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Effects of Parking Costs on Urban Transport Modal Choice

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The effects of parking costs on urban modal choice are investigated by using a standard binary-choice model and estimated by using the logit technique. Previous studies have misspecified the form of the parking-cost variable and the model normally estimated. After estimating the traditional and correctly specified models, the claim that parking taxes are an effective substitute for roadway pricing in influencing congestion is only partially supported. Aggregate elasticities for four policy-oriented variables are calculated. The elasticities provide a measure of the bias from misspecification and indicate the most effective policy variable for the reduction of automobile use.

This paper is concerned with estimating the effects of parking costs on individual choice of transportation mode for trips within urban areas. It has three basic objectives:

1. The determination of how to characterize the parking variable and incorporate it into a model of modal choice,
2. The calculation of the elasticity of modal choice with respect to parking costs, and
3. The determination of the way in which changes in one of the characteristics that determine the modal choices of individuals will affect the expected proportion of individuals taking the choice being considered.

{The third objective is implemented by examining the way in which changes in individual characteristics affect the mean of the distribution of population probabilities [cf. Westin (11)]}.

The first section introduces a model of individual choice of transportation alternatives that treats parking as a commodity, the demand for which is derived from the choice of the automobile as the transit mode. The second section describes the data and the implications of this model for the structural forms of the estimating equations. The third section presents the empirical results for an application of this model to data for Toronto. The fourth section presents the derivation of the elasticity of modal choice with respect to instrumental variables and empirical results for aggregate and individual elasticities.

BASIC MODEL

The variable to be explained is the individual's choice of transportation mode (automobile versus public transit). The econometric model used in this paper to represent this binary-choice problem is derived from a choice-theoretic framework, based on a microeconomic behavioral model developed by DeSerpa (2), in which individuals maximize utility in choosing among alternative goods and the times allocated to them, subject to income and time-resource constraints. In this model, the choice of any amount (X_i) of commodity i places only a lower bound on the amount of time (T_i) the individual must use in consuming X_i; a change in relative prices of either goods or times causes the individuals to substitute among goods of various time intersities and, therefore, to implicitly substitute among alternative uses of time. Others (5, 6, 7, 9, 10) have used similar theoretical approaches to demonstrate the relation between the microeconomics of choice behavior and binary-choice economitric models. These models suggest, that modal choice is a function of two categories of variables, transportation-system characteristics that affect the money and time costs of travel and user characteristics that serve as proxies for objective comfort characteristics.

Traditionally, modal-choice studies have simply added the costs of parking to the automobile running costs (7, 10). This procedure implicitly assumes that parking services and automobile use enter into the individual's production function in fixed proportions. It also implies that the decision about where to park is independent of modal choice, so that parking-location decisions are unaffected by variations in time costs.

In this paper, parking is defined as a commodity that is complementary to automobile trips. The individual is assumed to maximize a utility unction $[U(C_i)]$, where $C_i = F(X_i, T_i)$, subject to income and time-resource constraints. The explicit specification of the production functions that determine C_i is important for understanding the role of parking use. For transit, the service consumed is generated by the production function

$$C_T = F_T(X_T, T_T) \quad (1)$$

where X_T = transit service purchased and T_T = time spent in using X_T; for automobile use, the service consumed is generated by the function

$$C_A = F_A(X_A, T_A, X_P, T_P) \quad (2)$$

where

X_A = automobile service consumed,
T_A = time spent in using the automobile,
X_P = parking services used, and
T_P = time spent in moving from parking facility to final destination.

The consumption of parking is location specific because each location is characterized by a unique money and time cost and alternative parking locations are substitutes. The individual, in choosing his or her mode, is aware of some average parking cost about the destination point, but has some discretion with respect to the final location chosen. Although the individual faces a binary choice with respect to mode, he or she does not with respect to parking-location decisions.

Changes in parking costs cause both parking relocation and modal switching. As parking prices change, individuals tend to reallocate their money and time resources to less expensive substitute commodities in two ways: (a) by reallocation of time and money within the automobile mode by changing parking locations and (b) by reallocation of time and money by substituting other modes. The former effect is not captured in traditional modal-choice models.

