TRANSPORTATION RESEARCH RECORD 592

Perception and Values in Travel Demand

TRANSPORTATION RESEARCH BOARD

COMMISSION ON SOCIOTECHNICAL SYSTEMS
NATIONAL RESEARCH COUNCIL

NATIONAL ACADEMY OF SCIENCES
WASHINGTON, D.C. 1976

Transportation Research Record 592
Price $2.80
Edited for TRB by Marjorie Moore

subject areas
55 traffic measurements
84 urban transportation systems

Transportation Research Board publications are available by ordering directly from the board. They may also be obtained on a regular basis through organizational or individual supporting membership in the board; members or library subscribers are eligible for substantial discounts. For further information, write to the Transportation Research Board, National Academy of Sciences, 2101 Constitution Avenue, N.W., Washington, D.C. 20418.

Notice
The project that is the subject of this report was approved by the Governing Board of the National Research Council, whose members are drawn from the councils of the National Academy of Sciences, the National Academy of Engineering, and the Institute of Medicine. The members of the committee responsible for the report were chosen for their special competence and with regard for appropriate balance.

This report has been reviewed by a group other than the authors according to procedures approved by a Report Review Committee consisting of members of the National Academy of Sciences, the National Academy of Engineering, and the Institute of Medicine.

The views expressed in this report are those of the authors and do not necessarily reflect the view of the committee, the Transportation Research Board, the National Academy of Sciences, or the sponsors of the project.

Library of Congress Cataloging in Publication Data
National Research Council. Transportation Research Board.
Perception and values in travel demand.

(Transportation research record; 592)
1. Choice of transportation–Addresses, essays, lectures. 2. Urban transportation–Addresses, essays, lectures. I. Title. II. Series.
TE7.H5 no. 592 [HE336.C5] 380.5'08s [388.4] 76-30297
ISBN 0-309-02561-3

Sponsorship of the Papers in This Transportation Research Record

GROUP 1–TRANSPORTATION SYSTEMS PLANNING AND ADMINISTRATION
E. Wilson Campbell, New York State Department of Transportation, chairman

Transportation Forecasting Section
Charles V. Wootan, Texas A&M University, chairman

Committee on Traveler Behavior and Values
Peter R. Stopher, Northwestern University, chairman
M. E. Beesley, Nils Anders Bruzelius, Melvyn Cheslow, Ricardo Dobson, Stein Hansen, David A. Hensher, Frank S. Koppelman, Gerald Kraft, Thomas E. Lisco, Benjamin Matalon, Arnim H. Meyburg, Richard M. Michaels, David R. Miller, Robert E. Paaswell, Eugene D. Perle, Shalom Reichman, C. J. Ruijoroko, Geoffrey A. C. Searle, Alistair Sherret, Antti P. Talvitie, Peter L. Watson, Edward Weiner

James A. Scott, Transportation Research Board staff

The organizational units and the officers and members are as of December 31, 1975.

Contents

SA

Effects of Travel Time and Cost on the Frequency and Structure of Automobile Travel

Joel Horowitz, Environmental Protection Agency

Data from the Washington, D.C., area transportation survey were used to test three hypotheses concerning the effects of travel time and automobile operating cost on the frequency of nonwork automobile travel and the demand for multidestination automobile travel by households without access to transit for nonwork travel. The hypotheses are that (a) increases in travel time and automobile operating cost cause reductions in the frequency of nonwork automobile driver travel; (b) these reductions in travel frequency are compensated by increases in the average number of nonwork destinations visited per trip; and (c) reductions in travel frequency cause reductions in the frequency of automobile driver visits to nonwork destinations. Travel time was found to have a substantial effect on the frequency of nonwork automobile driver travel by the households under consideration. Households for which travel times are low have travel frequencies that are 13 to 48 percent greater than the travel frequencies of households for which travel times are high. Automobile operating cost was found not to have a statistically significant effect on the frequency of nonwork automobile driver travel. The reductions in travel frequency associated with increases in travel time are not compensated by increases in the average number of destinations visited per trip. Instead, the frequency of automobile driver visits to certain nonwork destinations—notably nonshop, nonwork destinations—is reduced.

Policy measures being considered or implemented to help alleviate energy and environmental problems caused by the use of automobiles in cities include parking restrictions and increased charges for automobile use, both of which are intended to discourage automobile travel by making it costly or inconvenient. In addition, environmental authorities are required to conduct preconstruction reviews of certain types of new transportation facilities, such as highways, to determine whether the automobile traffic generated by these facilities will cause violations of air quality standards. The policy measures are based on the premise that the demand for automobile travel depends on the cost and convenience of such travel. The requirement for review of new facilities derives, in part, from the same premise. The concern is that, by reducing the cost or increasing the convenience of automobile travel, new transportation facilities may cause automobile travel and automobile-related air pollution to increase.

The dependence of the demand for automobile travel on cost and convenience is likely to manifest itself in different ways for different types of travel. In the case of work and school travel (referred to simply as work travel), whose frequency and destination are fixed in the short run, the dependence of demand on cost and convenience is usually realized through the choice of mode. However, in the case of travel for purposes other than work or school (referred to simply as nonwork travel), nonautomobile modes frequently are unavailable, and dependence is more likely to involve travel frequencies and destinations. The dependence also may involve decisions on whether several destinations should be visited during a multiple-destination (and, possibly, multiple-purpose) tour.

Conventional travel demand models (1, 2) divide travel into units of single-destination trips and assume that the frequencies of these trips depend only on socioeconomic and land use variables. Thus, these models provide no information on whether changes in the cost and convenience of automobile travel cause changes in the frequency of nonwork automobile travel and the demand for multidestination automobile travel. Newer modeling approaches indicate that the frequency of nonwork automobile travel may depend on the cost and convenience of such travel. For example, recently developed disaggregate models of the demand for home-shop-home round trips (3, 4) suggest that the frequency of these trips is a decreasing function of the time and cost of travel from home to shopping destinations. However, the disaggregate models do not address the effects of travel time and cost on the demand for nonshop, nonwork travel or on the demand for multidestination travel.

Nonshop and multidestination travel has been addressed, to an extent, in surveys of traveler response to the 1974 gasoline shortage. A survey of driving habits before and during the gasoline shortage (5) reported that "both driving for shopping and driving on social and recreational trips decreased" during the shortage. A survey of driving habits during and after the gasoline shortage (6) reported that nonwork automobile travel decreased 13 percent during the shortage. The survey indicated that the principal cause of this decrease was reduced gasoline availability and that changes in gasoline cost had little effect on driving habits. The method of reducing automobile use most frequently considered by the respondents was to make multidestination trips. However, the survey did not indicate whether this consideration led to increased multidestination travel during the gasoline shortage.

This paper describes an effort to extend the foregoing work by developing estimates of the relationships between the frequencies of certain types of nonwork automobile driver travel, the extent of multidestination nonwork automobile driver travel, travel times, and travel costs. Specifically, the objectives of this effort were

1. To test the hypothesis that the frequency of nonwork, automobile driver, home-to-home round trips by households that do not have access to transit for nonwork travel is a decreasing function of the time and cost of travel. The hypothesis is restricted to households without access to transit for nonwork travel because of the predominance of such households in many cities and the potential policy importance of the response of these households to changes in the cost and convenience of automobile travel. In addition, restricting the hypothesis to households without access to transit simplifies the analysis by avoiding the need to estimate mode choice. The hypothesis focuses on round trips that originate and terminate at home because these are the predominant form of automobile travel for nonwork purposes.
2. To test the hypotheses that households without access to transit for nonwork travel tend to compensate for increases in the time and cost of travel from home to nonwork locations by (a) increasing the average number of destinations included in nonwork, automobile driver, home-to-home round trips; (b) visiting nonwork destinations while traveling between home and work; and (c) visiting nonwork destinations during round trips that originate and terminate at work.
3. To test the hypotheses that changes in travel times and costs result in changes in the frequencies of automobile driver visits to (a) shop destinations and (b) nonshop, nonwork destinations by households that do not have access to transit for nonwork travel.
4. To compare the frequencies of nonwork, automobile driver, home-to-home round trips by households for which travel times and costs are relatively high with the frequencies of such trips by households for which travel times and costs are relatively low and, thereby, to estimate the magnitude of the change in the frequency of nonwork, automobile driver, home-to-home round trips that may result from changes in the time and cost of these trips.

DATA

The data used in this analysis were obtained from the 1968 Washington, D.C., area transportation survey. The data consist of individual household trip records and socioeconomic information together with zone-to-zone travel times and distances for all pairs of traffic zones in the Washington area. The socioeconomic information used in the analysis consists of household size, automobile ownership, and income. The available income data were categorized as follows:

Scale	Income ($)	Scale	Income ($)
1	0 to 2999	6	10 000 to 11 999
2	3000 to 3999	7	12 000 to 14 999
3	4000 to 5999	8	15 000 to 19 999
4	6000 to 7999	9	20 000 to 24 999
5	8000 to 9999	10	25 000 or more

Households located in traffic districts in which more than 5 percent of recorded nonwork trips were made by transit were considered to have access to transit for nonwork travel and were excluded from this analysis. Households that do not own cars were found not to make nonwork automobile driver trips and were excluded also, as were households with incomplete travel or socioeconomic data. All other households in the Washington survey, 15 600 in total, were included in the data set used for the analysis.

TRAVEL FREQUENCY, TRAVEL TIME, AND TRAVEL COST VARIABLES

To test the hypotheses formulated for this analysis requires a unit of travel that encompasses both single- and multiple-destination travel. The unit must retain information on the number of destinations visited during multidestination travel. Moreover, the unit must be capable of distinguishing travel to nonwork destinations that occurs during travel between home and work from travel to nonwork destinations that takes place during nonwork, home-to-home round trips. The conventional travel unit, the trip, does not satisfy these requirements. A unit of travel that does satisfy the requirements was developed for use in this analysis by modifying Ginn's concept of the tour (7).

The definition of tour was modified as follows. A trip is defined in the usual way as a movement between two locations that requires the use of a vehicle. Home, work, and school are defined as base points. A tour is defined as a movement that begins and ends at a base point and is composed of one or more trips (e.g., from home to shop to home). The destinations, if any, visited between the base points of a tour (e.g., shop) are called nodes. Nodes always represent locations other than home, work, or school.

Three types of tours were defined for use in the analysis: tours for which both base points are home (type 1 tours); tours that include at least one node and have one base point at home and the other at work or school (type 2 tours); and tours that include at least one node and have both base points at work or school (type 3 tours). Based on this taxonomy of tours, the four objectives of the analysis can be restated as follows:

1. To test the hypothesis that the frequency of automobile driver type 1 tours by households without access to transit for nonwork travel is a decreasing function of the time and cost of travel from home to nonwork destinations;
2. To test the hypotheses that households without access to transit for nonwork travel tend to compensate for increases in the time and cost of travel from home to nonwork locations by increasing the average number of nodes included in type 1 tours and by substituting type 2 and type 3 tours for type 1 tours;
3. To test the hypotheses that changes in travel times and costs result in changes in (a) the frequency of automobile driver visits to shopping destinations and (b) the frequency of automobile driver visits to nonshop, nonwork destinations by households without access to transit for nonwork travel; and
4. To compare the frequencies of automobile driver type 1 tours by households for which travel times and costs are high with the frequencies of such tours by households for which travel times and costs are relatively low.

The variables used to characterize the time and cost of travel from home to nonwork locations were adapted from the concept of the inclusive cost of travel (3). The

Table 1. Variables used in the analysis.

Name	Definition	Mean	Standard Deviation
T1TOUR	Type 1 automobile driver tours per day	0.92	1.08
T2TOUR	Type 2 automobile driver tours per day	0.10	0.33
T3TOUR	Type 3 automobile driver tours per day	0.04	0.22
TOTALN	Total daily automobile driver visits to nonwork destinations	1.40	1.74
SHOPN	Total daily automobile driver visits to shopping destinations	0.56	0.88
NSHOPN	Total daily automobile driver visits to nonshop, nonwork destinations	0.84	1.36
T2NODE	Total daily automobile driver visits to nonwork destinations during type 2 tours	0.14	0.56
T3NODE	Total daily automobile driver visits to nonwork destinations during type 3 tours	0.06	0.39
NPT	Total daily automobile driver visits to nonwork destinations during type 1 tours divided by T1TOUR (defined only for households for which T1TOUR $\neq$ 0)	1.33	0.69
HHS	Household size	3.39	1.69
CARS	Automobiles owned	1.61	0.69
INC	Income on scale of 1 to 10	6.01	2.09
T[a]	Travel time variable in minutes	11.63	2.79
C[a]	Travel cost variable in 1968 dollars	0.22	0.06
C/INC	Travel cost divided by income	0.04	0.03
DUM 1	Dummy variable equal to one if INC = 1 and zero otherwise	0.03	0.17
DUM 2	Dummy variable equal to one if INC = 2 and zero otherwise	0.02	0.14
DUM 3	Dummy variable equal to one if INC = 3 and zero otherwise	0.06	0.24

[a]T and C are defined at the household level of aggregation.

Table 2. Coefficients in equation for type 1 tours and for average nodes per type 1 tour.

	Type 1 Tours[a]		Average Nodes per Type 1 Tour[b]	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0.072 64		1.310 29	
HHS	0.126 25	24.12[c]	-0.024 25	-5.37[c]
CARS	0.258 96	19.33[c]	0.036 00	3.14[c]
INC	0.039 56	4.98[c]	0.006 14	0.85
T	-0.022 49	-4.58[c]	-0.001 13	-0.26
C/INC	-0.016 75	-0.017	0.611 75	0.64
DUM 1	0.396 65	2.84[c]	-0.060 68	-0.46
DUM 2	0.260 52	3.33[c]	-0.027 52	-0.39
DUM 3	0.081 27	1.92	-0.057 28	-1.43

[a]R = 0.3027. [b]R = 0.0659. [c]Statistically significant at 0.01 level.

travel time variable is computed at the district level of aggregation and is the average travel time from home to the nonwork destinations visited by the households located in a traffic district. The travel cost variable is the average cost of operating an automobile between home and the nonwork destinations visited by the households located in a traffic district. When the district level, rather than the zonal level, of aggregation is used, the travel times and cost represent averages over large numbers of trips. The use of zonal level travel times and costs reduces the sensitivity of the analysis because of the large variances of the zonal level time and cost variables. Parking costs are not available in the Washington survey data and, therefore, are not included in the travel cost variable. However, the Washington data do indicate whether parking was free or paid. In the data set used for this analysis, 3 percent of the visits to nonwork, nonschool destinations had paid parking.

The complete set of travel frequency, travel time, travel cost, and socioeconomic variables used in the analysis is given in Table 1.

STATISTICAL ANALYSIS

Three of the four objectives of this analysis involve hypothesis tests. These tests were performed by estimating functional relationships of the form

$$Y = a_0 + a_1\,T + a_2\,(C/INC) + \sum b_i s_i \qquad (1)$$

where Y is selected according to the hypothesis being tested and

a_i and b_i = coefficients to be estimated,
T = travel time variable,
C = travel cost variable,
INC = household income, and
s_i = socioeconomic variables.

The coefficients were estimated by using ordinary least squares at the household level of aggregation. Hypotheses were accepted if the appropriate coefficients had the correct signs and were statistically significant at the 1 percent level. A functional specification in which cost was not divided by income also was tried but could not be estimated successfully because of a high degree of collinearity between the time and cost variables. This collinearity problem is not present in the specification shown.

To test the hypothesis that the frequency of automobile driver type 1 tours is a decreasing function of the time and cost of travel from home to nonwork destinations, T1TOUR was substituted for Y in equation 1. The resulting coefficient estimates and t-statistics are given in Table 2. The dummy variables were included to account for the travel characteristics of the lower income households. These households make more type 1 tours than can be explained by the other variables alone.

The coefficients of the socioeconomic variables in Table 2 indicate that the frequency of automobile driver type 1 tours is an increasing function of household size, automobile ownership, and, outside of the lower income classes, income. The coefficient of travel time is negative and statistically significant at the 1 percent level. Thus, the hypothesis that the frequency of automobile driver type 1 tours is a decreasing function of travel time is accepted. The coefficient of travel cost is negative but is not statistically significant. The hypothesis that the frequency of automobile driver type 1 tours is a decreasing function of automobile operating cost is not accepted.

The hypothesis that households compensate for increases in the time and cost of travel from home to nonwork locations by increasing the average number of nodes visited per type 1 tour was tested by substituting NPT, the average number of nodes per type 1 tour, for Y in equation 1. The coefficients of equation 1 were then estimated by using a data set restricted to households that made at least one type 1 tour. These coefficient estimates are also given in Table 2. The negative coefficient of household size and the positive coefficient of automobile ownership indicate that increases in household size and decreases in automobile ownership tend to result in fewer nodes visited per type 1 tour. Increases in household size and decreases in automobile ownership tend to increase the number of individuals that each household automobile must serve. This may reduce household members' use of the automobile during the

Table 3. Coefficients in equation for type 2 and type 3 tours and for nodes visited on tours.

	T2TOUR[a]		T2NODE[b]		T3TOUR[c]		T3NODE[d]	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0.064 78		0.081 64		0.000 87		-0.006 00	
HHS	-0.006 63	-3.99[e]	-0.012 08	-4.33[e]	-0.002 79	-2.49[f]	-0.005 98	-3.08[e]
CARS	0.032 58	7.63[e]	0.053 38	7.41[e]	0.019 04	6.59[e]	0.034 41	6.91[e]
INC	0.007 27	3.58[e]	0.010 23	2.99[e]	0.005 71	4.14[e]	0.005 71	2.41[f]
T	-0.002 58	-2.41[f]	-0.003 74	-2.08[f]	-0.001 48	-2.03[f]	-0.000 33	-0.264
C/INC	-0.198 50	-1.55	-0.184 25	-0.85	0.034 75	0.40	-0.063 25	-0.42

[a]R = 0.1025. [b]R = 0.0903. [c]R = 0.0860. [d]R = 0.0770. [e]Statistically significant at 0.01 level. [f]Statistically significant at 0.05 level.

Table 4. Coefficients in equation for total nodes, shop nodes, and nonshop nodes.

	TOTALN[a]		SHOPN[b]		NSHOPN[c]	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0.135 18		0.139 21		-0.006 16	
HHS	0.127 06	14.95[d]	0.054 15	12.28[d]	0.073 05	10.94[d]
CARS	0.457 62	21.01[d]	0.125 57	11.12[d]	0.331 88	19.39[d]
INC	0.078 73	6.10[d]	0.019 22	2.87[d]	0.059 91	5.91[d]
T	-0.038 74	-4.85[d]	-0.005 46	-1.32	-0.033 51	-5.34[d]
C/INC	1.370 00	0.84	-0.361 50	-0.43	1.786 00	1.39
DUM 1	0.307 86	1.38	0.127 02	1.08	0.174 72	0.98
DUM 2	0.220 94	1.74	0.055 96	0.85	0.163 28	1.64
DUM 3	0.021 03	0.31	-0.022 30	-0.62	0.042 25	0.78

[a]R = 0.2724. [b]R = 0.1808. [c]R = 0.2359. [d]Statistically significant at 0.01 level.

Table 5. Type 1 tour frequencies corresponding to 95th percentile, 5th percentile, and mean values of T.

			Tour Frequency			
HHS	CARS	INC	95th Percentile of T	5th Percentile of T	Mean of T	5th Percentile/ 95th Percentile
1	1	1	0.61	0.69	0.66	1.13
1	1	2	0.48	0.60	0.55	1.25
2	1	3	0.41	0.60	0.53	1.48
2	1	4	0.40	0.55	0.49	1.38
2	1	5	0.45	0.60	0.53	1.35
4	2	6	0.93	1.14	1.06	1.23
4	2	7	0.95	1.18	1.10	1.23
4	2	8	0.99	1.22	1.14	1.22
4	2	9	1.03	1.25	1.18	1.21
2	2	10	0.75	1.05	0.97	1.40

periods of time required for multidestination tours and, therefore, reduce the average number of nodes per tour. The coefficients of travel time and travel cost (Table 2) are not statistically significant. The hypothesis that households compensate for increases in travel time and cost by increasing the average number of destinations visited per type 1 tour is not accepted.

Another way that households might compensate for increases in the time and cost of travel from home is by selecting nonwork destinations that are convenient relative to the work place or the home-to-work route and by visiting these destinations during type 2 or type 3 tours. Such behavior would be suggested if increases in either the frequencies of type 2 and type 3 tours or the number of nodes visited on these tours were associated with increases in travel time and cost. Hence, the hypothesis that increases in the time and cost of travel from home to nonwork destinations cause type 2 and type 3 tours to be substituted for type 1 tours was tested by substituting T2TOUR, T2NODE, T3TOUR, and T3NODE for Y in equation 1. The results are given in Table 3.

The positive signs of the automobile ownership and income coefficients in Table 3 and the negative sign of the household size coefficient can be interpreted by observing that automobile driver type 2 tours can be made only if an automobile is driven to work and that automobile driver type 3 tours can be made only if an automobile is available at work. Thus, increases in automobile ownership and income, which tend to increase the likelihood that an automobile is driven to work, are associated with increases in the frequencies of type 2 and type 3 tours and with increases in the numbers of nodes visited on these tours. Increases in household size may increase the need for a car at home, thereby decreasing both the likelihood that a car is driven to work and the frequencies of type 2 and type 3 tours.

The coefficients of cost in Table 3 are not statistically significant. The coefficients of travel time are all negative and border on statistical significance. This suggests, contrary to expectation, that both the frequencies of type 2 and type 3 tours and the numbers of nodes visited on these tours tend to decrease as travel from home to nonwork locations becomes more time-consuming. In an effort to interpret this result, the travel times associated with type 3 tours and with detours to nonwork destinations during type 2 tours were examined. It was found that, as T increases, the time required to travel from work to nonwork destinations and the time involved in detouring from the home-to-work route to nonwork destinations also tend to increase, thus causing type 2 and type 3 tours to be more time-consuming and less frequent. Apparently households tend not to select nonwork destinations near the work place or the home-to-work route in response to increased difficulty of travel from home. The hypothesis that type 2 and type 3 tours are substituted for type 1 tours because of increases in the time and cost of travel from home to nonwork destinations is not accepted.

The foregoing results indicate that, as travel time from home to nonwork destinations increases, the frequency of automobile driver type 1 tours decreases. This decrease in type 1 tour frequency is not compensated by increases in the average number of nodes visited per type 1 tour or in the frequencies of type 2 and type 3 tours. All tour types are insensitive to changes in automobile operating cost. These considerations suggest that increases in travel time are associated with decreases in the frequency of automobile driver visits to nonwork destinations but that changes in operating cost do not affect the frequency of such visits. This hypothesis was tested by substituting TOTALN for Y in equation 1. The hypothesis that increases in travel time and cost cause decreases in automobile driver visits to shopping destinations was tested by substituting SHOPN for Y in equation 1. The hypothesis that increases in travel time and cost cause decreases in automobile driver visits to nonshop destinations was tested by substituting NSHOPN for Y in equation 1. The results are given in Table 4.

The signs of the coefficients of household size, automobile ownership, and income in Table 4 are the same as those in Table 2. This is to be expected, inasmuch as 86 percent of nodes are visited during type 1 tours. The coefficients of the cost variable are all not significant, indicating, as expected, that the number of nodes visited by a household is insensitive to changes in the cost of operating an automobile between home and nonwork destinations. When TOTALN is the dependent variable, the coefficient of travel time is negative and statistically significant. Thus, the hypothesis that the frequency of automobile driver visits to nonwork destinations decreases when the time associated with travel from home to these destinations increases is accepted. When NSHOPN is the dependent variable, the coefficient of travel time also is negative and statistically significant. However, when SHOPN is the dependent variable, the coefficient of travel time is not significant. The hypothesis that the frequency of automobile driver visits to nonshop, nonwork destinations decreases when the travel time from home to nonwork destinations increases is accepted. The analogous hypothesis for automobile driver visits to shop destinations is not accepted.

The magnitude of the change in type 1 tour frequency associated with changes in travel time was estimated for 10 example socioeconomic strata corresponding to different values of household size, automobile ownership, and income. The 95th percentile, 5th percentile, and average values of travel time associated with the households in each stratum were determined. These travel times and the corresponding automobile operating costs were substituted into equation 1 by using the coefficients given in Table 2. The resulting type 1 tour frequencies are given in Table 5. These frequencies reflect the effects of variations in travel time actually experienced by households in the Washington area. Households with low travel times make 13 to 48 percent more automobile driver type 1 tours than households with high travel times, depending on socioeconomic stratum.

CONCLUSIONS

The results presented here are consistent with the hypothesis that travel time can have a substantial effect on the frequency of nonwork automobile driver travel by households that lack access to transit for such travel. Acceptance of this hypothesis implies that to accurately forecast the effects of new or modified transportation facilities requires techniques that account for interactions between travel time and travel frequency.

Automobile operating costs do not have a statistically significant association with any of the travel frequency variables considered here. This does not necessarily imply that automobile operating costs have no effects on these variables. However, the results suggest that any such effects may be relatively small. For example, the coefficient estimates in Table 2 imply that a 1 percent increase in automobile operating costs would reduce the average frequency of type 1 tours by less than 0.08 percent with 95 percent confidence, whereas a 1 percent increase in travel time would reduce average type 1 tour frequency by 0.29 ± 0.12 percent with 95 percent confidence. Parking costs were not included in the analysis. Thus, the foregoing conclusions do not necessarily apply to them.

Reductions in nonwork travel frequency associated with increases in travel time appear not to be compensated by increases in the average number of nonwork destinations visited per automobile driver tour. Rather, the frequency of automobile driver visits to nonwork destinations is reduced. Changes in automobile operating costs appear to have little or no effect on the average number of nonwork destinations visited per automobile driver tour. Substitution of multidestination tours for single-destination tours is a frequently suggested means of conserving resources expended in travel. The results presented here suggest that, at least when the incentives to conserve resources take the form of increases in travel times or automobile operating costs, travelers may not take advantage of this approach to resource conservation.

ACKNOWLEDGMENTS

The author thanks Robert Dunphy and Frank Goodyear of the Washington Council of Governments for their assistance in obtaining Washington area travel data and David Syskowski of the Environmental Protection Agency for his assistance in processing the data. The views expressed in this paper are those of the author and are not necessarily endorsed by the Environmental Protection Agency.

