CHAPTER 7

Estimation Results and Conclusions

7.1. Introduction

This chapter presents the results of our efforts to estimate the parameters of the work modal split model and the complete shopping demand model. The latter consists of the choices of mode, time of day of travel, shopping destination, and frequency of travel.

Both linear probability models, estimated by ordinary least squares regression analysis, and logit models, estimated by maximum likelihood, were explored in the statistical estimation. Typically, the approach was to use regression analysis because of its much lower computational costs in the initial estimation stages to explore alternative measures of a variable or numerous alternative specifications of the model. Alternatives were evaluated in terms of the signs and magnitudes of estimated parammeters. Then, after reducing options by this exploratory analysis, the logit model was estimated for the important alternative specifications. Where applicable, results are reported for both the linear probability models and the logit models.

The empirical results are presented in terms of the parameter estimates, measures of the statistical reliability of the parameter estimates (i.e., t-statistics), various measures of the ability of the model to explain the data, and measures of the sensitivity of the choices being modeled to changes in the different policy variables.

Before turning to the actual results, it may be helpful to summarize briefly the results of the empirical analysis. To begin, it is important to recognize that we have regarded the empirical analysis principally as a means of testing and illustrating a modeling approach rather than an attempt to develop highly-tuned models for immediate planning purposes. No pretense is made of having developed the definitive model for any of the choices being examined. The estimation efforts are confined to relatively simple and straightforward types of trips—round trip home-to-work and home-to-shop trips with the only choice of modes being the auto driver (driving alone) and the bus transit with walk access. The more complicated types of trips have been avoided in this initial analysis.

Because of the rather small sample sizes, the models have deliberately been kept simple. In most cases only three or four explanatory variables can be used without introducing considerable multicollinearity. In addition, only the simplest mathematical forms of the models have been specified and estimated. Again, this stems from our basic objective, which is to test out the overall approach rather than concentrate on detailed model specification.

In spite of these limitations, however, the statistical results of the empirical analysis are highly encouraging. Relatively good models of the choice of mode have been obtained and it is easy to see the directions to take to improve these models. They could be improved and made more sensitive to the needs of policy-makers by attempting a more complete disaggregation of the transportation variables than was possible in this study. It is also clear in all the models that a more sensitive characterization of the size, composition, and socioeconomic characteristics of the households would improve the results.

Reasonably good models have also been obtained of the choices of shopping destination and trip frequency. These models are directly linked to the modal choice models since they incorporate measures of the inclusive price of travel as significant determinants of choice. In the trip destination model, the inclusive price of travel to each relevant shopping destination is measured by the attributes of the trip to that destination, weighted by the parameter of each attribute as estimated in the modal split model. This provides a natural measure of the "accessibility" of each destination to the trip-maker. The measure is a significant determinant of choice of destination and can be used to measure the effects on the distribution of shopping trips between origin–destination pairs resulting from selective changes in the transportation system.

In the trip frequency model, the overall inclusive price of travel is a weighted average of the inclusive price of travel to each relevant shopping area. The weights are the probabilities of choosing each alternative destination, as estimated in the trip destination model. The trip frequency model, therefore, measures the sensitivity of the number of shopping trips per day to changes in the time and cost of travel. Again, the inclusive price of travel is a significant determinant of this choice and provides a means of measuring the induced shopping travel resulting from changes in the transportation system.

The least successful results have been obtained for the choice of time of day of travel, but even for this model the results are promising and the directions to take to improve the model can be readily seen. Again, measures of the inclusive price of travel in the peak and off-peak were developed from the parameters of the modal choice model and introduced as determinants of the choice of time of day. This measure of relative price consistently takes the correct sign and is quite stable in magnitude, although the parameter estimate is not significant at conventional levels of significance. The results suggest, first, that changes in relative travel times do cause some people to shift in or out of the peak, but that these decisions are significantly affected by factors other than relative travel times. Again, the results indicate that a more sensitive characterization of the household would improve the results substantially and provide a significant measure of the separate effect of relative travel times on the choice of when to travel.

In summary, these results indicate that the modeling approach developed in this study is extremely promising. For one trip purpose—shopping—policy-sensitive models have been developed of each aspect of the travel decision: the decisions of where to go shopping, when to go, how frequently, and which mode to take. Moreover, these separate models are structured so that the individual pieces form a consistent whole. The separate models of the travel decision process combine into an overall demand model for urban travel. The set of equations which comprise the demand model can be used to measure the separate effects of a change in a transportation policy variable on: (1) modal split, (2) time of day of travel, (3) distribution of trips to destinations, and (4) frequency of trips per day for the given purpose. These effects can be measured for either across-the-board changes or selective changes in a policy variable. For example, the effects of an across-the-board decrease in transit fares could be estimated to see to what extent it induced travel overall, to what extent it attracted riders from autos, and to what extent it diverted riders from auto-oriented shopping areas to transit oriented areas. On the other hand, a selective change could be evaluated, such as a decrease in off-peak-hour transit fares, to estimate the potential for shifting riders from peak travel times. Another example of a selective change would be an increase in downtown parking charges. The model could be used to estimate the effect on auto travel to the downtown, and in addition could be used to estimate the extent to which any reduction in downtown auto trips was attributable to a reduction in trip frequency, to diversions to downtown transit trips, or to auto trips to non-downtown locations (e.g., to suburban shopping centers with plentiful free parking). The policy implications of these three alternatives are, of course, quite different.

The modeling approach, when fully developed for all trip types, can be used to generate trip tables, by mode, by time of day, by level of service for each important transportation variable, and by socioeconomic subclasses of the population.

7.2. Work modal choice

The work trip models presented below measure the determinants of the choice of mode for round trip home-to-work-to-home trips, in which both legs of the trip are taken in the peak. The observations are either auto drivers (driving alone) or transit riders (who walk to and from the transit stop). The transit mode is primarily bus, although there are also some streetcar trips. The sample is 115 observations of individual trip-makers drawn from the southern suburban corridor of the Pittsburgh metropolitan area and a central city corridor running from the downtown to the east. The trip-makers comprise a wide range of socioeconomic circumstances, and the trips themselves include suburban commuters to downtown, in-city trips, and cross-town trips. The observations are almost evenly split between auto and transit (54 percent auto).

For each individual trip, data have been prepared on the times and costs of travel for the actual trip taken at the actual time of day to the actual destination, and the travel times and costs for the alternative mode at the actual time of day to the actual destination. Socioeconomic variables on each household in the sample are also available, measuring car ownership, income, race, occupation, family size, number of workers, and so forth. Almost all the households in the sample own cars, but the number of cars per household varies.