The suppression of the parking-relocation decision in the traditional modal-choice models implies that such models will have a biased prediction of the responsiveness of changes in mode to changes in relative parking or modal running costs. The bias may enter in a number of ways. First, if parking costs are added to automobile running costs, one will find that, as the distance traveled increases, the automobile running costs increase and parking costs become a lower proportion of total automobile costs and could then conclude that an increase in parking costs will have little effect on the modal choices of more distant individuals. However, the lack of effect could also be attributed to the increasing differential between other service attributes of the two modes as distance increases. Second, if higher income individuals do consume more housing and thus tend to live at more distant locations, the lack of a parking-price effect may be attributed to an income effect rather than to a price effect. If one does not treat parking costs separately and stratify the data by income level, one cannot separate these effects.

ESTIMATING EQUATIONS

The general form of the equation used for estimating modal-choice behavioral models is

$$P_i = f(TSC_j, UC_k) \tag{3}$$

where

P_i = probability of selecting mode i,
TSC_j = jth transportation-system characteristic, and
UC_k = kth user characteristic.

Since the P_i are limited to the internal (0, 1) choice, the function f is nonlinear.

There are alternative methods for estimating probabilistic modal-choice models. The method used here is logit analysis (6, 8, 9). This technique estimates the probability of a particular choice of mode as a nonlinear function of the explanatory variables. The relationship is assumed to be S-shaped, which is logistic sigmoid (i.e., the cumulative distribution function for the logistic). The form of the logit model is

$$P = \left\{1 + \exp\left[-G(x)\right]\right\}^{-1} \tag{4}$$

where G(x) = linear function of explanatory variables and P = probability of choosing to use the automobile mode conditional on x.

Logit models will not be discussed in detail here because they are well documented in the literature (1, 3, 5, 6, 9). A computer program described by Nerlove and Press (8) was used in all of the estimations.

The data were taken from the 1964 Metropolitan Toronto and Regional Transportation Study (MTARTS) home-interview summary. The estimates used in this research are based on a subsample of 515 work trips. The dependent variable is the probability of choosing the automobile for all of the equations estimated.

The following criteria were used to select the subsample:

1. The trips originated within the boundaries of metropolitan Toronto;
2. The zone of origin was the same as the home zone because we are interested in home-based trips;
3. The trip destination was within the central business district;
4. The mode used for the trip was either private automobile or public transit; and
5. Each family had the use of an automobile, and at least one member of the family possessed a driver's license.

From the total sample of 84 064 trips, a final subsample of 3012 trips was selected. This number was significantly reduced to 515 trips because of missing or miscoded information.

All the data used in the estimation were taken from the computer tape provided by MTARTS. Some variables used in the estimation were calculated from information provided by MTARTS.

The real-route distance was not coded. Distance was calculated as the straight-line distance between centroids of the home and destination zones. The relation between the real or route distance (D_R) and the straight-line distance (D_{SL}) is $D_R = 1.4D_{SL}$ (12).

The travel-time variable used in the model is T_c/T_T. The data provided information on the departure and arrival times of the mode used. It also provided information on the excess vehicle time at the beginning and end of the trip.

The following procedure was used to estimate the time of travel for the mode not used for the given trip: A regression of the travel time on the straight-line distance for each mode was computed, and the regression estimate was then used as the proxy for the time required for the journey to work if that mode is used. The regressions were computed over the whole sample; the results for the automobile mode are:

$$T_{C_1} = 0.30 + 0.037D_{SL}, \quad T_{C_2} = 0.23 + 0.038D_{SL} \tag{5}$$

(R = 0.383 and N = 341.)

where

T_{c_1} = total travel time by automobile (h),
T_{c_2} = in-vehicle travel time by automobile (h),
D_{SL} = straight-line distance between origin and destination zone,
R = correlation coefficient, and
N = number of observations.

The regression results for public transit are

$$T_{P_1} = 0.31 + 0.072D_{SL}, \quad T_{P_2} = 0.16 + 0.072D_{SL} \tag{6}$$

($R = 0.59$ and $N = 430$.)

where

T_{P_1} = total travel time by transit (h) and
T_{P_2} = in-vehicle travel time by transit (h).

