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Choice-Model Predictions of Car-Pool Demand: Methods and Results

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The results of a number of car-pool strategies were predicted by using disaggregate choice models. Car pooling is explicitly considered as an alternative mode only for work trips. However, the effects of car-pooling incentives on interdependent travel choices and vice versa are also predicted. Forecasts are made by applying the models to each household individually, using revised values of the appropriate independent variables to simulate the particular transportation alternative being analyzed. These household predictions are then summed to represent predicted areawide changes in travel behavior. Before and after data from the implementation of car-pooling incentives and transit-service improvements were used to test the validity of the model's forecasts. Three such tests are reported. The results indicate that the work-trip modal-choice model successfully captures the effects of changes in level of service on modal choice. The predicted effects of several significant car-pooling strategies are presented. In general, traveler response to many car-pooling incentives is small. The most significant changes in travel behavior are predicted for those parking-related policies that combine disincentives for driving alone with incentives for car pooling.

Various strategies designed to increase ride sharing have been proposed and several have already been implemented. For example, strategies such as preferential lanes for high-occupancy vehicles, car-pool-matching and promotion programs (both areawide and employer-based), and preferential parking for car pools have existed for several years. This paper applies a methodology based on disaggregate travel-demand models to predictions of changes in travel patterns that will result from car-pooling incentives and from short-range transportation options in general.

The methodology is described briefly, and a number of validation tests that use before-and-after data are presented. Prediction results from case study applications of the methodology to various car-pooling-related policies are discussed. The paper concludes with a summary of major findings. [Both the methodology used and the analysis of prediction results by market segments are discussed in greater detail by Ben-Akiva and Atherton (1).]

METHODOLOGY FOR SHORT-RANGE TRAVEL-DEMAND PREDICTIONS

The methodology for predicting the changes in travel patterns that will result from short-range transportation options (including car-pooling incentives) is based on the application of disaggregate travel-demand models. These models are based on the multinomial logit, probabilistic choice model, which has been discussed by Domencich and McFadden (5) and Richards and Ben-Akiva (7). The data used to estimate the coefficients of these models are taken from home-interview surveys and represent a cross section of households. The dependent variables of the models are the reported travel choices made; the independent variables are the reported socioeconomic characteristics, engineering measures of travel times and costs, and survey estimates of employment and land-use characteristics in the urban area.

The models consider residential locations and work places as being fixed and predict automobile ownership, choice of mode for the work trip, and frequency, destination, and mode for nonwork travel. Car pooling is explicitly considered as an alternative mode only for work trips. However, the effects of car-pooling incentives on interdependent travel choices and vice versa are also predicted.

To apply these models to the forecasting of changes in travel behavior that will result from alternative car-pooling incentives, a sample enumeration technique is used. In this procedure, a randomly selected sample of households is used to represent the entire population of an urban area. Forecasts are made by applying the

models to each household individually, using revised values of the appropriate independent variables to simulate the particular policy being modeled. These household predictions are then summed to represent predicted areawide changes in travel behavior.

VALIDATION WITH ACTUAL CAR-POOLING EXPERIENCE

The most significant test of the validity of a predictive model is a comparison of the changes predicted with the actual observations made before and after a change in transportation service. Several such tests of the work-trip modal-choice model are reported by Cambridge Systematics (3). Three relevant tests having reliable before-and-after data are presented here. These are the Shirley Highway preferential-lane project, the Santa Monica Freeway diamond-lane project, and the Minneapolis bus-on-metered-freeway project. In each of these examples no disaggregate sample was available, and the model was applied by using average values for selected market segments.

The tests were conducted by using the incremental form of the logit model (1). This form predicts revised travel behavior that is based on existing travel behavior and changes in level of service, rather than using the full model to recalculate choice probabilities that are based on the full set of independent variables. Data requirements are greatly reduced by using such an approach; no knowledge of detailed socioeconomic and level-of-service data is required. Only existing shares and proposed changes in level of service are necessary. The incremental form of the logit model for a specific market segment is given by Equation 1.

$$P'(i|A) = [P(i|A)\exp(\Delta V_i)] \Big/ \sum_{j \in A} P(j|A)\exp(\Delta V_j) \qquad (1)$$

where

ΔV_i = change in utility for alternative i = $\Sigma \Theta_k \Delta X_{ik}$,
Θ_k = coefficient of the kth variable,
ΔX_{ik} = change in the kth independent variable for alternative i,
$P(i|A)$ = probability of choosing alternative i before change, and
$P'(i|A)$ = the predicted probability of choosing alternative i after the change.

The first test of the work-trip modal-choice model was conducted for the construction of new preferential lanes on Shirley Highway, which extends to the southwest from the center of Washington, D.C. In 1971, express bus service began on these lanes; bus level of service was further improved by increasing coverage and adding new buses designed for greater passenger comfort. In late 1973, car pools with four or more occupants were also permitted to use the preferential lanes. In addition to the improved bus service and the car-pool preferential lanes, there were other factors that affected the modal choices of commuters between 1970 and 1974 (e.g., increases in the price of gasoline). All of these factors were expressed in terms of changes in the level-of-service attributes and introduced into the work-trip modal-choice model to predict changes in corridor modal shares from 1970 to 1974. The results are given in Table 1. The error in the predicted bus ridership in the corridor is -2.9 percent, and the error in predicting the change in bus ridership is -12.9 percent. These results indicate that the model captured the changes in modal-choice behavior due to changes in the level-of-service attributes.

