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# Travel Behavior Methodology

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# Contents

# Trends in New York State Automobile Ownership Patterns 1973-1977

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**Data on all motor vehicles that have a gross vehicle weight of up to 2722 kg (6000 lb) registered to persons in New York State were analyzed with respect to age and sex of the owner. The study found that the increase in the vehicle fleet in New York State from 1973 to 1977 can be attributed solely to women. Increases in women's ownership are moderated somewhat by differential population growth by age cohort. The main determinants for the men's level of ownership appear to be economic conditions expressed in employment. As to the type of automobile owned, men generally register much heavier automobiles than do women, and the men's vehicles show somewhat larger increases in average gross vehicle weight. Disaggregated by age, men and women show similar patterns in the gross vehicle weight increase, which is probably a reflection of economic conditions. Vehicles registered to young men and women show an extremely high increase in gross vehicle weight, those registered to middle-aged persons show a very low increase, and those registered to older persons show a moderate but steady increase. At the very least, an ongoing statewide fuel-efficiency monitoring program for new automobiles is called for.**

New York State has considerable reason to be concerned about energy use in its transportation sector. In 1974, New York State imported 84 000 000 $m^3$ (530 000 000 bbl) of petroleum. Approximately half of the energy generated from such petroleum imports is used in transportation, where current technology offers little possibility for energy substitution (1). More important, through payments made for petroleum and petroleum products, New York State loses substantial economic resources to other states and overseas (2,3). The federal government has reacted with a mandatory corporate-average-fuel-economy (CAFE) standard (Public Law 94-163) for new automobiles through 1985. Such federal programs, however, are generally ill-prepared to cope with the effects of regional maldistribution: We could, for instance, find that the CAFE standards are attained on the federal level but still see large state-to-state variations.

In addition, the availability of crude oil as a natural resource or the lack of such, climatic differences, economic development, and a host of other regionally differing factors warrant the development of state or regional energy policy to supplement or even substitute for federal policy. This paper presents results of an ongoing effort of the New York State Department of Transportation to assess the background, trends, and effect of policy alternatives on energy usage in New York's transportation sector. Other reports are available (4-6) and more will be coming forth in the future. This paper is based on an earlier report (7) and represents a refinement of some of the earlier findings. Detailed backup information to the analysis in this paper is only included where necessary; the interested reader is referred to the earlier report (7) for a full presentation of all available background data.

## DATA AND METHOD

For a given state, total gasoline consumption is determined by automobile ownership and automobile usage patterns. On the individual level, an automobile's efficiency is determined by a variety of factors, the most important of which is vehicle weight (8). Thus, policies that aim, directly or indirectly, to reduce vehicle weight have a particularly high potential to reduce automotive fuel consumption. The federal program to increase new automobile efficiency to 11.7 km/L (27.5 miles/gal) by 1985 initially relies heavily on weight reduction as one means to achieve its goals (9).

The current study focuses on a segment of the New York State vehicle fleet defined as follows: all passenger and commercial vehicles of up to 2722 kg (6000 lb) gross vehicle weight (GVW) registered to private owners. Commercial vehicles were included because a van or a pickup truck owned for business purposes is frequently used for personal transportation as well. For this research, New York State's Department of Motor Vehicles cross-matched its vehicle license and drivers' license files to permit analysis of these vehicles by weight and the owner or registrant's age, sex, and county of residence. The period covered by these data is January 1973-June 30, 1977.

The following analysis deals with all of these variables except county. The same argument that was used to justify statewide analysis within the federal frame could be used for the inclusion of county data within a statewide analysis, but time constraints did not allow us to do so. Work to include this differentiation is in the planning stage.