REFERENCES

1. Urban Transportation Planning: General Information and Introduction to System 360. Federal Highway Administration, U.S. Department of Transportation, March 1972.
2. Guidelines for Trip Generation Analysis. Federal Highway Administration, U.S. Department of Transportation, June 1967.
3. A Disaggregated Behavioral Model of Urban Travel Demand. Report prepared by Charles River Associates, Inc., for the Federal Highway Administration, March 1972.
4. T. J. Adler. A Joint Choice Disaggregate Model of Non-Work Urban Passenger Travel Demand. MIT, Cambridge, MS dissertation, Feb. 1975.
5. J. R. Murray, M. J. Minor, N. M. Bradburn, R. F. Cotterman, M. Frankel, and A. E. Pisarski. Evolution of Public Response to the Energy Crisis. Science, Vol. 184, April 19, 1974, pp. 257-263.
6. R. L. Peskin, J. L. Schofer, and P. R. Stopher. The Immediate Impact of Gasoline Shortages on Urban Travel Behavior. Federal Highway Administration, April 1975.
7. J. R. Ginn. Transportation Considerations in an Individual's Activity System. Northwestern Univ., Evanston, Ill., PhD dissertation, Aug. 1969.

Generalized Attribute Variable for Models of Mode Choice Behavior

Bruce D. Spear,* Federal Highway Administration, U.S. Department of Transportation

This paper discusses how abstract transportation system characteristics like convenience can be quantified by using psychometric scaling techniques and can be included as explanatory variables in models of travel demand behavior. A survey was conducted to collect time and cost information on alternative modes of transportation for the journey to work and attitude data on 14 attributes representing convenience. Importance scores were derived for the attributes by using the Thurstone scaling technique. A generalized convenience variable was constructed based on a linear combination of individual satisfaction ratings of the convenience attributes weighted by their derived importance scores. Models of mode choice behavior were calibrated by using a logit function that was estimated by a maximum likelihood procedure. Comparisons were made between models that used only time and cost variables and those that included the generalized convenience variable. The goodness of fit was significantly better with models that included the convenience variable than with models that were based strictly on time and cost variables. It was concluded that the generalized attribute approach is a feasible concept that can significantly improve the explanatory power of conventional models of travel behavior.

A major problem confronting both transportation planners and researchers in travel behavior is how to build travel demand models that are sensitive to transportation system attributes other than time and cost. These models allow not only a better understanding of travel choice decisions but also prediction of the potential consequences of transportation policy decisions, such as the installation of bus shelters, transit routing or frequency changes, or adoption of a monthly fare pass, that do not directly affect travel times or costs.

A number of studies investigated factors that influence travel choice and concluded that attributes such as comfort, convenience, reliability, and safety play an important role in the average traveler's decision, particularly in the choice of travel mode (1, 3, 7, 10). Despite this recognition, relatively little work has been undertaken to incorporate these attributes in travel demand models. Studies that used proxy variables for these attributes produced models that were only marginally better than conventional time and cost models at explaining choice behavior (4, 11, 14).

Representing an attribute such as convenience with a proxy variable causes two problems. First, convenience is a generalized concept created by the individual traveler to describe his or her overall perceptions of various subattributes of the transportation system. Convenience, per se, is an ambiguous term having as many definitions as there are individuals in the population. Second, an individual's perceptions of various subattributes may not be directly related to some measured characteristic of the transportation system.

The research described in this paper develops a framework for including generalized attributes like comfort or convenience as explanatory variables in disaggregate mode choice models. This framework overcomes the problems associated with proxy variables yet does so in a way that allows the variable to be used in a planning context by defining subattributes that are amenable to prediction or manipulation.

GENERALIZED ATTRIBUTE VARIABLE

The structure of the generalized attribute variable is an application of Rosenberg's cognitive summation theory of attitude (8). That is, the value of a generalized attribute variable associated with a particular travel mode m, as perceived by individual i, is given by

$$A_{im} = \sum_{j=1}^{n} W_{ij} \times Y_{ijm} \qquad (1)$$

where

A_{im} = individual i's perceived value of the generalized attribute for mode m,
W_{ij} = relative sensitivity of individual i to a particular subattribute j,
Y_{ijm} = individual i's perceived satisfaction with travel mode m with respect to subattribute j, and
n = number of subattributes that contribute to the definition of the generalized attribute.

Equation 1 carries the assumption that an individual's

*When this research was performed, Mr. Spear was a graduate student at Cornell University.

sensitivity to a particular subattribute is independent of his perceived levels of satisfaction with alternative travel modes with respect to that subattribute. Given this assumption, equation 1 can also be written as a difference formulation:

$$A_{i1} - A_{i2} = \sum_{j=1}^{n} W_{ij} \times (Y_{ij1} - Y_{ij2}) \tag{2}$$

Because an individual's sensitivity to a subattribute is assumed to be independent of his satisfaction levels, only one sensitivity coefficient is needed.

A second assumption was made to avoid having to derive sensitivity coefficients for each individual. It was assumed that a population could be stratified into a finite number of subgroups in which individuals in a particular subgroup would have similar sensitivities to the subattributes of the generalized variable.

Equation 2 could then be modified as follows:

$$A_{i1} - A_{i2} = \sum_{j=1}^{n} W_j^s \times (Y_{ij1} - Y_{ij2}) \tag{3}$$

where s is the subgroup to which individual i belongs. Thus, individuals in the same subgroup will have identical values for their subattribute sensitivity coefficients, W_j^s. The value of the generalized attribute variable, however, will vary depending on the individual's perceived levels of satisfaction with the subattributes.

METHODOLOGIES FOR DERIVING SATISFACTION LEVELS AND SENSITIVITY COEFFICIENTS

The usefulness of the generalized attribute variable depends on the methodologies required to derive the sensitivity coefficients for various subgroups and individual satisfaction ratings for alternative travel modes. A variety of data collection and psychometric scaling techniques are available to obtain these data. However, because the objective of this research was to introduce and demonstrate the feasibility of the generalized attribute variable, no comparative analyses of alternative methodologies were made. Only those techniques that were actually used in the study are discussed below.

Individual Satisfaction Ratings

Ratings for alternative travel modes with respect to various service characteristics were obtained directly from the respondents by means of a subjective estimation questioning procedure. A sample question in which the respondent was asked to state which mode, if any, was more satisfactory with respect to a specific subattribute is given below.

Select the means of travel that you feel is best described by the statement to the left. If you feel that both choices are equally well described by the statement, circle the letters in the "no difference" column.

	Automobile	Public Transit	No Difference
1. Less chance of an accident	A	PT	ND
2. Arrive on time to work more often	A	PT	ND
3. More reliable in bad weather	A	PT	ND

The rating scores obtained from this procedure were used directly to represent the difference term ($Y_{ij1} - Y_{ij2}$).

Attitudinal responses may be acceptable for developing explanatory models of individual choice behavior. Before these models can be used in a planning context, however, some functional relationship must be established between the relative satisfaction levels of individuals and physical parameters of the transportation systems.

Group Sensitivity Coefficients

Sensitivity coefficients can be derived by using various psychometric techniques. For this study, it was assumed that individuals could ordinally rank various subattributes along a unidimensional continuum of importance to their mode choice decision. Given these rankings for a group of individuals, Thurstone's law of comparative judgment (12) can be used to derive an aggregate sensitivity scale where the scale value of each subattribute represents its relative importance to the group. A detailed description of the Thurstone scaling technique is given elsewhere (2, 13).

The Thurstone scaling procedure generates an interval scale rather than a ratio scale. This means that only the relative positions of the subattributes with respect to each other can be determined. The entire scale can be universally stretched or compressed without altering the relative distances between the scale values. Similarly, because no absolute zero point exists for an interval scale, a constant may also be added to each scale value without changing the scale itself.

These characteristics have significant implications for the use of interval scale values as sensitivity coefficients. First, they indicate that the sensitivity scale derived from the Thurstone scaling procedure can always be transformed to a scale that ranges between zero and one. Second, they imply that the set of subattributes selected to make up the generalized attribute variable should have at least one subattribute that is generally perceived as unimportant so that a realistic lower bound can be established for the scale. If this is not done, then the derived distances between subattribute scale values may be greatly exaggerated with respect to an absolute scale of importance.

GENERALIZED CONVENIENCE VARIABLE

The generalized attribute variable concept was empirically tested by constructing a generalized variable for convenience. To obtain the data necessary for constructing the variable and for building disaggregate mode choice models, a small-scale survey was conducted.

Questionnaire Design

The survey questionnaire consisted of two sections. One section paralleled conventional mode choice surveys by requesting information on travel times and costs and on socioeconomic characteristics of the trip maker. The other section was designed to collect importance rankings on a preselected list of stimulus phrases representing various subattributes and comparative satisfaction ratings for alternative travel modes with respect to those subattributes.

Fourteen stimuli were selected for the importance rankings. Twelve of these were chosen based on the results of previous studies (3, 7) as representatives of a broad range of stimuli associated with convenience. Stimuli representing travel time and cost were also included in the rankings to compare their perceived importances relative to the other subattributes. The stimuli included in the rankings were as follows:

1. Arrive at the intended time,
2. Able to travel in all weather,
3. Avoid a long wait,
4. Avoid leaving early for work,

5. Have the vehicle easily accessible to home,
6. Avoid numerous stops,
7. Have a choice of departure times,
8. Have understandable maps and schedules,
9. Pay as little as possible for the trip,
10. Travel in the shortest time,
11. Avoid a long walk,
12. Avoid changing vehicles,
13. Avoid paying daily for the trip, and
14. Avoid undesirable areas.

A paired comparison questioning procedure was used to obtain the importance rankings. A typical paired comparison question follows.

Select the one feature in each pair which you would most like to see provided by a transportation system. For each of the following questions ask yourself, "Would I rather..."

1. arrive at the intended time	or	avoid a long wait for the vehicle?
2. avoid leaving early to be on time for work	or	be able to travel in all weather?
3. have a choice of departure times	or	avoid a long walk?

To minimize the repetitiveness of the paired comparison questions, only 42 of the 91 possible stimulus pairs were presented. However, the comparisons were structured so that a complete comparison matrix could be constructed for each respondent, given the questionnaire responses. See Spear (9) for a discussion of this procedure.

Comparative satisfaction questions were used to obtain the satisfaction ratings for a binary mode choice decision between automobile and public transit.

Survey Sample

Surveys were conducted in two major U.S. cities: Boston and Chicago. Only the choice of mode for the work trip was investigated. Therefore, data collection was simplified by distributing questionnaires at preselected work locations in the two cities. There were two significant consequences of this survey procedure. First, because neither sample was probability based, no conclusions could be drawn regarding either the socioeconomic composition or the travel habits of the general population in the two cities. This did not seem to be a major constraint to the objectives of the research, however. A second consequence was that, because the surveys were conducted only at those locations where prior approval had been obtained from management, the completion rate was much higher than anticipated. Of the 350 questionnaires distributed in each of the two cities, 178 or 50.9 percent were returned from Boston and 219 or 62.6 percent were returned from Chicago. This return rate was highly satisfactory given that the questionnaire was self-administered and the respondents could expect no direct benefits for their efforts.

The socioeconomic compositions of the two samples were very similar. Therefore a number of mode choice models were constructed and calibrated by using the Boston data. The Chicago sample was used to test the geographical transferability and the predictive abilities of the Boston models.

RESULTS

Effect of Socioeconomic Factors on Group Sensitivity Scales

One of the assumptions of the generalized attribute variable was that a population could be stratified into a finite number of homogeneous subgroups and that everyone in a subgroup could be represented by a single set of sensitivity coefficients. The Boston data were analyzed to determine whether socioeconomic parameters could be used to stratify the sample into these subgroups. The sample was stratified by sex (two groups), age (four groups), income (five groups), education (six groups), and stage in the family life cycle (four groups). Group sensitivity scales were derived for each of the 21 subgroups and for the entire sample. The scales were then examined to identify socioeconomic trends, and compared with the sensitivity scale for the entire sample to determine if socioeconomic stratification was really meaningful.

One general finding of the analysis was that three reasonably distinct groups of stimuli could be identified in every sensitivity scale (Figure 1). The highest ranked group consisted of five stimuli (numbers 1, 2, 3, 5, 10) that represented subattributes associated with reliability, accessibility, and travel time. The second group of stimuli (numbers 4, 6, 7, 12) was generally ranked lower in importance than group one and represented subattributes associated with the flexibility of the transportation system and the physical effort required to make the trip. The lowest ranked group of stimuli (numbers 8, 11, 13, 14) represented various amenities which could be provided by the transportation system. Travel cost (stimulus 9) seemed to fluctuate between the second and third groups.

Despite the overall stability of certain stimulus groups, a few significant trends were found in the socioeconomic subgroups. Females were much more sensitive to the stimulus "avoid undesirable areas," probably because they interpreted it to represent personal safety. Older workers were less sensitive to travel time but more sensitive to any physical effort involved in making a trip. Sensitivity to travel cost decreased somewhat at higher income levels, but this trend was not so dramatic as might be expected.

Substratifications by more than one socioeconomic parameter were precluded by the small sample size. Further substratifications may have revealed additional trends in the stimulus sensitivities.

Constructing the Generalized Convenience Variable

The generalized convenience variable was built by using the formulation given in equation 3. The sensitivity coefficients W^s_j were the scale values of stimuli from the sensitivity scales, and the satisfaction differences (Y_{ij1} - Y_{ij2}) were obtained directly from the comparative satisfaction ratings of respondents. The stimuli "pay as little as possible for the trip" and "travel in the shortest time" were omitted from the convenience variable because they were to be used directly as quantitative variables.

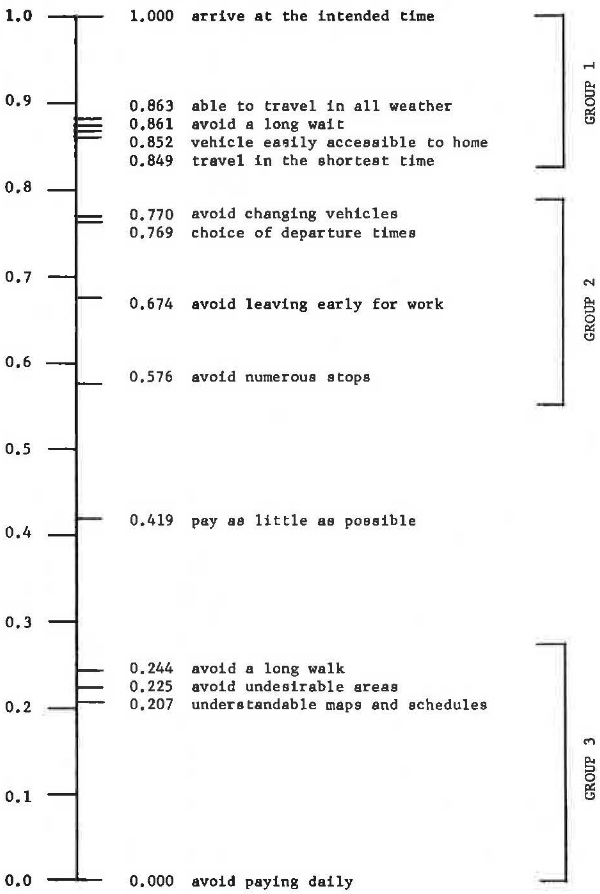
Convenience variables were constructed with sensitivity coefficients derived from the entire sample and from subgroup stratifications by sex, age, income, and stage in the family life cycle.

The feasibility of entering more than one generalized variable in the same model was also investigated. Generalized attribute variables were constructed for reliability by combining stimuli 1 and 2 and for perceived travel time by combining stimuli 3 and 10. When used in the same model with one or both of these variables, the generalized convenience variable omitted the redundant stimuli.

Mode Choice Modeling

Disaggregate binary mode choice models were constructed

Figure 1. Sensitivity scale for the Boston sample.



for various combinations of quantitative time and cost variables and generalized variables for convenience, reliability, and perceived time. The relationship between the explanatory variables and the probability of choosing one mode over another was postulated to be a logit function. The mathematical expression for this function is

$$P_1 = \frac{e^{G(x)}}{1 + e^{G(x)}} \tag{4}$$

where

P_1 = the probability of an individual selecting travel mode 1 and
$G(x)$ = a linear combination of the comparative attribute levels for the competing modes.

The models were calibrated by deriving a set of coefficients that, when multiplied by the values of the explanatory variables, generated the best fit of the observed data to the logit curve. The calibration was performed by using an iterative procedure with a maximum likelihood of fit criterion.

Twelve binary mode choice models were constructed by using the Boston data. The computer program that carried out the calibration procedure also generated several goodness-of-fit statistics. These statistics included a likelihood ratio test, a pseudo R^2 statistic, a correlation ratio, and an F-statistic for the correlation ratio. The goodness-of-fit statistics are discussed in a number of references (9, 11). In addition t-scores were computed for each of the estimated coefficients. Tables 1 and 2 give the results of the model building.

Based on their likelihood ratios and F-statistics, all 12 models were found to be statistically significant at a 99 percent confidence level. Subsequent comparisons

Table 1. Model coefficients.

Model	Constant	Travel Cost	Travel Time	Generalized Convenience	Generalized Reliability	Perceived Time
1	-1.0834	1.5951	-0.0058[a]			
2	0.5059[a]	1.4052	-0.0472	-1.1901		
3	-1.0496	1.3560	-0.0306[a]		-1.2078	
4	0.0233[a]	1.4057				-0.8992
5	0.6565[a]	1.2281		-0.8436		-0.1544[a]
6	-0.1688[a]	1.1864			-0.9745	-0.2619[a]
7	0.5887[a]	1.2217		-0.7783	-0.8733	-0.1491[a]
8	0.8414[a]	1.2474		-0.8030	-0.8986	
9	0.0156[a]	1.4503	-0.0205[a]	-0.6174		
10	0.5166[a]	1.4752	-0.0493	-1.1698		
11	0.4217[a]	1.4201	-0.0429	-1.0388		
12	0.5624[a]	1.4611	-0.0503	-1.1880		

[a]Not significant at the 95 percent confidence level.

Table 2. Model statistics.

Model	Included Variables	Likelihood Ratio	Pseudo R^2	Correlation Ratio	F-Value
1	Cost, time	48.6768	0.4221	0.3784	7.981
2	Cost, time, convenience	91.8166	0.6831	0.6036	19.969
3	Cost, time, reliability	80.3038	0.6218	0.5460	15.767
4	Cost, perceived time	56.9694	0.4793	0.4412	10.353
5	Cost, convenience, perceived time	80.5779	0.6233	0.5824	18.288
6	Cost, reliability, perceived time	76.3983	0.5997	0.5243	14.450
7	Cost, convenience, reliability, perceived time	80.6165	0.6235	0.5818	18.239
8	Cost, convenience, reliability	82.7171	0.6351	0.5955	19.302
9	Convenience stratified by sex	68.6573	0.5539	0.5699	17.372
10	Convenience stratified by age	93.2409	0.6903	0.6174	21.156
11	Convenience stratified by income	88.1381	0.6641	0.6028	19.036
12	Convenience stratified by family life cycle	94.0771	0.6945	0.6314	22.455

were therefore made on the basis of differences in the pseudo R^2 statistics and correlation ratios and on the t-scores of the estimated coefficients.

Travel cost differences were found to be statistically significant at a 95 percent confidence level in each of the models. The value of the cost coefficient also remained fairly stable, indicating that travel cost was relatively independent of the other variables included.

The coefficients of the travel time variable based on reported time differences were found to be insignificant at a 95 percent confidence level for three of the seven models in which the variable appeared. In the other four models, the coefficients were significant but had the wrong sign, indicating a preference for the slower mode. A subsequent check of the data confirmed this; within the Boston sample, more individuals chose the mode that they said was slower. This paradox was dismissed as an aberration caused by the small sample size and the relatively small differences in travel time between the competing modes. It does, however, lend support to LeBoulanger's argument (5) that attributes are not perceived in terms of absolute differences but rather in terms of some difference in satisfaction for the alternatives.

When travel time differences were replaced by the generalized time variable, the coefficients were found to be insignificant at a 95 percent confidence level whenever the variable was used in combination with another generalized variable. The generalized convenience and reliability variables, on the other hand, were both significant at a 95 percent confidence level when used together in the same model. In fact, these two variables were statistically significant for every model in which they appeared.

Models that included the generalized convenience or reliability variable were found to have significantly better goodness-of-fit statistics than models that omitted them. Furthermore, models using the generalized convenience variable consistently had better goodness-of-fit statistics than models using the generalized reliability variable or a combination of convenience and reliability. Model 4, which substituted the generalized time variable for reported travel time differences, had a significantly better fit than the strictly quantitative model 1; but, whenever generalized time was included with another generalized attribute variable, the models had poorer fits than comparable models using travel time differences. These results seem to indicate that, although the addition of a single generalized attribute variable can significantly improve the goodness of fit of strictly quantitative models, the creation of separate attribute variables from the same sensitivity scale worsens rather than improves the model.

Three of the four models that used a generalized convenience variable developed from socioeconomically stratified importance scales were found to be not significantly different from model 2 in terms of goodness of fit. Model 9, however, which used sex as the socioeconomic parameter, was found to be inferior to the other four models in terms of goodness of fit.

Prediction Capabilities of the Models

Models 1 through 8 were evaluated in terms of their abilities to estimate modal splits for the Chicago sample. Satisfaction ratings for each Chicago respondent were weighted by the sensitivity coefficients computed for the Boston sample to form appropriate generalized attribute variables. These variables, together with Chicago time and cost data, were used as input to the models.

The output of a binary disaggregate mode choice model is the probability of an individual choosing one travel mode over another. The expected number of public transit users in the Chicago sample was therefore computed as the sum of the probabilities for all individuals in the sample. Table 3 gives the expected number of transit users predicted by each of the models, together with the discrepancies between the observed and predicted values. The results of this analysis were generally encouraging. Only model 8 predicted a modal split that was significantly different from the observed split at a 95 percent confidence level. On the other hand, there was no significant improvement in the predictive ability of those models that included the generalized convenience or reliability variables. In fact, models using a generalized variable tended to overestimate transit patronage while the strictly quantitative model underestimated transit patronage.

CONCLUSIONS AND FUTURE RESEARCH NEEDS

The major objective of this research was to determine the feasibility of using a generalized attribute variable in models of travel demand behavior. The improvement made in the goodness of fit with these models was clearly demonstrated by the calibration results given in Tables 1 and 2. However, the contribution of the generalized attribute variable to the development of improved predictive or planning models is less obvious. Data given in Table 3 indicate that models that included the generalized variables did no better than the strictly quantitative models in estimating modal splits for another data set. On the other hand, the generalized attribute variable does introduce at least one additional transportation service parameter that can be manipulated. It therefore provides a mechanism for examining the potential impacts of policy decisions that do not directly influence travel time or costs. From this standpoint, the models can be viewed as significant improvements over strictly quantitative models.

The research also points out several problem areas that need to be investigated before the generalized attribute variable can be fully utilized as a transportation planning tool.

First, more research is needed to understand the influence of socioeconomic parameters on individual attitudes and sensitivities to transportation stimuli. This study has shown that some correlation may exist between attitudes and certain socioeconomic variables, but the small sample size prohibited any detailed investigation of these phenomena.

Second, the feasibility of including more than one generalized attribute variable in the same model needs to be investigated. It has been shown that multiple variables

Table 3. Modal-split estimates for Chicago data.

Model	Included Variables	Predicted Transit Users	Observed Versus Predicted[a] (%)
1	Cost, time	94	-4.08
2	Cost, time, convenience	107	+9.18
3	Cost, time, reliability	106	+8.16
4	Cost, perceived time	98	0.00
5	Cost, convenience, perceived time	97	-1.02
6	Cost, reliability, perceived time	106	+8.16
7	Cost, convenience, reliability, perceived time	106	+8.16
8	Cost, convenience, reliability	113	+15.31

[a]There were 98 transit users observed in the Chicago sample. Discrepancy measures represent the difference between the predicted transit users and 98, divided by 98.

constructed from the same sensitivity scale tend to decrease the goodness of fit of the model from that of a single generalized attribute variable. However, no work has been done on the behavior of generalized attribute variables constructed from separate unidimensional scales. Nicolaidis (6) has proposed a generalized variable based on multidimensional scaling techniques. Additional research in this area is needed to determine whether independent generalized attribute variables can be identified as orthogonal dimensions in a multidimensional space.

One final problem, which was not addressed explicitly in the research, is the relationship between individual satisfactions with various stimuli and the physical parameters of the transportation system on which those satisfactions are based. Clearly, if the generalized attribute variable is to be used in a planning context, transportation planners must be able to identify the impacts of a particular policy change on the comparative levels of satisfaction trip makers have for their travel alternatives.

Much of the research described can be accomplished with methodologies already available in the field of quantitative psychology. Thus, a great potential exists for simultaneously advancing the state of the art in psychological scaling and solving problems of current and significant interest to transportation planners.

ACKNOWLEDGMENTS

The author expresses his appreciation to Arnim H. Meyburg and Richard E. Schuler for their help in completing this research. Special thanks go to Peter R. Stopher, who served as chairman of the author's thesis committee.

REFERENCES

1. P. J. Claffey. User Criteria for Rapid Transit Planning. Journal of Urban Planning and Development Division, ASCE, Sept. 1964.
2. A. L. Edwards. Techniques of Attitude Scale Construction. Appleton-Century-Crofts, Inc., New York, 1957.
3. T. F. Golob, E. T. Canty, R. L. Gustafson, and J. E. Vitt. An Analysis of Consumer Preferences for a Public Transportation System. Transportation Research, Vol. 6, No. 1, March 1972, pp. 81-102.
4. C. A. Lave. A Behavioral Approach to Modal Split Forecasting. Transportation Research, Vol. 3, No. 4, Dec. 1969, pp. 463-480.
5. H. LeBoulanger. Research Into the Urban Traveler's Behavior. Transportation Research, Vol. 5, No. 2, June 1971, pp. 113-122.
6. G. C. Nicolaidis. Quantification of the Comfort Variable. Transportation Research, Vol. 9, No. 1, Jan. 1975, pp. 55-66.
7. F. T. Paine, A. N. Nash, S. J. Hille, and G. A. Brunner. Consumer Attitudes Toward Auto vs. Public Transport Alternatives. Journal of Applied Psychology, Vol. 53, No. 6, 1969, pp. 472-480.
8. M. J. Rosenberg. Cognitive Structure and Attitudinal Affect. Journal of Abnormal and Social Psychology, Vol. 53, 1956, pp. 367-372.
9. B. D. Spear. The Development of a Generalized Convenience Variable for Models of Mode Choice. Cornell Univ., Ithaca, N.Y., PhD dissertation, 1974.
10. P. R. Stopher. Choice of Mode of Travel for the Journey to Work. University College, London, PhD thesis, 1967.
11. P. O. Sucher. An Intra-City Study of a Proxy Variable for Convenience. Cornell Univ., Ithaca, N.Y., masters thesis, 1973.
12. L. L. Thurstone. A Law of Comparative Judgement. Psychological Review, Vol. 34, 1927, pp. 278-286.
13. W. S. Torgerson. Theory and Methods of Scaling. John Wiley and Sons, New York, 1958.
14. P. L. Watson. The Value of Time. Lexington Books, Lexington, Mass., 1974.