The t-statistics for the coefficients in Equations 5 and 6 are shown below.

Value	t-Statistic	Value	t-Statistic
0.30	9.54	0.31	12.67
0.037	7.62	0.072	14.9
0.23	7.27	0.16	6.06
0.38	6.38	0.72	14.3

The differences between T_{c_1} and T_{c_2} and between T_{P_1} and T_{P_2} are walking times at the beginning and ending of the trips. The constant term decreases from T_{c_1} to T_{c_2} and from T_{P_1} to T_{P_2}. The change is greater for transit than for automobile because the removed components are a larger proportion of transit.

The small decrease from T_{c_1} to T_{c_2} is due to the discretion that the individual has with respect to scheduling and location. The rather high constant term in the equation for T_{c_2} may be interpreted as the average effect of congestion on in-vehicle time because a large percentage of the sample trips were made in the peak periods and may also include the average time used looking for a parking location.

Explanatory Variables

The following transportation-system and user characteristics were used as explanatory variables:

T_c = overall travel time by automobile for a given trip;
T_T = overall travel time by transit for a given trip;
C_c = money cost of emphasizing the automobile for a given trip, which are here set equal to the marginal (equal to the average) running costs of the automobile (fuel, oil, tires) per kilometers traveled plus the parking fee;
C_T = money cost of using transit for a given trip;
PC = parking fee paid for a given trip;
F_c = money cost of using the automobile minus the parking fee ($F_c = C_c$ - PC);
$T_{\bar{t}}$ = $C_{\bar{t}}$;
EPC = inclusive price of parking (parking fee plus time costs), which is equal to PC plus the marginal value of time times walking time from parking location to destination (the time component is deducted from T_c when EPC is entered into the estimating equation);
Y = personal income of the trip maker;
A = dummy variable for age of the trip maker (1 if age is between 20 and 55 years, 0 if otherwise);
SX = sex (1 if female, 0 if male); and
SS = occupation-status dummy (1 if the individual is a white collar worker, or a middle or professional manager, 0 if otherwise).

The dependent variable is coded 1 if automobile is used, 0 if transit is used.

Travel Costs

The questions in the MTARTS survey relating to direct costs or money saved or lost by alternative modes were unusable or qualitative, which is disappointing because perceived cost is the relevant cost in this behavioral model.

For transit riders, the perceived cost is the fare, but the answer is less straightforward for automobile users. Individuals normally purchase an automobile for many uses, of which work is one; hence intuitively it seems reasonable to conclude that individuals will consider only the marginal running costsof a trip. This includes fuel, oil, tires, and maintenance at most and fuel at least. (The inclusion of parking costs should be entered as a separate cost variable.)

The running costs are calculated on an average automobile being driven at the average speed:

$$C_i = \bar{C} \times 1.4D_{SL} \tag{7}$$

where

C_i = cost of ith trip,
$\bar{C}$ = average running cost of automobile [approximately 2.5 cents/km (4 cents/mile)], and
1.4 = proportionality factor relating straight line to real distance.

The parking-cost variable was coded for those individuals who use the automobile, but not for transit riders. A parking-cost variable for that group was constructed from knowledge of their walking time at the end of their trip to their destination point, their zone of destination and its associated parking-rent gradient, and the trip purpose of the individual.

There are a number of methods that can be used to construct the EPC for transit users. The method here was to use the longer of the average distance walked by automobile users in that census tract or the distance walked from the transit terminus to the destination point. This establishes an outer bound for the transit user.

User Characteristics

The MTARTS home-interview survey also provides the following socioeconomic information: sex, age, occupation (social status), number of wage earners, household income, trip purpose, travel mode, driver's license, number of vehicles owned or leased, and number of persons in the household and their age distribution.

Parking Data

The data about parking fees and the fee structure across the urban area were not available from the MTARTS tape. This information was provided by the Toronto Parking Authority, City Parking Limited, and the Metropolitan Toronto Department of Public Works. These agencies provided information about hourly and daily rates of each parking facility and the location of each facility within the central business district. All parking data were for 1964 to be compatible with the MTARTS data.