So far, analysis of vehicle efficiency and consumer behavior toward fuel-efficient vehicles deals almost exclusively with new automobiles and, at best, takes the existing fleet as a given (10-13). Almost half of the New York State fleet is at least five years old (see Table below) (14), so we are ill advised to disregard the effect of old automobiles on the state's fleet's efficiency.

| Automobile Age (years) | Percentage of Fleet |
|---|---|
| New | 13 |
| 1 | 11 |
| 2 | 11 |
| 3 | 11 |
| 4 | 10 |
| 5 | 9 |
| 6 | 9 |
| 7 | 8 |
| 8 | 6 |
| 9 | 5 |
| 10 | 3 |
| 11 | 2 |
| 12+ | 2 |

A number of shortcomings of the data need to be pointed out:

1. Multiple automobile ownership is inherent in the data. Nationwide, the percentage of multiple automobile-owning households was 42 percent of all automobile-owning households in 1974 (15).
2. The cross-tabulations are by age and sex of the registrant. The registrant, however, does not have to be the primary user. In New York State sharply different insurance premiums based on the sex and age of the registrant provide incentives to register automobiles in the names of women or older persons.
3. The summary tabulation of automobiles without respect to automobile age makes it almost impossible

to separate effects of differential longevity of automobiles, changes in the automobile age distribution, and changes in vehicle size (measured by weight) from one another.

## TRENDS IN DEMOGRAPHICS AND THE VEHICLE FLEET IN NEW YORK STATE

### Size of the Fleet

Overall, the fleet has increased by 183 923 vehicles, from 7 759 378 in December 1973 to 7 943 301 vehicles in December 1976 (Figure 1). Female registrants account for all of this increase. Male registrants show a net loss over this period, in spite of a slight recovery in the male-registered fleet after the loss in 1974. This development initially contrasts with population trends. However, if we disaggregate automobile owner and population trends by age and sex (Figure 2), women show an across-the-board increase in vehicle registrations, moderated somewhat by population growth, which is not uniform for all age groups. For men, the analysis is slightly more complex. Men up to age 45 show a loss in registrations, which is moderated by the growth of that male population age cohort, and men older than 45 show a gain in registrations, which is moderated by the reduction in the size of that age cohort.

This crossover requires additional variables for a full explanation. Economic conditions, as described by employment, for instance, provide part of such an explanation: Young and middle-aged men have fared worse with respect to employment than did their share in the population (Figure 2). Young and middle-aged women, on the other hand, show gains in employment far ahead of the increases in the respective population size; thus a greater need is generated for personalized transportation and the economic resources to acquire additional vehicles are provided (Figure 2). The larger work force of women is supported by a substantial increase in labor-force participation, which reflects changed child-bearing habits as well as the emergence of nontraditional households, which showed a substantially larger growth than did traditional households. If we look at young and middle-aged men and women together, we cannot exclude the possibility of shifts in registrations from men to women under the differential insurance rates in New York State. From the foregoing analysis, we should expect to see an increasing number of vehicles registered

Figure 1. Fleet size, New York State fleet 1973-1977.

