1. The elderly and handicapped are not a homogeneous group, either separately or together: There are wide variations in travel behavior and mobility problems within each group;
2. The elderly and handicapped average about 7.0 and 5.3 one-way nonwork trips/week respectively;
3. Automobile availability to the elderly and handicapped is not signficantly less than that to the general population;
4. Travel of these groups is primarily by automobile, either as a passenger or a driver with bus travel constituting only about 13 percent of their nonwork trips;
5. For the handicapped, travel mobility is primarily a function of personal disability and the ability of the individual to use an automobile: Bus service improvements would appear to change this picture only slightly;
6. Specific barriers on the public bus system do not materially affect either total nonwork travel or modal split, but the availability of bus transportation affects both;
7. Bus systems that emphasize availability (coverage and frequency) as well as direct pickup appear to be the most promising for increasing the mobility of the elderly and handicapped; and
8. The widely divergent needs of these individuals imply that very specialized solutions will probably be required to solve their transportation problems.

A set of small-sample disaggregate models was developed to enable prediction of elderly and handicapped nonwork travel and modal choice. The models are generally sensitive to automobile and bus availability, family size, and the level of disability of the individual.

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Policy-Contingent Travel Forecasting With Market Segmentation

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Market segmentation of travel data gives a data base that is easy to use and interpret. This paper develops methods for tabulating travel data so that disaggregate travel-demand models can be applied to market segments. These methods result in improved accuracy of travel forecasts because aggregation bias is reduced. The approach also allows nearly immediate computation of demand elasticities. These procedures can be applied to most urban travel-data files by using cross-tabulation software. To demonstrate the methods and their accuracy, the work-trip modal split is simulated on Nationwide Personal Transportation Survey data by using a disaggregate logit model. Travel demand is forecast under a variety of transportation policies that involve automobile controls and transit level-of-service improvements.

An approach to the use of market segments with existing disaggregate demand models has been developed. The advantages of such an approach include accurate travel-demand forecasts with minimal data and computational resources. In the present case, the effects of a policy scenario can be calculated by most programmable calculators or within a few hours by hand.

The use of market segments is not a new technique. Usually, market segments are defined by the characteristics of the trip maker rather than by those of the trip. However, travel data are sometimes cross tabulated by distance and time as well as the socioeconomic characteristics of the trip makers. This format has been useful in segmenting the travel market so that the impact of policies on particular socioeconomic groups can be emphasized (1). Market segmentation has the additional advantage of reducing aggregation error when such data are analyzed with disaggregate logit models.

The application of multinomial logit models to market segments is actually an extension of the early development of logit analysis. Models of binary choice were originally developed from the application of statistical tools to contingency tables (2). These models gave the probability that a response to a stimulus would occur within a specified range. For a simple univariate model, a table giving the proportions of the sample that will respond at each level of stimulus will have sufficient information for the estimation of the model. Similarly, given a model such as an estimated logit equation, the proportion of a sample that will respond to stimuli within given ranges can be predicted.

This approach can be generalized to the common specification of disaggregate modal-split models. If only two modes are considered, then the response will be the proportion of trips by a given mode, for example, automobile. The approach becomes computationally more complex as the number of different types of stimuli (independent variables such as modal attributes) increases. Rather than a column of numbers representing the sample at each level of stimulus, a multidimensional array representing the number of travelers who have alternative levels of service among modes becomes necessary.

DATA AND MODEL PREPARATION

The data base used to test this approach is the journey-to-work trip record from urban households in the Nationwide Personal Transportation Survey (NPTS) (3). Thus, the results of simulations with these data can be viewed as representing the effects of national policies. Alternatively, the data can be used to reflect the effects of ubiquitous transportation level-of-service changes in an average urban area. Independent of the interpretation of the results of policy scenarios, the use of market segments with NPTS data can be replicated with data available from the transportation planning activities of most urban areas.