Perception of the Availability of Transportation Alternatives for Various Trip Purposes

Timothy J. Tardiff, University of California, Davis

Mode choice models require five decisions concerning model structure. These are the selection of (a) a statistical technique, (b) the method of comparing the characteristics of competing modes, (c) the method of representing socioeconomic variables, (d) objective or subjective measures of times and costs, and (e) objective or subjective criteria for separating those who choose among modes from those who are captive to a mode. The purpose of this paper is to examine the implications of the subjective approach to separating choosers from captives. To do this, various models that distinguish choosers from captives are developed. The data were obtained from a stratified probability sample of 223 households from the Santa Monica-west Los Angeles, California, area. Variables distinguishing choosers from captives for the work trip and the most frequent nonwork trip as well as personal and locational descriptors of the individual and information on the characteristics of the competing modes were available. Logit analysis was used to test the alternative models, and the conclusion reached was that models containing specific information about the characteristics of the competing modes were superior to models containing only locational and personal information on individuals. The implications of this finding in terms of predicting modal split, understanding transportation behavior, and transportation policy are noted.

Recent disaggregate models of mode choice have been based on common concepts. They key hypothesis governing most of these models is that people trade off time saving for increased costs, or vice versa, if necessary when they select a mode of travel for a particular trip (5, 7, 12, 14, 15). Because this choice is assumed to be made among a finite set of alternatives, appropriate statistical techniques for choice problems have been devised and used.

Several research approaches have been used in specific studies. This paper considers these approaches by answering five basic questions that distinguish existing mode choice models. The answer to the fifth question is considered in detail and is the key part of this paper. The other four questions are useful background for the key question.

RESEARCH QUESTIONS IN MODE CHOICE MODELING

Five questions dealing with alternative data analysis decisions are the basis of the formulation of a specific mode choice model. The first three of these have received extensive attention in the literature and are discussed briefly here. The fourth question is closely related to the main focus of the paper, the fifth question. These two issues form the background for the empirical work.

Questions 1 Through 3: The Structure of Choice Models

The first research question concerns the statistical technique used to calibrate the choice model. Although binary probit and discriminant analyses were used in early applications, the majority of recent studies have used binary and multinomial logit analysis.

The answer to question 2 results in a particular functional form for the comparison of the times and costs of competing modes. Although functional forms such as ratios and logarithms of ratios of competing times or costs have been used, a simple difference function has been used most extensively and has been shown empirically to yield results at least as good as the other two forms in binary situations (5, 12, 17). The difference function also appears to be the most appropriate for multinomial logit models.

The third question deals with the way in which variables describing individuals are represented in the model. The most common approach has been to add these variables as additional linear terms. This approach is consistent with the hypothesis that the trade-off mechanism involving time and cost is the same for all individuals. Two alternative approaches allow different trade-off functions for people with different characteristics. The first of these is to express the coefficient of the time or cost variable as a function of an individual descriptor, usually income (5, 10, 11). The alternative approach is to stratify the sample on the basis of the individual descriptors and calibrate a separate model for each stratum (3, 17). In this way, the coefficients of time and cost are allowed to vary for different individuals, which results in possibly different trade-off mechanisms.

Question 4: How to Measure the Characteristics of Competing Modes

The question on how characteristics of competing modes are measured has been addressed mainly with respect to time and cost. The two basic approaches are to measure time and cost objectively, i.e., through either some network model or replications of the actual trip, or subjectively, i.e., as reported by the trip makers. The issue of which approach is superior has not been resolved. Those advocating objective measures claim that this procedure is more appropriate for prediction purposes and for calculating real benefits in time savings from transportation improvements (1, 8); those advocating subjective measures claim that such procedures better represent the actual choice process and are better for calculating the value of time (4, 16). Determining systematic relationships between subjective and objective measures would be helpful in assessing the relative merits of the two approaches and in making the subjective models appropriate for prediction purposes. However, one recent study (13) indicated that the relationships between subjective and objective measures might not be straightforward.

Question 5: How to Separate Those Making a Choice Between Modes From Those Captive to a Mode

In most mode choice studies, the sample of those assumed to be making a choice has been smaller than the total sample of trip makers. In some situations, the reduction in sample size was considerable. The need to separate choosers from captives is based on the theoretical argument that only people actually making a choice should be included in a model representing a choice process. Further, some empirical studies (5, 9) have indicated that the separation of choosers from captives makes a difference in terms of the goodness of fit of the model.

In much the same way as in question 4, the two basic approaches to separating choosers from captives are to use either objective or subjective criteria. The objective approach, which has been used in most studies, is simply to specify as choosers those individuals meeting certain criteria, e.g., not needing the car for work, within a certain distance of a bus line, or car owners. The subjective approach is to define as choosers those people who perceive the existence of an alternative mode for the trip in question regardless of their objective characteristics.

Although the issue of objective versus subjective separation of choosers and captives has not been dealt with explicitly in the literature, the arguments justifying the alternative positions are analogous to those used in the time and cost issue. That is, the use of objective criteria facilitates the use of models for prediction because the choosers can be selected by using population distribution projections on the criteria. On the other hand, using those people who actually think they are choosing is more appropriate in terms of explaining behavior.

As in the case of the measurement of time and cost, the use of subjective selection of choosers and captives requires a procedure for relating this perception to objectively measured criteria if the models are to be used for practical predictive purposes. Lave (5) recognized this need and suggested that the techniques appropriate for mode choice modeling were appropriate for developing a model to distinguish those who perceive a choice from those who feel they are captive to a particular mode. Essentially, such a model views the decision of whether to be a chooser as a function of several independent variables.

Besides the question of developing a procedure for predictive purposes, the question of the perception of transportation alternatives has theoretical implications. It can be argued that the decision of whether to place oneself in a position in which alternatives are perceived is a more fundamental issue than the mode choice question because a person must perceive the existence of a choice before he or she will make one. In this sense, the decision of whether a choice of modes exists becomes one of the longer range transportation decisions such as automobile ownership (2, 6) or household location decisions.

This paper examines the issue of the perception of transportation alternatives by modeling the decision of whether one has a choice of modes. The issue of whether the subjective criterion is superior to objective criteria in separating choosers from captives is not directly addressed. Rather, the development of the model is useful in addressing some of the practical and theoretical issues implicit in the decision to use the subjective criterion.

Therefore, the models are primarily exploratory in nature. They illustrate the degree to which subjective choosers and captives can be distinguished by certain types of independent variables. In this way, it should be possible to determine whether this subjective categorization is systematically related to personal characteristics, location, and transportation-related variables or whether the perception is essentially random. A related question is whether the subjective criterion can be used for predictive purposes. Although the models developed in this study are not explicitly designed for predictive purposes, the quality and structure of such models should indicate the potential of similar models in this regard.

DEVELOPMENT OF THE MODEL

Data from a study of transportation attitudes and behavior (18) conducted in November-December 1973 were used in this study. A stratified probability sample of 223 households in the Santa Monica-west Los Angeles, California, area was selected. The size of the sample was based on the fact that, in a study using a random sample of this size, the probability of the mean response being within 6½ percent of the true mean for the entire population is 95 percent.

Alternative Model Structures

The variable indicating whether an individual perceives a choice of modes, the dependent variable in the models, is defined for both the work trip and the most frequent nonwork trip made by the respondent in the month preceding the interview. Because the only modes available to the people in the sample area are private automobile and bus, the dependent variable is defined to distinguish those who perceive the existence of a choice of modes from those who feel they are captive to a particular mode. This definition eliminates from the sample all respondents who either did not make the trip in question or used neither the car nor the bus. In addition, the heavy automobile orientation of the suburban Los Angeles sample area led to an extremely small number of people who perceived themselves as captive to the bus (three for the work trip and six for the most frequent nonwork trip). When these cases were eliminated, a dependent variable was left that distinguishes automobile captives from those who perceive the existence of a choice between the bus and the automobile. Finally, cases with missing data on the independent variables were eliminated, resulting in 104 cases for the work trip and 173 cases for the nonwork trip.

The dependent variable essentially divides the people making vehicle trips and having access to an automobile into those who consider the bus as a possible alternative to the automobile (or vice versa) and those who feel the automobile is the only viable mode. These two groups cover the great majority of individuals making vehicle trips in the sample area. However, the conclusions of this study may not be applicable in an area where there are a substantial number of bus captives.

The independent variables were structured into sets that yield models consistent with alternative hypotheses about the nature of the decision of whether to perceive the existence of alternative modes. The first set, which is consistent with the hypotheses that the perception of alternatives is a longer range decision than the choice of modes, uses variables that are independent of the characteristics of the available modes. In particular, variables that describe the individual and his location are included. These are the respondent's age (AGE) and sex (SEX), the ratio of automobiles in the respondent's household to licensed drivers (C/DL)—the best indicator of socioeconomic status (best in the sense of yielding the best fitting model), the perceived distance of the trip (TDIS) in kilometers, and the distance of the respondent's home to the closest bus line (BDIS) in blocks. SEX is given on a scale of 1 for males and 2 for females. Income (INC) given for the work trip, the respondent's occupation (OCC) given for the most frequent nonwork trip, and AGE are measured on seven-point scales. The scale values for each of these variables are given in Table 1.

The second and third sets of independent variables are both designed so that specific features of the modes used in making the trip can be included. In this way, the assumption that the perception of a choice situation is independent of and made prior to the actual choice of modes is relaxed. Therefore, acceptance of one of these models instead of the model using the first set of independent variables might suggest a simultaneous structure rather than a recursive structure for the perception and choice decisions. Although theoretically a simultaneous perception of choice and mode choice model could be developed, data limitations preclude the calibration of such a model here. However, rejection of the models involving the first set of independent variables would indicate that a simultaneous model might be worthy of future exploration with an appropriate data source. In practical terms, models developed from the second and third sets would be more difficult to apply because of the additional information on the specific trips in question.

The second and third sets of independent variables substitute information about the actual trip for some of the locational descriptors. Aside from AGE, SEX, C/DL, and TDIS, the second set uses travel time (TIME) in minutes on the actual mode used. The third set uses the three former variables and the actual cost of the trip (COST) in cents and excludes TDIS. Neither set 2 nor set 3 uses BDIS. Both TIME and COST are subjectively measured.

The fourth set yields further information about the extent to which specific data about the competing modes are related to the perception of whether a choice of modes exists. Because the models based on set 4 are designed as an extension of the hypothesis underlying the models using sets 2 or 3, set 4 includes variables from set 2 or set 3, whichever has the better statistical fit, and a variable measuring the overall comparative satisfaction of the two competing modes (CSAT). The attitudinal variable is the weighted sum of the differences in perceived satisfaction with the bus and automobile modes with respect to cost, convenience, reliability, comfort, safety, travel time, privacy, and reduction of smog. The weights in each case are the importance scores. Both importance and satisfaction scores are measured on five-point scales. In the former case, 1 equals very unimportant and 5 equals very important. In the latter case, 1 equals very unsatisfactory and 5 equals very satisfactory.

In summary, the empirical tests are the development of alternative binary logit models of the decision of whether a choice between modes is perceived. Symbolically, the models are of the following form:

$$P(\text{chooser}) = \exp L(X)/[1 + \exp L(X)] \quad (1)$$

where L(X) is a linear function of the variables of one of the alternative sets of independent variables.

Results

The alternative models for the work trip and most frequent nonwork trip are given in Table 2. The four logit equations corresponding to the four alternative sets of independent variables are given.

The conclusion apparent from the tests of the alternative models for the work trip is that none of the models that do not include the attitudinal variable explains the data very satisfactorily. In addition, of the three models tested, the one that includes perceived trip time for the chosen mode and the trip distance appears to be the best. For this model, the trip distance variable was statistically significant in a negative direction, and the time variable was close to being significant at the 0.05 level in a positive direction. Among the other independent variables, the direction of the relationships was such that the choosers tend to be (a) those who have fewer travel resources (cars and income), (b) women, and (c) younger people.

The directions of the relationships involving the trip distance variable and the travel time variable are interesting. Those who make longer work trips are less likely to perceive the existence of a choice situation, but, for a given trip distance, those who spend more time in travel are more likely to be choosers. In other words, although the automobile tends to be perceived as the only available mode for longer trips, as the time required for those trips increases, the likelihood of transit being a viable alternative also increases.

The final test involving the work trip was the addition of the attitudinal variable measuring the comparative satisfaction of the competing modes to the variables in the second set, which yielded a model superior to that of the third set in the previous test.

The addition of the attitudinal variable considerably improved the model. This variable was easily the most important. As expected, the variable was such that, as an individual perceived the bus as relatively more satisfactory, he was more likely to be a chooser. The addition generally leaves the relative importance of the remaining variables similar to that of the corresponding model that does not include the attitudinal variable.

The results of the tests of alternative models for the work trip indicate that information about the modes available for the trip, i.e., travel time and perception of the attributes of the competing modes, yields a better model than locational and personal descriptors of individuals. That is, the perception of the availability of a choice of modes is related to the quality of the available modes. A practical implication is that successful prediction of the choosers for a mode choice model using the subjective criterion to separate choosers from captives would require some fairly specific information about the available modes.

The results of the tests of the alternative models explaining the difference between choosers and captives for the most frequent nonwork trip were in many ways similar to those for the work trip. Again, the second set of independent variables yielded the best fitting model of those not including the attitudinal variable. Also, the structures of the nonwork trip models were similar to those of the corresponding work trip models. Specifically, forthe model using TDIS and TIME, the relationships involving these variables were both strongly significant and in the same direction as in the case of the work trip model.

There were a number of important differences between the work trip models and the corresponding nonworktrip models, however. First, all of the nonwork trip models that did not contain the attitudinal variable were statistically stronger than the corresponding work trip models. Second, although women were more likely to be choosers in the work trip models, for all nonwork trip models men were more likely to be choosers (statistically significant). Perhaps this finding reflects household priorities on automobile availability for particular trips. The final difference was that the attitudinal variable was of much less importance for the nonwork trip model. The nonwork trip model containing this variable was actually statistically weaker than the corresponding work trip model. Further, when the nonwork trip model using this variable was compared to the model using the second set of independent variables, the amount of improvement was small.

The major conclusion for the case of the most frequent nonwork trip is, not surprisingly, similar to the earlier conclusion for the work trip models. Although the information on the perception of modal attributes proved to be of less importance, specific information on the available modes, especially the travel time, resulted in an improvement in model performance.

Table 1. Scale values of age and socioeconomic variables.

Scale Value	AGE (years)	INC ($)	OCC
1	18 to 24	Under 4000	Higher executives of larger concerns, proprietors, major professionals
2	25 to 34	4000 to 7999	Business managers, proprietors of medium-sized businesses, lesser professionals
3	35 to 44	8000 to 11 999	Administrative personnel, owners of small businesses, minor professionals
4	45 to 54	12 000 to 14 999	Clerical and sales workers, technicians, owners of smaller businesses
5	55 to 64	15 000 to 24 999	Skilled manual workers
6	65 to 74	25 000 to 49 999	Machine operators and semi-skilled manual workers
7	75 and older	50 000 and more	Unskilled manual workers

CONCLUSION

This paper explores the implications of one of the decisions necessary to the development of specific mode choice models: the question of the criteria for separating choosers from captives. The issue of how those who perceive the existence of a choice of mode for a trip are distinguished from those who feel they are captive to a mode is examined.

The key conclusion from the empirical tests is that models containing information on the modes perform better than models containing only locational or personal descriptions of the individuals. From this conclusion various implications concerning prediction, travel behavior, and transportation policy emerge.

Before these implications are discussed, however, it is useful to mention several alternative approaches that might be tried in future studies of this nature. Such approaches might lead to somewhat different conclusions and implications from those of this study.

The subjective information on trip making (trip distance, travel time, cost) could be replaced by the corresponding objectively measured variables. Such an approach might make some difference in model structure and would also facilitate the use of the models for practical purposes. The nature of the independent variables used in the models could also be altered. Specifically, more information on the conceivably available alternatives could be used in place of information on only the chosen alternative. (The latter strategy was chosen here because only those who perceive the existence of a given alternative reported on its characteristics.) Information on all of the alternative modes could be used

Table 2. Models to distinguish choosers from captives for both work trip and most frequent nonwork trip.

		Equation 1		Equation 2		Equation 3		Equation 4	
Trip	Variable	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Work	Constant	0.51	1.20	-0.038	1.20	-0.11	1.16	0.050	1.29
	AGE	-0.027	0.15	-0.11	0.16	-0.024	0.15	-0.036	0.18
	SEX	0.47	0.44	0.41	0.45	0.56	0.43	0.75	0.50
	C/DL	-0.29	0.66	-0.31	0.67	-0.18	0.66	-0.38	0.76
	INC	-0.14	0.15	-0.063	0.16	-0.14	0.15	-0.017	0.17
	TDIS	-0.058[a]	0.028	-0.12[a]	0.047			-0.11[a]	0.047
	BDIS	-0.068	0.18						
	TIME			0.047	0.026	-0.0036	0.016	0.056[a]	0.028
	COST					-0.0025	0.0040		
	CSAT							0.032[b]	0.0094
	ρ^2	0.06		0.09		0.03		0.20	
Nonwork	Constant	0.89	0.89	-0.23	0.97	0.11	0.96	0.10	1.02
	AGE	-0.033	0.11	-0.046	0.11	-0.058	0.11	-0.049	0.11
	SEX	-1.11[b]	0.39	-1.11[b]	0.42	-1.07[b]	0.41	-1.09[b]	0.42
	C/DL	-0.75	0.47	-0.44	0.52	-0.46	0.50	-0.42	0.51
	OCC	0.25[a]	0.10	0.23[a]	0.11	0.21	0.11	0.21	0.11
	TDIS	-0.016	0.019	-0.12[b]	0.039			-0.12[b]	0.040
	BDIS	-0.12	0.16						
	TIME			0.073[b]	0.022	0.056[b]	0.017	0.070[b]	0.023
	COST					-0.016[a]	0.0061		
	CSAT							0.0062	0.0062
	ρ^2	0.07		0.143		0.139		0.15	

Note: For work trip models, N = 104 (46 choosers and 58 captives). For nonwork trip model, N = 173 (53 choosers and 120 captives).

[a] Logit coefficient significant at $p < 0.05$. [b] Logit coefficient significant at $p < 0.01$.

to form generalized prices or other accessibility measures in the binary case or could be disaggregated in the case of a multinomial model that distinguishes among various types of choosers and captives.

In terms of predicting which people will be choosers or captives and, ultimately, modal split, the results do not imply whether using the subjective criterion of separating choosers from captives is more satisfactory than using objective criteria. This issue was not addressed directly. However, given the fact that specific information about the modes in question appears to be desirable in the models examined here, using objective criteria may be simpler and more straightforward for practical purposes. This depends on the accuracy of the objective criteria in specifying that those who are assumed to be modal captives actually use that mode and on the accuracy of the corresponding choice model. The suggestion also is more applicable to the case of the work trip because of the greater importance of the attitudinal variable and the rather poor fit of the models not including this variable.

The important feature of the results in terms of explaining travel behavior is the apparent dependence of the perception of the availability of transportation alternatives on specific features of the trip-making experience. This dependence suggests that the decision to be a chooser or a captive might be a short-range rather than long-range transportation decision. It also leaves open the possibility that mode choice and the perception of the availability of alternatives occur simultaneously. In any event, the fact that whether a person is a chooser depends on his trip-making behavior is of theoretical, and possibly practical, importance.

Finally, the results are of possible importance to transportation policy makers. If one assumes that an alternative must be perceived to be available before it is used or even if one assumes that a transportation mode is valuable to citizens because of its option demand when it is perceived to be available for a given trip, as many economists might, knowledge of the factors that affect the perception of the availability of particular modes might be useful. In this regard, the positive relationship between being a chooser and travel time, as well as the positive relationship between the variables measuring the comparative satisfaction of the bus and car modes, is of primary interest. In terms of a policy maker who is interested in increasing the number of people who at least consider using some form of public transportation, a strategy of making the automobile relatively slower and of improving the attributes of the transit system relative to those of the automobile would appear to be effective.

ACKNOWLEDGMENTS

The data used in this paper were collected in a research project supported by funds from National Science Foundation grant for improving doctoral dissertation research in the social sciences. The data analysis was performed on the ULOGIT computer program, which was written by Daniel McFadden of the University of California, Berkeley.

REFERENCES

1. M. Ben-Akiva. Alternative Travel Behavior Structures: Structure of Passenger Travel Demand Models. TRB, Transportation Research Record 526, 1974, pp. 59-64.
2. L. D. Burns, T. F. Golob, and G. C. Nicolaidis. Theory of Urban-Household Automobile-Ownership Decisions. TRB, Transportation Research Record 569, 1976.
3. D. P. Costantino, R. Dobson, and E. T. Canty. An Investigation of Modal Choice for Dual Mode Transit, People Mover, and Personal Rapid Transit Systems. TRB, Special Rept. 170, in preparation.
4. J. Guttman. Avoiding Specification Errors in Estimating the Value of Time. Transportation, Vol. 4, No. 1, March 1975, pp. 19-42.
5. C. A. Lave. Modal Choice in Urban Transportation: A Behavioral Approach. Department of Economics, Stanford Univ., PhD dissertation, 1968.
6. S. R. Lerman and M. Ben-Akiva. Disaggregate Behavioral Model of Automobile Ownership. TRB, Transportation Research Record 569, 1976.
7. T. E. Lisco. The Value of Commuters' Travel Time: A Study in Urban Transportation. Department of Economics, Univ. of Chicago, PhD dissertation, 1967.
8. T. E. Lisco. Common Economics of Travel Time Value. TRB, Special Rept. 149, 1974, pp. 103-115.
9. C. H. Lovelock. Consumer Oriented Approaches to Marketing Urban Transit. Urban Mass Transportation Administration, University Research and Training Grant CA-11-0008, Research Rept. 3, 1973.
10. D. McFadden. The Measurement of Urban Travel Demand. Journal of Public Economics, Vol. 3, No. 4, Nov. 1974, pp. 303-328.
11. D. McFadden and F. Reid. Aggregate Travel Demand Forecasting From Disaggregated Behavioral Models. TRB, Transportation Research Record 534, 1975, pp. 24-37.
12. D. A. Quarmby. Choice of Travel Mode for the Journey to Work: Some Findings. Journal of Transport Economics and Policy, Vol. 1, No. 3, 1967, pp. 1-42.
13. S. Reichman. Subjective Time Savings in Interurban Travel: An Empirical Study. HRB, Highway Research Record 446, 1973, pp. 21-27.
14. S. Reichman and P. R. Stopher. Disaggregate Stochastic Models of Travel-Mode Choice. HRB, Highway Research Record 369, 1971, pp. 91-103.
15. P. R. Stopher. Factors Affecting Choice of Mode of Transport. University College, London, PhD dissertation, 1967.
16. P. R. Stopher. Discussion of paper, Alternative Travel Behavior Structures. TRB, Transportation Research Record 526, 1974, pp. 56-57.
17. P. R. Stopher and J. O. Lavender. Disaggregate Behavioral Travel Demand Models: Empirical Tests of Three Hypotheses. Transportation Research Forum, Vol. 13, 1972, pp. 321-335.
18. T. J. Tardiff. The Effects of Socioeconomic Status on Transportation Attitudes and Behavior. School of Social Sciences, Univ. of California, Irvine, PhD dissertation, 1974.

Methodology for Analyzing Errors in Prediction With Disaggregate Choice Models

Frank S. Koppelman, Transportation Center, Northwestern University

Predictions of future travel behavior and of the performance of alternative transportation systems are needed by transportation planners and decision makers to determine the desirability of alternative transportation plans. The usefulness of predictions, and consequently of prediction methods, depends on their accuracy. This paper presents a methodology for analyzing errors in prediction with disaggregate choice models. The paper describes the process by which disaggregate choice models are formulated and used for prediction. The sources of error in the model formulation and prediction process are identified. The interaction and propagation of these errors to the final prediction are analyzed. A set of error measures is proposed for evaluating the performance of alternative prediction models. A strategy is developed for analyzing the source of different components of the total error. An empirical analysis of errors in the prediction of mode choice to work illustrates the use of this approach for evaluating the accuracy of a set of prediction models, identifying major sources of error in prediction, and suggesting steps that can be taken to improve these prediction models.

Transportation planners and decision makers use predictions of expected travel behavior and transportation system performance to evaluate alternative transportation plans. The usefulness of predictions depends directly on their accuracy. Thus, an appropriate measure of the quality of prediction methods is the expected magnitude of errors in predictions that they produce. This paper identifies the primary sources of error in the travel demand prediction process, describes the way in which these errors contribute to total error in prediction, proposes a set of measures for evaluating the expected error of alternative prediction procedures, and describes a strategy to identify the portion of total error attributable to different model components.

MODEL FORMULATION AND PREDICTION PROCESS

Predictions of future travel behavior are based on hypotheses about the factors that influence travel behavior and the structure of those influences. Possible hypotheses range from simple "no change" and time trend predictions to relationships that describe the causal influence on travel behavior of changes in terms of socioeconomic and transportation service characteristics.

The model formulation and prediction process carries the hypotheses through the steps of model specification, data collection, estimation of model parameters, and prediction of future travel behavior. The model structure used to represent the travel behavior process in this paper is a disaggregate model of individual choice behavior (3, 10) that is explicitly aggregated (7) to obtain group predictions.

The aggregated prediction model consists of three components:

1. Disaggregate choice model,
2. Representation of the distribution of explanatory variables, and
3. Aggregation procedure that operates on the two other components to obtain the required aggregate prediction.