Both linear probability models and binary-choice logit models were estimated. In the exploratory analysis it was found that only a relatively few transportation variables could be entered in an equation without introducing considerable multicollinearity. Thus, the initial modeling efforts concentrated on determining the best ways to combine these variables so as to incorporate as many of the elements of the door-to-door trip as possible and still avoid excessive collinearity.

The best results were obtained with models (7.1) and (7.2) below, both of which are binary-choice logit models. These models measure the effect of each of the independent variables on the log of the odds of choosing auto over transit. That is, the models are of the form:

$$\log Q_i = \sum_{k=1}^{k} \beta_k z^{ki},$$

where

$Q_i = P_i/(1 - P_i)$ = odds that Mr. i will choose auto, and P_i is the probability of Mr. i choosing auto;

$$\begin{aligned} \log Q = {} & \underset{(3.79)}{-4.76} + \underset{(2.62)}{0.147}TW - \underset{(2.05)}{0.0411}(AIV - TSS) \\ & - \underset{(4.53)}{2.24}(AC - F) + \underset{(4.06)}{3.78}A/W; \end{aligned} \tag{7.1}$$

$$\begin{aligned} \log Q = {} & \underset{(7.48)}{-3.82} + \underset{(3.30)}{0.158}TW - \underset{(1.51)}{0.382}(AIV - TSS) \\ & - \underset{(4.45)}{2.56}(AC - F) + \underset{(4.62)}{4.94}A/W \\ & - \underset{(2.12)}{2.91}R - \underset{(2.02)}{2.36}Z; \end{aligned} \tag{7.2}$$

where the variables are defined as follows:

TW = transit walk time (in minutes),
AIV = auto in-vehicle time, equals auto line-haul plus park and unpark time (in minutes),
TSS = transit station-to-station time, equals transit line-haul plus wait and transfer time (in minutes, wait is defined as one-half the headway),
AC = auto parking charges plus vehicle operating costs (in dollars),
F = transit fare (in dollars),
A/W = autos per worker in the household,

R = race (0 if white, 1 if non-white),
Z = occupation (0 if blue collar, 1 if white collar).

The numbers in parentheses below the model parameters are t-statistics, which measure the statistical significance of the relationships measured by the parameters. For the sample sizes used in this study, t-statistics of about 1.64, 1.96, and 2.33 indicate the parameter is significantly different from zero at, respectively, the 5 percent, 2.5 percent, and 1 percent levels of significance on a one-tailed test.

In model (7.1), all the parameters have the expected signs and all are highly significant.[1] The variable $(AIV - TSS)$ is significant at the 0.025 level and all others at the 1 percent level or better. The parameter for TW measures the effect of an increase in walking time to and from the transit station on the odds of selecting auto over transit. Its positive sign indicates, as expected, that as transit walk time goes up, the odds of selecting auto go up. The signs of the parameters of $(AIV - TSS)$ and $(AC - F)$ indicate, as expected, that as auto time or cost increase relative to transit, the odds of choosing auto go down. Finally, the parameter for autos per worker is positive, indicating that the odds of selecting auto increase as car availability increases.

The inclusion of autos per worker, a measure of auto availability, deserves special comment. It is reasonable to assume that in the long run the consumer's decisions on mode and auto ownership are interrelated, with automobile purchases following from a decision that the auto mode is more desirable. On the other hand, in the short run, automobiles

[1] After the estimation for this study was completed, we discovered a minor computational error in the estimation program. We re-estimated eqs. (7.1) and (7.2) to examine the effects of this error. The original, uncorrected equations are given below as (7.1′) and (7.2′).

$$\log Q = \underset{(3.88)}{-4.77} + \underset{(2.69)}{0.147}TW - \underset{(1.98)}{0.0411}(AIV\text{-}TSS) - \underset{(4.53)}{2.24}(AC\text{-}F) + \underset{(4.06)}{3.79}A/W; \tag{7.1′}$$

$$\log Q = \underset{(2.36)}{-3.65} + \underset{(2.67)}{0.150}TW - \underset{(1.35)}{0.0369}(AIV\text{-}TSS) - \underset{(4.42)}{2.42}(AC\text{-}F)$$
$$+ \underset{(4.28)}{4.64}A/W - \underset{(2.05)}{2.67}R - \underset{(1.93)}{2.15}Z. \tag{7.2′}$$

Comparison of these results with the corrected equations presented above shows that eq. (7.1′) is almost exactly the same as (7.1), with a few changes in the third significant digits of parameter estimates and t-statistics. In eq. (7.2′) the differences are somewhat more pronounced, with errors in the second significant digits, but the substantive findings are still essentially the same. Because of the closeness of these test comparisons, we did not re-estimate the remaining equations in this chapter.

are likely to be treated as a fixed durable by the consumer, with mode choice made conditional on automobile holdings. Models (7.1) and (7.2), in this interpretation, reflect *short-run* mode choice behavior. One would expect that in the long run, changes in the attributes of alternative modes would change the number of autos per worker, introducing a long-run effect on modal split beyond the immediate short-run effect. This demand structure also has statistical implications: unless the short-run/long-run demand structure is of the "causal chain" form, a simultaneous equations bias will be introduced in our estimation procedure. An explicit simultaneous choice model for automobile ownership and mode choice has been considered by McFadden (1973b), applying instrumental variables methods to obtain consistent estimates. The results suggest that the simultaneous equations bias is not important, lending some credence to the "causal chain" form. In this study, we ignore these problems, and assume that the random component of the autos per worker variable is statistically independent of the drawing of individuals from the subpopulation facing each particular value of the autos per worker variable.

The parameters of the transportation variables in model (7.2) all have the correct sign and all except $(AIV - TSS)$ are highly significant.

As mentioned earlier, the specific groupings of the transportation variables were arrived at after exploration of various alternatives. The groupings are a bit unusual and merit some discussion. First, transit-walk is presented alone rather than relative to auto-walk time, as is the case for the other transport variables. This was done after finding that the auto-walk variable—which combines reported walk times for actual auto trips with estimated walk times for alternative auto trips—reduced the explanatory power of the model, suggesting the data are very inaccurately measured. Better results were obtained by simply assuming that auto-walk times were zero for all trips, which is what almost all surveyed auto travelers report. (See chapter 6 for a discussion of the data.)