The original home-interview tape from the survey was cross tabulated into market segments suitable for application of the original Charles River Associates work-trip modal-split model (4). This was a three-stage process: (a) the relevant variables are identified from the demand model, (b) the market segments are formed from the home-interview tape, and (c) the variables representing market segments are constructed for application of the demand model.

MODAL-SPLIT MODEL AND VARIABLES

The general form of the logit modal-split model is as follows:

$$P(a) = 1 \Bigg/ \left\{ 1 + \sum_{\substack{i=1 \\ i \neq a}}^{n} \exp[-\alpha(x_a - x_b) - \beta_y] \right\} \tag{1}$$

$$P(i) = \exp[-\alpha(x_a - x_i) - \beta_y] \Bigg/ \left\{ 1 + \sum_{\substack{j=1 \\ j \neq a}}^{n} \exp[-\alpha(x_a - x_j) - \beta_y] \right\} \tag{2}$$

$$\ln[P(a)/P(i)] = \alpha(x_a - x_i) + \beta_y \qquad (i \neq a) \tag{3}$$

where

- $P(a)$ = probability of automobile drive alone being the chosen mode;
- $P(i)$ = probability of alternative i being the chosen mode;
- x_a = vector of costs and times for making the trip by the automobile-drive-alone mode;
- x_i = vector of costs and times for making the trip by mode i;
- y = vector of socioeconomic variables and mode-specific constants; and
- α and β = estimated vectors of coefficients for the time, cost, and socioeconomic variables and for the mode-specific constants.

For the purposes of exposition, Equation 3 will be used. The estimated model is given by Equation 4.

$$\ln[P(a)/P(b)] = -4.77 - 2.24(C_a - C_b) - 0.411(T_a - T_b) - 0.114(S_a - S_b) + 3.79Y \tag{4}$$

where

- $P(b)$ = probability of transit being the chosen mode;
- C = costs of making the round trip by automobile (a) or transit (b) ($);
- T = in-vehicle and wait times for the round trip by automobile (a) or transit (b) (min);
- S = access walking time for the round trip by automobile (a) or transit (b) (usually assumed to be zero for automobile trips) (min); and
- Y = automobiles per worker in the household.

Because the model and its estimation are described in detail in other places, it will not be evaluated here except to note some of its t-statistics (4). The t-statistics of the coefficients in Equation 4 are given below.

Value	t-Statistic	Value	t-Statistic
4.77	3.88	0.114	2.69
2.24	4.53	3.79	4.06
0.0411	1.96		

For the sample size used to estimate Equation 4, which was 115 observations, t-statistics of 1.96 and 2.33 indicate that a parameter is significantly different from zero at the 2.5 and 1 percent levels of significance respectively for a one-tailed test, which means that all of the estimated parameters are highly significant. Another test of the model is whether the predicted probability of the selected mode for individuals is greater than 0.5. Equation 4 performed well in this respect also. The model predicted the correct choice of mode for 107 of the 115 observations that were used in its estimation, which is an accuracy level of 93 percent.

Construction of NPTS Market Segments

To construct the NPTS market segments, the work-trip records from the home-interview survey of urban areas were cross tabulated across three variables: trip distance, access distance to transit, and automobile availability. In the data base, there were 1774 such trips recorded. Of these, 221 were eliminated on error checks, usually because there were insufficient data on the record. Another 101 trips were eliminated because they involved more than one mode of travel. The remaining 1452 trip records form the basis of the market segments used for the analysis.

The market-segment categories are described below.

1. Distance—trip distance was divided into two categories with the following ranges: (a) short trips are less than 14.6 km (9.1 mile) and (b) long trips are greater than or equal to 14.6 km (9.1 mile). Several different methods could have been used for the determination of the ranges for the short and long-trip categories. For example, the dividing line could have been the median trip distance or that distance for which the total vehicle kilometers of travel (VKT) in each category are equal. In the ranges actually used, the mean trip distance [14.6 km (9.1 mile) on a round trip basis] was used as the dividing line; this number is between those that result from using the other two rules. The average distance characteristics for each mode category—where the mode categories are defined as (a) drive alone is automobile, truck, or motor-cycle; (b) transit is bus, streetcar, commuter train, subway, or elevated; and (c) car pool is automobile with other persons—are given below (1 km = 0.62 mile).