The disaggregate choice model relates the probability of choosing one out of a set of available alternatives to the estimated utility of each alternative for the individual decision maker. The utility of an alternative is defined in terms of the characteristics of the decision maker and the attributes of the alternative. The choice model may assume a variety of functional forms that are derived from the underlying assumptions about the individual's choice process (3).

The distribution of independent variables describes the presence in the aggregate prediction group of individuals with different socioeconomic characteristics or with access to different transportation service characteristics. That is, the distribution represents the frequency of occurrence in the prediction group of different values of the socioeconomic and travel service variables that influence individual travel choice decisions.

The aggregation procedure operates on the disaggregate choice model and the distribution of independent variables to produce aggregate predictions. The theoretically consistent aggregation procedure determines the share of the prediction group expected to choose an alternative by averaging choice probabilities for all individuals in the prediction group. Because this approach requires that the explanatory variables of each individual in the prediction group be predicted, a variety of alternative procedures with less extensive input data requirements have been proposed. These include the following (7):

1. Enumeration procedures that estimate expected shares by averaging the choice probabilities for a sample of the prediction group,
2. Summation-integration procedures that weight disaggregate choice probability estimates for different values of explanatory variables by the frequency of occurrence of these variables in the prediction group,
3. Statistical differentials that predict aggregate shares in terms of the moments of the distribution of explanatory variables,
4. Classification procedures that predict the expected choice shares for individual classes by using average values of variables for each class and that determine overall choice shares as a weighted average of the individual class choice shares, and
5. Naive procedures that predict the expected choice share by using average variable values for the entire prediction group.

The model formulation and prediction process describes the development and use of the aggregated prediction model. The steps in this process, shown in Figure 1, are described below.

1. Specification of disaggregate travel choice mode is based on the hypothesis that travel behavior represents an individual's choice response to the stimulus of a set of available alternatives (2, 3). The specification includes selection of a functional form of the model and selection of variables to be included.
2. Collection of data on individual choice behavior includes the characteristics of the individual, the choices available, and the alternative selected by the individual. The data collected are determined by the variables included in the model specification. However, cost or other constraints of data collection may require modification, verification, and estimation.
3. The distribution of influence variables that choice is separately predicted or determined by policy selection to represent the characteristics of the prediction group and the alternatives available to them.
4. The aggregation procedure applies the choice model to demographic and transportation service characteristics to predict aggregate travel behavior.

SOURCES OF ERROR IN AGGREGATE PREDICTION

Errors are introduced in each stage of the model formulation and prediction process (Figure 1). These errors are associated with the three major components of the aggregated prediction model structure.

Errors in the disaggregate choice model are the result of misspecification of the utility function and errors in the measurement of the independent variables. Manski (9) classifies these errors into four categories:

1. Omitted structure—variables that should have been included in the utility function are excluded;
2. Cross-sectional preference variation—members of the sample group on which the choice function is calibrated have different parameters in their utility function;
3. Instrumental variables—variables that should be included in the utility function have been replaced by other variables; and
4. Imperfect information—the reported value of a variable is incorrect.

Errors caused by applying a model calibrated on one data set (collected in one area during one time period) to a data set for a different time or place are specification errors. These errors of transferability are due to either omitted structure or cross-sectional preference variations. Transferability is an important characteristic of disaggregate models. Transferability depends on how well the relevant utility functions are specified and the quality of the data used. Atherton and Ben-Akiva (1) showed that a work trip mode choice model calibrated with Washington, D.C., data was not significantly different from a similar model calibrated with data collected in New Bedford, Massachusetts, and San Francisco.

Errors in the predicted distribution of independent variables are due to similar errors in specification and calibration of the models used to predict these distributions. These errors may also include random errors and bias errors. For the purpose of this paper, the models used to predict these distributions are considered to be independent of the travel modeling process. That is, the predictions of explanatory variables contain errors that are outside the control of the transportation analyst.

Errors in aggregation result from the use of approximate aggregation procedures to replace the theoretically consistent but impractical complete enumeration procedure described earlier. Errors in aggregation are deterministic. The errors introduced by approximate aggregate procedures are structural errors that cause bias in the predictions obtained.

INTERACTION AND PROPAGATION OF ERRORS TO AGGREGATE PREDICTION

Errors in the choice model and errors in variables interact to produce errors in the prediction of individual choice probabilities. These errors are propagated through the aggregation procedure to produce errors in aggregate prediction. The aggregation procedure also introduces error directly into the aggregate prediction (Figure 2).

The interaction and propagation of errors in estimated choice model parameters and predicted variables are determined by the formulation of the choice model and the aggregation procedures. This process is described for the binary choice logit model. Koppelman (8) presents a general analysis of error propagation for the general multiple-choice model structure. The binary logit choice model is represented by

$$P_t = \frac{\exp X_t'b}{1 + \exp X_t'b} \tag{1}$$

where

P_t = probability of individual t choosing an alternative and
$X_t'b$ = net utility of one alternative over the other as a linear additive function of variables X_t weighted by choice model parameters b.

Error propagation goes from the errors in model parameters to the error in individual choice probabilities. This propagation of random errors may be expressed approximately (5, 12) by

$$EV(P_t) = [P_t(1 - P_t)]^2 \, (X_t' \, A \, X_t + b \, Y_t b') \tag{2}$$

where

$EV(P_t)$ = error variance in the probability estimate for individual t,
A = variance-covariance matrix for errors in parameters, and
Y_t = variance-covariance matrix for errors in variables for individual t.

Error variances in predicted choice probabilities for pairs of individuals are correlated inasmuch as they have common errors in parameters (due to use of the same choice model) and may have correlated error in the prediction of variables due to use of a common prediction process. This relationship can be expressed in terms of the error covariance between pairs of predictions:

$$EC(P_t, P_{t'}) = [P_t(1 - P_t)]\ [P_{t'}(1 - P_t)]\ (X_t' A X_{t'} + bY_{tt'}b') \qquad (3)$$

where

$EC(P_t, P_{t'})$ = error convariance in the probability estimate for individuals t and t′ and
$Y_{tt'}$ = covariance matrix for measurement errors in variables for individuals t and t′.

This information is used to estimate the error variance in share prediction due to errors in parameters and variables for the complete enumeration and naive procedures. The share prediction by the complete enumeration procedure is

Figure 1. Model formulation and prediction with aggregated disaggregate model.

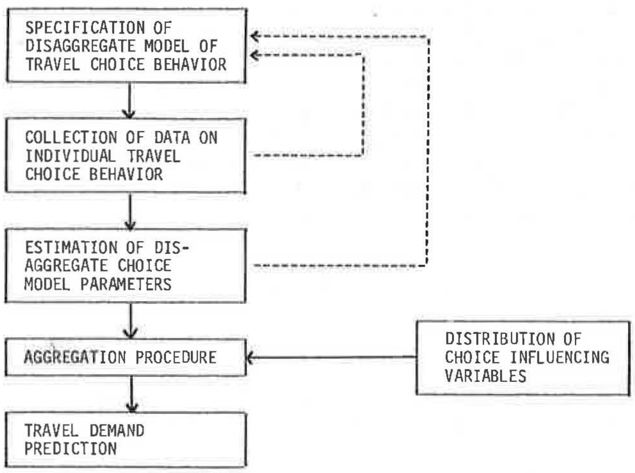


Figure 2. Interaction and propagation of error to aggregate predictions.

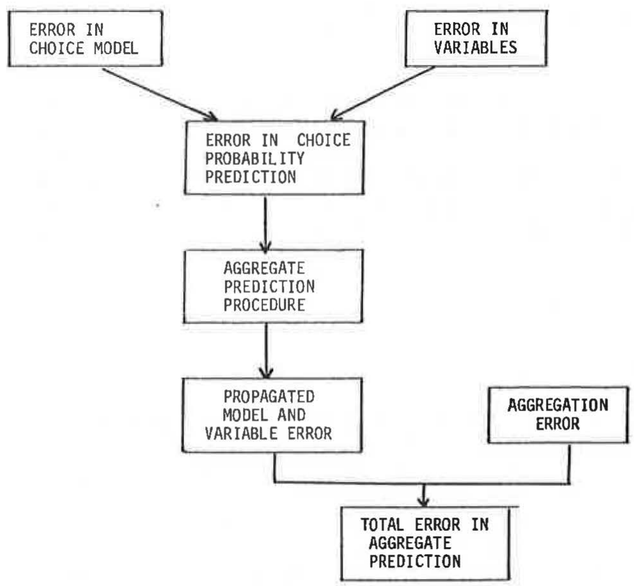


Table 1. Model specification estimation.

Variable	Symbol	Estimated Coefficient	Standard Error
1. Drive alone dummy	D_4	-2.62	0.36
2. Shared ride dummy	D_s	-2.36	0.27
3. Automobiles per licensed driver (drive alone)	$AALD_4$	3.64	0.38
4. Automobiles per licensed driver (shared ride)	$AALD_s$	1.51	0.24
5. Out-of-vehicle cost/income	OPTC/INC	-0.028	0.012
6. Total travel time	TTT	-0.024	0.005
7. Out-of-vehicle time/distance	OVTT/DIST	-0.077	0.055
8. Government worker (shared ride)	GW_s	0.77	0.16
9. Number of workers in household (shared ride)	$NWORK_s$	0.24	0.10

Note: Based on 874 observations: 621 observations included all choice alternatives; 253 observations included only the shared ride and transit alternatives.

Table 2. Percentage of errors in prediction for calibration data set.

Prediction Procedure	Error Type	Error Category: Model	Aggregation	Combined
Enumeration	Average	0	0	0
	Standard deviation	15.9	0	15.9
	Root mean square	15.9	0	15.9
Naive	Average	0	6.2	6.2
	Standard deviation	15.9	4.7	16.6
	Root mean square	15.9	7.7	17.7
Classification	Average	0	1.3	1.3
	Standard deviation	15.9	3.0	16.2
	Root mean square	15.9	3.3	16.2

Table 3. Percentage of errors in prediction for alternative data set.

Prediction Procedure	Error Type	Error Category: Model	Nontransfer Model	Transfer Model	Aggregation	Combined
Enumeration	Average	13.0	0	13.0	0	13.0
	Standard deviation	20.6	16.8	11.9	0	20.6
	Root mean square	24.4	16.8	17.7	0	24.4
Naive	Average	13.0	0	13.0	6.9	14.7
	Standard deviation	20.6	16.8	11.9	4.6	21.1
	Root mean square	24.4	16.8	17.7	8.2	25.7
Classification	Average	13.0	0	13.0	1.4	13.1
	Standard deviation	20.6	16.8	11.9	3.2	20.9
	Root mean square	24.4	16.8	17.7	3.5	24.7

$$S = (1/T) \sum P_t \tag{4}$$

where

- S = aggregate share of the group choosing the alternative,
- T = number of members of the group, and
- $\sum_t$ = summation over all members of the group.

The error variance in the aggregate share prediction by complete enumeration is a function of the error variance in the estimates of individual choice probabilities and the error covariance of choice probabilities for each pair of individuals in the prediction group:

$$EV(S) = (1/T^2) \left[\sum_t EV(P_t) + \sum_t \sum_{t' \neq t} EC(P_t, P_{t'}) \right] \tag{5}$$

When individuals in the prediction group are relatively homogeneous with respect to variable values and error in variables, the error variance in aggregate shares may be expressed in terms of error variance in parameters, error variance in variables, and error covariance in variables for pairs of individuals by

$$EV(S) = [P(1 - P)]^2 \left\{ \overline{X}' A \overline{X} + (1/T) b \overline{Y}_t b' + [(T - 1)/T] b \overline{Y}_{tt'} b' \right\} \tag{6}$$

where

- P = probability estimate of the average individual in the prediction group,
- $\overline{X}$ = average variable vector for the prediction group,
- $\overline{Y}_t$ = error covariance in variables for a representative individual, and
- $\overline{Y}_{tt'}$ = error covariance in variables for a representative pair of individuals.

Equation 6 illustrates the way in which error variance in parameters, error variance for individual variables, and error covariance in variables for pairs of individuals effect error variance in share prediction. It also illustrates the effect of prediction group size on the relative importance of these different sources of error. The effect of errors in parameters is independent of group size: The effect of errors in variables decreases as group size increases. The effect of error covariance in variable estimates increases with increasing prediction group size.

The naive aggregation procedure is equivalent to using the individual choice model structure (equation 1) to estimate choice shares based on average variable values in the prediction group. That is,

$$S_N = \frac{\exp \overline{X}'b}{1 + \exp \overline{X}'b} \tag{7}$$

where

- S_N = predicted aggregate share by the naive method and
- $\overline{X}$ = vector of average variable values.

The corresponding variance in share prediction by the naive procedure is

$$EV(S_N) = [P(1 - P)]^2 (\overline{X}' A \overline{X} + b \overline{Y} b') \tag{8}$$

where $\overline{Y}$, the error variance in average variable values, is given by

$$\overline{Y} = (1/T^2) \left(\sum_t Y_t + \sum_t \sum_{t' \neq t} Y_{tt'} \right) \tag{9}$$

When the error variance in individual variables is similar and the error covariance for pairs of individuals is similar, equation 9 can be substituted into equation 8 and simplified to give

$$EV(S_N) = [P(1 - P)]^2 \left\{ \overline{X}' A X + (1/T) b \overline{Y}_t b' + [(T - 1)/T] b \overline{Y}_{tt'} b' \right\} \tag{10}$$

The equality between equations 6 and 10 indicates that the propagation of errors through these aggregation procedures is similar when there is a high degree of homogeneity in variable values and errors in variable values for the prediction group. Under similar conditions, the propagation of random errors in parameters and variables by other aggregation procedures is also similar to that for the enumeration procedure.

The propagation of bias errors can be analyzed in a similar manner. The propagation of these errors to individual choice probabilities is

$$B(P_t) = P_t(1 - P_t) B(X'b) = P_t(1 - P_t) \left[\sum_k X_k B(b_k) + \sum_k B(X_k) b_k \right] \tag{11}$$

where B = bias.

The bias in share prediction by the enumeration procedure due to bias in parameters and variables is

$$B(S) = (1/T) \sum_t B(P_t)$$

$$= (1/T) \sum_t P_t(1 - P_t) \left[\sum_k X_{kt} B(b_k) + \sum_k B(X_{kt}) b_k \right] \tag{12}$$

The bias from different sources may be additive or offsetting, depending on the direction of the biases and the sign of the corresponding variable for bias in parameters or the corresponding parameter for bias in variables. When members of the prediction group have similar variable values and biases, the bias equation can be simplified to

$$B(S) = P(1 - P) \left[\sum_k \overline{X}_k B(b_k) + \sum_k B(\overline{X}_k) b_k \right] \tag{13}$$

The bias error due to bias in parameters and variables for the naive method is identical to that given in equation 13 for the complete enumeration method with relatively homogeneous groups. Under similar conditions, the propagation of bias error in parameters and variables by different aggregation procedures also is similar to that for the enumeration procedure.

Thus, for relatively homogeneous prediction groups, the effect of errors in parameters and variables on error in share predictions is essentially independent of the aggregation procedure used. However, as within-group variance increases, differences in error propagation also increase. The magnitude of differences in error propagation is much smaller than the magnitude of the propagated errors themselves except when the prediction group is very diverse and is located at or near the region of maximum curvature in the choice function.

ERRORS OF APPROXIMATE AGGREGATION PROCEDURES

Approximate aggregation procedures create errors in aggregate prediction in two ways. First, as already described, the propagation of parameter and variable errors to share prediction may be differentially affected by different aggregation procedures. Second, approximate aggregation procedures introduce structural bias into the aggregate prediction. The magnitude and direction of the structural bias depend on the type of aggregation procedure used, the distribution of independent variables in the prediction group, and the curvature of the choice function at the point of prediction. These are the same factors that determine differences in error propagation. The structural aggregation bias may appear to have a random component due to unobserved differences in location on the choice function (which determines the curvature of the choice function) and the shape and variance of the distribution of variables in the prediction group. A detailed description of the aggregation bias introduced by different aggregation procedures is given by Koppelman (8).

The variation in the magnitude of aggregation bias and differences in error propagation with changes in the prediction situation (location on the choice curve, distribution of independent variables, and so on) indicate that the prediction situation should be characterized so that the probable magnitude of aggregation bias can be evaluated (7).

ERROR MEASURES FOR EVALUATING PREDICTION MODELS

The accuracy of different prediction models can be expressed in terms of the expected error of predictions made by using the model. An error measure that describes the expected error in a prediction model for different prediction situations is discussed below.

Two decisions must be made in the development of a suitable error measure. The first is how to express the error that occurs in a single prediction. The second is how to aggregate the errors from single predictions to some average or expected error for a group of predictions by using a common prediction methodology.

The error measure chosen to describe the error in each prediction is defined by

$$BEM_w = (P_w - A_w)/P_w \tag{14}$$

where

BEM_w = basic error measure in prediction per unit of prediction for element w,
P_w = predicted value for element w, and
A_w = actual value for element w.

Equation 14 expresses the magnitude of the error as a proportion of the magnitude of prediction. It is free of the dimensions of prediction and thus allows comparability among errors for predictions expressed in different terms.

The overall error measure, based on the use of a quadratic loss function, implies that (a) the importance of an error is proportional to the square of its magnitude and (b) positive and negative errors are treated alike. The resultant measure is the root mean square error (11):

$$RMSE = \left[(1/N)\sum_w BEM_w^2\right]^{1/2} \tag{15}$$

where

RMSE = root mean square error and
N = number of predictions for which the measure is determined.

The individual error measures can be weighted to reflect their relative importance. A useful characteristic of this error measure is that it can be disaggregated into average error AE and standard deviation of error SDE:

$$AE = (1/N)\sum_w BEM_w \tag{16}$$

$$SDE = \left[(1/N_w)\sum_w (BEM_w - AE)^2\right]^{1/2} \tag{17}$$

The relationship among these error measures is

$$RMSE^2 = AE^2 + SDE^2 \tag{18}$$

The separation of the average and standard error portions of the expected error is important because each indicates different deficiencies in the model formulation and prediction process.

ANALYSIS OF ERRORS IN PREDICTION

A method for identifying the portion of total error that is attributable to each of the components of the aggregated prediction model was developed and is demonstrated below in an applied prediction context. Identifying the contribution of the components of the model structure to total error indicates which components need to be improved or replaced. This analysis also puts the errors contributed by each model component in perspective with respect to errors contributed by other components. To disaggregate errors requires an analysis procedure that identifies the separate components of error according to their source and whether they are due to average errors or standard deviation errors.

The analytic approach is to make multiple aggregate predictions of choice shares with a single disaggregate choice model and set of predicted choice variables but with different aggregation procedures. The prediction error resulting from use of the enumeration procedure, which includes no aggregation error, is determined by comparing the predicted choice shares with the observed choice shares adjusted for error in observed shares (4). The additional error due to aggregation bias is determined by comparing the predicted shares by the selected aggregation procedure with those by the complete enumeration procedure.

Sets of predictions and observed shares are compared in two prediction contexts so that the error due to transferability as well as errors in aggregation and nontransfer model errors can be analyzed. First, travel choice shares are predicted for the data set on which the choice model is calibrated. Given the assumption that the choice model is well specified, the only model errors are stochastic variation errors in parameter estimates. The input variables used are obtained from the observed data set and are considered to be accurate. This is equivalent to making a posteriori predictions, which are suitable for the analysis of the performance of the prediction model (6). Different aggregation procedures can be used in conjunction with this choice model and data base. The error in the choice model is obtained by comparing predictions by the enumeration method to observed shares. These predictions include no aggregation error. Aggregation error can be obtained by comparing predictions by an approximate aggregation procedure with the corresponding predictions by the enumeration procedure. Combined error in prediction is the square root of the sum of squared model errors and aggregation errors.

Second, predictions are made for a different data set from that on which the models are calibrated. In this case, errors of model specification that affect transferability are included. The error in the choice model including specification error affecting transferability is obtained by comparing predictions by the enumeration method to observed shares. The model error affecting transferability can be isolated from other model error based on the assumption that nontransfer model error is the same as the model error for prediction with the calibration data set (except for adjustment for differences in the average size of prediction groups as indicated in equation 6). Aggregation error and combined error can be analyzed as described for the estimation data set.

The types of errors included in the different sets of predictions are as follows:

Data Set	Perfect Aggregation Procedure	Approximate Aggregation Procedures
Calibration	Choice model	Choice model and aggregation bias
Alternative	Choice model and transfer	Choice model, transfer, and aggregation bias

Analysis of differences between sets of predictions and between individual prediction sets and observed shares is used to identify

1. Errors from the choice mode,
2. Error that affects transferability, and
3. Aggregation error.

The method of error analysis is illustrated by an empirical study of mode choice prediction for worktrips to the CBD in the Washington, D.C., metropolitan area. Two subsets of data were created. The first included 874 work trips from 17 districts in the District of Columbia and Maryland. The second included 486 work trips from 12 districts in Virginia. A three-mode logit choice model (drive alone, shared ride, transit) was specified and calibrated by using the first data set. The model specification and parameter estimates are given in Table 1.

Aggregate share predictions were made for each of the districts in both data sets by the enumeration, naive, and classification procedures. The enumeration and naive procedures were described earlier. They are, respectively, the average of the individual choice probabilities (equation 4) and the probability of choice for average socioeconomic characteristics and level-of-service attributes (equation 7). The classification procedure consists of classifying each prediction group in terms of choice set availability (individuals without a driver's license or with no car available to the household do not have the drive alone alternative), using the naive procedure to predict choice share for each class, and taking the weighted average of choice shares for the classes as the group share prediction. Errors in the prediction for each district are summarized in terms of average error, standard deviation of error, and root mean square error according to equations 15, 16, and 17.

Table 2 gives the error measures obtained. Average error, standard deviation of error, and root mean square error are given for (a) model error, determined by comparing observed shares and predicted shares by the enumeration procedure; (b) aggregation error, obtained by comparing predicted shares by each method and predicted shares by the enumeration procedure; and (c) combined error, obtained by combining model error and aggregation error. Data given in Table 2 indicate that

1. Aggregation error for the naive and classification procedures is small compared to model error,
2. Aggregation error by the classification procedure is substantially smaller than that by the naive procedure, and
3. The effect of aggregation error on combined error is substantially smaller than the aggregation error itself.

Table 3 gives error measures for prediction of mode shares for a geographically distinct (in terms of home base location) data set. These error measures are the same as those used in Table 2 except that model error is disaggregated into nontransfer model error, obtained by adjusting model error estimated in the previous case (no transfer error) for differences in size of the prediction group, and transfer model error, obtained by adjusting model error for nontransfer model error. Data given in Table 3 indicate that

1. Model error and observed share error are larger than those for the calibration data set partially because of increased nontransfer model error (due to smaller prediction sample size) and partially because of transfer error;
2. Transfer and nontransfer model errors are of similar magnitude (based on root mean square error), and total model error is substantially larger than for prediction with the estimated data set (24 versus 16 percent);
3. Transfer model error includes an average component as well as a random component;
4. Aggregation error for the naive and classification procedures is similar in magnitude that for prediction with the estimation data set; and
5. The effect of aggregation error on combined error is substantially smaller than the aggregation error itself.

The overall results indicate that aggregation error by the naive and classification procedures is small compared to model error. In addition, total error in prediction using these aggregation procedures is similar in magnitude to the error in observed shares based on samples of 40 to 50 observations per aggregate group. (Expected observed share errors based on samples of 40 to 50 observations per prediction group are about 20 to 25 percent of prediction values.)

These results indicate that aggregate share prediction based on disaggregate choice models is relatively accurate when compared to sampling and errors due to model specification may be more important than errors due to aggregation.

Continuing emphasis should be placed on prediction with disaggregate models, and particular effort should be addressed to improving the specification of the underlying choice model. Furthermore, the preceding analysis demonstrates the feasibility of using the proposed methodology for analyzing prediction errors to evaluate alternative prediction methods and to diagnose sources of prediction error.

SUMMARY

This paper develops an approach to the analysis of errors in prediction. The sources of error in prediction are identified as coming from elements of the model formulation and prediction process. The types of errors generated in each of these elements are described.

The process by which errors enter, interact with one another, and are propagated to the final prediction is analyzed. The analysis indicates that the propagation of random and bias errors in model parameters and explanatory variable values to errors in aggregate share prediction is relatively independent of the method of aggregation used.

A method of analysis is proposed for use in identifying the sources of total error in prediction by use of pairwise comparisons among predictions by different methods and between these predictions and observed shares in the data set. The analysis method is empirically applied to demonstrate the feasibility of using this approach to evaluate alternative prediction methods and to diagnose areas of potential improvement in the prediction process.

ACKNOWLEDGMENTS

This research was supported by the Office of the Secretary, U.S. Department of Transportation. The empirical data used were provided by the Metropolitan Washington Council of Governments.

I wish to acknowledge the helpful comments and suggestions of Moshe Ben-Akiva and Steven Lerman of MIT.

REFERENCES

1. T. J. Atherton and M. E. Ben-Akiva. Transferability and Updating of Disaggregate Travel Demand Models. Paper presented at 55th Annual Meeting, TRB, 1976.
2. M. E. Ben-Akiva. Structure of Passenger Travel Demand Models. Department of Civil Engineering, MIT, Cambridge, PhD thesis, 1973.
3. A Disaggregated Behavioral Model of Urban Travel Demands. Charles River Associates, 1972.
4. R. Cole. Data Errors and Forecasting Accuracy. In Economic Forecasts and Expectations (J. Mincer, ed.), Columbia Univ. Press, 1969.
5. M. G. Kendall and A. Stuart. The Advanced Theory of Statistics, Volume 1, Third Ed. Griffin and Co., London, 1969.
6. L. R. Klein. An Essay on the Theory of Economic Prediction. Academic Bookstore, Helsinki, 1968.
7. F. S. Koppelman. Guidelines for Aggregate Travel Prediction Using Disaggregate Choice Models. Paper presented at 55th Annual Meeting, TRB, 1976.
8. F. S. Koppelman. Travel Prediction With Models of Individual Choice Behavior. Center for Transportation Studies, MIT, Cambridge, CTS Rept. 75-7, 1975.
9. C. F. Manski. The Analysis of Qualitative Choice. Department of Economics, MIT, Cambridge, PhD dissertation, June 1973.
10. D. McFadden. The Revealed Preferences of a Government Bureaucracy. Institute of International Studies, Univ. of California, Berkeley, Technical Rept. 17, 1968.
11. H. Theil. Applied Economic Forecasting. North Holland Publishing Co., Amsterdam, 1966.
12. J. W. Tukey. The Propagation of Errors, Fluctuations and Tolerances: Basic Generalized Formulas. Department of Mathematics, Princeton Univ., Technical Rept. 10, 1957.