The variable $(AIV - TSS)$ was constructed after experimenting with various combinations of its constituent variables. The first approach was to include two separate explanatory variables. One measured the difference between auto in-vehicle time (line-haul plus park and unpark) and transit in-vehicle (line-haul) time, which seems a natural pairing. The variable is designated Δ in-vehicle below. The other measured transit wait plus transfer time, the out-of-vehicle elements of the station-to-station time. These results for the logit model are presented below.

Variable	Parameter	t-statistic
Constant	−4.762	3.70
Transit walk	0.1472	2.66
Δ in-vehicle	−0.0410	0.92
$(AC-F)$	−2.241	4.49
A/W	3.782	4.04
Wait + transfer	0.0411	1.27

(7.3)

It can be seen that the parameters for the two variables, Δ in-vehicle and wait + transfer, are almost exactly the same, but entered separately, neither variable is significant because of collinearity problems. Thus, there is good empirical reason to combine them. Similarly, auto in-vehicle time was separated from transit line-haul plus wait and transfer time (designated as transit station-to-station time below) to test to see whether taking the difference of the two variables is appropriate. The results are as follows.

Variable	Parameter	t-statistic
Constant	−4.814	1.83
TW	0.1470	2.67
Auto in-vehicle	−0.03901	1.31
Transit station-to-station	0.04178	2.03
$(AC-F)$	−2.250	4.14
A/W	3.773	3.95

(7.4)

Again, the two parameters are almost exactly equal and opposite in sign, and there is good reason for using their difference as the appropriate explanatory variable.

These comparisons indicate that in this sample of work trips, travelers attach the same weight to a minute spent at the bus stop waiting for a bus or transferring as they do riding in either the bus or an auto. It seems somewhat counter-intuitive that all station-to-station transit time would be equally distasteful, as one might expect travelers to find out-of-vehicle time more onerous than the in-vehicle time. In subsequent empirical analysis it will be useful to re-examine this issue, as it has important policy implications for transit planners. Moreover, the equal weights for auto and transit time are also highly interesting, as they indicate that a minute of transit time is no more or less onerous than a minute spent in the auto; in these results there is no special preference for auto travel per se.

An interesting additional comparison that can be made along these lines is to compare the weights for transit-walk time with that for $(AIV - TSS)$. The magnitude of the transit walk parameter is three to four times that for $(AIV - TSS)$ in models (7.1) and (7.2). This suggests that while work travelers may regard all in-vehicle or station-to-station time equally, they find a minute spent walking to or from the station three to four times more onerous than a minute spent at the station or enroute in either an auto or a transit vehicle.

A similar breakdown was made of the individual cost variables, and the findings were the same. There was no significant difference between the weights attached to the three cost variables. It is not surprising that auto parking costs and transit fares are evaluated the same by travelers since both are out-of-pocket charges, but it is somewhat surprising that auto operating costs are evaluated similarly.

Model (7.2) differs from (7.1) only in the inclusion of two socioeconomic variables, race and occupation. These variables were the only measures of the socioeconomic characteristics, other than measures of car ownership, which were found to be significant. All the car ownership variables described in chapter 6 were tested and A/W was found to yield the most significant results. As mentioned earlier, its parameter has the expected sign. The parameters for occupation and race indicate, respectively, that everything else equal, white-collar workers prefer transit and blue-collar workers auto, while whites prefer auto and non-whites transit. The parameters on both variables are significant at the 2.5 percent level. These results are somewhat puzzling and they may be picking up the effects of transportation or income variables not included explicitly in the model. Income, not surprisingly, in view of the expected unreliability of the income data, is never significant in any of the specifications of this model. Similarly, the weather variables, temperature and rain, were not found to be significant.

A final point in evaluating the logit modal choice models concerns their ability to predict the actual choice of mode. Both models perform extremely well in this regard.

The three alternative measures of "goodness of fit" discussed in chapter 5 are the likelihood ratio index, the R^2 index, and the prediction success table. For the models above, the indices are as follows.

	Model (7.1)	Model (7.2)
Likelihood ratio index	0.687	0.731
R^2 index	0.995	0.999

As indicated earlier, the likelihood ratio index is the more satisfactory index of goodness of fit from the standpoint of statistical theory, while the R^2 index is more closely comparable to the multiple correlation coefficient in linear regression. The prediction success table compares the choices predicted by the model (7.1) (using maximum calculated probability as a criterion) with the choices actually made.

Actual choice	Predicted choice: Auto	Predicted choice: Transit
Auto	58	4
Transit	4	49
Percent correct	94	92
Overall percent correct = 93		

We see that this model is highly successful in predicting actual choices, with an overall percentage of 93 correct predictions. In fact, the model predicts the observed choice with a probability of 0.9 or more for 85 of the 115 observations. Model (7.2) is equally good.

Eq. (7.5) below presents the unconstrained linear probability model estimates of eq. (7.1) for comparison with the logit results. This model, estimated by ordinary least squares regression analysis, is of the form,

$$P_i = \sum_{k=1}^{K} \beta_k z^{ki},$$

where the dependent variable P_i is the probability that Mr. i will take auto. In the regression analysis, P_i takes the value 1 if the individual takes auto, and zero if he takes transit. The parameters of the model measure the change in the probability of choosing auto associated with a unit change in the accompanying explanatory variable. The estimated model, with t-statistics in parentheses below the coefficients, is as follows,

$$P = 0.210 + \underset{(3.39)}{0.0124TW} - \underset{(1.61)}{0.00335(AIV - TSS)}$$
$$- \underset{(8.42)}{0.269(AC - F)} + \underset{(5.84)}{0.297A/W} \tag{7.5}$$

The multiple correlation coefficient for the model is 0.65. As with eq. (7.1), all the coefficients have the correct sign. The relative magnitudes of the coefficients for transit-walk and $(AIV - TSS)$ are again on the order of three to one. In this model, however, the parameter for $(AIV - TSS)$ is not quite significant at conventional levels of significance.

7.3. Shopping choice of mode

As was the case with the analysis of work trip choice of mode, this analysis compares the actual choice of mode for the actual time of day and destination to the alternative mode for the actual time of day and destination. The sample is 140 individual shopping trips drawn from the same Pittsburgh corridors. The range of observations is in all respects similar to that for the work trip sample except that the trips are no longer confined to peak-hour travel because very few observations were found where shoppers both go and return in the peak. The same two modal alternatives are compared, auto drivers and transit riders (with walk access).