The second test of the work-trip modal-choice model was undertaken for the Santa Monica Freeway diamond-lane project, which was implemented on March 15, 1976, and discontinued on August 13, 1976. When this project began, the use of the median lane was reserved for buses and car pools with three or more persons. Initially, this resulted in severe congestion in the nonpreferential lanes and on alternate parallel arterials in the corridor and long delays at entrance ramps, while the preferential lane was sparsely used. However, by the tenth week of the project, which is the point in time for which the model was applied, conditions had changed considerably. Travel times in the nonpreferential lanes had decreased to their preproject level and the ramp delays had decreased somewhat, but preferential vehicles still enjoyed a 24 to 32-km/h (15 to 20-mph) speed differential.

At the same time that the preferential lane was implemented, significant improvements were made to transit service in the corridor. The improvements included express bus service to the Los Angeles central business district (CBD), improved distribution and feeder service, park-and-ride lots, and extended route coverage. Approximately 50 new buses were put into service to effect these improvements. Each of these factors was expressed in terms of changes in the level-of-service attributes and introduced into the model. In addition, a dummy variable that captures the promotional and awareness aspects of car-pooling programs was set equal to one. The predicted and observed corridor modal shares for the tenth week of the project are given in Table 1. Although the predictions for the transit modal share are accurate, the predicted changes in the two-person and three-or-more-person car-pool shares overestimate those observed. One probable reason for this is because only 10 weeks had elapsed at the time the after data were recorded, travel in the corridor had not yet passed the transition period. It is also possible that seasonal effects, which are not accounted for in the analysis, may have had a significant impact on the observed changes in travel behavior.

The final test presented here was conducted on before-and-after data from the Minneapolis express-bus-on-metered-freeway (I-35) project that was implemented in 1972. In this project, buses are given priority access to the freeway by express bus ramps. At the same time, automobiles are metered onto the freeway so that traffic volumes allow a desired level of service. In addition, express bus service on I-35 to the CBD was gradually improved from 36 trips to 118 trips during the morning peak period over a 2-year period.

Each of these factors was expressed in terms of changes in level-of-service attributes and introduced into the model to predict changes in modal shares from 1972 to 1974. The results of this model application are also given in Table 1. Here again, the relatively small prediction errors suggest that the model has successfully captured the effects of changes in level of service on modal choice.

RESULTS

The base values for Washington, D.C.; Birmingham, Alabama; and Denver used in the model are given in Table 2.

The model was used to analyze the effectiveness of a number of car-pooling policies. These include

1. Employer-based actions (e.g., car-pool matching and promotion),
2. Parking availability and cost (e.g., preferential parking measures),
3. Traffic regulation and control (e.g., preferential traffic control), and

4. Travel cost (e.g., fuel-price increases).

The predicted impacts of these policies for the Washington, D.C., metropolitan area are summarized in Table 3. For each policy, the predicted percentage changes from base values are given for work-trip modal shares (drive alone, shared ride, and transit), work-trip automobile occupancy, vehicle kilometers traveled (VKT) (for work, nonwork, and total), and fuel consumption. (These percentage changes represent the areawide percentage changes that will result from a policy regardless of the actual proportion of the areawide population affected by that policy.) The predicted impacts for a limited number of these policies for Birmingham and

Table 1. Before-and-after validation tests for corridor modal shares.

Example	Mode	Base Modal Share (before)	Actual Modal Share (after)	Predicted Modal Share (after)	Actual Change	Predicted Change	Error in Prediction[a] (%)	Error in Predicted Change[b] (%)
Shirley Highway	Automobile	67.8	57.3	58.5	-10.5	-9.3	2.0	-12.9
	Bus	32.2	42.7	41.5	10.5	9.3	-2.9	-12.9
Santa Monica Freeway	Drive alone	70.1	66.6	66.7	-3.5	-3.4	0.1	-19.9
	2-person car pool	22.3	22.2	21.3	-0.1	-1.0	-4.2	90.0
	≥3-person car pool	6.0	7.6	8.4	1.6	2.4	9.5	33.3
	Bus	1.6	3.6	3.5	2.0	1.9	-2.9	-5.3
Minneapolis bus project	Drive alone	47.2	43.0	42.0	-4.2	-5.2	-2.4	19.2
	Car pool	19.8	18.0	18.0	-1.8	-1.8	0.0	0.0
	Transit	33.0	39.0	40.0	6.0	7.0	2.5	14.3

[a] Given by (predicted - actual)/predicted. [b] Given by [| predicted - base | - | actual - base |]/| predicted - base |.

Table 2. Base values.

Location	Work-Trip Modal Shares			Work-Trip Automobile Occupancy	VKT (km/d)			Fuel Consumption (L/d/household)
	Drive Alone	Shared Ride	Transit		Work (per worker)	Nonwork (per household)	Total (per household)	
Washington, D.C. (excluding weekend travel)	0.53	0.25	0.16	1.24	17.7	24.1	41.8	10.6
Washington, D.C. (including weekend travel)	0.53	0.25	0.16	1.24	17.7	40.2	57.9	14.8
Birmingham, Ala. (excluding weekend travel)	0.68	0.24	0.08	—	12.9	22.5	35.4	8.9
Birmingham, Ala. (including weekend travel)	0.68	0.24	0.08	—	12.9	37.0	49.9	12.7
Denver (including weekend travel)	0.78	0.19	0.03	—	20.9	30.6	49.9	10.0

Note: 1 km = 0.62 mile; 1 L = 0.26 gal.

Table 3. Predicted areawide impacts.