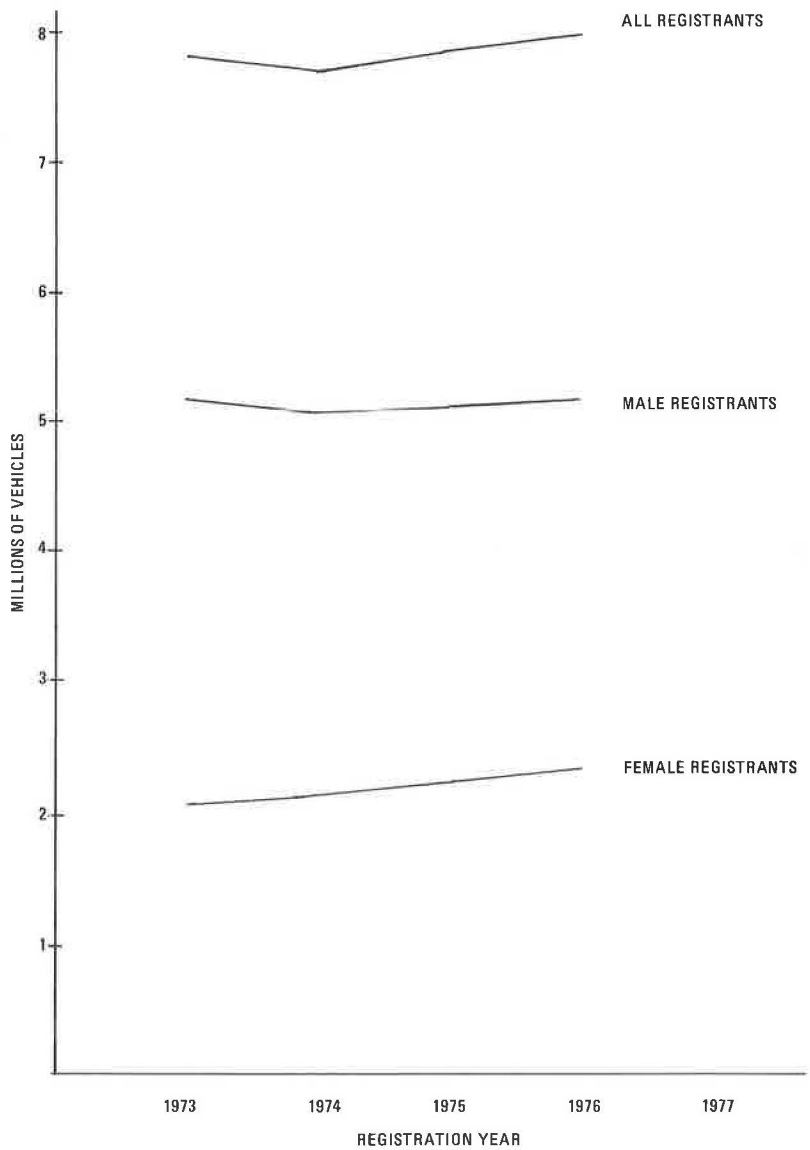


Figure 2. Changes in fleet size, population and employment, by sex in early 1970s.

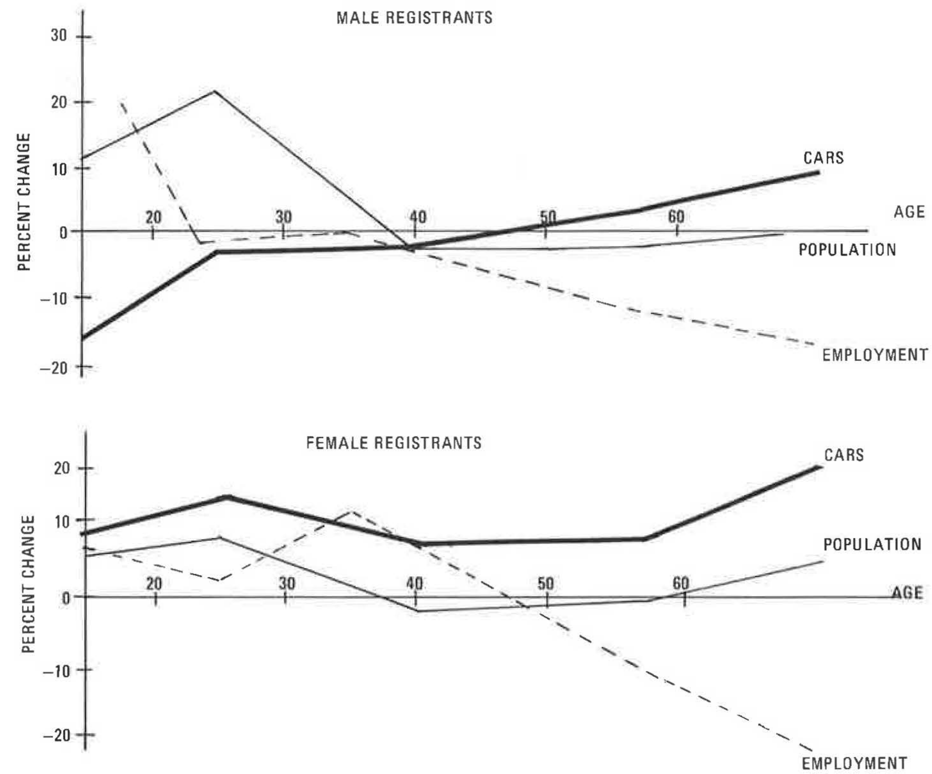



Table 1. Selected automobiles: trends in weight, 1972-1977.