Both linear probability and logit models were tested, with the logit models consistently yielding more satisfactory results. The best results obtained for the logit model are as follows:

$$\log Q = \underset{(4.07)}{-6.78} + \underset{(1.14)}{0.374TW} - \underset{(2.04)}{0.0654(AIV - TSS)}$$
$$- \underset{(2.46)}{4.11(AC - F)} + \underset{(2.03)}{2.24A/W}; \tag{7.6}$$

$$\log Q = \underset{(3.20)}{-6.20} + \underset{(0.97)}{0.398TW} - \underset{(1.60)}{0.0636(AIV - TSS)}$$
$$- \underset{(2.27)}{4.66(AC - F)} + \underset{(1.99)}{2.63A/W} - \underset{(1.72)}{2.19R} - \underset{(1.39)}{1.53Z}. \tag{7.7}$$

The variables are as defined earlier and the numbers in parentheses below the model coefficients are t-statistics. Again, a range of alternative combinations of the transportation variables was explored and a wide range of socioeconomic variables was tested. Although the final model specifications are the same as for work modal split, no deliberate effort was made to parallel the two.

The coefficients of the transportation variables in eqs. (7.6) and (7.7) all have the expected signs. However, the t-statistics are low for transit-walk in both equations and for $(AIV - TSS)$ in (7.7). Nevertheless, the magnitudes of these parameters are quite stable even though the t-values decrease when additional variables are included, which is encouraging.

The relative magnitudes of the parameters for transit-walk and the variable $(AIV - TSS)$ are on the order of six to one, suggesting that shoppers find walking to and from the transit station even more onerous relative to time spent waiting or enroute in the vehicle than do persons making work trips. As in the work model, auto in-vehicle time and all the components of transit station-to-station time have been constrained to have the same absolute parameter value. Again, this was arrived at empirically, based on the results of the following two models.

	Model (7.8)		Model (7.9)	
Variable	Parameter	t-statistic	Parameter	t-statistic
Constant	−6.65	4.31	−6.38	3.50
TW	0.303	0.855	0.274	0.449
Δ in-vehicle	−0.0287	0.403		
Wait + transfer	0.0647	1.61		
AIV			−0.0486	0.508
TSS			0.0531	1.17
$AC \cdot F$	−4.10	1.93	−4.06	2.32
A/W	2.01	1.93	1.89	2.48

Model (7.8) shows that while the parameter for transit wait and transfer time is considerably larger than that for the difference between auto in-vehicle time and transit line-haul time, the difference between the two parameters is not statistically significant. Again, it will be interesting in subsequent analyses to see if a basis emerges for disaggregating these variables. Model (7.9) shows that when the parameters for auto in-vehicle time and transit station-to-station time are compared, they are almost exactly the same in magnitude and opposite in sign, giving an empirical basis for combining them into one variable.

In model (7.7), the same two socioeconomic variables are present as were found in the work modal split model. Again, these were the only socioeconomic variables other than the car ownership variables that were even remotely significant. The weather variables were not significant. All the car availability variables were tested and it was again found that cars per worker yielded the most satisfactory results. The parameters for race and occupation have the same signs as they did in the work modal split model, which is again somewhat puzzling. In this model, however, the parameter for the occupation variable is no longer significant.

These models were even more successful then the work trip model in predicting mode choice. The prediction success table for model (7.6) is given below.

Actual choice	Predicted choice: Auto	Predicted choice: Transit
Auto	74	1
Transit	5	60
Percent correct	93	98
Overall percent correct = 96		

This model predicts the correct choice with probability 0.5 or better in 96 percent of the cases, and with probability 0.9 or better in 83 percent of the cases.

The other two measures of goodness of fit, described in chapter 5 and illustrated above for models (7.1) and (7.2), were not calculated for the shopping trip models because of problems in regenerating the data sets.

7.4. *Shopping choice of time of day of travel*

This model compares the actual time of day for the actual mode and destination with an alternate time of day for the actual mode and destination.

The times of day compared were those for which both legs of the trip occurred in the off-peak and those for which one leg occurred in the off-peak and the other in the peak. Very few trips were found which both originated and terminated in the peak, so this option was not analyzed.

The sample consists of 73 observations drawn from the in-city households in the file. The analysis was confined to in-city trips because it was felt that our estimates of the off-peak travel times were more reliable for the in-city trips. This is especially true for transit trips because for many of these trips the operating schedules provided a good guide to the differences between peak and off-peak travel times. Of the 73 observations, 10 are auto trips and 63 are transit. We considered deleting the auto observations but decided instead to use a dummy variable to see if there were any significant differences between the two modes.

The data again provide a reasonably good cross-section of trips, containing both downtown-oriented and in-city cross-town trips. There are no suburban-to-downtown trips, however.

Although the model compares the door-to-door travel times and costs for the two time of day alternatives, it is important to recognize that the only differences contained in the data are between peak and off-peak auto in-vehicle times and all the components of transit station-to-station times. Walk times, auto parking, and vehicle operating costs and transit fares were not varied between the peak and off-peak.

Based on the theory of chapters 3 and 4, inclusive prices of peak and off-peak travel were formed for each observation, using the parameters from the shopping modal split model to weight the separate components of travel time and cost. These prices were used in the empirical analysis in place of the individual travel time and cost variables. The inclusive price is defined as follows,

$$\hat{p}^{ji} = -\sum_k \beta_k z_k^{ji} \qquad \text{for each mode } j,$$

where $\hat{p}^{ji}$ is the inclusive price for Mr. i on the actual mode j taken by him. β_k are the relevant parameters for each variable for that mode, as estimated in the modal split eq. (7.6), and z_k^{ji} are the travel time and cost variables for Mr. i for his actual mode. Weighted averages of these prices across modes were not computed because the times and costs for the alternative modes in the alternative times of day had not been developed.

Both linear probability models and binary-choice logit models were estimated with the linear probability models used largely to explore alternatives for final estimation by the logit model. The best results, none of which are terribly satisfactory, are presented below:

$$\log Q = \underset{(3.02)}{1.02} - \underset{(1.42)}{1.97}(\hat{p}^0 - \hat{p}^m) - \underset{(1.83)}{0.691}PSC - \underset{(1.43)}{0.984}S; \quad (7.10)$$

$$\log Q = \underset{(2.79)}{0.843} - \underset{(1.48)}{2.07}(\hat{p}^0 - \hat{p}^m) - \underset{(2.04)}{0.701}PSC; \tag{7.11}$$

$$\log Q = \underset{(0.0041)}{0.00232} - \underset{(1.25)}{1.66}(\hat{p}^0 - \hat{p}^m) - \underset{(1.46)}{0.997}S + \underset{(1.41)}{1.71}W/R. \tag{7.12}$$

Here:

$Q_i = P_i/(1 - P_i)$	= odds that Mr. i will choose to both depart and return in the off-peak rather than traveling one leg of the trip in the peak;
$\hat{p}^0; \hat{p}^m$	= the inclusive prices of travel (as defined earlier) for the actual mode for off-peak–off-peak and mixed off-peak–peak, respectively;
PSC	= number of pre-school children in the household;
S	= sex of head of household (0 = male; 1 = female);
W/R	= the number of workers per number of residents in the household.