Policy	Percent Change From Base Value							
	Work-Trip Modal Shares			Work-Trip Automobile Occupancy	VKT (km/d)			Fuel Consumption (L/d/household)
	Drive Alone	Shared Ride	Transit		Work (per worker)	Nonwork (per household)	Total (per household)	
Employee incentives								
Washington[a]	-1.4	4.4	-2.1	1.1	-0.62	0.17	-0.15	-0.11
Birmingham (all workers regardless of employer size)[a]	-4.4	16.1	-9.9	—	-2.1	0.08	-0.3	-0.2
Denver (employer size ≥50)[a]	-2.9	13.0	-10.0	—	-1.4	—	-1.4[b]	-1.2[b]
Preferential parking								
Washington[a]	-2.7	8.2	-3.6	1.9	-0.74	-0.24	-0.16	-0.13
Denver (including subsidized car pools)	-3.44	15.4	-10.8	—	-1.7	—	-1.7[b]	-1.5[b]
Preferential parking with pricing disincentives								
Washington[a]	-8.6	17.7	1.4	4.8	-4.1	0.88	-1.1	-0.97
Preferential lanes								
Washington[a]	-1.7	2.9	1.1	0.9	-1.3	0.22	-0.39	-0.32
Fuel price doubled								
Washington[c]	-1.8	1.9	2.9	0.8	-1.6	-8.0	-6.1	-5.7
Birmingham[c]	-1.0	1.6	4.1	—	-1.2	-6.7	-5.6	-4.8
Denver[c]	-0.92	2.6	3.6	—	-0.77	-16.0	-10.0	-10.0
Fuel price tripled								
Washington[c]	-3.6	4.0	6.0	1.6	-3.3	-14.9	-11.5	-10.7

[a] Using base value excluding weekend travel. [b] Values for work trips only. [c] Using base value including weekend travel.

Denver are also given in Table 3.

Employer-Based Matching and Promotion

This policy represents the implementation of employer-related car-pool incentive programs, such as intra-company advertising, car-pool-matching assistance, and promotion. Incentives such as these cannot be readily quantified in terms of travel time and travel cost. This makes their representation somewhat of a problem, which is solved here by the use of a dummy variable.

Since car-pooling incentives such as these are feasible only for organizations with a relatively large number of employees, the most logical criterion for determining the availability of such incentives to an individual worker is employer size. For this particular policy, a lower bound of 100 employees was used to differentiate between large and small employers in Washington. This dummy variable was set equal to one for those workers employed by organizations with at least 100 employees and zero otherwise. For Birmingham, however, employer-size data were not available, and this dummy variable was set equal to one for all workers. In Denver, a lower bound of 50 employees was used. As shown in Table 3, the implementation of car-pool-matching assistance and promotion programs by large employers in Washington resulted in a 4.4 percent areawide increase in the number of workers in car pools. However, while the work-trip VKT were reduced by 0.62 percent, the increased number of automobiles remaining at home (and therefore available for use by other family members for other trip purposes) resulted in a 0.17 percent increase in nonwork-trip VKTs, which offset 36 percent of the work-trip VKTs savings.

The potential areawide effectiveness of this policy is muted somewhat by two conditions existing in the Washington area. These are that

1. By restricting the availability of car-pool incentives to those workers employed by large employers, only 68 percent of the work force is affected and
2. Forty-four percent of the work force already has these incentives available.

The result is that only 24 percent of the working population is affected by this policy. In other urban areas, where the initial level of employer-based car-pool incentives is lower or a greater proportion of the work force is employed by large employers, this policy would be more effective in terms of increased car pooling and VKT reduction. In Birmingham, for example, the initial level of employer-based car-pool incentives was assumed to be zero and thus, the entire work force was affected by the policy. As shown in Table 3, the percentage increase in shared ride was almost four times that in Washington. The initial level of employer-based incentives was assumed to be zero in Denver also. In this case, however, the lower bound was 50 employees, which resulted in a percentage increase in shared ride approximately three times that in Washington (Table 3).

Preferential Parking Measures

Two sets of preferential parking measures were analyzed for Washington. These were

1. A program implemented by large employers (i.e., those with more than 100 employees), who gave subsidized, preferential parking locations to car-pool vehicles and
2. Car-pool incentives coupled with areawide parking-price disincentives aimed at single-occupant vehicles.

The first set of measures is represented in the model by setting parking cost equal to zero and decreasing walking time from parking location to final destination for the shared-ride alternative and by increasing walking time for the drive-alone alternative for those workers employed by large employers. The magnitude of these changes in round-trip walking times are -4.27 min for shared ride and +1.64 min for drive alone. These values were calculated on a basis of the cumulative walking-time distribution for parked vehicles during the peak period in the Washington area and the percentage of all automobiles used for car pools. In addition to these employer-based, car-pool parking incentives, the second set of measures included minimum parking charges for the drive-alone alternative of $2.00 in the CBD and $1.00 elsewhere in the metropolitan area (for work trips only).

The predicted results of these two parking policies are given in Table 3. For the first policy, the shared-ride share increases significantly, and the shares of both drive alone and transit decrease. For the second policy, an even greater increase in shared ride is predicted. In this case, however, while the drive-alone share drops markedly, the transit share shows a slight increase. This occurs because the first policy consists primarily of car-pool incentives, and therefore shared ride will draw from both drive alone and transit. In the second policy, however, the drive-alone disincentive dominates, and more commuters will shift from drive alone to transit than from transit to shared ride.

A preferential parking measure similar to the first one discussed for Washington was analyzed in Denver. Here, however, parking costs were assumed to be subsidized by the employer (essentially, this affects only CBD workers) and the lower bound for employer size was set at 50 employees rather than 100. The results (based on the analysis of work trips only) given in Table 3 show a percentage increase in ride sharing that is almost double that in Washington.

Preferential Traffic Control

This policy was analyzed only in Washington and consisted of preferential lanes for multiple-occupancy vehicles. It was analyzed on an areawide basis by identifying those trips that would use facilities for which a preferential-lane policy would be feasible. This approach, rather than one of analyzing one specific facility, was taken because of the relatively small sample used in forecasting (i.e., 800 households for the entire Washington metropolitan area), which results in an extremely small and statistically unreliable subsample of observed work trips on any given facility.

