-time elasticity of -0.82, which is very close to the -0.86-value given here. CRA also computed elasticities for in-vehicle and out-of-vehicle transit time. However, because the bus time used in this study is actually a door-to-door travel time, the components of time elasticities must be summed to make an equivalent comparison. Thus, their total transit-time elasticity is -1.1 and their transit access time is -0.71. In the present study, the equivalent values are -2.1 and -0.32. The larger difference in the transit elasticities may be due to the fact that, in the CRA study, all transit modes—commuter rail, subway, bus, and streetcar—were combined into a single modal classification, which reduced the accuracy of their estimated transit-demand relationships.

Several observations can be made from the elasticities given above. First, automobile users appear to be about three times more responsive to changes in automobile time than to changes in automobile cost (CRA cost-to-time ratio for automobile travel is about 4.5). With regard to the inelastic nature of the automobile-cost variable, it is evident that a significant increase in automobile cost had to occur (which was the case with the five-fold increase in parking cost) to observe such a large shift away from the automobile mode. Second, because travel appears to be very sensitive to changes in automobile time, it could be expected that there will be a large amount of mode shifting if the university phases out the center parking lots in an attempt to have a pedestrian campus by the process of introducing automobile-free zones.

Last, the demand for bus travel is quite elastic with respect to bus time, in marked contrast to bus walk time, which is highly inelastic. Initially one might expect the elasticity of bus walk time to be greater than that of total transit time, which includes in-vehicle time. Although the respective coefficients given in Tables 3 and 6 indicate that travelers weight a minute of bus walk time about the same as a minute of total transit time, the elasticity for bus walk time is less because the values of bus walk time are generally much smaller than the values of total transit time. Consequently, a 1 percent change in bus walk time is much less in absolute terms than a 1 percent change in total transit time. This observation has also been noted in a recent study by CRA (4). It appears, therefore, that a very productive way to attract passengers would be to improve service by increasing bus frequencies and better scheduling. Conversely, there will be substantial reductions in bus ridership if headways are increased or if schedules become unreliable.

CONCLUSIONS

By using a longitudinal data base of individual travel behavior that was a product of planned, phased changes in

the transportation system, the accuracy of forecasts from disaggregate modal-choice models was evaluated. In terms of the actual setting from which the data were drawn, the disaggregate, behavioral models of modal choice were able to forecast future modal shares with reasonable and acceptable levels of accuracy. Only a relatively small sample of specially collected data was required to estimate the models. Because these results are only a single test in one setting of the forecasting capability of disaggregate models, additional research efforts are desirable and may be particularly appropriate in a more complex, urban environment.

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