As can be seen from these equations, the difference in the inclusive price of travel is never significant, but it always has the correct sign and is quite stable in magnitude. The sign of the parameter indicates that as the inclusive price of travel rises in the off-peak relative to the peak, travelers switch on the margin to the peak, and vice versa. The results suggest that if the variables are properly measured, this approach can be used to measure the effect of changes in relative off-peak and peak travel times or costs on the diversion of trips from the peak to the off-peak. The t-statistics in eqs. (7.10) and (7.11) are not very much below the conventional levels of significance, and it might not require much refinement of the data or the model or increase in the number of observations to obtain significant parameter estimates.

None of the other variables tested yield significant parameters, except for the number of pre-school children. Its sign indicates that, other things equal, families without pre-school children tend to shop in the off-peak. The signs on the other socioeconomic variables in these equations suggest that families with female heads of household tend to make mixed peak–off-peak shopping trips, while families with a lower proportion of workers to total family members tend to shop in the off-peak.

None of the other variables tested were even remotely significant, including the socioeconomic variables, the weather variables, or the dummy for mode. However, it became evident in analyzing this model that the household variables available for this study did not provide a good characterization of the composition of the household. Basically, the variables on the household data tape describe the head of the household, and provide very little information about the makeup of the household beyond that. The data needed to build up a more sensitive characterization of the household are largely available from the individual trip records, but they were not summarized in any form. In retrospect, it appears that we should have manually built up characterizations of the composition of the households from the individual trip records. The few available variables which provide meaningful information on the constraints on time of travel—especially the presence of pre-school children—seem to improve the model. In subsequent analyses it will be useful to develop a good characterization of the family for analyzing choice of time of day of travel in terms of the constraints imposed on it by family composition and socioeconomic circumstances. This should substantially improve the empirical results of this model.

With regards to the ability of the models to predict the correct time of day of travel, the results are encouraging. Since there are two choices, on a random basis the correct choice should be selected for about 50 percent of the observations. The prediction success table for model (7.11) is as follows.

Actual choice	Predicted choice: Off-peak	Predicted choice: Mixed
Off-peak	42	4
Mixed	17	10
Percent correct	71	71
Overall percent correct = 71		

7.5. *Shopping choice of destination*

This model compares the trip to the actual destination at the actual time of day for the actual mode with the trips to the alternative destinations at the actual time of day for the actual mode. The relevant alternative destinations were determined for each observation by constructing a matrix of shopping destinations for each origin zone in the sample and selecting as alternatives those destinations that appeared in the matrix for the origin zone in which the observation was located.

The sample for this analysis consists of 63 observations from the southern suburban corridor of the Pittsburgh area. The suburban corridor was chosen rather than in-city trips because alternate destinations were easier to identify and locate exactly for suburban households than for in-city families.

The trips comprise a good cross-section of radial downtown shopping trips and suburban cross-town trips. However, all the trips are made by auto and there is much less variation in some of the socioeconomic variables than there was for the other trip models. There are no nonwhite households, no households with female heads, and no elderly (age 65 and over) households.

In modeling choice of destination there were always more than two options, so a simple binary-choice model is no longer appropriate. Further, the number of options varies from observation to observation, ranging from three to five.[1] Moreover, the alternatives are unranked as there is no obvious pairing of one household's destinations with another. Given the multiple-choice aspect of the problem, the linear probability model estimated by regression analysis no longer yields satisfactory statistical properties, as discussed in chapter 5. The multiple-choice logit model, estimated by maximum likelihood methods, was employed in the estimation. Because the alternatives are unranked, it is necessary to express their attributes in generic terms rather than in terms that are specific to each alternative. The differing numbers of alternatives faced by different observations in the sample are accounted for by requiring that the probabilities for each observation sum to one over their available alternatives.

Since there are a relatively large number of alternatives, it is imperative that the number of explanatory variables be reduced to a small number. For example, if there were four alternatives for a given observation and three transportation variables per alternative, twelve transportation variables would be needed to describe the choices available to the tripmaker unless some means were selected of combining variables.

[1] While only three to five destinations were chosen for each observation, the procedure is perfectly general and can be extended to any number if there is reason to do so.

For this model, as in the case of the time-of-day model, the transportation variables for each destination are combined into an inclusive price of travel to that destination. The procedure is the same as before. The transportation variables are weighted by the parameters from the shopping modal split model and summed to obtain an overall price of travel to each destination for the given household. All the trips are by auto. Thus the formula is simply

$$\hat{p}^i = -\sum_k \beta_k z^{ki}.$$

Eq. (7.6) is used for the parameter estimates. Thus, for example, if a round trip for a given household i to a given destination j required 40 minutes in-vehicle time, \$1.00 to park, and \$0.60 for vehicle operating costs, the inclusive price of that trip would be estimated as

$$\hat{p}^{ji} = 0.0654(40) + 4.11(1.00) + 4.11(0.60) = \$9.19.$$

Constructing these inclusive prices enabled the accessibility of each alternative destination for a given household to be represented by a single number. This is a natural measure of accessibility to a destination because it weights each attribute of the trip by the empirically estimated disutility of that attribute. To generalize on this procedure, if several modes were relevant for a given household, the inclusive price would be defined as the weighted average of the inclusive price for each mode. The appropriate weights in this computation would be the probabilities of selecting each mode, as estimated from the modal split model.

In the results presented below, the model estimated is of the form:

$$\log Q_i = \beta_1(z_1^{ji} - z_1^{li}) + \beta_2(z_2^{ji} - z_2^{li}) + \ldots;$$

$Q_i = P_{ji}/P_{li} =$ the odds that Mr. i will select destination j over l.