After potential locations of preferential lane and ramp treatments were identified, differential time savings were estimated as follows for three broad categories of work trips. For trips from outside the beltway to the inner core, a differential of 16 min was used (8 percent of the sample). For trips (a) from outside to inside the beltway, (b) along the beltway, or (c) from inside the beltway to the inner core, a differential of 8 min was used (31 percent of the sample). For all other trips, e.g., outbound commute or circumferential within the beltway, no time savings were assumed (61 percent of the sample). No time savings were assumed for nonwork trips. These travel time differentials were based on the following assumptions: (a) an average base speed of 56 km/h (35 mph) on all facilities, (b) an average preferential lane speed of 81 km/h (50 mph), (c) an average nonpreferential lane speed of 48 km/h (30 mph), and (d) average preferential-lane lengths of 16 and 8 km (10 and 5 miles) respectively for the first two categories of work trips described above.

The predicted impacts of this preferential lane policy are given in Table 3. The shared-ride modal share increased 2.9 percent, while that of transit increased by only 1.1 percent. The reason for this difference becomes evident if one looks at the results for workers residing in suburban areas. Here, the difference is even greater, which suggests that for those workers for whom preferential lanes are most attractive, transit availability is somewhat limited. Here again, the decrease in work-trip VKT is partially offset by increased nonwork travel.

Fuel Price Increases

Two policies in which the price of gasoline was increased were analyzed for Washington. In one case, the base price was doubled, and in the other, the base price was tripled. Unlike the preceeding policies, these policies are directed not only towards work trips, but also directly affect weekday and weekend nonwork travel.

These policies are represented in the model by increasing the portion of automobile-travel cost that is represented by fuel costs. In this case, fuel costs represent 70 percent of automobile-operating costs: On the average, automobile-operating costs represent 50 percent of automobile-travel costs, the remainder being parking costs. Therefore, doubling the price of gasoline, for example, would result in an approximate 35 percent increase in out-of-pocket travel costs.

The impacts predicted for these policies are given in Table 3. In both cases, the reduction in nonwork travel is greater than that predicted for work trips despite the increased automobile availability for nonwork trips. This agrees with the idea that nonwork trips, being more discretionary in nature, are more sensitive (more elastic) to changes in travel costs. While travel costs will increase by the same amount for both drive-alone and shared-ride vehicles, the assumption that costs are borne equally among car-pool members results in a significantly smaller cost increase per person for shared ride. Because of this, the shared-ride modal share increases, although transit shows the larger gain in modal share.

Similar impacts are predicted for Birmingham and Denver for the policy of doubling the price of gasoline, although in Denver the much higher sensitivity of nonwork travel to fuel-price increases relative to the other two cities results in a significantly larger decrease in total fuel consumption.

Summary

In addition to the results tabulated here, strategies have been analyzed for both Washington and Birmingham by using an earlier version of the model system (2). Similar studies evaluating the effectiveness of alternative car-pooling policies have also been conducted by others (4, 6). While a direct comparison of the results from these studies is difficult because of the differences in data used and policy definitions, it appears that the results reported here are more conservative than others.

CONCLUSION

The use of the methodology developed in this study was demonstrated by an analysis of car-pooling strategies, but the methodology can also be used to analyze a wide variety of short-range transportation alternatives. Before-and-after tests have shown the validity of applying the work-trip modal-choice model to the prediction of impacts of short-range transportation policies on travel behavior in several urban areas.

Several car-pooling strategies were analyzed. A specific car-pool strategy would be either an incentive, i.e., a direct inducement to workers to share rides by improving the level-of-service attributes available to car pools, or a disincentive, i.e., an indirect inducement for car pooling by worsening the level-of-service that attributes for solo drivers. The major conclusions are

1. Car-pooling incentives will attract transit as well as drive-alone commuters and, because the potential areawide increase in ride sharing is small, the decrease in VKTs will be small;
2. Automobile disincentives are much more effective than car-pooling incentives in increasing ride sharing and transit use, but these policies are less acceptable to the public and therefore less likely to be implemented;
3. A coordinated program of both incentives and disincentives could effectively increase car pooling and reduce congestion, VKT, and fuel consumption, and significant parking incentives and disincentives appear to be the most effective ways to increase car pooling;
4. Car-pooling strategies directed at work trips result in increased automobile travel for nonwork purposes because of increased automobile availability during work hours for nonworking members of a household, and the increased nonwork VKTs offset by approximately one-third the reduction in work VKTs; and
5. The effectiveness of a particular car-pooling strategy will vary significantly among urban areas because of differing base conditions.

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Discussions

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In the past several years, we have seen a change in emphasis in transportation planning from long-range to a shorter time frame and a corresponding change in the alternatives being analyzed from capital-intensive fixed-guideway systems to those having a more operational character. An implication of this is that transportation modelers may be no longer needed because these newer alternatives might best be evaluated through intuitive procedures. I think the papers presented here give us a clear indication that technical analysis or modeling is very much a part of planning in this era of transportation-system management.

Horowitz and Sheth have demonstrated that psychological scaling techniques can be meaningfully applied to the determination of the attributes of transportation supply that have an impact on travel behavior. They successfully use these techniques to develop initiatives to encourage ride sharing and show why several previous promotional techniques have had minimal success.

Small presents the results of a pioneering effort to bring together modeling techniques in the areas of traffic-flow and travel-demand analysis. Previous works dealing with the effects of priority-lane allocation on traffic flow have suffered from the lack of acknowledgment of the effects that changes in performance level have on travel demand. At the same time, previous travel-demand models have typically begun with some assumed change in system performance in determining the effect of priority lanes on modal use. Small has demonstrated that these disciplines can be brought together to analyze the desirability of priority-lane allocation. This is clearly a worthwhile activity in planning for such facilities. Small also develops the concept of benefit versus cost, which is a commendable addition to transportation-system-management planning procedures.