Full Price of Parking

The value of time for use in the full parking-price variable was calculated from the data set by using the technique developed by McFadden (6) and was 58 percent of the wage rate.

Model Specifications

Three models were specified and estimated to test the effects of different specifications of the effect of parking costs on modal choice. Model 1

$$G(x) = b_0 + b_1 T_c/T_T + b_2 C_c/C_T + b_3 A + b_4 SX + b_5 SS + b_6 Y \quad (8)$$

where $b_0, \ldots, b_n$ are estimated parameters, is a variant of the modal-choice models used in other studies. It will serve as a benchmark against which the estimates of this data can be compared with those of other studies. It incorporates parking costs with the modal running-cost variable: Because $C_c = F_c + PC$, the relative cost coefficients can be compared with those in models 2 and 3 in which modal money and parking costs are separated. Model 2

$$G(x) = b_0 + b_1 T_c/T_T + b_7 F_c/F_T + b_8 PC/F_T + b_3 A + b_4 SX + b_5 SS + b_6 Y \quad (9)$$

separates parking costs and modal running costs. This permits examination of the separate influences of changes in modal money costs and changes in parking fees on modal choice and the determination of whether or not individuals capitalize money costs at the same rate despite differences in the service purchases; i.e., whether $b_7 \leq b_8$. It also allows comparison of the relative magnitudes of the relative cost and relative fare variables. If $b_2 > b_7$ and b_8 is significant, the effect of a change in parking costs measured in model 1 will be upwardly biased. Model 3

$$G(x) = b_0 + b_1 T_c/T_T + b_7 F_c/F_T + b_9 EPC/F_T + b_3 A + b_4 SX + b_5 SS + b_6 Y \quad (10)$$

is a variation of model 2 that incorporates an inclusive parking price, a formulation suggested by McFadden (6). EPC combines the money and time costs associated with parking. The time element associated with the terminal end of the trip, which was previously included in the overall trip time, is now included in the full price rather than in T_c. This permits an estimation of the effects of changes in parking fees on the full price of parking and a comparison of the coefficient estimates of models 2 and 3. A priori, one would expect that $b_9 < b_8$ and that the elasticities calculated from these variables would have the same relation because parking costs as a proportion of full costs decrease with distance.

EMPIRICAL RESULTS

The parameter estimates of models 1, 2, and 3 are given in Table 1. The estimates of all three models are of the expected signs and the magnitudes agree with those of previous modal-choice studies. The likelihood ratio, $-2 \log \lambda$, tests the hypothesis of dependence between the dependent and explanatory variables. The values of the likelihood ratio for all three models indicate that the null hypothesis of independence between dependent and explanatory variables can be rejected. Because the focus of this paper is on the relative cost and parking variables, only these will be discussed.

The values of b_2 and b_7 differ significantly when parking costs are and are not included in modal running costs. The high estimate of b_2, the coefficient of the relative-cost variable (in which parking fees are included), would seem to indicate that, for a given change in relative modal costs, the effect on modal switching will be perceived to be the same regardless of the source of the change in relative costs. The low estimate of b_7, the coefficient of the relative fare variable, and the relatively higher values of b_8 and b_9, the coefficients of the parking costs variables, indicate that changes in relative modal fares have a negligible effect on modal switching, but changes in parking costs have a higher effect on inducing individuals to switch to transit. If one attempts to measure the effects of changes in parking costs on modal choice through the relative-cost variable, the results will be upwardly biased.

The sign of the coefficient for the parking variable indicates that parking services and automobile use are complements in the case of the work trip. These two services, parking and automobile use, may well be substitutes in the non-work-trip case in which variable parking duration is allowed. The magnitudes of b_8 and b_9 indicate that individuals are relatively more responsive to changes in parking costs than to changes in relative modal fares in their modal-choice decision. However, the effect of changes in parking costs on automobile use is not as great as some have previously believed. This is because changes in parking costs allow parking relocation as well as modal switching effects.

The value of b_9 is expected to be less than that of b_8 because changes in either parking fee or time costs will cause changes in full price according to its' proportion of full price.