Mode	Distance (km) Short Trips	Distance (km) Long Trips	Time (min) Short Trips	Time (min) Long Trips
Automobile drive-alone	13.89	53.52	29.04	64.53
Transit	14.05	59.10	50.95	109.83
Car pool	12.81	58.73	31.33	73.85

2. Transit accessibility—the transit accessibility categories were determined by the distance from home to the nearest public transportation that could be used for the journey to work. The data were originally coded in blocks and were later transormed to kilometers [one block equals approximately 0.13 km (0.083 mile)]. These categories and their ranges in distance are as follows: (a) high transit accessibility is zero to two blocks, (b) middle transit accessibility is three to six blocks, and (c) low transit accessibility is more than six blocks. These ranges, which were selected after an examination of more refined breakdowns, showed the groupings that would tend most to equalize the number of trips among categories. The trip characteristics for these categories are summarized below (1 km = 0.62 mile).

Transit Access	Distance (km)	Trips (%)
High	0.109	37.7
Middle	0.574	16.3
Low	2.132	46.1

3. Automobile availability—household automobile availability was divided into the following two categories: (a) automobiles per worker are less than or equal to 0.5 and (b) automobiles per worker are greater than 0.5.

These categories arise naturally from the bimodal distribution of the data; most work trip makers have either 0 or 1 automobile/worker in the household. These characteristics are summarized below.

Automobile Availability	Automobiles per Worker	Trips (%)
<0.5	0.020	89.7
>0.5	1.753	10.3

Table 1 gives the modal splits, number of trips, and VKT for each of the twelve market segments. The modal splits and total trips were computed directly from the data, but some assumptions were necessary to compute the VKT. That part of the VKT that can be attributed to the automobile-drive-alone mode is the sum of the round-trip distances for each trip made by this mode. However, the information in the data base does not allow a direct compuation of the VKT incurred by car pools because the distribution of car-pool sizes, i.e., the number of passengers per vehicle, is not known and therefore the number of vehicles used for this mode is not known. To derive an estimate of the VKT that can be attributed to car pools, a distribution of one, two, and three-passenger car pools was created, and each person in the car pool was credited with an equal share of the car-pool VKT. The distribution of car-pool sizes is derived from the predictions of the modal-split model. This distribution varies from cell to cell, but its aggregate ratio is 0.78:0.17:0.04 for one-passenger: two-passenger: three-passenger car pools respectively. The NPTS distribution, tabulated from a different part of the survey, is that, for all travel, the ratio of car-pool sizes is 0.72:0.17:0.11 for one-passenger: two-passenger: three-passenger carpools respectively. Thus, the two independent estimates of passengers per automobile are in reasonably close agreement.

There is a large amount of flexibility in deciding the number of variables to be cross tabulated, the number of categories to be used, and the ranges to be applied. The decisions made about each of these issues reflected a desire to minimize the number of market-segment cells and, at the same time, capture the essential information of the modal-split model in data points having small associated variances. New variables and more refined breakdowns of the variables already chosen increase the number of cells multiplicatively rather than additively; for example, if in addition to the variables already chosen, a cross tabulation that used two categories of trip time was performed, the number of market-segment cells would increase from 12 to 24. Unless broad ranges of categories are created and relatively few variables are selected, the data base can easily become overly cumbersome, which loses the advantage of using market segments.

Although the choices of ranges and variables are basically rather arbitrary, there were some rules and reasons behind the decisions actually made. Some of the more important of these (in addition to those already presented) are listed below.