| | GVW (kg) | | | | | | |
|---|---|---|---|---|---|---|---|
| Automobile[a] | 1972 | 1973 | 1974 | 1975 | 1976 | 1977 | Δ 1974-1977 |
| Impala | 1782 | 1877 | 1907 | 1913 | NA | 1617 | -290 |
| Monte Carlo | 1590 | 1684 | 1781 | 1781 | 1772 | 1747 | -34 |
| Cutlass | 1551 | 1717 | 1780 | 1691 | 1674 | 1641 | -139 |
| Nova | 1355 | 1390 | 1448 | 1500 | 1461 | 1440 | -8 |
| Vega | 979 | 1007 | 1075 | 1095 | 1108 | -[b] | |
| Pinto | ·934 | 959 | 1076 | 1132 | 1111 | 1049 | -27 |
| Corolla | 805 | 821[c] | 823 | 986[d] | 1010 | 914 | +91 |

Note: 1 kg = 2.2 lb.
[a] Basic model. [b] Discontinued. [c] Estimate from similar model. [d] Change in model designation.

to women of all age groups, as well as to older men; however, an increase in registrations for young and middle-aged men should only occur if the employment of these persons improves.

## Trends in Vehicle Weight

In spite of a petroleum supply crisis in 1973-1974 and increased marketing of smaller and scaled-down automobiles, average GVW of the New York State fleet increased steadily between 1973 and 1977 (1 kg = 2.2 lb).

| Year | Average GVW (kg) | Change |
|---|---|---|
| 1973 | 1581 | |
| 1974 | 1589 | +8 |
| 1975 | 1596 | +7 |
| 1976 | 1608 | +12 |
| 1977 | 1616 | +8 |

There are three effects reflected in the GVW figures: changes in the age distribution, differential longevity by automobile size (larger automobiles tend to last longer than do small automobiles), and the average GVW of each model year as it enters the fleet. Separation of the effects of these three sources of variation from one another would be important, but the only effect we can account for with some certainty is due to changes in the age distribution. We have some knowledge of the development of GVW by model type (Table 1) but are unable to properly account for the effect of differential longevity without extensive analysis.

The basic method for the extraction of the model year effect from the fleetwide average GVW is as follows: The average, fleetwide GVW in any given calendar year can be written as the weighted average of the average GVW by model year of all model years on the road in that calendar year; the weights used are the percentages, which reflect the composition of the fleet in the given calendar year in terms of vehicles of all model years on the road in in that calendar year.

For 1975, for instance:

$$1596 \text{ kg} = 0.823\ GVW_{73-} + 0.108\ GVW_{74} + 0.069\ GVW_{75} \qquad (1)$$

where 1596 kg (3518 lb) is the fleetwide New York State average GVW for 1975; $GVW_{73-}$ is the average New York State GVW of automobiles of vintage 1973 and earlier; $GVW_{74}$ and $GVW_{75}$ are the contributions of model years 1974 and 1975, respectively, to the fleetwide 1975 average GVW; and 0.823, 0.108, and 0.069 are the percentages of the vehicles of those vintages in the 1975 New York State fleet.

By using the fleetwide average New York State GVW from the table above and known age distributions, we obtain the following system of linear equations:

$$\begin{bmatrix} 1581 \\ 1584 \\ 1596 \\ 1608 \\ 1616 \end{bmatrix} = \begin{bmatrix} 1.0 & 0 & 0 & 0 & 0 \\ 0.8987 & 0.1013 & 0 & 0 & 0 \\ 0.823 & 0.108 & 0.069 & 0 & 0 \\ 0.718 & 0.1013 & 0.0857 & 0.095 & 0 \\ 0.646 & 0.10 & 0.081 & 0.101 & 0.072 \end{bmatrix} \times \begin{bmatrix} GVW_{73} \\ GVW_{74} \\ GVW_{75} \\ GVW_{76} \\ GVW_{77} \end{bmatrix} \quad (2)$$

The solution of this system of equations yields 1581 kg (3485 lb) for $GVW_{73-}$ and the following values for the remaining variables (1 kg = 2.2 lb):

| Year (XX) | $GVW_{XX}$ (kg) | ΔGVW |
|---|---|---|
| 1974 | 1666 | |
| 1975 | 1664 | -2 |
| 1976 | 1701 | +37 |
| 1977 | 1691 | -10 |

The trends in these numbers (as reflected by the changes from year to year in the last column) is reason for concern. Even if we were to allow that the effect of differential longevity could influence the trend as well as the level of the solution, we find that this trend does not really reflect the development observed in GVW by model (Table 1).