Alternative Sampling Procedures for Calibrating Disaggregate Choice Models

Steven R. Lerman, Department of Civil Engineering, Massachusetts Institute of Technology
Charles F. Manski, Department of Economics, Carnegie-Mellon University

In this paper, three sampling techniques for calibrating disaggregate travel demand models are considered: random, stratified, and choice-based sampling. In a random sample, the probability of all members of the population being in the sample is equal; in a stratified sample, the population is divided into groups based on one or more characteristics and each group is sampled randomly but at different rates; and in a choice-based sample, the number in the sample selecting each alternative is predetermined, i.e., the sample is based on the outcome of a behavioral choice process. Existing disaggregate choice calibration methods yield consistent parameter estimates for random and stratified sampling techniques. Although maximum likelihood estimation for the third technique is extremely complex, an alternative, tractable estimator whose estimates are both consistent and asymptotically normal exists. This new estimation technique can be applied by using existing capabilities in ULOGIT or other multinomial logit estimation programs with only minor revisions. This implies that choice-based samples such as on-board surveys and roadside interviews can now be used for disaggregate model calibration. This should substantially reduce the cost of data collection in disaggregate model development. In addition, it opens an entire range of questions regarding the most appropriate sample design for future data collection efforts oriented toward the development of disaggregate choice models for urban travel demand forecasting.

The development of travel demand models invariably involves the use of a data sample. From 1950 to 1970, when most major urban areas undertook large-scale urban transportation planning studies, home interview surveys were the principal source of such data. However, these surveys were relatively expensive then and are even more so now. It is not surprising that most urban areas are reluctant to repeat a major home interview survey, and agencies that have done so have taken update samples that are substantially smaller than those taken previously.

The large-scale home interview survey was generally viewed as an essential element in the development of traditional aggregate demand models. Because aggregate models use data at the zonal level, fairly large random samples were required to calibrate them. However, in the past decade transportation analysts have begun to rely heavily on disaggregate choice models that use observations of individual decision makers rather than geographically defined groups. One major advantage cited for such models (1) is the efficiency with which they use available data and their consequent potential for reducing the time and effort expended on data collection.

Most of the existing research using disaggregate choice models has relied on data from some variant of the home interview survey. The type of sampling used has generally been random, i.e., the probability of being selected is the same for all members of the population. Some studies have used stratified sampling in which the population is divided into groups based on some characteristics and each subpopulation is sampled randomly.

The assumed need for a random or stratified sample has often limited the usefulness of disaggregate choice models. For example, in a city with low transit use such as Los Angeles, a large random sample of observations from the population may not include a single transit user. In general, inferences regarding transit preferences are impossible in such a situation. Intuitively, a sample designed so that the number of transit users is predetermined might circumvent this problem. Such a sampling process is termed choice-based, because the observations are drawn based on the outcome of the decision-making process under consideration.

Choice-based samples are extremely common in transportation analysis. On-board transit surveys and roadside interviews, for example, are both choice-based if one is considering the mode choice process. Such samples can frequently be obtained fairly inexpensively and are often used to evaluate the performance of a particular mode or to assist in determining how service should be altered to better meet the travel desires of current users. However, choice-based samples have not been used for calibrating disaggregate choice models because of the way in which the parameters of disaggregate choice models are generally estimated. Choice models are typically calibrated by using the maximum likelihood method. It is shown later that each of the three sampling methods results in a different distribution of observed choices and characteristics in the sample and, hence, has a different associated likelihood function. Existing estimation programs maximize the likelihood appropriate for random and stratified samples. However, the likelihood function for choice-based samples is not maximized by these programs. This likelihood function is significantly more complex and is not computationally tractable. A major finding of this study is that another, more tractable function exists that, when maximized, also yields consistent parameter estimates for choice-based samples. This result should have a significant impact on the entire model calibration process. Many models that previously relied on home interview surveys costing at least $40 per interview can now be developed by using alternative survey techniques that may prove an order of magnitude less expensive.

To discuss alternative sampling and estimation procedures requires first that the sampling processes be defined in analytic terms. This is done below, but it is assumed that the reader is familiar with the basic elements of disaggregate choice models (1, 2, 7). After the definition, a brief discussion of consistency, a desirable property of parameter estimation techniques, is presented. Existing estimation procedures that maximize the likelihood of the observed choices given the observed characteristics are discussed. These methods yield consistent parameter estimates only in random and stratified samples. Then, an estimation procedure for choice-based samples and an intuitive rationale for its consistency are presented. A formal proof of the consistency of this estimator is given by Manski (5). The various trade-offs that exist in the design of a sampling procedure are explored, and the basic conclusions and recommendations of the paper are summarized.

Although all of the results described in this paper are applicable to the commonly used multinomial logit model, they are by no means limited to it. In fact, they apply to almost all reasonable disaggregate choice models. Thus, the techniques proposed here should prove to be useful for the multinomial probit model now under development (4, 6) as well as later generations of models that have not yet been developed.

BASIC SAMPLING CONCEPTS AND NOTATION

Sampling, as used in this paper, refers to the process of selecting a finite set of observations from some larger population. Each observation sampled is described by two variables, i and z, where

- i = the observed choice of the sampled decision maker (e.g., whether the decision maker took the transit or automobile mode to work) and
- z = a vector of characteristics of the decision maker and the choice alternatives available (e.g., a vector consisting of household income, automobile ownership, and travel time by automobile and transit).

The entire decision-making population can be characterized by a distribution of (i, z) pairs. This probability distribution is P(i, z). The sampling process describes the way in which members of the population are drawn from this distribution. Any type of sample also has a distribution of i's and z's, which is denoted as f(i, z).

Throughout this paper it is assumed that some behavioral choice process exists that is governed by a vector of parameters θ. This process might be the multinomial logit model or some other assumed form. It will often be convenient to indicate that the choice process depends on θ by denoting the probability that i is chosen from a choice set characterized by attributes z as $P(i|z,\theta)$. In addition, the joint distribution of i and z in the population is written as $P(i,z|\theta)$ and the corresponding sampling distribution as $f(i,z|\theta)$.

Based on this notation, the alternative sampling procedures can be formalized.

1. In a random sample, such as that used in traditional home interview surveys, the distribution of i and z in the sample is identical to that of the population, i.e.,

$$f(i,z|\theta) = P(i,z|\theta) \tag{1}$$

2. A stratified sample is a sample drawn nonrandomly with respect to the choice set or decision maker characteristics. For example, a sample of half low-income households and half high-income households is a stratified sample if there was no bias within any income group with respect to transit and automobile users. In this case, the sampling procedure is defined by f(z), the probability of sampling an observation with characteristics z. The distribution of i and z in the sample is

$$f(i,z|\theta) = f(z)P(i|z,\theta) \tag{2}$$

3. A choice-based sample is a sample that is drawn based on the actual choices made by decision makers. For example, a sample of travelers, half of which was taken at a transit station and half at a roadside interview, would be a choice-based sample. The sampling procedure is defined by some f(i), the probability that an observation is drawn from the subpopulation selecting alternative i, and the sampling distribution is

$$f(i,z|\theta) = f(i)P(z|i,\theta) = [f(i)P(i|z,\theta)P(z)]/P(i|\theta) \tag{3}$$

where the last expression relies on Bayes rule that

$$P(z|i,\theta) = [P(i|z,\theta)P(z)] \Big/ \left[\sum_z P(i|z,\theta)P(z)\right] \tag{4}$$

and

$$P(i|\theta) = \sum_z P(i|z,\theta)P(z) \tag{5}$$

(The z's are treated here as discrete variables. However, an extension to continuous z's is straightforward.)

Intuitively, each type of sampling method generally produces a different sample. For example, a stratified sample with a disproportionate share of low-income households might be expected to have a greater share of transit users than a random sample. Similarly, a choice-based sample with a disproportionate share of transit users might have a greater number of travelers residing near transit stations. In short, each sampling method leads to a different distribution of choices and characteristics in the sample, and there is no a priori reason to expect that an estimation technique that produces meaningful parameter estimates for one sampling method will be useful for samples drawn by other methods.

CONSISTENCY

The goal of any estimation procedure is to find a $\hat{\theta}$ that in some sense comes close to the true parameter value, θ. This paper focuses principally on finding consistent estimates of θ. Although consistency is perhaps the most basic desirable property of a parameter estimate, all the methods presented also produce asympototically unbiased, normally distributed estimates.

Consistency is a statistical property that refers to the behavior of a parameter estimate as the sample size gets increasingly large. Obviously, in finite samples $\hat{\theta}$ does not exactly equal θ. (θ denotes the true parameters, i.e., fixed, nonrandom numbers, and $\hat{\theta}$ denotes a parameter estimate, which is generally random in nature since it depends on the particular sample drawn from the population.) However, it would be desirable for the probability that $\hat{\theta}$ is within any given distance of θ to approach one as the sample size grows larger. This is what is meant in intuitive terms by a consistent estimate. More formally, $\hat{\theta}$ is a consistent estimate of a true parameter θ if, for any arbitrarily small positive α,

$$\lim_{T\to\infty} \text{Prob}\,(\|\hat{\theta}_T - \theta\| < \alpha) = 1 \quad (6)$$

where

T = sample size,
$\hat{\theta}_T$ = parameter estimate associated with the sample of size T, and
$\| \ \|$ = a distance measure.

CONSISTENCY OF EXISTING ESTIMATION PROCEDURES IN RANDOM AND STRATIFIED SAMPLES

If the model is correctly specified, the property of consistency holds for virtually all commonly used estimation techniques, including the maximum likelihood method used for estimating the parameters of the multinomial logit model.

A well-known theorem that the maximum likelihood estimates are consistent is used below to indicate that existing disaggregate model calibration procedures yield consistent estimates for random and stratified samples. In general the maximum likelihood estimator seeks a $\hat{\theta}$ that satisfies the following condition:

$$\operatorname*{Max}_{\hat{\theta}} \prod_{t=1}^{T} f[(i,z)_t|\hat{\theta}] \quad (7)$$

where $(i, z)_t$ denotes the actual value of the (i, z) pair for the tth observation in the sample. Typically, this problem is solved by taking the logarithm of the likelihood function, inasmuch as the likelihood function is maximized when its log is. Thus, we seek

$$\operatorname*{Max}_{\hat{\theta}} \sum_{t=1}^{T} \log f[(i,z)_t|\hat{\theta}] \quad (8)$$

Equation 8 is the log likelihood for any sampling distribution f. If the function $f(i, z|\hat{\theta})$ obeys certain regularity conditions, general theorems ensuring the consistency of maximum likelihood estimates can be applied. McFadden (7) presents one such set of conditions for the multinomial logit model.

Existing calibration procedures for disaggregate choice models do not directly maximize the likelihood function; rather, they solve the following problem

$$\operatorname*{Max}_{\hat{\theta}} \sum_{t=1}^{T} \log P(i_t|z_t,\hat{\theta}) \quad (9)$$

This function is the likelihood of the observed choices conditional on the values of z $\hat{\theta}$ and does not reflect the sampling process. It can readily be shown, however, that for random and stratified samples the $\hat{\theta}$ that maximizes equation 9 also maximizes equation 8. Hence, under sufficient regularity conditions, equation 9 yields consistent parameter estimates. Stated more formally, if the sampling process for (i, z) pairs is random or stratified, then $\hat{\theta}$ that is a solution to equation 9 is also a solution to equation 8 and is, therefore, consistent for θ. To see this, observe that in both random and stratified samples (a random sample is treated here as a special case of a stratified sample in which f(z) = P(z) for all values of z)

$$f(i,z|\hat{\theta}) = P(i|\hat{\theta})f(z) \quad (10)$$

Thus, equation 8 can be written as

$$\operatorname*{Max}_{\hat{\theta}} \sum_{t=1}^{T} [\log P(i_t|z_t,\hat{\theta}) + \log f(z_t)] \quad (11)$$

where $f(z_t)$ is not a function of $\hat{\theta}$. It follows that maximizing the left portion of equation 11 is equivalent to maximizing the entire expression. Note that this result is not applicable to choice-based samples because in such samples the sampling distribution of z depends on the parameter θ.

ESTIMATION TECHNIQUE FOR CHOICE-BASED SAMPLES

Inasmuch as existing estimation software packages do not maximize the likelihood function for choice-based samples, a relevant question is why not develop one that does. Examination of the appropriate log-likelihood function shows why this would be extremely difficult:

$$\sum_{t=1}^{T} \log [P(i_t|z_t,\hat{\theta})P(z_t)f(i_t)]/P(i_t|\hat{\theta}) \quad (12)$$

The term $P(i_t|\hat{\theta})$ is the marginal probability that alternative i_t is selected over the entire relevant population at $\hat{\theta}$. This probability is in general a complex integral or summation and is not analytically tractable. Furthermore, its computation requires knowledge of the probabilities P(z), which is rarely available. These problems point to the need for a simpler procedure.

Maximization of the function

$$\sum_{t=1}^{T} \log P(i_t|z_t,\hat{\theta})^{[P(i_t|\theta)/f(i_t)]} \quad (13)$$

produces consistent parameter estimates (5). This function is identical to that in equation 9 except that it requires $P(i_t|\theta)$ and $f(i_t)$, the true shares of the population and sample choosing alternative i_t; it does not require the evaluation of $P(i_t|\hat{\theta})$ for $\hat{\theta} \neq \theta$.

Conditions sufficient for the above estimation method to be consistent are quite general and apply to most commonly used choice models. First, the choice probability must be continuous in $\hat{\theta}$. Second, all the choice probabilities must be positive; none may be zero. Finally, the sampling process and choice model must be such that θ is identifiable, i.e., the $\hat{\theta}$ that satisfies equation 13 must exist in large samples and be unique.

The similarity between the functions in equations 13 and 9 is not insignificant. Basically, the proposed estimation technique for choice-based samples is computationally identical to the maximum likelihood method in random or stratified samples except that each observation is exponentiated by a factor $P(i_t|\theta)/f(i_t)$. If the number in the sample choosing alternative i is less than the corresponding marginal probability [i.e., if $f(i_t) < P(i_t|\theta)$], then this factor is greater than one. In a loose sense, each observation is weighted. For this reason we have termed this estimator the weighted maximum likelihood estimation method.

It is interesting to note that when f(i) is identical (by chance or design) to $P(i|\theta)$ for all i, the weighted maximum likelihood estimation method is computationally identical to maximizing the sample likelihood as though the sample were random or stratified. Thus, when the choice-based sample is drawn such that the fraction choosing each alternative in the sample is identical to the corresponding marginal population probability, the use of a computer estimation program that maximizes the likelihood of a random or stratified sample will produce consistent estimates for a choice-based sample. In all cases where the sample shares and the population marginal probabilities are not identical, the weighted maximum likelihood estimator will in general produce different estimates from the unweighted one, and the unweighted estimates will not have the consistency property (6).

McFadden (7), however, has demonstrated that there is a special case in which inconsistency is confined to a subset of all the parameters and that consistent estimates for this subset of parameters can be obtained by a simple transformation of the estimation results. This case is when the choice model is of the logit form and there is a constant term in the utility of every alternative except one. (One constant term must generally be omitted in the logit model in order for the maximum of equation 9 to be unique.) In this case, we can express the choice probability model as

$$P(i_t|\theta) = \frac{\exp \gamma_i + X_{it}\,\phi}{\sum_{j\in A_t} \exp \gamma_j + X_{jt}\,\phi} \tag{14}$$

where

γ_i, γ_j = constant terms associated with alternatives i and j respectively [the γ's are parameters of the model to be estimated; in the previous notation, $\theta = (\gamma_1, \gamma_2, \ldots, \gamma_N, \phi)$];
X_{it}, X_{jt} = vectors of all the attributes of alternatives i and j respectively for decision maker t;
ϕ = a vector of parameters; and
A_t = the set of available alternatives for decision maker t.

A typical example of this situation is a logit model of mode choice in which each mode has an alternative-specific constant term. If an unweighted estimation method is used in this case, McFadden has shown that

1. The estimates of ϕ are consistent and
2. If each of the estimates of the γ (denoted as $\hat{\gamma}$) is modified so that

$$\tilde{\gamma}_i = \hat{\gamma}_i - \log\,[f(i)/P(i|\theta)] \tag{15}$$

then $\tilde{\gamma}_i$ is a consistent estimate for γ_i.

In practical terms, McFadden's result implies that, as long as there are constant terms for every alternative except one, only the constant terms are affected by the use of choice-based samples for estimating the multinomial logit model. The inconsistent constant terms can then be corrected by a simple transformation.

In more complicated situations, such as destination choice models in which it is impractical or impossible to define a separate constant for every alternative, the effect of using a nonweighted estimation procedure on a choice-based sample is still unknown. Inasmuch as some of the parameter estimates will certainly be inconsistent, the use of the weighted estimation procedure in these cases is clearly indicated. In cases for which McFadden's result is applicable, the decision between a weighted and unweighted procedure depends on still unresolved statistical questions about the efficiency and robustness of the two techniques. The approaches have virtually identical computation and data requirements, and the weighting procedure can be performed by some of the existing multinomial logit estimation programs such as ULOGIT, a program developed cooperatively by the Urban Mass Transportation and Federal Highway administrations. (Minor modification of existing software is required to obtain correct t-statistics, but this can readily be done as a postprocessing step to the actual model calibration.)

CHOICES IN SAMPLE DESIGN

The availability of a practical estimation procedure for choice-based samples inevitably leads to the question of what type of sampling approach is best. Unfortunately, the answer to that question is extremely specific to the situation, depending among other things on

1. The cost of various sampling methods,
2. The choice situation being modeled,
3. Characteristics of the decision-making population, and
4. The cost to society of estimation errors in terms of losses from misdirected policy.

Random samples often require a major expenditure of time and funds to collect. For many general transportation modeling situations, a random sample must be based around travelers' homes; a sample taken anywhere else inevitably is choice-based because the respondent has of necessity already made a trip choice. This requirement for a home-centered survey has as its consequences all of the problems associated with such data collection efforts: high cost; low response rates by frequent travelers; undercounting in many inner-city areas; and failure to interview all the trip makers in the household, which leads to an undercounting of discretionary trips. On the other hand, home interview surveys generally offer the opportunity for longer interviews than are offered by other techniques because the respondent is not traveling somewhere or doing something else.

A further disadvantage of random sampling is that it offers no opportunity to increase the amount of information in a sample of fixed size. Loosely, the more variation that exists in the data, the more reliable the resulting choice models will be. In random sampling this variation cannot be controlled; rather, the random outcome of the sampling process determines how much variation there will be in a given sample.

Stratified sampling eliminates one aspect of this problem. Even when the characteristics of the decision maker population vary little, the sample can have a high variance. For example, high-income households can be sampled at different rates from households with low incomes, thereby increasing the sample's expected variance over what could be obtained in a purely random sample. Stratified samples, however, may often be even more expensive than random ones. The sample design must often distinguish among various survey candidates based on characteristics that may be difficult to observe, and it may often be necessary to begin an interview to find out in which stratum a respondent belongs.

For example, if automobile ownership were used for stratification it would be necessary to select observations through a preinterview, which might or might not lead to a full interview. It is questionable whether such a procedure would be economically justifiable; once the interview was begun it might prove more efficient to complete it. In cases where the stratification was more readily observable (e.g., housing type), stratified samples would probably prove highly effective.

In general, choice-based samples are the least expensive. Their proper use requires that values of $P(i|\theta)/f(i)$, the ratio of the share of entire population choosing each alternative to the sample share, be known. Fortunately, because $P(i|\theta)$ is an aggregate statistic, under varying situations information about it might be obtained from several sources.

1. Published data—Because $P(i|\theta)$ is an aggregate figure, it may be published in census data, Bureau of Labor statistics, transit industry data, or other conventional sources. For example, the Bureau of the Census collects and publishes mode choice to work information for SMSAs.
2. Random subsamples—Part of the entire sample may be randomly drawn, and the remainder may be choice-based. Thus, if the random portion is reasonably large, the share of the sample choosing alternative i may be an extremely good estimate of $P(i|\theta)$. A good example of this is a random home interview survey supplemented with an on-board transit survey. This approach might prove most valuable when small home interview surveys yield a very low number of transit riders.
3. Supplementary surveys—Data for estimating choice models are often quite detailed and are therefore expensive to collect. In contrast, merely finding out what alternatives members of the population selected is generally quite simple. For this reason, finding $P(i|\theta)$ for any given population can probably be accomplished by a very efficient supplemental survey. For example, a random telephone survey that asks about mode of travel without collecting or coding any additional data would be sufficient to obtain estimates of $P(i|\theta)$ for a mode choice model.

In all probability the question of sample design will remain a judgmental problem. Far too little is known about the detailed properties of any of the estimators discussed in this paper to completely formalize the explicit analysis of sample design. However, it is clear that the choice-based estimation procedure developed in this paper opens a new dimension to the possible sampling alternatives. Decisions about sample design should recognize the potential efficiencies of using choice-based samples and weigh the possible benefits and costs of this technique against those of random and stratified samples.

CONCLUSIONS AND RECOMMENDATIONS

The relative efficiency of disaggregate choice models over their aggregate counterparts significantly reduces data collection requirements. However, the full potential of such models has not yet been realized because no computationally tractable way of using choice-based samples has been demonstrated to yield consistent parameter estimates. This paper describes such a method and presents some of the significant ramifications of using choice-based samples for demand model estimation.

More generally, it seems clear that transportation planners in the past paid scant attention to the question of sample design. However, if sampling costs continue to rise as they have and if large quantities of funds for surveying are unavailable, a great deal more thought into sample design will be required.

The weighted maximum likelihood estimator described here opens an entire range of possible designs that were not previously usable in the calibration of disaggregate choice models. In many contexts, appropriate use of choice-based samples should greatly reduce data collection costs and improve model estimation results by permitting the analyst to prespecify characteristics of the sample. Study resources previously dedicated to data collection could then be reallocated to the task of developing improved model specifications.

ACKNOWLEDGMENTS

This research was sponsored by the Federal Highway Administration, U.S. Department of Transportation, in the interest of information exchange. The federal government assumes no liability for its contents or use thereof.

The work described in this paper was performed at Cambridge Systematics, Inc. The authors are grateful for the advice of Louise Skinner, the project monitor, David Gendell of the Federal Highway Administration, and William A. Jessiman of Cambridge Systematics. All errors and omissions are of course the authors' responsibility.

REFERENCES

1. M. E. Ben-Akiva. Structure of Passenger Travel Demand Models. Department of Civil Engineering, MIT, Cambridge, PhD dissertation, 1973.
2. T. Domencich and D. McFadden. Urban Travel Demand—A Behavioral Analysis. North-Holland, Amsterdam, 1975.
3. J. Guttman. Avoiding Specification Errors in Estimating the Value of Time. Transportation, Vol. 4, No. 1, March 1975.
4. J. A. Hausman and D. A. Wise. A Generalization of Probit Analysis to Polytomous Choice. In preparation.
5. C. F. Manski and S. R. Lerman. The Estimation of Choice Probabilities From Choice-Based Samples. Working Paper, May 1976.
6. C. F. Manski and S. R. Lerman. An Estimate for the Generalized Multinomial Probit Choice Model. In preparation.
7. D. McFadden. Conditional Logit Analysis of Qualitative Choice Behavior. In Frontiers in Econometrics (P. Zarembka, ed.), Academic Press, New York, 1973.

Application of Disaggregate Techniques to Calibrate a Trip Distribution and Modal-Split Model

Martin F. Richards, Martin and Voorhees Associates

A trip distribution and modal-split model for use in a transportation planning study for Tilburg, Netherlands (170 000 population), was developed by using disaggregate models. The procedures adopted were based on the functional similarity of multinomial logit and Wilson's entropy maximizing model. A model system with four modes and six market segments was developed by using readily available software. Although it was impossible to develop a simultaneous trip distribution and modal-choice model, a satisfactory sequential model system, in which the mode choice utility functions were used as generalized prices in the distribution model, was obtained. This paper describes the basic philosophy of the approach, some of the problems encountered, and some of the results.

This paper describes a recent application of disaggregate modeling techniques in the development of a distribution and modal-split model system for use in an urban transportation planning study being undertaken in Tilburg, Netherlands. This study covers three municipalities in southern Netherlands with a total population of about 170 000. Tilburg is a town that developed in the last century and has a very good road system; it is also well served by an extensive bus network, although only some 2 percent of intraurban trips are made by bus. The first phase of the study began in 1972 when 4500 home interviews (9 percent sample) were conducted (3).

BASIC MODELING PHILOSOPHY

The most widely used disaggregate travel demand model is the logit model, which, in its multinomial form, can be written

$$\mathrm{Prob}(a{:}A_t) = \frac{\exp U_a(X_a, S_t)}{\sum_{a=1}^{A_t} \exp U_a(X_a, S_t)} \tag{1}$$

where

$\mathrm{Prob}(a{:}A_t)$ = probability of individual t choosing alternative a out of A_t, the full set of alternatives available to him, and

$U_a(X_a, S_t)$ = utility of alternative a to individual t (usually regarded as a function of the variables that characterize alternative a, denoted by X_a, and the socioeconomic variables that describe individual t, denoted by S_t, and described as the utility function).

A description of the derivation of logit and its main characteristics can be found in the literature (5, 9, 11). As usually applied in mode choice studies, logit is of similar functional form to the modal-split model that can be derived from Wilson's entropy maximizing model (12). This model, used widely in the United Kingdom, can be written

$$\frac{T_{ijm}}{\sum_{m=1}^{M} T_{ijm}} = \frac{\exp \beta C_{ijm}}{\sum_{m=1}^{M} \exp \beta C_{ijm}} \tag{2}$$

where

T_{ijm} = number of trips from i to j by mode m,

C_{ijm} = generalized cost of traveling from i to j by mode m, including any relevant modal constant or handicap, and

β = constant.