1. The variables were selected to conform to the independent variables in the logit model. Both access time to transit and automobiles per worker are direct inputs to the model, and the model treats line-haul costs and times as functions of trip distance, which makes this variable an obvious choice on which to make a cross tabulation.
2. Although trip-time data are available and are an input of the model, trip time is so closely proportional to trip distance that it was deemed unnecessary to create an extra variable for cross tabulating by time or trip.
3. Those variables that contribute most to the aggregation problem require more refined categories. Earlier research has indicated that automobiles per worker and access to transit cause more variation in logit-model log-odds functions than do other variables (5). Subdivision into eighteen market segments did not substantially increase the accuracy of model predictions.

Thus, the market segments created are dictated by the requirements of the model and the empirical testing of its performance. In this sense, the market segments presented here are intended to suggest things that can be done for the application of nonlinear disaggregate models. Because models and data bases vary, the cross tabulations performed by others for policy-evaluation purposes will also vary. In particular, the classic purpose of market segmentation is to emphasize socioeconomic groupings rather than trip characteristics. The methodology for market segmentation in such a case would be quite different.

Construction of Mode-Specific Variables

The independent variables required for application of the modal-split model must be constructed from the variables used for creating the market-segments data. The variables of the model, in the two-mode case of automobile drive alone and transit, are given in Equation 4. The variables available from the data have been given above. In addition to the two modes represented in Equation 4, it is also useful to construct data that represent automobile with passenger modes.

The formulas for constructing the mode-specific variables are given below:

1. Automobile drive alone: $C_a = 0.035 \times$ automobile-drive-alone distance, T_a = automobile-drive-alone

time, and $S_a = 0$;

2. Transit: $C_b = 0.4928$, T_b = transit time, and $S_b = 2 \times 19 \times$ distance to transit.

3. Car pool with k passengers: $C_{ck} = C_a[1 + (k/3)]/(k + 1)$, $T_{ck} = [(k/3) \times$ automobile-drive-alone distance/(car-pool distance for short trips ÷ car-pool time for short distance)] + automobile-drive-alone distance/(car-pool distance ÷ car-pool time) + (20 × k), and $S_{ck} = 0$;

4. Driver serve passenger: $C_d = 2 \times C_a$, $T_d = 3 \times T_a$, and $S_d = 0$; and

5. Automobiles per worker: y = 0 if <0.5 automobiles/worker or 1 if >0.5 automobiles/worker.

Most of these equations are self-explanatory, but the following assumptions should be noted:

1. The cost for an automobile trip is \$0.022/km (\$0.035/mile) [1969 data (6)].
2. Transit fare is the 1969 national average of \$0.4928 for a round trip (7).
3. Walking speed to transit is 12 min/km (19 min/mile).
4. For each distance category, the average automobile-drive-alone trip distance increases by one-third for picking up and dropping off each potential car-pool passenger (8).
5. Car-pool passengers make arrangements to share costs equally.
6. Car-pool line-haul speeds for picking up and dropping off passengers are equal to the speed for car-pool trips in the short-distance category.
7. The schedule delay associated with each potential car-pool passenger is 20 min.
8. The driver-serve-passenger mode involves a household member who drives the trip maker to work and returns home for the first leg of the round trip and then drives from home to the workplace and returns with the passenger for the second leg.
9. The automobile-per-worker variable was set to zero or one, and the model was calibrated on the automobile-per-worker coefficient to obtain a value of 4.60.

Although most of the above assumptions represent straightforward interpretations of the data, the heuristic nature of the construction of the automobile-with-passenger variables deserves further comment. In the absence of adequate level-of-service data on the availability of car-pool alternatives to non-car-pool, work trip makers, some judgments about this mode are necessary. When the problem of designing an optimal household survey to collect car-pool data is considered, it is easy to see why such data do not exist. Meanwhile, the modeling of shared rides will continue to be one of the weakest parts of the total travel-demand system. The major justifications for using the approach described here are that the assumptions are consistent with intuition about car pools and that the model predicts car-pool modal split reasonably well.