This pattern, obviously, does not have to mean that New Yorkers buy larger automobiles; an alternative explanation for the increase is that they load their automobiles with heavy options. Irrespective of the reasons, we observe a less than desirable change in fleet efficiency.

That our concern should not only be about new automobiles but also about used automobiles as well is evidenced by the table below, which shows much more massive shifts in registration than new automobiles alone could produce (1 kg = 2.2 lb).

| Weight Class (kg) | Model Year 1973-1974 | 1974-1975 | 1975-1976 |
|---|---|---|---|
| < 1134 | +4 922 | +36 496 | -11 651 |
| 1135-1588 | -75 872 | -14 032 | -15 078 |
| 1589-1814 | -82 854 | -43 813 | +26 037 |
| 1815-2268 | +52 229 | +81 801 | +95 204 |
| >2269 | +41 214 | +42 331 | +46 989 |
| Total | -60 361 | +102 783 | +141 501 |

In consideration of the problems experienced when the new automobiles were introduced into the fleet during 1974-1976, we should expect some of these moves to be due to differential longevity. Due to different usage patterns (12), large automobiles have the potential to remain in the fleet longer, a situation that may be aggravated as replacement decisions are deferred. This deferral of replacement is reflected in new automobile registrations in New York State. (This table excludes vehicles registered commercially to private persons.)

| Year | New Privately Owned Registrations |
|---|---|
| 1970 | 777 726 |
| 1971 | 792 173 |
| 1972 | 819 090 |
| 1973 | 874 280 |
| 1974 | 670 349 |
| 1975 | 618 753 |
| 1976 | 699 393 |
| 1977 | 713 964 |

The drop between 1973 and 1974 is dramatic, and the level of the late 1960s has not been reached again. Even cursory inspection reveals that this pattern is not reflected to the same extent in fleet size; additional evidence of increasing pressure on the used-automobile market stems from the price index of used automobiles (increase of 83 percent since 1967 and a dramatic increase in the rate of growth around 1974 versus an increase of 41 percent for new-automobile prices during the same period) (13).

Despite reservations about the quality of the data, the trends of average GVW disaggregated by the sex and age of the registrant are examined. Only fleetwide trends can be examined since we do not know the fleet-age distributions disaggregated for these fleet segments.

Disaggregation by sex shows that women, in general, register much lighter automobiles than do men and that the increase in weight of automobiles owned by women was less than that of the automobiles owned by men (Table 2).

This finding is in line with the view that women are more energy conscious than men (16), but other economic factors probably contribute more to the explanation of this finding. It is also quite possible that a substantial share of automobiles registered to women belong to multiautomobile households. At least for new automobiles, it has been demonstrated that a second automobile tends to be smaller than the first automobile in multiautomobile households (12). Since the automobile insurance rates in New York State favor women over men (heavily so in the younger age groups), we would expect many second automobiles to be registered in the names of women rather than men.