The best results of this model are as follows:

$$\log Q_i = \underset{(3.76)}{-1.06}(\hat{p}^{ji} - \hat{p}^{li}) + \underset{(3.72)}{0.844}(E^{ji} - E^{li}); \tag{7.13}$$

$$\begin{aligned}\log Q_i = {} & \underset{(3.78)}{-0.602}(\hat{p}^{ji} - \hat{p}^{li}) + \underset{(3.71)}{0.832}(E^{ji} - E^{li}) - \\ & - \underset{(1.52)}{0.521}(PSC^{i}*\hat{p}^{ji} - PSC^{i}*\hat{p}^{li}).\end{aligned} \tag{7.14}$$

Here the inclusive prices of the alternative destinations, $\hat{p}^{ji}$ and $\hat{p}^{li}$, are as defined above for each observation i. The variables E^{ji} and E^{li} are measures of the amount of shopping opportunities at each destination, and are defined as retail employment in the destination zone as a percentage of total retail employment in the Pittsburgh region. The variable PSC^i is the number of pre-school children in household i and is entered as an interaction term with the inclusive price alternatives for each household i.

It can be seen from these equations that the inclusive price of travel is a highly significant determinant of choice of shopping destination. As the "price" of travel to a given destination j increases relative to the household's alternative destinations, the odds of their traveling to that destination drop.

The measure of the relative size of the shopping areas is also a highly significant determinant of choice of destination. It has a positive sign indicating that the greater the relative retail trade opportunities (as measured by employment) at a given destination, the greater the odds of traveling to that destination to shop.

The interaction variable shows the effect of pre-school children on the choice of destination. It corresponds to a slope dummy variable on price. Its negative slope indicates that as the number of pre-school children increases, travel becomes increasingly onerous. Although the variable is not significant, it has the correct sign and illustrates an alternative specification of the price variable. The significant parameter estimates for price are highly satisfactory given the dimensions of the estimation problem and the relatively crude models tested. They indicate that a natural measure of accessibility can be developed which can be used to meaningfully measure the effect of geographical changes in transportation service levels on the distribution of trips between zones. The typical observation has four destination options. Thus, on a random basis, the correct destination would be selected about 25 percent of the time. For model (7.14), the actual destination is predicted about 46 percent of the time.

7.6. *Shopping trip frequency*

This model compares households which took one shopping trip in the 24-hour survey period with those which took no shopping trip. The hypothesis is that the more accessible the household is to its relevant shopping areas the more frequently it will travel to them. Alternatively, the more costly or time consuming it is to make a shopping trip, the more carefully the household will plan its shopping trips and the less frequently trips will be made. It is through the trip-frequency model that the earlier choice models are integrated into an urban travel demand model.

Although the model presented in this section is limited to the choice between no-trip and one trip per day, it can readily be extended in a multiple-choice framework to daily frequencies greater than one. The analysis in this study was limited to zero and one trip because only four households in the sample reported more than one shopping trip in the surveyed day.

The sample for this model consists of 80 households, 24 of which recorded no shopping trips and 56 of which recorded one trip in the survey period. All the households are drawn from the southern suburban corridor. Again, this was done to enable alternate destinations to be identified and correctly located. The sample is essentially the same one described earlier for the choice-of-destination model, with the households recording more than one trip per day deleted, and a sample of zero-trip households from the same areas added. The sample provides a good cross-section of downtown and suburban cross-town trips, but is limited to auto travel and is further limited in terms of socioeconomic variety, as discussed earlier.

Before undertaking this analysis, it is necessary to construct the potential shopping trips for the zero-trip households. That is, if the household were to take a shopping trip, where would it go, by what mode, and at what time of day? This is done in a straightforward way, employing the results of the previous stages of analysis.

First, the relevant destinations are selected by use of the matrix of shopping destinations developed earlier to analyze choice of destination. Then the times and costs of travel to each destination are generated from the network information. Finally, inclusive prices of travel to each destination are computed from the parameters estimated in the modal choice model. In this study the inclusive prices of travel for the zero-trip households were based only on the times and costs of off-peak auto trips, because the sample of zero-trip households was drawn from a suburban area where all the observed shopping trips were made by auto. But, as described earlier, this could be generalized by constructing a weighted average of the inclusive price of travel for each mode to a given destination, using as weights the computed probabilities from the modal choice function.

To generalize further, the inclusive price could also be averaged over times of day of travel, using as weights the computed probabilities of time of day of travel from the time-of-day model. However, given the quality of the alternate time-of-day data for suburban auto trips, there seemed little point in applying this refinement.

The final preparatory step before attempting to model the effect of the cost or disutility of travel on trip frequency is to develop an overall price of travel for each household. Each household has a number of alternative destinations, for each of which there is an inclusive price of travel. The natural measure of the overall price of travel to shop for each household is some weighted average of the inclusive prices of travel to each of the household's alternative destinations. The obvious weights to use are the computed probabilities from the choice of destination model. Thus, we define the overall price of shopping for household i as

$$\hat{\hat{p}}^i = \sum_d P_i(d)\hat{p}^i(d),$$

where $P_i(d)$ is the estimated probability of household i selecting its dth destination, and $\hat{p}^i(d)$ is the inclusive price of travel for household i to its dth destination. This overall price was computed for both the zero-trip households and the one-trip households in the sample, using the probabilities computed from eq. (7.13).

Note that $\hat{\hat{p}}_i$ provides a natural measure of the accessibility of household i to shopping; in similar fashion, the accessibility of a particular shopping location to shoppers could be estimated by aggregating over households for a particular destination d. Both measures of accessibility would be useful in land-use planning, in shopping center location studies, and in urban development analysis.

A weighted average of the shopping opportunites at each destination was developed by weighting the zonal employment figure by the computed probabilities from the choice of destination mode. Thus, we define

$$\hat{E}^i = \sum_d P_i(d)E^i(d),$$

where $P_i(d)$ is as defined above and $E^i(d)$ is the percentage of the region's retail trade employment found in observation i's destination zone d. The two variables $\hat{\hat{p}}^i$ and $\hat{E}^i$ provide measures of the cost of travel to shop for household i and the shopping opportunities which the traveler i receives if he takes a trip, respectively.

The trip frequency models were estimated using the binary-choice logit model. The best results were as follows,

$$\log Q_i = \underset{(3.16)}{-1.72}(\hat{\hat{p}}^i - 0) + \underset{(3.62)}{3.90}(\hat{E}^i - 0), \tag{7.15}$$

where,

Q_i = the odds that household i will make a daily shopping trip,
$(\hat{\hat{p}}^i - 0)$ = the comparison between taking a trip and incurring price $\hat{\hat{p}}$, and not taking a trip and incurring zero cost of travel,
$(\hat{E}^i - 0)$ = the comparison between taking a trip and obtaining proximity to $\hat{E}$ shopping facilities or opportunities, and not taking a trip and obtaining proximity to zero facilities.