MODEL APPLICATION AND PERFORMANCE

The use of the model to predict modal splits and VKT has the following steps:

1. Each of the mode-specific variables for each of the 12 market segments is constructed by using the formulas and data given above.
2. For each market segement, a log-odds function for the automobile-drive-alone mode versus each of the other modes is calculated by using Equation 4, the variables constructed in the previous step, and 4.60 substituted for the coefficient on y.
3. For each market segment, the probability of an individual choosing a given mode, other than automobile drive alone, is computed by using Equation 2. The automobile-drive-alone probability is computed from Equation 1.
4. The modal splits for each market segment are computed as follows: (a) automobile-drive-alone modal split = automobile-drive-alone modal-choice probability; (b) transit modal split = transit modal-choice probability; and (c) car-pool modal split = sum of one-passenger, two-passenger, and three-passenger car-pool and driver-serve-passenger modal-choice probabilities.
5. The VKT for each market segment is the sum of the following VKT calculations for each mode: (a) automobile-drive-alone VKT = automobile-drive-alone modal-choice probability × automobile-drive-alone distance × total trips, (b) k-passenger car-pool VKT = k-passenger car-pool modal-choice probability × [1 + (1/3)] × automobile-drive-alone distance × total trips, and (c) driver-serve-passenger VKT = driver-serve-passenger modal-choice probability × 2 × automobile-drive-alone distance × total trips.
6. The aggregate modal split is computed as the weighted average of the predicted modal splits for each market segment.
7. The aggregate VKT is computed as the sum of the VKT across the market segments. With these procedures, the model was used to predict the modal splits and VKT for each of the cells in the NPTS market-segment data base. The actual values and the aggregate predictions are given below (1 km = 0.62 mile).

Value	Modal Split: Automobile Drive Alone	Transit	Car Pool	VKT (without driver serve passenger)	VKT
Actual	0.637	0.160	0.202	31 849	–
Predicted	0.635	0.159	0.206	31 335	32 040

The predicted modal splits conform closely to the actual modal splits. The first VKT (that without driver-serve passenger values) corresponds to the VKT that can be calculated from the data and does not include the VKT that are attributable to one-half of the driver-serve-passenger trips (that half which is traveled by the driver without a passenger is not captured by the NPTS data). The second VKT includes all of the VKT associated with driver-serve-passenger trips as well as with other automobile-oriented trips. When the first VKT is used as a basis for comparing the predicted to the actual, the model predicts the VKT within 1.6 percent. For most applications of the model, this error is well within the range of predicted effects and within the errors that might have other causes, such as data errors or parameter estimation errors. In general, the model performs well in replicating the aggregate figures from the data.

The modal split and VKT estimate for each market segment are given in Table 1. A comparison of the actual and predicted values indicates potential biases and the areas of greatest error. As expected, the error associated with any given market segment is greater than the aggregate error. The highest errors are those associated with the market segments that have the fewest total trips (basically, the six market segments in which automobiles/worker <0.5). There appears to be some tendency for the model to overpredict driver-serve-passenger trips for short-distance trips and underpredict car-pool trips for long-distance trips. In general, the errors associated with individual market segments tend to cancel when aggregated.

FORECASTING EFFECTS OF TRANSPORTATION ALTERNATIVES

The procedures developed above were applied to a variety of transportation policy scenarios to forecast the effects of these policies on trip-making behavior. The approach to investigating a particular policy is relatively straightforward: The policy is examined from the question of how it would affect the independent variables in the logit model. This effect is quantified by changing the values of the independent variables from those that they were in the base case. With the new values of the variables, the logit model is applied to the NPTS market-segments data and modal splits, and the VKT are forecast. The predicted modal splits and the VKT with the policy effects are then compared to the base-case predictions to forecast the impact of the policy.

Gasoline Tax

The model was used to predict the effects of a 100 percent gasoline tax [in addition to the existing gasoline taxes (which are assumed to be 7 percent to the state and 4 percent to the federal government)]. One of the purposes of this exercise is to compute the implied price elasticity of gasoline. This provides a test of the approach because the result can be compared to other, independent gasoline-price-elasticity estimates.

The effect of a 100 percent gasoline tax will be to increase automobile operating costs per kilometer by 50 percent. The pump price of gasoline is increased by 69 percent when a 100 percent tax rate is applied to the pretax cost of gasoline.