Table 2 gives the results of estimates of models 1 and 2 when the data are stratified by income class. The relative magnitudes of the relative cost, relative-fare, and parking-costs variables are similar to those shown in Table 1.

ELASTICITY OF MODAL CHOICE

A measure of the sensitivity of the change in the probability of choosing the automobile with a change in one of the explanatory variables is provided by the point elasticity. The elasticity may be defined as

$$\xi = (\partial E[P]/\partial X_i)(X_i/E[P]) \quad (11)$$

Table 1. Parameter estimates using binary logit models.

Parameter	Explanatory Variable	Model 1 Value	Model 1 t-Statistic	Model 2 Value	Model 2 t-Statistic	Model 3 Value	Model 3 t-Statistic
b_0	Constant (automobile preference effect)	1.84	5.87	1.44	6.51	1.07	6.14
b_1	T_c/T_t	-2.00	8.30	-1.73	7.05	-1.83	7.46
b_2	C_c/C_t	-0.159	4.09	—	—	—	—
b_7	F_c/F_t	—	—	-0.013	1.46	-0.021	1.87
b_8	PC/F_t	—	—	-0.244	6.81	—	—
b_9	EPC/F_t	—	—	—	—	-0.205	6.12
b_3	A	0.47	3.93	0.396	3.15	0.419	3.38
b_4	SX	-0.85	6.00	-0.84	6.16	-0.85	6.43
b_5	SS	-0.02	0.19	0.049	0.38	0.008	0.068
b_6	Y	0.096	3.07	0.103	3.13	0.167	4.82

Notes: Sample size = 515; dependent variable is automobile transit choice (0 if transit is used, 1 if automobile is used) for the work trip; $-2 \log \lambda$ = 246.9, 284.7, and 275.1 for models 1, 2, and 3 respectively.

Table 2. Parameter estimates by income group.

Income Class ($ 000)	-2 log λ	Constant (Automobile Preference Effect)		Age		Sex		T_c/T_T		F_c/F_T		C_c/C_T		PC/F_T	
		Value	t-Statistic	Value	t-Statistic	Value	t-Statistic	Value	t-Statistic	Value	t-Statistic	Value	t-Statistic	Value	t-Statistic
4 to 6	42.01	3.24	4.52	0.238	0.818	-1.12	3.14	-3.91	4.63	-0.041	1.22	—	—	-0.652	1.49
6 to 8	39.65	4.03	4.61	0.027	0.091	-1.01	3.11	-3.66	3.99	-0.037	1.12	—	—	-0.259	3.59
8 to 10	42.23	2.65	4.25	0.438	1.53	-0.61	1.99	-2.24	3.48	-0.069	1.17	—	—	-0.237	3.32
>10	27.29	6.06	4.08	1.06	2.75	-1.49	3.37	-4.41	4.47	-0.025	1.32	—	—	-0.291	3.18
4 to 6	43.25	3.38	4.54	0.295	1.04	-1.09	3.22	-3.88	4.01	—	—	-0.091	1.48	—	—
6 to 8	46.57	3.66	4.09	0.156	0.575	-0.97	3.34	-3.58	4.29	—	—	-0.178	1.88	—	—
8 to 10	46.56	2.65	3.91	0.443	1.65	-0.78	2.34	-2.46	3.90	—	—	-0.17	2.21	—	—
>10	35.23	4.39	4.15	1.03	3.12	-0.93	2.85	-4.09	5.09	—	—	-0.283	2.02	—	—

where ξ = elasticity of choice of mode with respect to variables X_i and $E[P]$ = expected probability of choosing the automobile.

One can simplify this expression by substituting $E[P] = \exp G(X)/[1 + \exp G(X)]$ and differentialing. Then

$$\begin{aligned}\xi &= \left(\partial\left\{\exp G(x)/[1 + \exp G(x)]\right\}/\partial G(x)\right) \times \partial G(x)/\partial X_i \times \\ &\quad [X_i/\exp G(x)]/[1 + \exp G(x)] \\ &= \left\{\exp G(x)/[1 + \exp G(x)]^2\right\} \times b_i \times [X_i/\exp G(x)]/[1 + \exp G(x)] \\ &= (1 - E[P])b_iX_i \qquad (12)\end{aligned}$$

ξ becomes intractable if the transportation-system characteristics are expressed in terms of differences because at some point X_i may be zero. The elasticity is a linear function of the X_i's and is proportional to the probability of choosing the other mode.