Both the price and employment variables in eq. (7.15) have the correct sign and are highly significant. The model states that for shopping the frequency of travel is significantly inversely related to the time and cost of travel. If travel times are reduced through improvements in the transportation system, the frequency of shopping should increase. The model can be used to predict the expected increase or decrease in the number of shopping trips induced by the change in the transportation system.

A number of alternative models were estimated to test the significance of each of the available socioeconomic variables (including car ownership) and weather variables. None of them was significant, which may be because the sample has little variance in the socioeconomic variables, as discussed earlier. Interestingly, the only such variable which resulted in a t-statistic greater than 1.0 was family income, and this was the only choice model for which income was even remotely significant. The equation is as follows,

$$\log Q_i = \underset{(3.30)}{-2.25}\hat{\hat{p}}^i + \underset{(2.39)}{2.85}\hat{E}^i - \underset{(1.02)}{0.199}Y_i. \tag{7.16}$$

The results suggest that wealthier families shop less frequently, which seems plausible since they are more likely to have the necessary facilities to carry larger stocks of goods.

The prediction success table for model (7.15) is as follows.

Actual choice	Predicted choice: One trip	Zero trip
One trip	45	9
Zero trip	11	15
Percent correct	80	62
Overall percent correct = 75		

7.7. *Summary and implications*

This chapter has presented the estimation results for a work choice of mode model and a complete shopping demand model, consisting of choice of mode, choice of destination, time of day of travel, and choice of trip frequency. Each aspect of trip demand is seen to be sensitive to the performance of the transportation system. Thus, this modeling approach can be used to evaluate the effects of change in the transportation system on: where people travel, at what time of day, by which mode, and how frequently. In combination with data on the locational distribution of the population and retail employment, as well as measures of performance of the transportation system, these equations can be used to develop trip tables by mode and time of day in which the number of trips, and the distribution between zones, modes, and alternative times of day vary according to the levels of transportation service assumed for the system.

Before closing this chapter, it will be interesting to examine the relative sensitivity of the various trip choices on changes in the various transportation variables. To do this, it is useful to write out the following summary set of work and shopping travel equations.

Work modal split

$$\log\frac{P(a)}{1-P(a)} = \underset{(3.79)}{-4.76} + \underset{(2.62)}{0.147}TW - \underset{(2.05)}{0.0411}(AIV - TSS) - \underset{(4.53)}{2.24}(AC - F) + \underset{(4.06)}{3.79}A/W \tag{7.1}$$

Shopping demand model

Modal split

$$\log\frac{P(a)}{1-P(a)} = \underset{(4.07)}{-6.78} + \underset{(1.14)}{0.374TW} - \underset{(2.04)}{0.0654}(AIV - TSS) - \underset{(2.46)}{4.11}(AC - F) + \underset{(2.03)}{2.24A/W} \quad (7.6)$$

Time of day (off-peak vs. mixed peak–off-peak)

$$\log\frac{P(\text{off-peak})}{1-P(\text{off-peak})} = \underset{(2.79)}{0.843} - \underset{(1.48)}{2.07}(\hat{p}_0 - \hat{p}_m) - \underset{(2.04)}{0.701PSC} \quad (7.11)$$

$$\begin{aligned} &= 0.843 - 2.07[P(a)\{0.0654(AIV_0 - AIV_m) \\ &\quad + 4.11(AC_0 - AC_m)\} \\ &\quad + (1 - P(a))\{0.374(TW_0 - TW_m) \\ &\quad + 0.0654(TSS_0 - TSS_m) \\ &\quad + 4.11(F_0 - F_m)\}] - 0.701PSC \end{aligned}$$

Destination

$$\log\frac{P(j)}{P(l)} = \underset{(3.76)}{-1.06}(\hat{p}^j - \hat{p}^l) + \underset{(3.72)}{0.844}(E^j - E^l) \quad (7.13)$$

$$\begin{aligned} &= -1.06[P(a)\{0.0654(AIV^j - AIV^l) \\ &\quad + 4.11(AC^j - AC^l)\} \\ &\quad + (1 - P(a))\{0.374(TW^j - TW^l) \\ &\quad + 0.0654(TSS^j - TSS^l) \\ &\quad + 4.11(F^j - F^l)\}] + 0.844(E^j - E^l) \end{aligned}$$

Frequency (one trip per day vs. no-trip)

$$\log\frac{P(1)}{1-P(1)} = \underset{(3.16)}{-1.72\hat{\hat{p}}} + \underset{(3.62)}{3.90\hat{E}} \quad (7.15)$$

$$\begin{aligned} &= -1.72\sum_d P(d)\,[P(a)\{0.0654AIV_d + 4.11AC_d\} \\ &\quad + (1 - P(a))\{0.374TW_d + 0.0654TSS_d \\ &\quad + 4.11F_d\}] + 3.90\hat{E} \end{aligned}$$

(where the subscript d designates alternative destinations).

In describing the results of the work and shop modal split equations, we have already discussed the relative sensitivity of choice of mode to the different travel time variables. Briefly, for work trips, each minute of transit-walk time is seen to be about three to four times as onerous, and for shopping trips about six times as onerous, as a minute spent on any of the other components of travel time; and, in addition, there is no distinction between a minute spent waiting at the transit station, transferring, in the transit vehicle, or in the automobile. Based on the current modal split results, these are all weighted equally by workers or shoppers in the sample.

The only other transportation variable in the model is money costs —fares, parking charges, and vehicle operating costs—each of which is weighted equally. We did not compare the relative sensitivity of money costs to time spent traveling, but this can be done by examining the ratio of their parameters, which provides a measure of the value of time spent walking or otherwise enroute.[2] Thus, the estimated values of time per person for work and shopping trips, respectively, are as follows.