The forecasts of aggregate modal split and VKT under the assumption of a 100 percent gasoline tax are given in Table 2. The elasticities of the VKT are -0.256, -0.184, and -0.128 with respect to automobile operating costs, the pump price of gasoline [which is within the range of short-run elasticities estimated by econometric studies of gasoline demand (9)], and the pretax cost of gasoline respectively. The predicted 12.8 percent decrease in VKT is predicted to occur as a one-third increase in transit trips, an 11.2 percent decrease in automobile-drive-alone trips, and an 8.7 percent increase in car-pool trips.

Because of space limitations, the effects by market segment, which have been discussed by Charles River Associates (8), are not given here. The gasoline tax has its greatest impact on long trips with good to fair transit access. This is to be expected because, on a per-trip basis, the tax will have its highest dollar impact on long trips. The result is that the model predicts a higher incentive for mode switching on long trips for this scenario.

Transit Speed

In this scenario, it is assumed that a combination of shorter headways and faster transit will cause a uniform 10 percent decrease in transit line-haul-plus-wait time per trip. Access time to transit is assumed to be unchanged. This scenario was modeled by multiplying the transit line-haul-plus-wait time by and then applying the logit model to the NPTS market segments.

The predicted aggregate effects of this policy are given in Table 2. The predicted decrease in VKT was 3.22 percent, and the predicted increase in transit trips was 12.6 percent. One of the interesting results of this exercise is the relatively high elasticity of transit modal split with respect to transit speed (1.26). The biggest impacts occur on relatively long trips with good to medium transit access. As with the case of a gasoline tax, the effect of a uniform percentage decrease in transit time will have its largest absolute impact on long trips. Consequently, those trip makers who have longer trips have the most incentive to switch modes. The 10 percent decrease in transit time implies a saving of about 10 min for long trips, but only about 5 min for short trips. Also, as would be expected, the transit-speed policy has little predicted effect on trip makers who have poor access to public transit.

Transit Access:

Uniform Improvement

Because the weights that trip makers place on access time to transit are higher than the weights that they place on line-haul time, it can be assumed that the effect of decreasing access time would be greater than would be the effect of decreasing line-haul-plus-wait time. The results of various transit access scenarios indicate that this hypothesis deserves more consideration.

The first of a series of scenarios for the improvement of transit access involved decreasing transit-access time by a uniform 10 percent for all market segments. In the base-case projections, the access times to transit for high, middle, and low-access categories were 2.58, 14.25, and 50.35 min respectively. Thus, only short transit trips with poor access would have time savings for equal percentage declines in access time that were equivalent to those for equal percentage declines in line-haul-plus-wait time. In all

Table 1. Actual and predicted modal splits and VKT for NPTS market segments.

Market Segment			Observed Values					Predicted Values				
			Modal Split					Modal Split			VKT	
Automobiles per Worker	Trip Length	Transit Access	Automobile Drive Alone	Transit	Car Pool	Total Trips	VKT	Automobile Drive Alone	Transit	Car Pool	Without Driver Serve Passenger	With Driver Serve Passenger
>0.5	Short	High	0.603	0.197	0.200	315	3 002	0.598	0.140	0.261	3 041	3 286
>0.5	Short	Middle	0.589	0.113	0.298	124	1 228	0.667	0.041	0.292	1 335	1 442
>0.5	Short	Low	0.780	0.006	0.214	355	4 285	0.695	0.001	0.303	3 984	4 304
>0.5	Long	High	0.644	0.178	0.178	135	5 337	0.559	0.345	0.096	4 404	4 407
>0.5	Long	Middle	0.711	0.132	0.158	76	3 231	0.749	0.122	0.129	3 323	3 324
>0.5	Long	Low	0.798	0.027	0.175	297	14 158	0.851	0.002	0.147	14 758	14 767
<0.5	Short	High	0.014	0.836	0.151	73	77	0.040	0.942	0.018	48	51
<0.5	Short	Middle	0.083	0.917	0.000	24	27	0.132	0.811	0.058	51	55
<0.5	Short	Low	0.000	0.083	0.917	12	63	0.650	0.056	0.284	126	137
<0.5	Long	High	0.042	0.792	0.167	24	167	0.016	0.981	0.003	23	23
<0.5	Long	Middle	0.083	0.833	0.083	12	82	0.057	0.933	0.010	40	40
<0.5	Long	Low	0.400	0.000	0.600	5	191	0.696	0.184	0.120	203	203