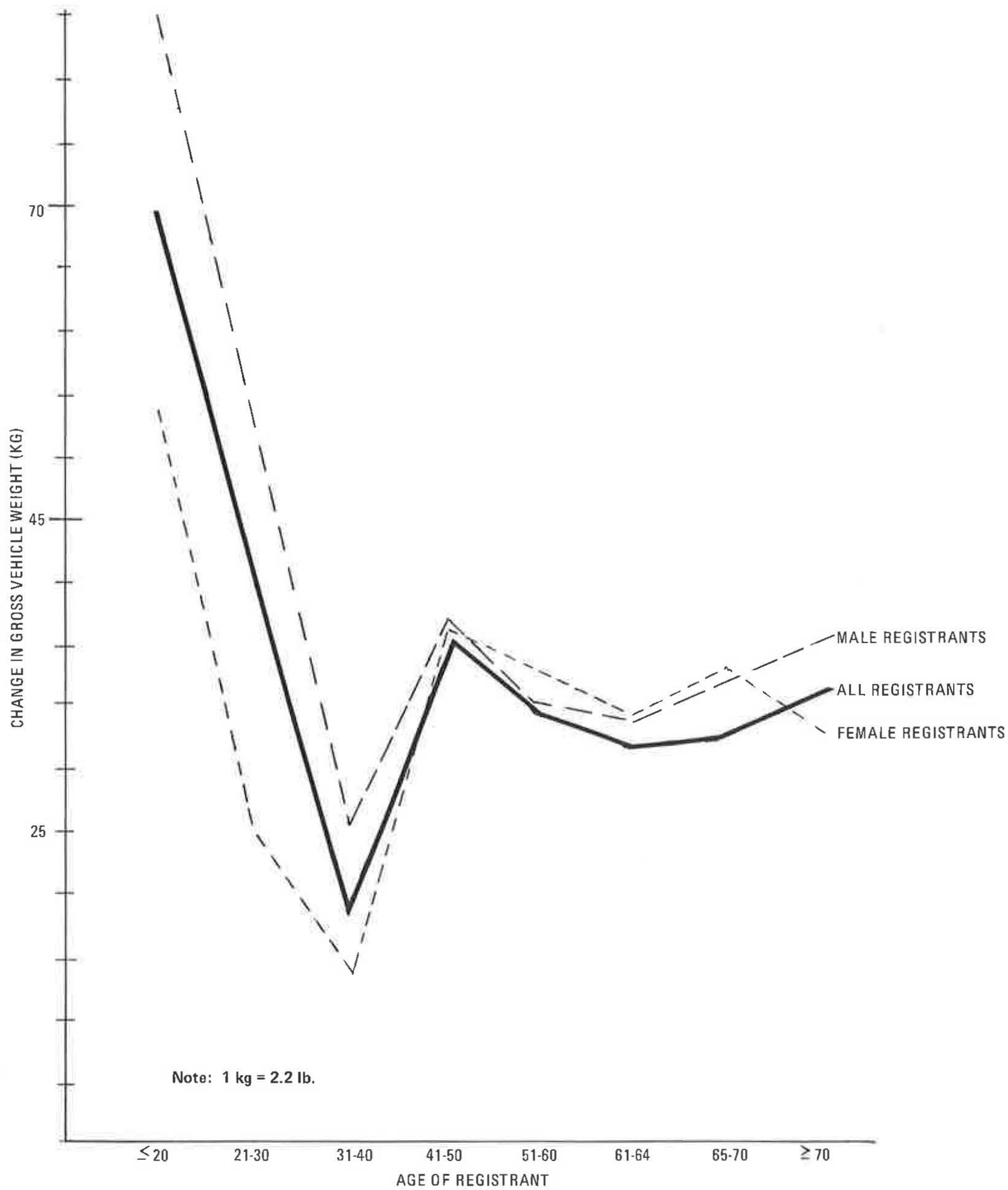
Finally, in a comparison of average GVW increases by sex and age of the registrant, we find virtually the same pattern for men and women (Figure 3). Age, obviously, is a very important discriminator. Not surprisingly, there appear to be three distinctly different age groups that correspond rather well to the three groups identified in the examination of vehicle registrations. This points to a common cause in these patterns, which we believe to be largely economic. The level of discretionary income tends to be very low at a young age, to be higher but largely tied up for the establishment of a household for middle-aged persons, and to rise dramatically in the last few years of employment when dependents have left the household and most major purchases (e.g., a house) no longer constitute a severe drain on earnings. This leads us to hypothesize that increases in automobile prices have forced young people into the clunker segment of the used-automobile market, which is generally heavier in GVW than the somewhat broader segment previously accessible to them. Middle-aged people, due to the severe strain on their resources by other household-related expenses, have probably found it hard to frequently trade automobiles and thus have escaped the market pressures that would force them into relatively cheaper but heavier automobiles. In addition,

Table 2. Average GVW: male and female owners.

| Year | Male Average | Male GVW (kg) Δ | Female Average | Female GVW (kg) Δ |
|---|---|---|---|---|
| 1973 | 1608 | | 1507 | |
| 1974 | 1618 | +10 | 1515 | +8 |
| 1975 | 1630 | +12 | 1520 | +5 |
| 1976 | 1641 | +11 | 1530 | +10 |
| 1977 | 1650 | +9 | 1536 | +6 |
| 1973-1977 | | +42 | | +29 |

Note: 1 kg = 2.2 lb.