Work

$$\text{(1) Transit-walk} = \frac{0.147}{2.24} = \$0.0656 \text{ per minute}$$
$$= \$3.94 \text{ per hour.}$$

$$\text{(2) Auto in-vehicle or transit station-to-station} = \frac{0.0411}{2.24}$$
$$= \$0.0183 \text{ per minute}$$
$$= \$1.10 \text{ per hour.}$$

Shopping

$$\text{(1) Transit–walk} = \frac{0.374}{4.11} = \$0.091 \text{ per minute}$$
$$= \$5.46 \text{ per hour.}$$

[2] To see this let $Y = \log Q_i$. Then the value of transit-walk time equals

$$\frac{\partial Y}{\partial F}\Big/\frac{\partial Y}{\partial TW} = \frac{\partial TW}{\partial F}.$$

This is $\frac{0.147}{2.24}$ for work trips, for example. The same procedure is followed for the other components of time.

$$\text{(2) Auto in-vehicle or transit station-to-station} = \frac{0.0654}{4.11}$$
$$= \$0.0159 \text{ per minute}$$
$$= \$0.95 \text{ per hour.}$$

To make a comparison between these estimates and those generated by the value-of-time studies, it is necessary to set them relative to the wage rates. We have no wage rate data, and the reliability of the family income figures is suspect, but rough comparisons can be attempted using the income figures. The average yearly family income in the sample used to estimate the work trip modal split function is \$8800 and there are 1.5 workers per household in the sample. If we assume that the latter figure consists of one full-time and one-half part-time worker (working half time), the average annual income per full-time equivalent is \$7040. Assuming 2080 hours per year, this implies a wage of \$3.40 per hour. If all workers are assumed to work full time, the average wage is about \$2.85 per hour. Thus, the estimated average value of time is on the order of one-third the estimated wage rate, which is comparable to the findings of the value-of-time studies.

These estimates of the value of time provide a measure of the trade-offs between time and costs similar to the trade-offs between walking time and the other components of time. They suggest that, on the average, for work trips a ten-minute savings in round-trip line-haul time would have the equivalent effect of a fifteen- to twenty-cent decrease in fares. Alternatively, a ten-minute decrease in transit-walk time would have the equivalent effect of a fifty-cent decrease in fares. For shopping trips, the ten-minute savings in line-haul time is worth slightly less and the savings in walk time slightly more. Similar trade-offs can be examined for other components of time.

Next, we turn to the sensitivity of time of day of travel decisions, destination decisions, and trip frequency decisions. The most interesting comparisons are between the effects of a change in a transportation variable on these decisions contrasted to the effects on modal choice decisions. We shall see that time of day, destination, and trip frequency decisions are far more responsive to changes in relative travel times and costs than are modal choice decisions.

To make these comparisons, it is useful to employ the concept of demand elasticity. This can be defined as the percentage change in the number of trips demanded, associated with a one-percent change in a transportation variable. As derived in chapter 4, the elasticity formulas for the logit model are the following:

$$E_i = (1 - P_i)\beta_k z_k^{li} \qquad \text{(for an individual)},$$

$$E = \frac{\sum_i P_i(1 - P_i)\beta_k z_k^{li}}{\sum_i P_i} \qquad \text{(aggregated over individuals)},$$

where the elasticity measures the percentage change in the frequency of making a given choice, in response to a one-percent change in a given variable z_k^l for attribute k and alternative l.

Now, let us compare (1) the elasticity of demand for modal choice with respect to a given transportation variable, and (2) the elasticity of demand for time of day of travel with respect to a given transportation variable. Let the variable be auto in-vehicle time. To make this comparison we will consider a hypothetical individual. From the elasticity formula it can be seen that it is necessary to specify the present in-vehicle time, the existing probability of choosing auto, and the existing probability of both leaving and returning in the peak. Suppose the individual's present auto in-vehicle time is thirty minutes round trip, the probability of his currently choosing auto is 0.5, while the probability of his currently choosing round-trip off-peak travel is also 0.5. Then the two choice elasticities with respect to auto in-vehicle time are as follows:

$$\text{Elasticity of choosing auto} = (0.5)(-0.0654)(30) = 0.98,$$

$$\begin{aligned}\text{Elasticity of choosing round trip off-peak} &= (0.5)(-2.07)\\ &\quad(0.0654)(30)\\ &= -2.03.\end{aligned}$$

Thus, in this hypothetical example, the decision of when to make the trip is twice as responsive to a small change in the transportation variable as the decision of which mode to use. The reason is that for the time-of-day elasticity the imputed price is multiplied by 2.07. While the illustration assumes a hypothetical individual, the basic finding is quite general. That is, because of the large estimated parameter on the imputed price in the time-of-day equation, the elasticity for shopping trips of time-of-day travel will be substantially greater than that for choice of mode, for any of the transportation variables in the model, unless there are offsetting differences in the existing probabilities of choice.

Similar comparisons with the destination and trip-frequency models yield similar results. For example, for trip frequency the imputed price is weighted by -1.72. Thus, an across-the-board change in auto in-vehicle time (to all destinations) in the above example would result in an elasticity of demand for trip frequency of about -1.69. Again, unless there are off-setting differences in the existing probabilities of choice, the trip frequency elasticity will be substantially greater than the modal choice elasticity.

For the destination model, the imputed price is only weighted by -1.06, which would yield essentially the same elasticity for a given transportation variable as the modal choice model. However, because there are typically a greater number of relevant alternative destinations (which are close substitutes) than alternative modes, the resulting elasticities may accordingly be higher. For example, suppose the probability of selecting a given destination is on the order of 0.25, whereas the probability of selecting a particular mode is 0.5. If this were the case, the elasticity of demand for a given destination would be 50 percent higher than that for choice of mode, with respect to a particular transportation variable (i.e., 0.75 versus 0.5).

It is important to note that these are elasticities evaluated for a hypothetical individual. As suggested in chapter 4, the sample average elasticities are likely to be lower in magnitude than the corresponding elasticities of a hypothetical individual, with independent variables equal to the sample mean, because individuals with relatively extreme probabilities contribute little to the numerator of the formula for the aggregate elasticity. Limited empirical experience suggests that sample average elasticities are one-half to three-fourths the corresponding elasticities valued at sample means.

One important policy conclusion of these results, if they persist under further investigation, is that transportation policy-makers may have far stronger tools at hand for dealing with congestion than alternative modes of transportation. Changes in tolls, parking charges, or fares which differentiate between peak and off-peak travel, or between different areas of the region according to relative congestion, will cause shoppers to rearrange their travel patterns and thereby spread out the traffic volumes over less congested times of day or areas of the city. Moreover, any change in travel time or cost will change the overall number of shopping trips per day. So selective changes in transportation variables will not only rearrange trip patterns between modes, times of day, and destinations, they will cause significant changes in the amount of shopping travel as well. Further, these results indicate that increases in capacity will significantly induce additional shopping travel. Failure to anticipate this induced travel—by basing capacity plans on a fixed volume of trips—will result in lower levels of service than had been planned.