Ben-Akiva and Atherton apply an advanced model system to the evaluation of a wide range of strategies aimed at encouraging increased ride sharing. They skillfully model a number of behavioral effects that are often ignored in work of this nature. Their paper will be useful to policy officials because it illustrates the comparative effectiveness of various strategies in reducing travel and fuel consumption. They have also contributed to transportation-system-management planning methodology by demonstrating the use of sample-by-sample enumeration techniques in quantifying the impacts of various strategies on different geographic areas and income groups. Also, the planning practitioner will benefit from learning about the incremental form of the logit model, which should facilitate policy analysis in areas where the enumeration approach is not practical.

While I am pleased by the research represented here, I do have some concerns. The data used by Horowitz and Sheth were not based on a random sample, but on an uncorrected choice-based sampling procedure in which a roughly equal number of car-pool and single-occupant automobile commuters were surveyed at their places of employment. This resulted in a biased sample that may have influenced their results. For example, the average trip distance for car-pool commuters was 26.2 km (16.3 miles), while that for single-occupant automobile commuters was 17.8 km (11.2 miles). Thus, the respondents are not from the same sampling frame and are not thinking of the same trip when responding to the questionnaire. For example, when a single-occupant automobile respondent views a car pool as inconvenient, he or she is doing so for an 17.8-km (11.2-mile) trip. He or she would probably view it as less inconvenient for the 26.2-km (16.3-mile) trip evaluated by the average car pooler. Thus the differences between the means of the various variables thought to explain behavior in part reflect the difference in sampling frames.

The papers by Small and by Ben-Akiva and Atherton use logit-model formulations that contain demographic, travel-time, and travel-cost measures. Both resulted in relatively large negative car-pool bias coefficients, indicating that there are probably important behavioral variables that are not included in the model specifications. Perhaps incorporation of some of the softer attributes studied by Horowitz would reduce the size of these coefficients and lead to additional policy sensitivity.

All of the papers interpreted the policy implications of their findings well, although I believe that Small might have gone further in testing a range of occupancies qualifying for use of the priority lanes. The paper would also have been improved by a case-study application of the techniques to an operational priority lane to demonstrate their ability to reproduce an observed response.

Of the strategies tested by Ben-Akiva and Atherton, the doubling and tripling of the price of fuel had the greatest effect on travel and fuel consumption. The results of these particular tests should probably be interpreted with caution because, as the authors point out, the models do not predict the probable shift in automobile-size distribution that would result. Perhaps more moderate tests would have been advisable with the current formulation.

While I have discussed several areas in which the research reported in these papers might have been improved, I would like to conclude by noting that these papers represent a significant contribution to the knowledge of the effects of a wide range of strategies on car-pool demand. In addition, they demonstrate the effective application of analytical planning procedures to evaluating transportation-system-management strategies. As such, they represent an area of research that should assist the practicing planner.

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These papers by Horowitz and Sheth, Small, and Ben-Akiva and Atherton improve our ability to predict both car-pool demand and demand for travel by all other modes. Forecasts of impacts of policies to promote car pooling are of little use if they do not include impacts on other travel modes and their associated effects on such factors as energy consumption, traffic congestion, and air quality.

I would like to congratulate Horowitz and Sheth for a well written and neatly packaged piece of work. Their paper introduces some complicated concepts in simple and easily understood fashion. However, they have used data on stated general intentions to change from solo driving to car pooling rather than behavioral data on persons who actually changed modes in reaction to a change in a choice situation that they confront; for example, a new preferential lane for car pools or an employer-based car-pool-matching program. In addition, the attitudinal data on intentions simply asked how likely it was that the respondent would join a car pool within the next two or three months. I would much rather

see them gather policy-related attitudinal responses to such questions as "How likely are you to join a car pool if you were offered a list of fellow employees who live near you to car pool with?" Data on such attitudes could help isolate promising markets for car-pool-matching programs and other car-pool-promoting policies. A useful extension of this paper would include behavioral data, not only for what it would tell us about car-pooling behavior, but also for investigating the relations between stated intentions or attitudes and actual behavior. Attitudinal data are, of course, usually much easier to collect than behavioral data.

The first conclusion of the paper, namely that "demographic and travel characteristics are poor indicators and predictors of the choice between driving alone and ride sharing" is subject to misinterpretation and needs restatement. This conclusion can be taken to mean that similar travel patterns (same origins and destinations as produced in a car-pool-matching program) do not lead to car-pool formation. That is not what is meant at all, and the authors might be more specific.

Examination of the cognitive profiles presented in the paper for actual car poolers and solo drivers in terms of attribute-by-attribute evaluations of ride sharing and solo driving is quite fascinating. Our objective in promoting car pooling is to change people's evaluations of car pooling by promotional campaigns that have the effect of bringing these attribute-evaluation profiles closer together in the belief that this will bring about actual car-pooling behavior. Generally, car pooling is regarded by solo drivers as less convenient than solo driving, but not substantially cheaper or less energy consuming or air polluting. The conclusion one draws from these data is that we ought to be promoting car pooling as a convenience, rather than as being cost saving. This is, I think, a very significant finding. It is a sobering conclusion, but consistent with the results of transit travel forecasting that transit use is less likely to grow from fare decreases than from making use of the private automobile less convenient.

Finally, Horowitz and Sheth reach some interesting conclusions about the identity of groups most likely to car pool. They identify employees of high socioeconomic status and those from large households who have relatively recently moved their places of residence or employment as being the most likely persons to change to car pooling on the basis of their attribute-evaluation profiles. This contrasts with their findings that actual car poolers have been at their present residences and employment locations longer than solo drivers. This disparity between attitude and behavior is again an indication of the usefulness of before-and-after behavioral data as opposed to data about general attitudes and intentions. The persons who finally begin to car pool in response to a multitude of factors may not be the persons who state that they are likely to car pool.