Figure 3. Change in average New York State GVW, 1972-1977, by sex.




since these persons are likely to acquire relatively new automobiles as a bounce-back effect from the previously owned rather old automobiles, they do not need to follow a steady, frequent pattern of trading. We hypothesize that such a pattern lies behind the steady increase in GVW found for older persons who own automobiles.

OUTLOOK

In the 1976 and 1977 model years, the strong trend to increase the weight of models came to a halt (Table 1). The start of a substantial scaling-down program is expected to continue over the next few years (17). Specifically, the U.S. Department of Transportation (DOT) expects that scaling down alone will be sufficient to achieve 1981 CAFE standards but that substantial changes in engineering, design, and materials will be required to meet the standards thereafter (9). Manufacturers, who have over the past years introduced a variety of new subcompact models (Chevette, Fiesta, Omni-Horizon) priced to meet the Japanese competition (and generally below comparable prices for European automobiles) are likely to meet or exceed the 1978 CAFE standard of 7.7 km/L (18 miles/gal). In New York State, the CAFE figure for the first nine months of the 1978 model year was an estimated 8.9 km/L (19.0 miles/gal). However, since three of the four American automobile manufacturers (Ford, Chrysler, and American Motors) have admitted that they lose money on each of the small automobiles they sell and the fourth manufacturer (General Motors) has declined to make public statements, we should not expect American manufacturers to push sales of these very efficient vehicles more than necessary to meet CAFE standards.

There is some short-term relief on petroleum imports due to larger domestic production in Alaska, substitution of other sources, and conservation efforts (14), but demand for petroleum products in the transportation sector continues to increase. This does not have to mean that conservation goals in transportation are not met; considering the composition of the vehicle fleet with respect to average fuel efficiency by model year (18) and age distribution, an increase in demand for petroleum products has to be expected for several more years to come.

## CONCLUSIONS

Among all the trends observed in this study, two are reasons for concern from an energy conservation point of view: the continued increase in vehicle registrations, which is possibly linked to an increase in multi-automobile households, and the lack of a strong decrease in average GVW in the 1977 model year. This latter trend is particularly disturbing since it can have a variety of meanings. These include a temporary bounce-back effect after the difficult years of 1974-1976, a last chance to own a big automobile rush, and outright consumer rejection of smaller vehicles. In the light of these possibilities, the 1978 model year takes on particular importance in the analysis of this trend. This model year showed not only very substantial scaling down in size but also a number of new, smaller models in the American market. Thus, in the light of the wide range of policy implications represented by the above consumer attitudes, it is virtually mandatory that New York State institute on ongoing new-automobile fuel-efficiency monitoring program. In view of the pervasive influence of older automobiles on the fleet efficiency, an extension of this monitoring program to older automobiles might be indicated as well. Depending on the trends observed under this program, one or several of the policy programs described in another paper (7) should be considered for implementation.

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# Psychological and Socioeconomic Correlates of Automobile Size

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**Since Americans use 25 percent of all energy consumed in the United States for automotive travel, a primary place to conserve energy appears to be through increased fuel efficiency of the automobile fleet. Achievement of national energy conservation goals through this approach depends on both advances in fuel economy technology and changes in consumer purchase patterns. Knowledge of which psychological and socioeconomic variables correlate with the purchase of fuel-efficient vehicles will make it possible to market vehicles that have optimal attribute mixes to the groups that will be most receptive to promotions for fuel-efficient vehicles. Information on psychological and socioeconomic correlates of automobile buying patterns can also be used to generate and assess forecasts of sales in response to motor vehicle options. This paper focuses on a select set of psychological and socioeconomic correlates of automobile size. Several interesting correlates of automobile size were found. Analysis of the relationship between consumer awareness of fuel-efficiency ratings and size of vehicle purchased reveals that buyers of small automobiles acquainted themselves with the fuel-efficiency ratings, but no evidence suggested that awareness of the ratings caused consumers to purchase fuel-efficient vehicles. Multivehicle households have a smaller average automobile size than single-vehicle households. If this relationship continues and the number of multiautomobile households increases, sales of small-sized automobiles can be expected to increase. Other size correlates were found with respect to consumer evaluation of the relative importance of vehicle attributes, household income, and region of the country.**