Wilson's modal-split model is a submodel of a simultaneous trip distribution and modal-split model that can be written

$$T_{ijmn} = a_{in} P_{in} b_j A_j f_n(C_{ijm}) \tag{3}$$

where

T_{ijmn} = number of trips from zone i to zone j by mode m made by person type n,

P_{in} = number of trip productions in zone i by person type n,

A_j = number of trip attractions in zone j,

$f_n(C_{ijm})$ = function for a specific person type of the generalized cost of travel from zone i to zone j by mode m, and

$$a_{in} = \left[\sum_{j=1}^{J} \sum_{m=1}^{M} b_j A_j f_n(C_{ijm}) \right]^{-1}$$

$$b_j = \left[\sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} a_{in} P_{in} f_n(C_{ijm}) \right]^{-1}$$

As a singly constrained (or balanced), production model, i.e., with b_j set equal to unity, the model can be written

$$\frac{T_{ijmn}}{P_{in}} = \frac{A_j f_n(C_{ijm})}{\sum_{j=1}^{J} \sum_{m=1}^{M} A_j f_n(C_{ijm})} = \frac{\exp \ln A_j + \beta_n C_{ijm}}{\sum_{j=1}^{J} \sum_{m=1}^{M} \exp \ln A_j + \beta_n C_{ijm}} \quad (4)$$

Equation 4, like equation 2, has a functional form similar to a special case of logit in which the coefficient of the attraction variable, $\ln A_j$, is constrained to 1.0. It is interesting to note that the functional form of the attraction variable, i.e., the logarithmic transformation, is that that has been found to be the most suitable by both Richards and Ben-Akiva (9) and Adler and Ben-Akiva (1) in developing simultaneous destination and modal-choice models for shopping trips. Furthermore, by using retail employment as a proxy for the attractiveness of the shopping center, Richards and Ben-Akiva (9) estimated the coefficient of this variable to have a value of 0.74, which is relatively close to the value of 1.0 implied in equation 4.

Although distribution models are generally applied in the doubly constrained form in which the attraction variable is equal to an independently estimated number of attractions per zone, it is questionable whether this is always a desirable procedure when the attraction model is insensitive to accessibility, as is usually the case; thus, regardless of the effect on accessibility of alternative plans, the total number of trips to a zone remains fixed. The use of a properly specified, singly constrained, production model not only offers the possibility of overcoming this deficiency but also has considerably greater behavioral justification.

The structure of the total transportation model system implies a specific decision-making process on the part of the traveler. Brand (2) summarized the alternative assumptions. If we assume that there is a hierarchy of decisions and that the relative valuation of the choice attributes, or independent variables, remains constant within any given hierarchy, then we have to determine those relative values. It has been argued (4) that it is best, in the case of a sequential destination choice and mode choice situation, to determine the relative valuation of the alternative modes in the modal-split model and then to apply this as a generalized price in the trip distribution model, in which the coefficient of the generalized price is determined.

Conventional urban transportation models have tended to regard all trip makers as having identical valuations of the various attributes affecting the relevant travel choice (e.g., mode) and also as having identical sets of alternatives from which to choose. This practice can give rise to models that fail to adequately explain the behavior of groups within the population and thus lead to prediction errors, especially when the characteristics of the population relevant to travel demand change over time. A particular example of this is the effect of car availability on mode choice; car availability is a function of (among other things) ability to drive. Although Wilson's model permits the use of market segments, it has rarely been applied in transportation planning studies to more than two person types. This can be partly attributed to the trip production modeling procedure that has dominated in the United Kingdom in recent years (13), but it is also due to the problems of calibrating models with a finer system by using traditional procedures. The latter comment also applies to the use of more than two modes.

Although transformation of the disaggregate models into aggregate models was a possible source of problems, it seemed likely that use of a segmentation system based on choice sets as well as a relatively fine zoning system could reduce the aggregate error to an acceptable level. The former of these assumptions has since been given increased credence by Koppelman (6).

TILBURG STUDY

The similarity between logit and Wilson's entropy maximizing model forms the basis for the development of the trip distribution and modal-split models for Tilburg. Such an approach had three major advantages: First it facilitated the calibration of a multimodal model; second it facilitated the application of a number of market segments; and third better models could be developed by using disaggregate rather than aggregate data. Yet the final models are essentially conventional in form; they are compatible with other elements of the model system, and they were developed and can be applied by making extensive use of existing computer programs.

The original intention was to develop a singly constrained, production, simultaneous destination and modal-choice model for all trip purposes except home-based work and home-based school. Work and school were excluded because, with Dutch planning legislation, the absolute number of jobs and school places in any zone can be assumed to be fixed.

Unfortunately, after a series of models for home-based shopping trips with different specifications was calibrated, as well as at least one basic model for each other trip purpose, it appeared that, within the data, time, and budget constraints of this study, no satisfactory specification could be found for a simultaneous destination and modal-choice model that could be readily transformed into an aggregate model and would be independent of zoning systems. The original concept of a simultaneous destination and modal-choice model was therefore abandoned, and a sequential destination choice and modal-choice model in which calibration of the modal-choice model preceded the destination choice model was used instead. The modal-choice model remained a disaggregate model, but the destination choice model became a doubly constrained aggregate model in which the modal-choice utilities were used as generalized prices.

The scope of a market segmentation system for the Tilburg study was constrained by the possibilities offered by both the trip production model and the program to be used for forecasting trip distribution and modal split. The trip production model scheduled for use in the Tilburg study is a person-based cross-classification model. Two dimensions of the classification system are the availability of a car within the household and the personal possession of a driving license. The aggregate trip distribution and modal-split program available for the study was limited to six market segments. Given this, the market segmentation system was based on car and moped availability, availability being defined by simple binary variables:

1. Possession or lack of possession of a driving license,
2. Household possession or lack of possession of at least one car, and

3. Household possession or lack of possession of at least one moped.

All of these variables could then be introduced in the utility function of the disaggregate model as simple dummy variables. Thus the market segmentation system applied in this study related only to vehicle availability and not to the valuation of the level-of-service variables used. Ideally it should have applied to both.

A random sample of 2000 trips for each purpose class (except those for which less than 2000 observations were available) was selected from the home interview files. Although experience to date with disaggregate models has shown that samples of 500 observations can be adequate for model calibration (9), the Tilburg data set presented a particular problem in that the probability of using the bus was very low, between 1 and 3 percent averaged over all trips for a given purpose. Lerman, Manski, and Atherton's (7) work undertaken since the study was completed indicates how this problem could be overcome.

Although five significant models could be defined (car driver and car passenger are different modes), for primarily economic reasons walking and bicycle modes were grouped together. Moped was only considered a valid mode for persons from a household with a moped; car was considered a valid mode for all persons although the probability of choosing car is influenced by the values of the coefficients of a set of dummy variables representing license and car availability. Bus and walk-bicycle were considered to be valid modes for everyone.

The home interview data had been coded to a fine zoning system, consisting of 506 zones; the population of the study area was 170 000. Level-of-service data therefore had to be based on zonal centroids, but to maintain the maximum interzonal variability in the values of the level-of-service variables this zoning system (fine zones) was used for model calibration purposes. For forecasting purposes, however, such a fine zoning system could not be used because of the lack of necessary socioeconomic data at this level and economic constraints. A coarser zoning system was therefore derived. This system, which consisted of 162 zones (superzones), was used for all aggregate model work, including calibration.

In-vehicle travel time data for car, moped, and bus were obtained from modal networks, as were bus access, waiting, and transfer times and costs. In-vehicle travel time for bicycle was derived from the moped network by using a constant speed of 12 km/h. Out-of-pocket travel costs for car and moped were derived by multiplying the distance over the minimum generalized cost path by 7.5 and 2.5 cents/km respectively. Out-of-vehicle and intrazonal travel times for bicycle, moped, and car were estimated manually.

The modal-choice utility functions were originally intended to contain in-vehicle travel time, out-of-vehicle travel time, and out-of-pocket travel costs as independent variables, but early model specifications revealed a major problem due to correlation between in-vehicle travel time and out-of-pocket travel costs for both car and moped and between similar variables for different modes. This was undoubtedly caused by the lack of congestion in Tilburg; journey speeds are thus fairly constant throughout the network. Because the models were to be used to evaluate alternative transportation policies, some of which would be based on various car restraint measures to be represented as additional travel costs, it was decided, reluctantly, to replace the individual variables by a composite generalized time variable, i.e., a conventional generalized cost variable scaled in time (8).

The generalized time variable was applied as a mode-specific variable; i.e., its coefficient was allowed to vary between modes. This was necessary for at least car and moped because generalized cost increases less rapidly with distance for moped than for car (travel times are similar within the urban area but moped is cheaper than car); thus use of a generic variable would imply that moped becomes increasingly attractive relative to car with increasing trip length. Furthermore, the coefficients of the generalized time variables for the other modes were found to be significantly different from each other. This finding is contrary to that reported by Richards and Ben-Akiva (9) for Eindhoven, where the coefficients of in-vehicle travel time for home-work-home journeys were found to be similar for five modes. Nevertheless, the relative values determined for Tilburg seem to reasonably reflect the relative inconvenience or effort associated with the use of the different modes, even though they imply that the value of one unit of generalized time is not constant over modes; a minute is not always perceived as a minute in the choice of modes.

For the models described here, a modal constant was included for each mode except car. Three car-specific dummy variables were used to represent car availability; there was no dummy variable for someone without a license coming from a carless household, and this therefore represents the base situation.

In the singly constrained distribution model, the variable A_j represents the relative attractiveness of zone j, while in a conventional doubly constrained model it represents the absolute number of trip attractions. For the Tilburg study the usual definition of A_j was maintained, i.e., trip attractions. But the observed number of attractions, $A_{j_{obs}}$, was not the relevant variable for use in calibrating a singly constrained production model because it can be expected that this represents a function of the basic attractiveness of the zone, as a function of employment and other content variables, and the accessibility of that zone. The trip attraction model used, however, is a simple cross-classification model in which attractions per land use class (per purpose) are treated as a function of the employment in that class.

HOME-BASED WORK TRIP

Of the modal-choice models calibrated for work trips, the utility function U_m of the one considered the most suitable for use in the forecasting model had the general specification given in Table 1. A full set of statistics for all the models described are given in Table 2. These statistics were based on the following number of observations and cases:

Purpose	Observations	Cases
Work	2135	5170
Social	1933	4458
Recreational	1506	3255

The coefficients of the disaggregate modal-choice model were used in an aggregate modal-choice model by using the observed trip matrices at the superzone level. For the aggregate modal-split model, as well as the trip distribution model, the eight market segments were collapsed to six by grouping people having either a license and no car or no license and a car because the coefficient of the dummy variables for these two had the same value. The calculated and observed model shares per market segment are given in Table 3. The calculated shares compare favorably with observed shares except for the bus mode; this was probably due to its low probability of choice. The calculated shares

Table 1. Utility function for home-based work and social trips.

U_n			
Home-Based Work	Home-Based Social	Item	Mode
-0.03	-0.06	Generalized time	Car
-0.12	-0.19	Generalized time	Moped
-0.15	-0.18	Generalized time	Walk-bicycle
-0.02	-0.03	Generalized time	Bus
+4.28	+3.85	Persons with driving license and car	Car
+1.72	+1.76	Persons with no license but with car	Car
+1.70	+0.82	Persons with license but no car	Car
+4.33	+2.99		Moped
+5.47	+3.98		Walk-bicycle
+0.70	+0.56		Bus

for each of the three main modes are within 2.5 percent. Within the market segments there is greater error, however, especially between walk-bicycle and moped. The similarity of bicycle and moped could be a reason for this, since, except for the third market segment, the share of car is always well reproduced. The observed and calculated average trip costs, a conventional calibration test, were also considered as being satisfactory.

Application of the estimated modal utility functions (per market segment) in the distribution model (with the coefficient of the generalized price variable set equal to 1.0) followed by calculation of modal split yielded the predicted distribution and modal-split values. These results can again generally be considered satisfactory, although there are clearly some specific values that should be improved.

Table 2. Statistics for mode choice models.

	Work		Social		Recreational	
Variable	Coefficent	S.E.	Coefficient	S.E.	Coefficient	S.E.
Car						
License	4.284	0.298	3.853	0.179	3.318	0.199
No license	1.716	0.353	1.757	0.175	0.813	0.192
No car, license	1.702	0.763	0.817	0.316		
Walk-bicycle constant	5.469	0.367	3.981	0.267	22.829	0.341
Moped constant	4.327	0.386	2.987	0.318	13.116	2.344
Bus constant	0.703	0.763	0.563	0.560	30.773	9.885
Generalized time						
Car	0.000 30	0.000 20	-0.000 62	0.000 19		
Walk-bicycle	-0.001 48	0.000 17	-0.001 80	0.000 15		
Moped	-0.001 16	0.000 34	-0.001 86	0.000 32		
Bus	-0.000 24	0.000 12	-0.000 32	0.000 10		
ln generalized time						
Walk-bicycle					-2.867	0.180
Moped					-1.660	0.334
Bus					-3.789	1.160
CBD constant, car					0.377	0.201

Table 3. Observed and calculated modal shares by market segment and trip purpose.

		Home-Based Work				Home-Based Social				Home-Based Recreational			
Market Segment	Model	Car	Walk-Bicycle	Moped	Bus	Car	Walk-Bicycle	Moped	Bus	Car	Walk-Bicycle	Moped	Bus
Car, license, moped	Observed	9 118	4654	3186	75	7 216	1 609	1073	57	2545	1009	222	0
	Predicted (MS)	8 974	4014	4037	1	7 301	1 317	1210	172	2561	785	419	11
	Predicted (D)	9 226	3757	4044	54	7 228	1 392	1208	126	2642	762	364	9
Car, license, no moped	Observed	19 758	9098	80	115	15 643	3 169	–	146	5690	1811	51	51
	Predicted (MS)	19 860	9083	0	30	15 639	3 016	–	268	5911	1665	0	27
	Predicted (D)	20 696	8256	0	123	15 628	3 042	–	277	5951	1631	0	22
Car or license, moped	Observed	615	5848	8403	304								
	Predicted (MS)	1 252	6607	7214	42								
	Predicted (D)	1 239	6626	7212	100								
Car or license, no moped	Observed	843	5335	96	273								
	Predicted (MS)	1 049	5408	0	78								
	Predicted (D)	1 024	5433	0	83								
No car, no license, moped	Observed	253	7310	7842	217								
	Predicted (MS)	212	7679	7865	39								
	Predicted (D)	248	7553	7974	109								
No car, no license, no moped	Observed	353	8064	0	349								
	Predicted (MS)	337	8425	0	124								
	Predicted (D)	262	8531	0	116								
Car, no license, moped	Observed					2 395	4 292	3676	382	732	2922	1687	48
	Predicted (MS)					2 667	4 161	3519	385	971	2616	1749	33
	Predicted (D)					2 285	4 309	3761	390	968	2733	1639	47
Car, no license, no moped	Observed					4 588	6 979	–	465	1665	4423	0	40
	Predicted (MS)					4 711	6 739	–	688	1638	4466	0	94
	Predicted (D)					3 919	7 538	–	672	1613	4512	0	73
No car, moped	Observed					1 071	8 423	6699	1013	650	3240	1548	21
	Predicted (MS)					1 024	7 705	7577	896	481	3009	1907	67
	Predicted (D)					920	8 361	7165	761	468	2848	1989	59
No car, no moped	Observed					2 206	11 247	–	2179	836	6696	0	310
	Predicted (MS)					1 762	12 393	–	1548	1182	6471	0	150
	Predicted (D)					1 389	13 151	–	1163	1267	6405	0	130

Note: Predicted (MS) is modal split only. Predicted (D) is distribution and modal split.

Table 4. Model coefficients for home-based recreational trip.

U.	Item	Mode
-2.87	ln generalized time	Walk-bicycle
-1.66	ln generalized time	Moped
-3.79	ln generalized time	Bus
+3.32	Persons with driving license and car	Car
+0.81	Persons with no license but with car	Car
+22.83		Walk-bicycle
+13.12		Moped
+30.78		Bus
+0.38	Trips to CBD only	Car

Note: Generalized time is in minutes times 100.

HOME-BASED SOCIAL TRIP

Specifications of the utility function of the mode choice model selected are given in Table 1. For the aggregate models all persons from a carless household were grouped together. Application of the mode choice model specification in the aggregate modal-split model resulted in modal shares given in Table 3.

Application of the values of the modal utility functions in the distribution model, followed by modal split, gave the predicted distribution and modal-split values.

The calculated shares for the four market segments of people from car-owning households are all satisfactory. The modal shares for the two market segments for people from carless households are, however, not so good, and most of the differences in the overall modal shares are due to these two segments. Although the no car, no license, moped and no car, no license, no moped segments represent 39 percent of all home-based social trips in the base year, this proportion will decline with increasing car ownership. It was therefore decided not to apply any adjustment, although better fit could almost certainly have been obtained by setting the generalized coefficient for these market segments to a value other than unity.

HOME-BASED RECREATIONAL TRIP

As with the home-based social model, the original intention of a singly constrained simultaneous trip distribution and modal-split model was replaced by a sequential model system using a doubly constrained distribution model.

Development of a mode choice model proved considerably more involved for recreational trips than for the two purposes discussed previously. A specification similar to that described for home-based work proved satisfactory except that the coefficient of car generalized time was both positive and significant. The coefficient of the dummy variable for people with a license from carless households was not significantly different from zero in this model, indicating that for this purpose possession of a license had no effect on the probability of a person from a carless household choosing car.

After trials with alternative specifications, a model with the natural logarithms of the four mode-specific generalized time variables was tried. This is comparable in aggregate model terms to using a power function (C_{ij}^{λ}) rather than an exponential function ($\exp \beta C_{ij}$). In this model all the coefficients were significant and had the expected sign with the exception of the ln generalized time variable for car, which had a coefficient not significantly different from zero. The model was then rerun, and the coefficients given in Table 4 were obtained. The implication of this model is that choice of car is determined by car availability and the level of service offered by alternative modes; in the base year, choice of car was not directly affected by the level-of-service variables relating directly to car. This could be caused by the correlation problems previously referred to; it could also reflect a definite lack of sensitivity to car level-of-service variables in the choice of car for intraurban recreational trips. Such a lack of sensitivity, within reasonable limits, does not seem totally unreasonable; 72 percent of all trips made by persons from a car-owning household were by car.

Use of such a model for forecasting purposes could create problems if extreme measures relating to car usage were to be applied. However, such extremes are unlikely in the context of the current study, and even if they were the reliability of any of the models calibrated for the base year is questionable for such an application.

Application of the model specified above in the aggregate modal-split program resulted in the modal shares per market segment given in Table 3. These can again be regarded as satisfactory, although some individual values show a difference relative to the observed values that is somewhat larger than might ideally be desired.

Use of the modal-split functions in the aggregate distribution model resulted in a serious overestimation of car trips and an underestimation of walk-bicycle trips. To obtain satisfactory results required that a different generalized price parameter be applied to each pair of market segments. The best values were as follows:

Market Segment	Value
Car and license	2.0
Car, no license	1.2
No car	1.0

The results obtained when these factors were applied are predicted (D) values in Table 3.

CONCLUSIONS

Experience with the application of the basic model philosophy to Tilburg is, in some respects, disappointing. But analysis of the results obtained would seem to indicate that the problem is related more to the characteristics of the area to which the models were applied than to the model system itself. There is, however, a reasonable degree of consistency in the results across the various purposes; for instance, the effect on the probability of choosing car of having a car and license relative to having neither is remarkably constant over all purposes.

The results of the study highlight two particular problems affecting the development of such models. One is that variability is not only required within alternatives but also between alternatives. The second is that of estimating a satisfactory model for alternatives with a low choice probability. Neither of these problems are exclusive to the use of disaggregate models; they are also relevant to aggregate models, even though they are not always apparent.

ACKNOWLEDGMENTS

This paper is based on work undertaken for the Greater Tilburg Transportation Study by Buro Goudappel en Coffeng and the permission of both Buro Goudappel en Coffeng and the Municipality of Tilburg is gratefully acknowledged. The ideas on which this paper is based have not been developed by the author alone; Moshe Ben-Akiva and Steve Lerman of MIT and Cambridge Systematics, Inc., made a major contribution toward the development of the approach, and Koos Mars and Pieter Terpstra of Buro Goudappel en Coffeng did much of the work on the implementation of the system.

REFERENCES

1. T. J. Adler and M. E. Ben-Akiva. Joint-Choice Model for Frequency, Destination, and Travel Mode for Shopping Trips. TRB, Transportation Research Record 569, 1976.
2. D. Brand. Separable Versus Simultaneous Travel-Choice Behavior. TRB, Special Rept. 149, 1974, pp. 187-206.
3. Verkeers-en Vervoersstudie Groot-Tilburg, Technies Rapport 3: verwerking van de gegevens. Buro Goudappel en Coffeng B. V., Netherlands, 1974.
4. A Disaggregate Behavioral Model of Urban Travel Demand. Charles River Associates, 1972.
5. D. A. Hensher. A Probabilistic Disaggregate Model of Binary Mode Choice. In Urban Travel Choice and Demand Modelling, Australian Road Research Board, Victoria, Special Rept. 12, 1974.
6. F. S. Koppelman. Travel Prediction With Models of Individual Choice Behavior. Department of Civil Engineering, MIT, Cambridge, PhD thesis, 1975.
7. S. R. Lerman, C. F. Manski, and T. J. Atherton. Non-Random Sampling in the Calibration of Disaggregate Choice Models. Report prepared for Federal Highway Administration, 1976.
8. P. T. McIntosh and D. A. Quarmby. Generalised Costs and the Estimation of Movement Costs and Benefits in Transport Planning. U.K. Department of the Environment, London, MAU Note 179, 1970.
9. M. G. Richards and M. E. Ben-Akiva. A Disaggregate Travel Demand Model. D. C. Heath, London, 1975.
10. D. N. M. Starkie. Transportation Planning and the Policy-Modelling Interface. Transportation, Vol. 3, No. 4, 1974.
11. P. R. Stopher and A. H. Meyburg. Travel Demand Estimation: New Prescription. Traffic Engineering and Control, Vol. 15, No. 19, 1974.
12. A. G. Wilson. Entropy Maximizing Models in the Theory of Trip Distribution. Journal of Transport Economics and Policy, Vol. 3, No. 1, 1969.
13. H. J. Wootton and G. W. Pick. Trip Generated by Households. Journal of Transport Economics and Policy, Vol. 1, No. 2, 1967.

Public Policy Development: The Matrix for Decision Making

Richard M. Michaels, Urban Systems Laboratory, University of Illinois at Chicago Circle

On issues in the public domain, decisions on programs and resource allocation are the responsibility of political actors. That is, any allocation of public resources is determined on the basis of a social judgment about the priority needs of that society and the acceptability of the means and level of investment required to satisfy those needs. In the United States at least, the responsibility for such social judgments is delegated to elected officials or those appointed by them.

Because most public policy issues involve technologies of varying levels of sophistication, the decision process is usually compromised in two important ways. One is that, outside of a few areas, technology has neither been viewed nor used as an explicit instrument of public policy. The other is that policy making is based on inadequate information whose direct and indirect impacts and long-term and short-term effects on the society have been inadequately evaluated.

The first problem essentially leads to the use of existing technologies rather than to considerations of new alternatives. The result is that technologies are expanded beyond the limits of their utility, which produces wholly unexpected and often undesirable side effects. Many examples of this in this century are well documented (2).

The second consideration of information and evaluation is a technical problem. But it is a problem of providing that analysis in terms that have utility to policy makers and that are adapted to their decision-making process and value system. This involves at least three crucial dimensions:

1. Evaluation of alternatives in a cost-effectiveness or comparative framework including indirect as well as direct effects;
2. Evaluation of the temporal framework within which policy alternatives will produce benefits to the society, i.e., the social rate of return to the society; and
3. Evaluation of acceptability of the alternatives as a social and political policy.

The first dimension involves a framework for identifying alternative means to achieve a policy goal and should include social, legal, and technological means. However, aside from comprehensiveness in identifying the alternatives, the problem is one of finding a common metric that is acceptable to policy makers and that they feel confident in using. This has been discussed at length by Baker, Michaels, and Preston (1), who hypothesized that a subjective metric meets these criteria. In addition, they suggested that a dollar metric treated as a measure of perceived value is an obvious candidate. Hence, if a matrix of policy alternatives and their direct and indirect effects can be constructed in which the cells contain an equivalent dollar value, the result will be a cost-effectiveness matrix whose marginals define the relative net costs of the alternatives. Baker, Michaels, and Preston developed such a model in detail.

The second dimension is essentially to derive a social time rate of return for the alternatives evaluated. Based on reasonable estimates for creating, producing, and implementing the alternative set, it is possible to estimate the social return, if any, in dollars that will accrue to the public and when. This is quite similar to conventional investment analysis except that it can be quite a bit simpler. It hinges on the availability of the cost-effectiveness matrix because it provides the total social return on each policy alternative.

The third dimension is quite different from the previous two. When we talk about acceptability we are involved in a wholly subjective domain. Policy makers, in general, make decisions under uncertain conditions, and in one domain there is very high uncertainty indeed: Will any decision on a policy alternative be acceptable to the society? If it is not, the policy will never be implemented or, if implemented, will not be used by the people for whom it has been developed. Experiences in urban transport and public housing policy during the last decade are examples of how basic the issue of social acceptability is. This is, of course, a political problem but fundamentally a subjective one and one that must be dealt with at the subjective level. Doing so is an integral part of the policy process and no less important than so-called objective analyses.

This paper is concerned with policy analysis and largely with the social acceptability dimension. Further, it focuses on a specific policy issue: energy conservation in urban transportation. The purpose is to examine the implications of the more subjective considerations in policy development and to suggest a means for including these dimensions in the larger policy development process.

EVALUATION OF POLICY ALTERNATIVES

Since the so-called Paley report, it has been well-known that the United States would become a net importer of petroleum between 1970 and 1985 depending on the rate of growth of petroleum usage. There are a variety of ways to avoid or reduce dependence on external sources. One obvious approach is to initiate programs and policies that reduce use in existing consuming systems. The concern in this paper is with oil conservation, specifically in urban transportation.

After the policy analysis process described, the following realistic set of possible alternative means of conserving energy in urban transportation was identified:

1. Institutional rearrangements—land use, regional public transit;
2. Legal sanctions—speed limits, rationing;
3. Economic rewards—gas taxes, horsepower taxes;
4. Value changes—change in preference for automobile to that for public transit, car pooling to reduce travel, curtailment of travel; and
5. Technological advances—new power source, personal rapid transit (PRT), substitution of communication for travel, smaller vehicles.