Note: 1 km = 0.62 mile.

Table 2. Aggregate effects of travel-forecasting scenarios.

Scenario	Modal Split: Automobile Drive Alone	Transit	Car Pool	VKT
Base case	0.635	0.159	0.206	32 040
100% gasoline tax	0.564	0.212	0.224	27 940
10% transit-speed increase	0.619	0.179	0.209	31 010
10% transit-access-time decrease	0.631	0.163	0.205	31 780
Low transit-access improvement	0.600	0.202	0.198	29 795
Low and middle transit-access improvement	0.583	0.225	0.193	28 735

Note: 1 km = 0.62 mile.

other cases, the time savings from a 10 percent reduction in line-haul-plus-wait time would be much greater than the time savings from a 10 percent reduction in access time. This helps to explain some of the results given below.

The aggregate effects of this policy are given in Table 2. The decrease in the VKT caused by this policy is predicted to be 0.7 percent, and the predicted increase in transit trips is 2.5 percent. Both the VKT and the transit-ridership elasticities are much lower for access times than for line-haul-plus-wait times.

The market segments having the greatest impact are those where access to transit is in the middle category; those with good transit access are relatively insensitive to further improvements, and those with poor access would not find a 10 percent improvement sufficient inducement to switch modes.

Low-Transit-Access Improvement

The results of the previous section indicate that making transit available to everyone would induce significant increases in transit ridership. Therefore, this scenario assigned to the low-transit-access market segment the same access time that the middle-access group currently has. All other variables were unchanged although it is unlikely that any real transit service design that provided such a large change would not also affect accessibility in other market segments and line-haul and wait times in all market segments.

The aggregate results are given in Table 2. The change in average access for the whole population is 62.9 percent, and the decrease access time for the market segment that previously had low transit availability was 71.7 percent. This change caused a decrease in VKT of only 7 percent for an elasticity of 0.111 and a transit-patronage increase of 27 percent for an elasticity of -0.429. These elasticities are higher than those in the previous access-time scenario. For households in which the number of automobiles per worker is greater than 0.5, the predicted change in VKT is 10.2 percent. The effect of the policy on households with low automobile-ownership rates is quite dramatic, but because these contribute relatively little to the VKT, they have a small impact on the aggregate effects.

Low and Middle-Transit-Access Improvements

To evaluate the effect of improving transit access for those in the middle-transit-access market segment the low access category is again assigned the same access that the middle-access group currently has and the middle-access group is assigned the access time that the high-access group currently has.

The aggregate results of this policy are given in Table 2. The percentage change in VKT is 10.3, and the implied elasticities are somewhat higher for both VKT and transit ridership. The conclusion that may be drawn from this series of scenarios is that improvements in transit access are more effective when moderate service is made better than when poor service is made only adequate.

CONCLUSION

The preceding results show that the use of market segments with behavioral demand models is promising for quick policy contingent forecasting. The examples presented are somewhat simplistic and indicate that a module that translates complex policy issues and planning alternatives into quantifiable demand-model inputs is needed. This module could be a manual activity that uses existing planning resources to determine the effects of a policy or system on the level of service for the relevant market segments. Moreover, this approach would allow quick parametric representations of level-of-service changes that are consistent with Urban Mass Transportation Administration guidelines for alternatives analysis. Other areas of future research include applying the approach to nonwork trips and linking the demand effects with cost models to determine the cost-effectiveness of and trade-offs among policies.

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