Small's paper is a neatly done equilibrium analysis of the consequences for bus, private automobile, and car-pool use and users of reserving a freeway lane for buses or for buses and car pools. Varying the number of freeway lanes and the before conditions on degree of congestion with no reserved lanes are added features of this paper.

In general, this paper shows that congestion relief on the general-purpose (unreserved) lanes actually occurs when a lane is reserved for buses and three-or-more-occupant car pools when the before conditions are characterized by heavy and very heavy congestion. This is truer when one lane is taken from a five or four-lane facility rather than from a three-lane facility. That is, in the case of a three-lane facility, (slight) congestion relief occurs on the two unreserved lanes only when the before conditions are characterized by very heavy congestion. These conclusions are consistent with calculations done in Massachusetts in preparation for the spring 1977 opening of a reserved lane for buses and three-or-more-occupant car pools on the heavily congested four-lane (each way) Southeast Expressway in Boston. In the Boston calculations, it was predicted that congestion on the unreserved three lanes would not significantly increase with the reservation of a bus and car-pool lane and, of course, delays to buses and car pools would be eliminated.

The third and final paper discussed here is Ben-Akiva and Atherton's excellent and comprehensive set of predictions of the use of several modes, including car pooling, that will result from many proposed alternatives for increasing car pooling. The authors use their multinomial logit, disaggregate, demand forecasting model, which was estimated and tested by using data from several urban areas in different parts of the country. The model provides quite reasonable forecasts of the consequences of the specific policies tested and documented in the paper. The conclusions of the paper on the impacts of various car-pooling strategies appear consistent with the results of previous studies. However, the use of a demand-model system that includes work and non-work-trip models enables the authors to go beyond previous findings in certain ways; e.g., leaving a car home and car pooling to work results in increased nonwork vehicle kilometers of travel (VKT) by nonworking members of the household that offsets by approximately one-third the reduction in work-trip VKT from car pooling.

All three specific comments on the paper relate to the details of the way in which the authors have modeled car-pooling behavior. The first comment relates to a possible difficulty in forecasting car-pool use resulting from preferential lane strategies by the use of a model estimated using cross-sectional data. That is, longer trips tend to exhibit a higher car-pooling modal split. If this bivariate cross-sectional relation is reflected in the multinomial-logit model, car-pooling use in response to preferential lanes that reduce car-pool travel times may tend to be underestimated. The model used in the paper did underestimate the car-pool formation that resulted from the Santa Monica Freeway reserved (diamond) lane. Can this effect be the explanation for this underestimation?

My second comment on the model relates to the way in which employer-based car-pool-matching and promotion programs are represented. Such employer-based car-pool programs are certainly the most widely applied car-pool-promotion strategies at the present time. The authors indicate that car-pool-promotion programs are represented in the work-trip modal-choice model by a dummy variable that picks up the effects of employer-based car-pool programs. It is not stated whether the data used to estimate the model included an indication of the presence or absence of an employer car-pool program at the place of work for each work-trip observation. If these data are available, they represent a substantially improved data base over that normally available.

My third and final comment relates to the property of the logit model by which users of a new mode (e.g., car pooling) are drawn from the existing modes in proportion to their existing modal shares. Is this property operative in the forecasts being made in this paper, and if so, do the authors think that this (separability) property is reasonable? The issue is very important to transit officials who are concerned that car-pool-promotion programs may divert transit users into car pools, particularly in areas that have very high transit use. Putting their minds at ease would help to generate support for car-pool programs.

Authors' Closures

Abraham D. Horowitz and Jagdish N. Sheth

We thank Gendell and Brand for their excellent analyses and insightful comments and appreciate the many positive comments they have made.

We shall concentrate here on their criticisms and methodological questions. At issue, it seems, there are the following three main points.

1. The nonrandom sampling procedure, especially the oversampling of car poolers, has resulted in biased data, such as significant differences in the average trip distance between solo drivers [17.8 km (11.2 miles)] and car poolers [26.2 km (16.3 miles)]. This may explain differences in car-pooling attitudes between solo drivers and car poolers rather than any fundamental psychological differences.

The answer to this criticism is relatively simple and straightforward. First, there are two different and independent populations, those who car pool and those who drive to work. Over or undersampling a particular population cannot affect the parameter (average trip distance) of another population. Second, given the budget constraints, a simple random-probability sample would have produced very few car poolers. A smaller sample size based on random probability would have resulted in an estimator with a higher variance. It was necessary to oversample car poolers precisely to reduce the variance of the estimator. Finally, the shorter trip distance among solo drivers, coupled with their attitude that car pooling is more inconvenient, indicates that it is not the trip distance, but some other psychological factor that produces a greater negative attitude toward car pooling. Otherwise, we should expect just the opposite.

2. It is much better to conduct an experiment and measure its impact by before-and-after changes in the actual behavior of solo drivers rather than collect survey data and stated general intentions and preferences.

We agree with this comment in principle, but not in practice. First, experiments are extremely difficult to carry out in the area of public services because of the large numbers of legal and political constraints. Second and more importantly, to design experiments one needs very good hypotheses and theories, which we simply do not as yet have in the area of urban transportation. It is still a matter of learning more about the realities of urban transportation. Otherwise, the experiments will be carried out on wrong policy variables and result in no main effects and numerous side effects.

We think that it is a better strategy to first conduct a survey and identify potential areas of policy variables and then design proper experiments to measure their behavioral impacts. For example, our study clearly indicates that experiments based on economic incentives would fail to motivate solo drivers to switch to car pooling.