These alternatives were first rated in terms of their direct and indirect effects. This was done as a simple seven-point rating scale on each of 12 criterion dimensions. It was concluded that seven of these policy alternatives were significantly more effective than the others (Table 1).

The next stage in the analysis was to develop the net dollar costs, direct and indirect, for each of these seven policy alternatives. This was done by using the method described earlier. Note that energy savings are actually an indirect effect of implementing a transport policy. Although all seven alternatives provide a substantial savings of oil, five produce a net social benefit and two produce a net social cost.

The second consideration from a policy standpoint is estimating the rate of social return. Basically, this can be done by determining how long it will take from initiation of a policy to its nationwide implementation. These functions were estimated for the seven alternatives and are shown in Figure 1. If extensive research and development are involved or if there are other delays to implementation, the rate of return function shows a net and increasing cost over that initial time period. It is not until these functions cross zero that a net social return accrues. If the alternative produces a social benefit, then ultimately the net return will attain a zero cost, and this crossover point defines an expected time to recovery of the social investment. Clearly, for policy alternatives that produce a net cost, the social return function will produce an accumulating positive cost to the society.

SUBJECTIVE EVALUATION OF POLICY ALTERNATIVES

The third element of policy analysis is the acceptability of the alternative means to attain a social goal. The policy maker must have some insight into whether the society will permit implementation of the atternative or whether the alternative if implemented will be used in the way the policy proposes. This issue is of equal importance to the other two phases of policy analysis. The history of public policy in this century has demonstrated this fact repeatedly.

Given this frame of reference, it is reasonable to suggest five factors that bound attitudes toward policy alternatives at the aggregate level:

1. Technological feasibility—This is essentially an indicator of how close to subjective acceptability the perceived mechanics of the alternative are;
2. Social acceptability—Here the concern is with attitudes toward innovation and change as they are perceived to impact the larger social group or community;
3. Attitudes toward the economic costs of a policy alternative—Again the issue is not objective dollar costs or objective rates of return but the subjective meaning inherent in the magnitude of investment associated with a policy alternative;
4. Political acceptability—When a policy is proposed, it will usually impact the political structure and through that the institutional arrangements by which a society operates; and
5. Temporal acceptability—With or without objective information, the society may be expected to have a subjective judgment about the acceptable delay to problem solution (such a time window is an essential consideration in policy development).

Evaluation of these five dimensions can be based on attitudinal measures that provide policy makers some insight into subjective responses to the policy alternatives they are considering. The simplest scaling approach has been chosen to test this hypothesis: categorical judgment.

In a pilot study, 50 respondents were given a global description of each of the seven conservative policy alternatives and were asked to rate each on the acceptability dimensions by using a nine-point scale. The scales were internally consistent on each alternative, and all the discriminant dispersions were the same. The scale values on each dimension were normalized, and a matrix of judgments and policy alternatives were generated. Because the procedure generates equivalent interval scales, the values for each alternative are additive. Hence, the column totals are an overall measure of subjective judgment of the acceptability of the seven alternatives. Because the variance is approximately one unit, it may be concluded that the alternatives were perceived as different. Basically, two alternatives were perceived as highly acceptable: improved traffic control technology and switching to smaller automobiles. Two were judged as mildly acceptable: car pooling and improved public transit. The remaining three were either neutral or slightly negative. Within each dimension, however, there were large differences. These may be evaluated independently and in a variety of ways. However, for present use the column totals do provide a simple summary measure of the subjective perception of the acceptability of the alternatives.

POLICY ANALYSIS MATRIX

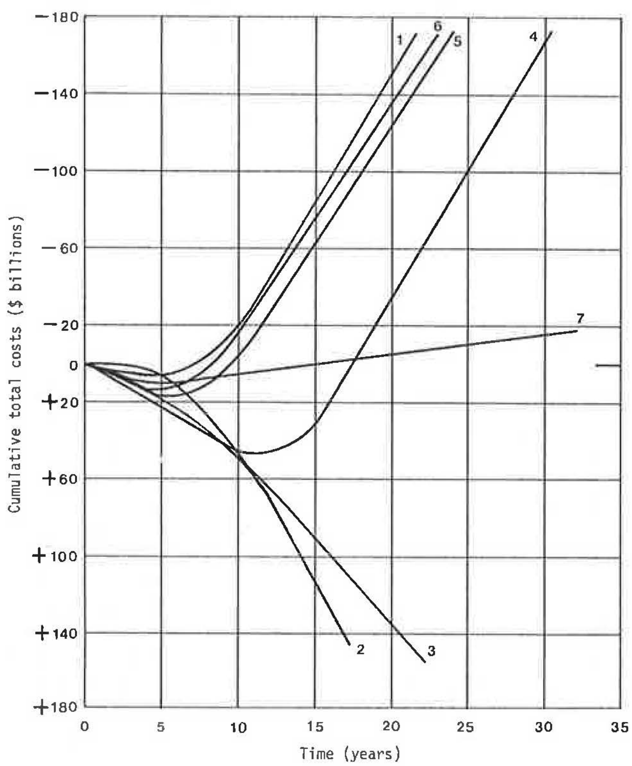
In this policy analysis we have generated four different and independent measures of the seven oil-conservation alternatives. If these four analyses in fact measure different dimensions of importance to policy making then there should be no significant correlation among the four. A rank correlation was used to compare the four measures. The largest correlation coefficient is 0.6, which is not significant. Hence, we can conclude that the four

Table 1. Summary of evaluation of oil-conservation policy alternatives.

Policy Alternative	Oil Savings (m^3/day)	Societal Costs (billion $)	Time to Implement (years)	Acceptability Rating
1. Land use change	33 390	-14.5	13	-2
2. Regional transit	14 310	+15.2	9	4
3. Car pooling	30 210	+9.6	8	5
4. PRT	34 980	-20.0	18	3
5. Traffic control	27 030	-12.8	14	9
6. Substitution of communication	15 900	-12.7	10	2
7. Smaller vehicles	58 830	-1.1	7	7

Note: 1 m^3/day = 6.29 bbl/day.

Figure 1. Cumulative societal costs of seven oil-conservation alternatives.



dimensions are independent.

It is especially interesting to note that subjective acceptability is independent of all the objective measures. Respondents clearly do have attitudes toward and preferences for the policy alternatives and these systems are seen within that subjective framework. As a factor in itself, these acceptability functions define a unique and important dimension for consideration in policy making.

The policy development process described in this paper represents an attempt to provide evaluative information to public decision makers in a form and content responsive to their needs. The process is based on two assumptions. One is that data and their analysis should be open rather than closed. By definition, decision makers need to be able to make decisions.

The second assumption is that public policy making has an essential linking function between the society and its decision making. Because on matters of social concern attitudes and values determine the acceptability of policy alternatives, some measures of these attitudes and values are essential criteria for the policy-making process. Any policy development process that overlooks that element not only is incomplete but also will be unresponsive to a basic concern of public policy makers.

REFERENCES

1. R. F. Baker, R. M. Michaels, and E. S. Preston. Public Policy Development Linking the Technical and Political Processes. Wiley-Interscience, New York, 1975.
2. R. M. Michaels. Transportation Technology and Its Effects on the Human Environment. In Transportation and the Changing South (T. E. Nichols, ed.), North Carolina State Univ., 1967.

Behavioral Impacts of the Energy Shortage: Shifts in Trip-Making Characteristics

Mary D. Stearns, Transportation Systems Center, U.S. Department of Transportation, Cambridge, Massachusetts

This study analyzes shifts in daily trip frequency, mode, and purpose during the 1973-74 national energy shortage. Because aggregate societal shifts may obscure intra-societal variation, it is necessary to examine disaggregated impacts by income level to locate their distribution and magnitude.

ANALYSIS

The analysis uses data from the National Opinion Research Center's Continuous National Survey, collected at the onset (November-December 1973) and peak (February 1974) of the 1973-74 energy shortage (1). The respondents are 18 years old or older, live in the contiguous United States, and are not institutionalized.

Respondents are disaggregated by economic level by using Newman and Wachtel's (3, 6) definition of poverty level, which combines total household income, based on the federal government's 1972 definition of poverty, and household size. Threshold values for households below the poverty level are as follows (3, 6):

People in Household	Income ($)
1 to 2	<3000
3 to 4	<5000
5 to 6	<7000
7 or more	<9000

Statistical tests, including student t-test and standard error of the difference, were used to determine significant shifts in trip characteristics ($p \leq 0.05$).

Although it was recognized that the seasonal factor influences trip making, the focus on shifts ought to reveal relative differences in which monthly variations affect most population segments equally.

RESULTS

Modal Shifts

Respondents reported significantly fewer daily trips during the peak of the energy shortage. The changes in daily trips and in the percentage of respondents who made no daily trips are given below:

Sample	Daily Trips	No Trips (%)
Above poverty level	4.2 to 3.6	13 to 16
Below poverty level	2.1 to 2.2	33 to 33
Aggregate	3.8 to 3.1	15 to 16

(Changes in daily trips for those above the poverty level and in the aggregate were statistically significant, $p \leq 0.05$.) The mean aggregate number of daily trips by all modes including walking decreased by 19 percent between the onset and the peak of the energy shortage. Automobile driver trips also decreased 19 percent from 3.2 to 2.6 per respondent. These decreases are larger than the 1970 to 1974 December-February 9 percent mean intermonthly decrease in vehicle-kilometers traveled (5).

However, only respondents whose incomes were above poverty level significantly decreased their trip frequency, from 4.2 to 3.6. This result coincides with research that showed that higher income suburban residents who own automobiles reported significant trip reductions (4).

In addition, the trip frequency of below poverty level respondents was relatively constant and equalled approximately half the rate of the respondents above poverty level. One-third of the respondents below poverty level made no daily trips, not even a walking trip. By contrast, only one-sixth of the respondents above poverty level reported zero trips.

There were no significant aggregate modal shifts, as shown below. The small percentage of changes are in the expected directions but are not statistically reliable. Above poverty respondents reported no significant modal shifts or a pattern similar to the aggregate shifts. By contrast, respondents below poverty level significantly ($p \leq 0.05$) reduced use of one mode, the automobile driver mode. The percentage of modal shifts during the energy shortage was as follows:

Population	Automobile Driver	Automobile Passenger	Transit	Walking
Above poverty level	71 to 69	16 to 18	2 to 3	9 to 9
Below poverty level	59 to 46	20 to 24	3 to 5	18 to 22
Aggregate	69 to 66	6 to 19	2 to 4	10 to 11

MODAL SHIFT BY TRIP PURPOSE

The meaning of the reported modal shifts is better understood when the shifts are identified by trip purpose. The percentage of modal shifts by mode was as follows:

Mode	Home	Work	Shopping	Social-Recreational
Automobile driver	71 to 68	72 to 73	71 to 61	59 to 47
Automobile passenger	16 to 18	11 to 13	18 to 19	24 to 32
Transit	2 to 3	4 to 4	1 to 1	1 to 4
Walking	9 to 10	12 to 9	10 to 18	13 to 14

There were no significant modal shifts for the home or work trips. Aggregate modal elasticity occurred only for shopping and social-recreational trips. The increased use of walking for shopping trips suggests that respondents may have tried to make more use of locally available facilities. The aggregate decrease in automobile driving for shopping is parallel to increased walking.

The other significant shift in modal usage ($p \leq 0.05$) was decreased automobile driving for social-recreational trips. It is likely that more deliberate sharing of travel facilities occurred on social-recreational trips and, perhaps, an increased incidence of shared activities.

Data given in Table 1 show that significant modal shifts by trip purpose only occurred with the automobile driver mode. Respondents above poverty level markedly reduced automobile driving for social-recreational trips. This reduction made the frequency of automobile driving by higher income respondents for social-recreational trips more similar to that of poor respondents. The only significant modal shift reported by respondents below poverty level was reduced automobile driving for shopping.

The lack of significant modal shift for the work trip should be noted. Mode selection may be relatively inflexible for certain trip purposes, probably because of unavailability of an alternative, the level of service required for that trip purpose, and the existence of household trade-offs involving residential location and perceived need for services (2).

These results are similar to Peskin, Schofer, and Stopher's report (4) that the energy shortage did not alter journey-to-work patterns or transit use of suburban respondents.

Table 1. Percentage of modal shift by trip purpose and economic level.

Mode	Purpose	Above Poverty Level	Below Poverty Level
Automobile driver	Home	73 to 71	56 to 48
	Work	73 to 75	65 to 57
	Shopping	73 to 67	50 to 35[a]
	Social-recreational	61 to 48[a]	46 to 42
Automobile passenger	Home	16 to 18	23 to 19
	Work	10 to 11	18 to 22
	Shopping	18 to 19	20 to 18
	Social-recreational	25 to 32	20 to 33
Transit	Home	2 to 3	5 to 5
	Work	4 to 4	1 to 6
	Shopping	1 to 1	1 to 2
	Social-recreational	1 to 4	6 to 5
Walking	Home	8 to 7	16 to 26
	Work	12 to 9	16 to 9
	Shopping	8 to 13	20 to 41
	Social-recreational	10 to 13	28 to 20

[a]Statistically significant, $p < 0.05$.

CONCLUSIONS

The energy shortage had minor aggregate impacts but some significant disaggregate impacts. Certain population groups were substantially affected by the energy shortage; for example, households below poverty level reported significant modal shifts. The energy shortage is associated with significant alterations in trip frequency, mode, and purpose in the total society and for certain income groups.

Income appears to be associated with discretionary trip making. Previous suggestions that only the availability of energy, rather than its cost, affected travel behavior of higher income respondents appear to be supported by this study (4). Higher income respondents apparently reduced trip frequency by making more efficient trips through the use of "trip-stringing" for the shopping trip.

However, respondents below poverty level reacted differently to the energy shortage. Their trip frequency and purpose distributions were unchanged, suggesting that they made essential trips. However, low-income respondents showed a significant modal shift away from automobile driving, possibly because of the cost of gasoline.

The increased costs due to the energy shortage markedly altered the trip-making patterns of poor respondents in terms of mode and purpose but minimally influenced the trip making of other people.

Poor respondents' relatively constant trip frequency and probable economic constraints on mode choice suggest that their life-style may be based on obtaining necessities that permit little monthly or seasonal variation.

By contrast, it is difficult to determine whether the reduced trip frequency and selective reduction in trip purpose (with little corresponding modal shift) of respondents above the poverty level were affected by the energy shortage or represent monthly variations. It is possible that monthly variations chiefly affect higher income respondents because they make discretionary trips.

The results of this study suggest that travel elasticity is differently apportioned by income level. Therefore, disaggregate as well as aggregate behavior responses must be examined to determine potential changes.

The study results provide intellectual stepping-stones toward an improved understanding of the structural requirements of full social participation in today's society. The income-related differentials in trip frequency and modal usage indicate that a portion of trip making is one of society's luxuries and that automobile ownership is mandatory for full societal participation. Contemporary social structures providing opportunities mandate automobile access as shown by the inflexibility of the work trip characteristics for all population segments.

ACKNOWLEDGMENT

This study was performed under the Transportation Systems Center's transportation energy policies project sponsored by the Office of Transportation Energy Policy.

REFERENCES

1. A Compendium of Questionnaire Items, Cycles 1 Through 12. National Opinion Research Center, Univ. of Chicago, NORC Rept. 125, July 1974.
2. J. B. Lansing and G. Hendricks. Automobile Ownership and Residential Density. Survey Research Center, Institute for Social Research, Univ. of Michigan, Ann Arbor, 1967.
3. D. K. Newman and D. D. Wachtel. The American Energy Consumer. Ballinger Press, Cambridge, Mass., 1975.
4. R. L. Peskin, J. L. Schofer, and P. R. Stopher.

The Immediate Impact of Gasoline Shortages on Urban Travel Behavior. U.S. Department of Transportation, April 1975.
5. Traffic Volume Trends. Federal Highway Administration, 1974, 1975.
6. Let Them Freeze in the Dark. Washington Center for Metropolitan Studies, Feb. 1, 1974.

Incentives and Disincentives to Ride-Sharing Behavior: A Progress Report

Joseph B. Margolin and Marion Ruth Misch, Program of Policy Studies in Science and Technology, George Washington University
Ricardo D. Dobson, Federal Highway Administration, U.S. Department of Transportation

Ride sharing is a social and economic activity in which a vehicle is shared by two or more individuals. A common form is car pooling, but van pooling and bus pooling are alternative forms. Because the individuals in a pool are members of an organized social group with meaningful functions and roles, participation should be responsive to behavioral and economic principles underlying group formation and maintenance.

Several studies have contributed to the understanding of traveler behavior in ride-sharing situations. Through in-depth interviews with car poolers, Barkow (1) highlighted the role of social factors in ride sharing. He believes that pooler contacts should be handled by humans and not computers. Andrle and Dueker (2) report on a before and after study of car pool matching programs in Iowa City. The farther a person lived from work, the more interested he said he was in joining a pool. After survey data, however, revealed that individuals had overstated their willingness to join car pools. The matching programs were not effective at significantly enhancing the car pooling rate, and it was concluded that a matching program by itself is an insufficient incentive to alter commuting patterns. The California Department of Transportation supported a study to devise a car pool action program (3). The results supported Barkow's emphasis on the importance of differential psychological and social factors affecting various groups in ride sharing.

This investigation of ride sharing differs from previous research in a variety of ways. First, the study is essentially an exploratory examination of behavioral incentives and disincentives for different groups of potential poolers. Second, the study design is a sequence of (a) hypothesis generation, (b) hypothesis testing, and (c) consideration of feasibility. Finally, a combination of survey and panel discussion methodologies is used. The contrasting methodologies are used to check the validity of findings and conclusions from different perspectives.

The behavioral orientation of the study is designed to lead to the development of policy options that induce individuals to join or form car pools. Because not all people are equally responsive to identical policy options, an effort is being made to define homogeneous groups of potential poolers—groups that show varying sensitivity to different policy scenarios. The study has two specific objectives: to obtain valid and meaningful data about consumer attitudes toward ride sharing and to develop more sensitive methods for such study. The problem addressed is the lack of in-depth information about what specific incentives and disincentives affect different groups of users.

To achieve these objectives, a three-phase study was designed. In the first phase, ride-sharing incentives and disincentives among potential and actual ride sharers were explored in depth. In the second, a survey built from the motivational information derived in phase 1 will be carried out with a larger sample. In phase 3, ride-sharing strategies derived from the incentives and disincentives discovered will be explored with groups of users and of transportation professionals for feasibility on a pilot basis.

RESEARCH DESIGN

Phase 1 was qualitative and was designed to produce hypotheses about incentives and disincentives for ride sharing. A series of consumer panel discussions was held with small groups of intraurban transportation users. In these, people discussed their transportation experiences, preferences, satisfactions, and dissatisfactions. The panels were homogeneous groups, that is, people who share important life situations or characteristics such as age and type of occupation or socioeconomic status and commuting patterns, as well as combinations of these. Group discussions were used because they elicit information from more people at lower cost and they take advantage of group interaction. In the process of discussing travel problems with each other and with the research staff, people soon go beyond the first answers that come to mind to the less conscious forces that operate when they make transportation decisions.

Phase 2 will survey 500 respondents to quantify the hypothesis by making a first estimate of how widely and to whom the hypothesized incentives and disincentives of phase 1 apply.

In phase 3, those hypotheses that prove to be widespread in the population segments examined will be used to develop program plans and policies that may facilitate car pooling and other forms of ride sharing. Then, as in phase 1, further homogeneous panels will be assembled to react to these strategies and to provide qualitative feedback about their acceptability.

METHODOLOGY

The validity and reliability of the sequential approach depend on careful design of the behavioral science methodological tools used.

Phase 1 Consumer Panels

The panels were selected to include groups that were believed to be potential ride sharers. For example, because an increasing majority of intraurban automobile travel is from suburb to suburb, special emphasis was placed on that commuter group. Some of the homogeneous consumer groups interviewed were

1. CBD-CBD blue-collar commuters,
2. Exurban-suburban blue-collar commuters,
3. Suburban-CBD white-collar commuters,
4. Suburban-suburban white-collar commuters,
5. Suburban-suburban commuting executives and professionals,
6. Satellite city-suburb commuters,
7. Suburban high school drivers,
8. Handicapped (varied in terms of disabilities and employment), and
9. Aging (commuting and noncommuting).

The discussions were operated according to group dynamics theory and techniques established during the last 25 years and widely tested in such diverse areas as industrial psychology and group psychotherapy. Groups were kept small—6 to 10 volunteers met with 2 or 3 research staff members—to allow maximum participation. The advantage of including more than one staff member is that, when staff members raise questions with each other or take exception to each other's point of view, participants see the importance of people expressing their own diverse views. It also avoids that overdependence on the leader that tends to develop when there is only one. The sessions began with a brief, anonymous questionnaire about transportation habits and preferences, including demographic questions, number of automobiles and licensed drivers in the household, access to public transportation, and other personal transportation facts. In addition to focusing attention at the start of the session on the subject matter for discussion, these miniquestionnaires provided information about transportation preferences before the session influenced people.

The discussion began with open-ended and highly general questions raised by the staff, for example, "What are some of your most troublesome transportation problems?" This allowed panel members to discuss what was on their minds without being led by what was on the researchers' minds. Although details of all of the techniques used to manage the discussions cannot be given—for instance, how to deal with the inevitable leader's helper who avoids responding by trying to encourage others to speak—the general approach has been clarified. Sessions were $1\frac{1}{2}$ to 2 hours long. Typically in that period of time, groups aired either complaints or idealistic attitudes, then moved to a more balanced consideration of possibilities and alternatives, and finally brought out some main problem or point of view.

Data from the panels were analyzed in several ways. First, the brief questionnaires were tallied to identify the profile of each group. Next was a thematic analysis of the discussion in which issues raised, opinions expressed, and experiences reported were examined for recurrent, significant themes. Quantification is only minimally useful here since a group may spend considerable preliminary time on extreme positions or a few individuals may dominate the talk initially. The results of the thematic analysis were then compared with the questionnaire data. This revealed issues not raised in the session. At times it also revealed that the force of peer influence on the discussion broadened the possible transportation alternatives that people are willing to entertain—an important finding in itself inasmuch as the leverage of peer group influence has been little used in a systematic way to increase ride sharing.

A theoretical tool that has proved highly useful in analyzing such data is Kurt Lewin's decision-making theory. This includes a feedback process wherein each decision, or action, modifies the individual decision maker's attitude and thereby affects his or her subsequent decisions. The theory explains the fact that attitudes do not remain fixed: Action commits the individual psychologically to support and justify that action. Thus, a person who submits a car pool application becomes somewhat more committed to car pooling by taking the step. If a person actually joins a car pool, he or she will then be likely to become more confirmed in attitudes and perceptions that favor car pooling. This has important group dynamic ramifications because each car pool member will strengthen not only his or her own attitude toward the car pool but those of fellow members.

Phase 2 Survey Questionnaire

Survey questionnaires for phase 2 are being constructed in three parts. One covers transportation practices, including past experience with various modes, vehicle ownership, transportation costs, and the like. General demographic data will also be obtained. The main section is being devoted to incentives and disincentives for car pooling derived from phase 1 data.

The particular incentives and disincentives revealed in phase 1 are detailed in as operational a manner as possible. For example, the independence and convenience mentioned so often in the brief questionnaires usually had overlapping meanings during the consumer panel discussions. Independence, for example, was often used to convey, "There is no need to plan. I can move when I want to." "I do not have to rely on anyone else in order to go." On the other hand, convenience often meant, "I do not have to rely on anyone else in order to go." "I do not have to wait." People will therefore be asked operational and explicit questions, rather than the more ambiguous, "Do you find it convenient?"

Two methods of administration will be used: face-to-face individual interviewing and a telephone series so that the costs and benefits of the two approaches can be assessed. Data analysis from the survey will depend on the structure and content of the questionnaire in its final form.

Phase 3 Strategies and Panels

Phase 3 strategies will be constructed after the effect of the several incentives and disincentives individually and in combination has been determined in phases 1 and 2. Scenarios for the implementation of given strategies will be constructed and discussed with both travelers and transportation policy makers. If the hypotheses can survive the rigorous testing of this sequential study design, they will have demonstrated considerable credibility.

Through this research we are seeking not only valid information, but also a policy tool. The origin of the issues and hypotheses in the life conditions of travelers and their ultimate testing by those who would decide on, or participate in, the ride-sharing strategies that emerge are expected to lend a quality to the final product that is closer to reality than might be achieved through more classical methods.

Another significant implication of this approach for policy decision making resides in its greater relationship to planning than to forecasting. If we define forecasting as expected developments as extensions of historic patterns, the approach of this study provides the transportation sector with additional tools and options, options not available in extrapolations from past travel patterns. The extensive study of human attitude and interaction and the emphasis on development of principles and scenarios should provide insight into the personal decision-making process itself. This, in turn, will improve our capability for planning to meet unforeseen problems and contingencies as conditions change.

EARLY FINDINGS

The following early findings illustrate the kinds of issues and questions being obtained.

1. Why different groups drive and what driving means to them are based on varied motivational patterns. Teenagers frankly admit that they derive considerable satisfaction from "having the wheel." They prefer not to car pool because, in a car pool, they do not drive all the time. Closely related is the feeling of freedom from parents that comes while driving. Exurban laborers, on the other hand, do not need the automobile as an expression of either adulthood or physical mastery of the environment. Instead, they need urgently to get to the job on time and are less tied to the driver role by psychological bonds.
2. Ride-sharing matches offered through computerized car pool systems revealed some interesting incentives and disincentives. (a) The request to send name, address, telephone number, and hours of employment to a downtown address runs counter to current concerns about privacy, as well as to police department urging that this information not be given to strangers; (b) when the printout is received, potential car poolers have a powerful resistance to telephoning a stranger; and (c) the process takes from several weeks to several months or more. The desire for a prompt, simple response in which the potential car pooler can see and assess possible car pool mates was directly expressed in many panels.
3. A number of additional incentives and disincentives were highlighted by the following observations: (a) Fringe parking is less acceptable than parking in a shopping center because of robbery and vandalism problems; (b) suburbanites bemoaned the lack of circumferential public transportation; and (c) many panelists objected to the trend toward small cars because they limit car pools to two or three people and because of their safety problems.