The elasticities may be calculated in three different ways. The probability may be estimated for a specific individual by using individual values of the explanatory variables. The elasticity would then be estimated by Equation 12. The second method, which is referred to below as the individual elasticity (ξ), is to estimate the logit function across individuals for the set of explanatory variables. The probability is then estimated from the sum of the parameter estimates times the mean value of each explanatory variable, given the distribution of characteristics over the population. The expected probability ($E[P]$) is then used in Equation 12 to determine ξ. The third method, developed by Westin (11), is to determine the probability for each category or class within the distribution for each explanatory variable. These probabilities are then aggregated, and $E[P]$ is determined from these weighted probabilities and used in Equation 9 to estimate ξ', which is referred to as the aggregate elasticity. Westin has shown that the difference between (ξ) the individual elasticity and ξ' is determined by the ratio $E[P](1 - E[P])/E[P](1 - P)$. The difference between ξ and ξ' occurs because ξ is determined from the mean value of the explanatory variables, which are aggregated, and the probability P is then determined, but ξ' is the mean of the aggregate of probabilities, which are estimated for each class in the distribution of characteristics. One would expect ξ and ξ' to be very close.

The table below gives both the individual and the aggregate elasticities for C_c/C_T, F_c/F_T, PC, and EPC.

Elasticity	C_c/C_T	F_c/F_T	PC	EPC
ξ_i	-0.34	-0.068	-0.38	-0.25
ξ_i'	-0.29	-0.059	-0.31	-0.19

The decrease in the relative-cost elasticity when parking costs are and are not included, i.e., in C_c/C_T and F_c/F_T respectively, demonstrates the nonresponsiveness of modal switching to changes in transit fares. It is also evident that the relative-cost elasticity upwardly biases the expected change in mode when relative running costs change but downwardly biases the expected change in modes when parking fees change. The parking-fee elasticity is larger than both the relative-cost and relative-fare elasticities, but is somewhat smaller than previously suggested (4).

CONCLUSIONS

The models developed and the empirical results obtained in this research point to the following conclusions:

1. The form of the parking-cost variable is crucial if one hopes to obtain unbiased estimates of the effects of charges in parking costs on modal choice. The response to modal switching will be overestimated if one simply adds the parking costs to the modal running costs. The parking variable was entered in the estimations in two forms. The parking-cost variable (PC) allows one to estimate the effects on modal choice of any changes in the many costs of parking. The full-price variable for parking (EPC) is somewhat more flexible than PC because it allows one to estimate the effects of a number of parking-policy changes, whether they relate to changes in parking fees (such as a parking tax) or changes in time costs (such as parking restrictions).

2. The sign of the coefficient of the parking variable indicates that parking services and automobile use are complements for the work trip. The relatively low elasticities, especially in those of the EPC, can be attributed to the fact that changes in parking costs result in parking relocation as well as modal switching. It is only those individuals who are on the margin of relocating or switching modes who tend to switch. These individuals are generally those who have located some distance from their destination point and who represent a small proportion of the total parking. This point is more precisely captured in the EPC variable.

The elasticity of the probability of automobile use with respect to parking costs indicates that a 10 percent increase in parking fees will result in a 3.1 percent decrease in automobile users as a percentage of current automobile users. If automobile and transit uses are split 50:50 for the work trip, 3.1 percent of the automobile users will switch modes. If this split is 75 percent automobile and 25 percent transit, a change in parking costs may cause a 10 or 15 percent increase in transit use as a percentage of current transit use. Such large changes would require a coordinated transit investment; i.e., a parking pricing policy.

If a parking authority attempts to introduce parking fee changes of a local nature, i.e., at one or two points, the effect on automobile use will be negligible because the affected individuals will simply relocate.

3. The use of the technique suggested by Westin for making aggregate predictions from individual data leads to calculated aggregate elasticities that are slightly smaller than the individual elasticities. These elas-

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.