3. It is much better to ask the respondent whether he or she will join a car pool if a certain situation arises than to ask about general intentions to join a car pool within the next two or three months.

This is a very good criticism and we fully agree with it. In fact, it is a major weakness of all attitudinal research that specific situational aspects are not taken into consideration (21). We have collected data on several if-and-what scenarios, such as increased gasoline prices, parking restrictions, and environmental pollution. Unfortunately, we did not have the space to analyze and report the situation-bound intentions in this report.

Kenneth A. Small

The thorough and perceptive comments by the discussants of these papers leave little to explain or refute. At the same time, they raise some important points that are shared by my own paper and that of Ben-Akiva and Atherton.

The two papers contain some basic similarities in both methodology and results. Both use disaggregate models and a sample-enumeration (forecasting-sample) procedure. Both find that traveler response to typical policies is rather moderate, that disincentives to low-occupancy automobiles are more powerful than incentives to car pools or transit, and that the overall effect of car-pooling incentives is muted by their tendency to divert transit riders to car pools in significant numbers.

Furthermore, as Gendell notes, the calibration of our modal-split models results in a large pure-mode bias against car pooling. Why? I believe the results are correct; i.e., given equal values of those time, cost, and socioeconomic variables that we have identified as influencing travel behavior, car pooling is perceived as much less desirable than lower-occupancy automobile. But this opens to consideration two possibilities: Perhaps this bias can be altered by such policies as matching services and promotional campaigns, and perhaps it can be explained by including such additional variables as attitudinal measures. The latter would be most helpful in directing the policies undertaken with regard to the former, and it is here that a synthesis with the attitudinal approach exemplified by Horowitz and Sheth would appear especially productive.

Moshe Ben-Akiva and Terry J. Atherton

Gendell and Brand have provided very useful discussions that raise several important concerns.

1. The magnitude of alternative specific constants: Gendell is concerned with the large negative constant in the car-pool utility function of the modal-choice model used in our study. He states that the existence of a large negative car-pool constant indicates that important behavioral variables were omitted from the model. Therefore, he suggests that some of the softer attributes studied by Horowitz and Sheth be included in the model.

The existence of an alternative specific constant is due to omitted variables, but is also influenced by the definition of alternative choices (e.g., modes) that is used in the estimation and application of a choice model. This is demonstrated below for the logit model.

Consider a logit model with no alternative specific constants as follows:

$$P(i|C) = \exp V_i \Big/ \sum_{j \in C} \exp V_j \tag{2}$$

where $P(i|C)$ is the choice probability of alternative i, given choice set (C), and V_i is the systematic utility of alternative i. Suppose that some of the alternatives in C have identical systematic utilities and consequently equal choice probabilities. Partition C into nonoverlapping subsets of alternatives with equal systematic utilities as follows:

$$C = \{1, 2, \ldots, i, \ldots, J\} = \{A_1, A_2, \ldots, A_k, \ldots, A_L\} \tag{3a}$$

and

$$V_i = V_k \quad (i = 1, \ldots, n_k) \tag{3b}$$

where

- J = number of elemental alternatives in the choice set,
- L = number of subsets of identical elemental alternatives ($L \leq J$),
- A_k = subset of identical alternatives,
- V_k = systematic utility of alternatives in A_k, and
- n_k = number of elemental alternatives in A_k.

We can now rewrite the model as shown by Lerman (13):

$$P(A_k|C) = n_k \exp V_k \Big/ \sum_{l=1}^{L} n_e \exp V_e$$

$$= \exp(V_k + \ln n_k) \Big/ \sum_{l=1}^{L} \exp(V_l + \ln n_l) \tag{4}$$

If n_k is not known, its natural logarithm serves as an alternative specific constant. In this case, the constants result not from omission of attributes from the utilities but from lack of knowledge about the true elemental alternatives in choice sets of individuals and the need to define aggregate or combined alternatives for practical purposes.

There are a variety of car-pooling arrangements, such as with or without cost sharing and door-to-door collection and distribution versus common meeting point. All possible elemental car-pooling alternatives are represented in the modal-choice model by a single car-pool mode. Because it is impossible to collect sufficient information and model explicitly all possible car-pooling arrangements, the model must include a car-pool specific constant even if all of the relevant attributes are included. There is no unique natural count of the number of elemental car-pooling alternatives.

The often used example of the red and blue bus alternatives is derived from the same problem of an arbitrary definition of alternatives. In this case, an individual can be expected to perceive one alternative bus mode and the analyst is assumed to specify two alternative bus modes. These are identical modes except for color, which is assumed to have no effect on the choice of mode. Thus, if the true model without mode-specific constants is expressed as

$$P(\text{bus}) = \exp V_{\text{bus}}/(\exp V_{\text{bus}} + \exp V_{\text{automobile}}) \tag{5}$$

then the definition of two identical bus modes implies a model with constants as follows:

$$P(\text{red bus}) = \exp(V_{\text{bus}} + \ln 0.5)/[\exp(V_{\text{bus}} + \ln 0.5) + \exp(V_{\text{bus}} + \ln 0.5) + \exp V_{\text{automobile}}] \tag{6}$$

These constants are set such that the sum of the red and blue bus probabilities is the same as the bus probability in the true model.

However, evidence in the form of large constants is not required to observe that important attributes that influence modal choice are missing from the existing models. Attributes, such as comfort, reliability, and safety, cannot easily be measured and because of the lack of data are omitted from the existing models. This problem, however, cannot be solved by a direct substitution of reported attitudinal data into the existing choice models.