POLICY IMPLICATIONS

These findings suggest a number of strategies that have policy implications for the design of car pooling programs. Factors that are relevant for these strategies include characteristics of the traveler, interpersonal needs, program locus, and program mechanisms. The following strategies are illustrative:

1. Organizing car pools quickly and on a face-to-face basis within the place of work;
2. Organizing car pools at the home end under the auspices of a civic association, PTA, or similar group; and
3. Appointing, training, and perhaps reimbursing a car pool coordinator whose functions would be (a) getting together pools made up of people who are likely to stay together, (b) salvaging and reassembling car pools that break up, and (c) identifying the forces that hold groups together or weaken them and feeding this information to ride-sharing program planners and decision makers.

These strategies apply particularly, although not exclusively, to commuters. They are based on the facts that (a) many travelers desire a more personal introduction to car pooling and to potential car pool mates because of fears of crime and violence that frequently prevail; (b) assistance is needed to overcome people's frequent reluctance to take the initiative in forming car pools; (c) people will react more favorably to a quick response to their expressed interest; (d) they want a reliable means of transportation; and (e) group decision making is a potent factor in car pooling behavior.

The structure of the strategy, however, must also meet the differing needs of highly diverse population groups. Two other strategies are suggested.

1. Commuting buses or company van pools should be organized for exurban laborers to bring them as close to their widely dispersed homes as possible and to provide a service in which the company shares the problem of getting laborers to work on time. At present, data reveal that a significant portion of these workers have no special attachment to driving, but they are pressured (by threatened loss of pay for even minor tardiness) not to rely on the promptness of coworkers.
2. For teenagers, informal car pooling should be encouraged. The well-known urge of the teenager to drive is tied to an acute need for autonomy. Advantage can nevertheless be taken of their gregariousness, so long as car pooling is not stringently formalized with schedules and assigned riders, which appear to the average teenager to be yet another schoollike burden imposed by adults. The program would need to be organized by the teenagers themselves and provide for flexible picking up of friends as the occasion permits.

SUMMARY

This has been a progress report on a three-phased behavioral and exploratory study of incentives and disincentives to ride sharing. This study falls in the category of planning research, rather than travel forecasting, because it investigates not what people are projected to do but what they currently do and why. The rationale is to provide causal, as well as historical, information about ride-sharing behavior.

Because the study uses a small number of population segments and is exploratory in nature, generalization of findings is limited. Nevertheless, it is anticipated that the validity of the conclusions will be considerably strengthened if the hypotheses derived from the phase 1 consumer panels are reaffirmed by the phase 2 survey and the phase 3 group discussions of possible ride-sharing strategies based on these hypotheses. Those hypotheses supported by all phases of the study will be ready for larger scale research. Certainly, the distinct differences among groups explored to date suggest the need for expanded explorations of carefully delineated, homogeneous population segments.

Finally, if the methodology tested in the study proves to be valuable for producing viable hypotheses about ride-sharing behavior, its application to behavioral aspects of other travel modes should be tested.

REFERENCES

1. B. Barkow. The Psychology of Car Pooling. Ontario Ministry of Transportation and Communications, 1974.
2. S. Andrle and K. J. Dueker. Attitudes Toward and Evaluation of Car Pooling. Institute of Urban and Regional Research, Univ. of Iowa, Iowa City, Technical Rept. 32, 1974.
3. A Study of Techniques to Increase Commuter Vehicles Occupancy on the Hollywood Freeway. Alan M. Voorhees and Associates and Behavioral Science Corporation, 1973.

Parametric Access Network Model

Antti Talvitie, University of California, Berkeley
Tom Leung, Department of Civil Engineering and Environmental Science, University of Oklahoma

Parametric models are calibrated for the access portions of rail and bus trips. The models are designed to predict average zonal travel times as a function of the transportation system, zone size, and volume-related characteristics of a zone. The calibrated models are access walking, driving, and bus-riding time for rail trips and walking time to a stop for bus trips. Corresponding models are developed for the within-zone variance of the access time. These models provide input to the existing travel demand forecasting process by systematizing the way in which the access times are currently obtained for network coding. The importance of these values for travel forecasting has been repeatedly demonstrated in the past. These models also enable the use of large zones to help simplify and speed up the transportation plan analysis and evaluation process. The predictive accuracy of the final models is evaluated in terms of standard indexes of forecasting accuracy. The results show that the coefficients of determination are high and that the coefficients of variation are low for all the models. Thus, the models should find an immediate use in transportation planning.

The demand for transportation depends, among other things, on the level of service, i.e., access time, in-vehicle time, and travel cost, provided by the transportation system. These variables both characterize the transportation system and serve as the basis for travel demands. Thus, the values of these variables are needed both for calibration of travel demand models and for forecasting purposes.

Currently, no satisfactory systematic methods exist for calculating the access-egress travel times even though some progress has been made in modeling the access travel times. Two studies (1, 2) were found to be pertinent starting points to the present research.

The research reported here is an extension of the work by Talvitie and Hilsen (2). It uses simulation to create the data on which the statistical calibration of access models can be based and, thus, does away with expensive data gathering. The models developed in the present research are also specific to a station and, if necessary, a bus line. In this way, the mixing of demand (which station to choose) and supply (what it takes to get to the station) sides is eliminated. Another new feature of the present access supply models is the explicit inclusion of intrazonal transportation system attributes in the models.

NEED FOR ACCESS SUPPLY MODEL DEVELOPMENT

Recent studies show that travel demand models must be policy sensitive and behavioral in order for them to be truly useful in transportation systems analysis. A traveler, confronted with questions of whether to make a trip, where to go, when to make the trip, which mode to take, and which route to choose, bases his decisions on the level of service provided by the system and the activity system around him. Research by Kraft and Wohl (3) pointed out that the level of service provided by the transportation system must be described for complete door-to-door trips.

Domencich, Kraft, and Valette (4) suggested that travelers react differently to different components of travel time and cost. It is desirable to segment the times and costs into their component parts so as to bring the effect of policy actions into much sharper focus.

The explicit modeling of the supply of access systems is also needed to obtain information on the access mode choice and access station choice. If the attributes of different access modes to different stations and lines are accurately represented, then the use of access-station selection models (5) becomes possible and the desired information on access mode and station can be obtained.

To model the mean (and variance) of the access times requires that the underlying system of transportation be defined; hence, it becomes possible to compute costs of such access systems and relate them to the performance (travel time) obtained by the system.

PROPOSED STUDY MODEL

In this study, two types of supply models for the access-egress portion of a trip are developed. The first type is inclusive models, which apply to all the people in the zone. The second type is restricted models, which apply only to those people who can choose the alternative whose time is being modeled.

The reason for developing both types of models is that it has not been clearly established yet which of the two types of models is the more appropriate counterpart for current (and future) travel demand models. Theoretical arguments tend to favor the restricted models (e.g., modeling choice is appropriate only if the choice exists); however, there are practical reasons for favoring the inclusive models (e.g., how do we know who in the zone does and does not have a choice?). Perhaps the consistency of the supply and demand models is a better yardstick; whichever supply model was used in developing the demand models should also be used in forecasting.

Three models that deal with a rail trip are calibrated. They are the access walking time to station, the access driving time to station, and access riding time in bus to station. The access driving time can also be applied to the access driving time to the ramp of the line-haul expressway for the automobile mode. One access model, walking time to a bus stop, is developed for the bus trip. However, bus walk time can also be considered a segment of a rail access trip if the traveler walks to a bus stop in order to take the bus to a rail station.

In addition to these models, which estimate the zonal mean access time, corresponding models for the within-zone variance or standard deviation of the access times are developed. These models are for the variance of the access time in a zone and not, of course, for the mean access time of the zone.

The supply models developed in this study have the following functional form:

$$\text{Access time}_j^m(L) = S(\text{zone size variable}_j, \text{transportation system variables}_j, \text{volume}_j) + e_j$$

where

j = zone,
m = access mode of travel,
L = estimate of the access time,
S = supply function, and
e = error term.

Three types of variables are considered in the above model. The zone size variable describes the area of a zone. The volume variable is represented by trip density per square kilometer per day in a zone. Transportation system variables are separated into two groups: those characterizing the zone(e.g., area, spacing between arterials, and signalization) and those characterizing the transportation system serving the zone (e.g., bus stop frequency per kilometer, number of bus lines, distance of the station from the zone centroid). The parametricization of these variables allows us to develop statistical models that relate these variables to the mean access travel time of a zone.

DATA AND METHOD

In developing the supply models, a simulation approach is used. The values of the dependent variables are generated by the method of simulation; multiple regression analysis is then used to estimate the parameters of the model.

The input data set can be specified in the following three groups:

1. Characteristics of each zone—zone size, arterial spacing, traffic signals, and the number of lanes on the main arterials and intersections;
2. Characteristics of the public transit system—station coverage, frequency of the bus stations, bus route-kilometers, spacing between parallel bus lines; and
3. Volume characteristics—trip density.

In addition, the following assumptions were made.

1. Speed on local streets is 40 km/h (25 mph), and total delay is 10 s.
2. Capacity for each lane of the arterial is 1700 vehicles per hour of green.
3. Vehicles are evenly distributed among the lanes going in one direction.
4. If the signals are synchronized, the vehicle can either stop once or go through the system without delay. If unsynchronized, the vehicle has a 50 percent chance of stopping at each intersection it goes through.
5. Intersections are 0.8 km (0.5 mile) apart.
6. All study zones are squares.
7. Walking speed is 4.8 km/h (3 mph).
8. Buses stop at every station for 30 s.
9. Frequency of bus stops for each line within a zone is uniform.
10. Passengers can get on the bus anywhere along the line. The time spent to pick them up is negligible.
11. The volume on the arterial is a function of the arterial spacing and trip density (6).
12. The peak-hour volume on the arterials can be obtained as a percentage of the 24-hour traffic volumes. The percentage of the peak-hour volume in the morning peak direction was assumed to be 65 percent (7).
13. To approximate the mean delay at a signalized intersection, a typical volume relationship (8) was used. This was modified for the volume-capacity ratio to be on the x-axis.
14. The speed of the vehicle can be obtained as a function of the volume-capacity ratio (9).

These assumptions and the specific input data provide a framework for logical and mathematical relationships, analytical equations, and probabilities required to simulate the values of the explanatory variables. These simulation models are described below.

DRIVE MODELS

The input dat were used to derive the volume-capacity ratio for the zonal arterials. This volume-capacity ratio was used to obtain the zonal speed and the mean delay for each intersection. A randomly located individual was next generated inside the traffic zone, and his or her travel time on local streets and on the main arterials to reach the station-expressway ramp was calculated. For zones with unsynchronized signals, the number of intersections he or she had to go through in driving to the station was also recorded.

Similar models are developed for both inclusive and restricted cases. In the latter, no travelers were generated within 0.8 km (0.5 mile) of the station, because they are assumed to walk to the station only.

WALK MODELS

The walk models are very simple. Information on the location of the rail station or on the bus lines and the frequency of the bus stops in put, and a randomly located individual is generated. By assuming a walking speed of 4.8 km/h (3 mph), his or her walk time to the station or to the nearest bus line is easily obtained and recorded.

Again, similar models were developed for the restricted case, where people are generated only within the walking distance of 0.8 km (0.5 mile) of the rail station or 0.4 km (0.25 mile) of the bus line.

BUS RIDE MODELS

Speed and mean delay were derived for the bus ride models in the same way as in the drive models. Again, the travel time for a randomly located individual was obtained by recording the traveled distance, the number of stops the bus has to make, and intersections the bus has to go through to reach the station.

EXPLANATORY VARIABLES

From the simulation models, the mean and standard deviation of the zonal access time are obtained. They are the dependent variables for the supply models. The independent variables are the attributes of the zones and their intrazonal transportation system. The variables are defined below. (SI units are not given for the variables of this model inasmuch as its operation requires that they be in U.S. customary units.)

1. DISTI, distance from centroid, is the distance to the station (or to the expressway ramp) from the centroid of the zone in miles. If the station or ramp is 0.5 mile (0.8 km) outside of the zone, it is the straight-line distance from the centroid to the boundary of the zone.
2. AREA is the number of square miles in each zone.
3. Dummy is a variable to identify whether the station is inside the zone. Dummy equals 0 if the station is inside the zone and 1 if the station is outside.
4. COVER, coverage, is the ratio of the area of the circle of 0.5-mile (0.8-km) radius that is inside the zone to the area of the zone.
5. YI, Y_i or Y_o, is the smallest distance from the side of the zone to the nearest bus line in miles. It is positive if the line is inside the zone and negative if the line is outside.
6. BS, bus line spacing, is the distance between parallel lines. If there is only one bus line, spacing equals $2 \times (\text{AREA}^{1/2} - \text{YI})$.
7. COVER-B is the ratio that represents the portion of the area of the rectangle of area that is inside the zone.
8. FRE is the bus stop frequency in miles between stops.
9. DISTO is the straight-line distance from the boundary of the zone to the station or ramp in miles. If the station is inside the zone, DISTO = 0. Once the vehicle gets outside the zone, a synchronized signal system is assumed.
10. SIGN, signals, is a dummy variable for the synchronization of traffic lights in the zone. SIGN = 0 if synchronized, and SIGN = 1 × (average number of intersections) if unsynchronized.
11. TDPSQ, trip density, is the trip density of a zone per square mile per day. The value used in the expression is scaled down by dividing it by 1000.
12. LANE is a dummy variable for the number of lanes on the zonal arterials, and it equals 0 if two lanes and 1 if four lanes.
13. AS, arterial spacing, is the distance between parallel arterials.
14. DIST is the distance to the station from the boundary of the zone on a straight line joining the station and the centroid of the zone. It is positive if the station is outside the zone and negative if the station is inside the zone.

ESTIMATION OF MODEL COEFFICIENTS AND EVALUATION OF MODEL ACCURACY

The method of least squares was used to estimate the coefficients of the supply models.

The models developed were evaluated on the basis of standard indexes regularly used in econometric studies to measure predictive accuracy and goodness of fit. For this purpose the following measures are given in Table 1:

1. The coefficient of determination (r^2),
2. Coefficient of variation = (standard error of estimate)/(mean of the dependent variable), and
3. F-value of the model.

On the basis of these measures, the relative accuracy of the ordinary least squares models may be inferred. Another criterion for judging the performance of the models is the sign of the coefficients; the coefficients must have a proper sign if a model is to be useful.

ESTIMATION RESULTS AND EVALUATION OF MODELS

The forms for the models are given in Table 1. The estimated mean and standard deviation for the walk, drive, and ride models are given in Table 2. Table 2 also gives the model parameters and the statistical significance of the relationships measured by the parameters. The elasticities were calculated at the mean value of the variables.

Walk Models

Reasonably good results were obtained for the walk models. All the parameters have the correct sign, and most of them are highly significant.

In the walk, restricted models, coverage and its square are the important variables in determining the walk time to a rail station or to a bus stop. In addition, whether the bus line is within the zone and the distance adjacent bus stops appear to be relevant for the average zonal walk time to a bus stop.

For the walk, inclusive models, the size of the zone is an important variable. Logically, the larger the zone is, the longer the walk time is. Another obviously significant factor is where the station or bus lines are situated. In the walk to rail station model this is specified by the distance of the rail station from the centroid of the zone and whether the station is inside the zone. In the walk to bus stop, variables for number of lines and bus line spacing determine the number of lines serving the zone and their exact location. The elasticity with respect to these variables shows that walk time is very sensitive to the location of the bus lines and rail stations.

Examination of the t-statistics and the elasticity of the bus stop frequency variable shows that the bus stop frequency plays an important role in the walk, restricted model, although its presence is not significant in the walk, inclusive model. In the former, pedestrians walk to a bus line located closer than 0.4 km (0.25 mile) and a large part of the walk time consists of the distance between the bus stops. For the walk, inclusive model everybody inside the zone is allowed to walk to a bus stop. In this case, naturally the distance between the lines rather than the distance between the bus stops plays an important role in determining the walk time. Bus

Table 1. Form of models.

Model	Form	Elasticity About Mean	n	F-Value Mean	F-Value σ	CV Mean	CV σ	r^2 Mean	r^2 σ
1. Walk to rail station, inclusive	T = a + bX	$e_{\bar{x}} = b\bar{X}/\bar{T}$	39	352.45	175.22	0.08	0.11	0.97	0.94
2. Walk to rail station, restricted	T = a + bx + cx^2 + dY	$e_{\bar{x}} = (b + 2c\bar{x})(\bar{x}/\bar{T})$ $e_{\bar{y}} = d\bar{Y}/\bar{T}$	10	169.75	51.15	0.03	0.10	0.98	0.96
3. Walk to bus stop, inclusive	T = a + bx	$e_{\bar{x}} = b\bar{x}/\bar{T}$	66	166.44	120.68	0.19	0.26	0.89	0.85
4. Walk to bus stop, restricted	T = a + bx + cx^2 + dy	$e_{\bar{x}} = (b + 2c\bar{x})(\bar{x}/\bar{T})$ $e_{\bar{y}} = d\bar{y}/\bar{T}$	30	377.93	51.49	0.03	0.11	0.98	0.89
5. Drive to station or ramp, inclusive	T = ae^{bx}	$e_{\bar{x}} = b\bar{x}$	151	193.53	185.41	0.10	0.31	0.90	0.88
6. Drive to rail station, restricted	T = ae^{bx}	$e_{\bar{x}} = b\bar{x}$	151	257.64	176.47	0.10	0.40	0.91	0.88
7. Ride to rail station	T = ae^{bx}	$e_{\bar{x}} = b_{\bar{x}}$	54	103.60	49.78	0.06	0.12	0.92	0.92

Table 2. Means and standard deviations of model variables.

Model	Variable	Parameter Mean	Parameter σ	t-Value Mean	t-Value σ	Elasticity Mean	Elasticity σ
1	CONST	4.76	2.85				
	DISTI	12.3	4.3	14.42	10.37	0.45	0.42
	AREA	1.69	0.66	12.28	9.84	0.31	0.32
	Dummy	3.41	-1.12	3.40	2.30	0.04	-0.03
2	CONST	9.79	-0.46				
	COVER	-10.53	7.39	13.82	8.79	-0.19	0.68
	$COVER^2$	7.39	-4.46	10.67	6.05		
	Dummy		0.51		1.96		0.125
3	CONST	0.89	-0.25				
	AREA	0.18	0.11	2.16	1.65	0.10	0.11
	YI	1.91	0.98	3.42	2.19	0.10	0.08
	BS	3.84	2.71	17.80	15.62	0.72	0.91
4	CONST	4.92	0.23				
	COVER-B	-7.85	2.99	13.58	5.19	-0.29	0.28
	$COVER^2$-B	5.21	-2.08	12.12	4.89		
	FRE	5.37	1.66	24.16	7.55	0.32	0.29
	Dummy	0.32		2.66		0.03	
5	CONST	1.08	0.27				
	DISTO	0.35		7.68		0.35	
	SIGN	0.04	0.10	4.11	11.2	0.07	0.18
	AREA	0.04	0.05	6.86	8.75	0.19	0.24
	TDPSQ	0.06	0.08	13.9	17.8	0.73	0.98
	AS	0.76	1.04	13.3	17.4	0.57	0.78
	LANE	-0.35	-0.51	6.32	8.83	-0.26	-0.39
	DISTI	0.28	0.27	18.4	7.74	0.24	0.23
6	CONST	0.95	0.19				
	SIGN	0.07	0.10	9.79	10.04	0.12	0.18
	AREA	0.05	0.06	11.83	9.01	0.26	0.29
	TDPSQ	0.06	0.08	19.89	17.46	0.76	0.97
	AS	0.84	1.19	19.00	17.49	0.63	0.89
	LANE	-0.40	-0.61	9.59	9.35	-0.31	-0.46
	DISTI	0.28	0.30	11.31	7.73	0.25	0.25
7	CONST	1.52	0.34				
	$AREA^{1/2}$	0.07	0.09	7.34	7.48	0.39	0.84
	TDPSQ	0.02	0.05	3.00	5.88	0.26	0.65
	AS	0.47	0.69	5.15	6.22	0.41	0.62
	BS	0.45	0.34	6.13	3.60	0.45	0.31
	DISTO	0.53	0.14	16.73	3.66	0.53	0.14
	1/FRE	0.08	0.07	6.14	4.57	0.41	0.36
	YI		0.37		3.23		0.14

stop frequency did not appear to be significant for this model and was dropped off (a troubling result).

The standard deviation models were obtained by using the same or sometimes even fewer variables than were used in the mean models. Data in Table 1 indicate that the mean models are more accurate than the standard deviation models. The r^2 for the former is about 0.96 while it is 0.91 for the latter. Examination of the accuracy of the models with respect to their coefficients of variation shows that the standard error in the mean models ranges from 3 to 19 percent of the mean, while it ranges from 11 to 26 percent of the mean in the standard deviation models.

Drive and Ride Models

Semilog forms were used in these models. The linear model was rejected because it estimated some negative travel times, which are unrealistic. The semilog form was chosen because it ensured that the predicted travel time will always be positive and also because the relationship between travel time and volume resembles an exponential function. The model parameters all have the right sign and are highly significant.

The only parameter with a negative sign in the models is the variable for the number of lanes on the arterials. The addition of one lane to the zonal arterial will decrease the travel time as expected.

Zone size, trip density, spacing of arterials, and the distance to the station ramp from the boundary of the zone are important variables in determining both the drive and the ride time to a rail station or to a ramp of a line-haul expressway, while zone size, bus stop frequency, distance of the rail station from the boundary of the zone, and spacing between bus lines are the major contributing variables in the bus ride models. Also, the fact that all the supply elasticities are less than unity indicates that the supply is inelastic.

As with the walk models, the models for the mean travel time are better calibrated than the models for the standard deviation. r^2 for a mean model is about 0.91, and it is 0.89 for the standard deviation model. Examining the accuracy of the models with respect to their coefficients of variation shows that the standard error in the mean models ranges from 6 to 10 percent of the mean and from 12 to 40 percent of the mean in the standard deviation model. In summary, all the models appear to be quite good.

FUTURE RESEARCH

The research into network parametricization-network aggregation reported here will be continued. Specifically, three important and distinct areas of research have been identified for continuation of this research. First, because of the importance of access travel times on travel demand, the modeling of intrazonal transportation system will be continued by incorporating zonal (possibly trip end) density distributions in the model and redefining some of the variables to be clearer and more policy oriented. Around the stations and also along the guideway and bus lines, the development densities tend to be higher than elsewhere in the zone. The implication of this is that the access times and their variables, obtained from the present models, may be higher than in actuality. Also, including density distribution in the model enables the analyst to test the effect of zoning changes on travel demand and choice of mode.

Second, parametric models should be developed for line-haul facilities. Line-haul travel times can be modeled as a function of volume of travel, operating policy, and capacity and spacing of the line-haul facilities. This parametricization of the line-haul system (both between and within zones in order to keep the advantage of large zone sizes) allows the line-haul transportation system to be represented in the form of an equation (it can be envisioned as a link). As a first step, the networks will be parametricized for three modes: automobile, bus, and guideway.

As a result of these two research tasks, a parametric representation of the entire transportation system can be accomplished; that is, access-egress and line-haul can be represented by relatively simple equations instead of a large and involved network. These parametric equations should be extremely helpful in developing multimodal networks for detailed analysis by using current transportation model systems. By anticipating modal line-haul volumes and with the help of demand models perhaps, one can make initial estimates regarding the spacing, operating policy, and capacity of the line-haul system. Similarly, the sensitivity of these network components can be analyzed by using the model coefficients. In fact, the parametric network models, as proposed here, are the supply side analog of the developing behavioral travel demand models.

The objective of the third research effort is a more formal integration of the network supply and travel demand models for a powerful sketch planning tool. Even though a satisfying backward-seeking model would clearly be desirable, it may not be implementable for more than 10 to 20 zones at this time. The design testing approach (e.g., UTPS) is implementable for any number of zones. A range of multimodal alternatives can be quickly evaluated with respect to demand, capacity, and extent of line-haul and access facilities needed. This all can be done without coding networks because the networks are represented by equations. Sensitivity analysis of each plan can also be readily performed by using the coefficients of the demand and supply equations.

Another advantage of parametric network representation, coupled with large traffic zones, is the opportunity to humanly interpret and visualize the results. This contrasts with the often too detailed and unclear networks, too numerous zones, and thick computer printouts of line volumes, which, even when plotted, are only of marginal help in the initial stages of transportation system planning.

CONCLUSIONS

The development of parametric networks is possible. The equations given in this paper were developed quite quickly. Nevertheless, they appear to model the access system rather well and thus are immediately applicable. Given the relative importance of the access for travel demand and transportation planning, modeling of the access component should be included in the standard transportation planning model system such as UTPS. This should be a relatively easy task. Each zone is now characterized by its population, employment, and so forth; this description should be extended to include the few basic characteristics of the internal transportation system and the way it relates to the line-haul system.

Explicitly modeling the access supply and access mode-station choice provides another important advantage: the use of large zones. This in turn speeds up planning processes. Finally, large zones provide more reliable and quicker predictions of land use activities.

ACKNOWLEDGMENT

This report was produced as part of a program of research and training in urban transportation sponsored by the Urban Mass Transportation Administration, U.S. Department of Transportation. The results and views expressed are the independent products of university research and are not necessarily concurred with by the Urban Mass Transportation Administration.

REFERENCES

1. P. Rassam and R. Ellis. Access Characteristic Estimation System. Office of High Speed Ground Transportation, U.S. Department of Transportation, Northeast Corridor Transportation Project, Vol. 1, Dec. 1969.
2. A. Talvitie and H. Hilsen. An Aggregate Access Supply Model. Paper presented at 15th Annual Meeting, Transportation Research Forum, San Francisco, Oct. 1974.
3. G. Kraft and M. Wohl. New Directions for Passenger Demand Analysis and Forecasting. Transportation Research, Vol. 1, No. 3, 1967.
4. T. Domencich, G. Kraft, and P. Valette. Estimation of Urban Passenger Travel Behavior: An Economic Demand Model. HRB, Highway Research Record 238, 1968.
5. P. Liou and A. Talvitie. Disaggregate Access Mode and Station Choice Models for Rail Trips. TRB, Transportation Research Record 526, 1974, pp. 42-52.
6. Chicago Area Transportation Study. Vol. 4, Chicago, 1962.
7. Traffic Volume Characteristics. Nashville Metropolitan Area Transportation Study, 1959.
8. N. A. Irwin, N. Dodd, and H. Von Cube. Capacity Restraint in Assistant Problems. HRB, Highway Research Record 297, 1961.
9. Highway Capacity Manual—1965. HRB, Special Rept. 87, 1965.