Choice behavior is determined by perceptions and attitudes. These, in turn, are determined by physical characteristics and past and present behavior. The existence of this reverse causal link from behavior to attitudes and beliefs (the phenomenon of cognitive dissonance) was noted in the context of travel decisions recently by Golob and others (11) and by Brown (9). For policy analysis, in which the consequences of changes in policy variables and physical attributes need to be predicted, this second relation must also be modeled. Thus, the incorporation of softer attributes requires more complex models that have not yet been studied. Models explaining behavior in terms of attitudes and beliefs have been estimated, but have not been used effectively in transportation analyses because models predicting perceptions and attitudes in terms of physical characteristics and previous behavior have not been developed. Such demand models involving simultaneous equations or a dynamic structure with an explicit history of behavior should be the subject of future research to find ways in which softer variables could be incorporated.

2. Automobile-type choices: Gendell points out that models predicting probable shifts in automobile-size distribution were not included in our analysis, and therefore our tests of the effects of large fuel-price increases should be interpreted with caution. The reported results should be interpreted only as a short-run trend under the present average fuel economy.

An automobile-type choice model was not available when the study was conducted. Recent work by Lave and Train (12) and an ongoing project at Cambridge Systematics are directed toward the development of disaggregate automobile-type choice models that could be added to the model in future applications.

In the course of the study, we did use an aggregate automobile-type model developed by Chamberlain (10) in some of the tests. This model is sensitive to aggregate economic variables and fuel price and was used to predict the higher average fuel economy that would be caused by a fuel-price increase. When this predicted change in average fuel economy is used, the predicted travel-demand changes are markedly different from those reported in the paper. There was less mode changing and, as a result, a significantly smaller decrease in work-trip and nonwork vehicle kilometers of travel was predicted to result from a fuel-price increase. However, a significantly larger decrease in fuel consumption was also predicted. For the policy of doubling the fuel price, a reduction in the range of three to four times greater than that reported in the paper was predicted. Thus, it is obvious that automobile-type choice is highly sensitive to fuel price and should be explicitly included in such an analysis.

3. Downward-biased travel-time coefficient: Brand comments that the predicted increase in car pooling due to reduced car-pool travel times may be underestimated. It is always possible that the model will be misspecified such that the coefficient of travel time will be biased. If the coefficient is biased toward zero, a change in travel time will be predicted to have a smaller effect than would actually occur. Brand supports this possibility by the existence of a positive correlation in cross-sectional data between trip length and car pooling and by the underestimation of car pooling in the Santa Monica Freeway before-and-after test.

However, there could be other reasons why the car-pooling predictions are downwardly biased. There could be simultaneous changes in factors other than travel time that affected modal choice, but they were not considered in predictions. One such factor in the case of the Santa Monica Freeway preferential lanes was the added car-pooling publicity and promotion during the first weeks of operation. Repeating the Santa Monica predictions, but including this effect by the use of the car-pool-promotion-and-awareness dummy variable, we obtained an almost perfect prediction of the increased car pooling. This,

of course, could be a coincidence. Nevertheless, it provides a plausible explanation to the initial car-pool underprediction that is not based on a downwardly biased travel-time coefficient, as suggested by Brand.

The coefficient of the car-pool-promotion-and-awareness dummy variable in the modal-choice model was estimated by using data taken from a home-interview survey of the Metropolitan Washington Council of Governments in 1968. These data are less than ideal, but they are among the best available. In particular, this dummy variable was defined on a basis of the limited car-pooling promotion and matching available at that time to employees in the large federal office buildings.

4. Uniform cross elasticities: Brand's final comment is directed to the logit model's property of uniform cross elasticities. Car-pooling incentives will cause the choice probabilities of all other modes to decrease by the same proportion. However, this property is valid only for disaggregate predictions. It is not valid for aggregate predictions, as the results reported in the paper demonstrate. [The difference between disaggregate and aggregate elasticities has been shown by Ben-Akiva (8).] It is an unreasonable property for aggregate predictions, but there is no empirical evidence to reject it, if the model is otherwise well specified, for the disaggregate predictions.

Thus, given the successful before-and-after tests of the modal-choice model, there is no apparent reason to suspect the validity of the predicted diversions from transit to car pools. The only way to avoid a shift from transit to car pools is to accompany car-pooling incentives with transit-service improvements in areas having heavily used transit services.

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Analysis and Prediction of Nonwork Travel Patterns of the Elderly and Handicapped

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This paper summarizes a recent survey of 165 randomly selected elderly and handicapped persons in the Albany, New York, standard metropolitan statistical area. The respondents were administered a 6-min questionnaire on nonwork travel habits, perceived barriers to travel, and intended travel if barriers were removed. Four disaggregate models were constructed relating total travel and modal choice to system, demographic, mode availability, and physical handicap factors. The results show that, contrary to present thinking, the elderly and handicapped vary widely in mobility problems and travel patterns and there is no homogeneity within each group; travel mobility is primarily a function of physical disability, availability of an automobile, and the individual's ability to use it; specific bus-service improvements will not materially affect transit demand, but will ease the travel burden; and improvements concentrating on service availability and direct pickup appear to be the most promising.

In recent years, public transportation systems have been encouraged (and mandated) to give special attention to the services provided to the elderly and handicapped. Off-peak transit fares for these persons are now required as a condition for federal transit-operating assistance under section 5 of the Urban Mass Transportation Act of 1974; federal regulations also require full consideration of these persons in transit system design and operation. The unified work programs prepared annually by metropolitan planning organizations also include similar requirements. These activities are generally consistent with the attitudes of the citizens of New York, 85 percent of whom support reduced fares and special services for the elderly and handicapped (1).

The study discussed here was undertaken in the Albany, New York, standard metropolitan statistical area (SMSA) to determine the factors influencing nonwork travel demand by the elderly and handicapped and to develop a method of estimating their nonwork travel demand. Further results are given by Hartgen and others (2).

DATA

Numerous studies, as well as common sense, suggest