Americans use 25 percent of all energy consumed in the United States for automotive travel; therefore, a primary place to conserve energy appears to be through increasing the fuel efficiency of the U.S. automobile fleet (1). In accordance with these considerations, the Energy Policy and Conservation Act of 1975 has designated mandatory fuel economy standards for motor vehicles sold within the United States (Public Law 91-163). Manufacturer achievement of the corporate average fuel economy standards depends both on advances in fuel economy technology and on consumer purchase patterns. Ensuring that motor vehicle sales patterns are compatible with national energy conservation goals requires more extensive and better-organized information on consumer attitudes and behavior toward fuel-efficient vehicles.

An understanding of consumer motor vehicle ownership correlates is potentially very useful to the achievement of energy conservation goals. Knowledge of which psychological and socioeconomic variables correlate with the purchase of fuel-efficient vehicles will make it possible to market vehicles with optimal attribute mixes to the target groups that are most likely to be receptive. Information on psychological and socioeconomic correlates of automobile buying patterns is also useful in generating and assessing forecasts of sales in response to motor vehicle options offered to consumers. Since correlations do not necessarily imply causal relationships, it is important to identify causal patterns when appropriate data are available. When such data are not available, caveats should be included in the interpretation of automobile size correlates.

This paper focuses on a selected set of psychological and socioeconomic correlates of automobile size. Three data sets are examined to both confirm findings across data sets and to extend the range of relationships that could be examined. Both correlational and causal analysis methods are used to identify quantitative relationships that characterize consumer motor vehicle buying patterns.

## STUDY DESIGN

### Data Sets

Each of the three data sets, although initially compiled to address somewhat different issues concerning automobile purchase, use, and ownership, contains information on automobile size. Depending on data availability, various correlational and causal relationships between automobile size and psychological and socioeconomic factors are tested.

The Abt data set was gathered by Abt Associates (2). The data were initially collected to assess the impact of the Federal Energy Administration (FEA) - U.S. Environmental Protection Agency (EPA) fuel economy information program on new automobile purchases. This program was developed to provide information for the consumer on motor vehicle fuel economy in the form of both fuel efficiency labels affixed to the windows of new automobiles and light trucks and the publication of an annual fuel-economy guide for new automobile buyers.

A telephone survey was conducted among a national sample of new (1976) automobile buyers. The sample was obtained from the registration lists of R. L. Polk and Company and was stratified by automobile size. A total of 796 interviews was completed and the following information obtained:

1. Make and model of new 1976 vehicle purchased,
2. Make and model of vehicle replaced,
3. Make and model of other vehicles considered during the purchase period,
4. Reasons for purchasing the particular vehicle,
5. Fuel economy of new vehicle,
6. Importance of various vehicle attributes,
7. Vehicle usage patterns,
8. Gasoline-buying habits,
9. Awareness of and attitudes toward the gasoline-economy label,
10. Awareness of and attitudes toward the 1976 fuel-economy guide for new automobile buyers, and
11. Demographics, including age, education, income, and household size.

The Peskin data set was developed as a part of a study, sponsored by the Federal Highway Administration (FHWA) to assess the impact of the 1974 gasoline shortage on urban travel behavior (3). A small-scale home interview survey was conducted among households in the northern suburbs of Chicago. Households that had a high level of automobile ownership were chosen because it was assumed that such a sample would be affected most by gasoline price increases and decreased availability. A total of 425 households on 24 blocks was contacted. The response rate was 27 percent; interviews were completed with 159 households. The interview questionnaire was designed to collect information on travel behavior during the energy crisis, at the time of the interview (1975), and in the future. Respondents were asked to anticipate their responses to price and availability scenarios. Demographic data, including number of automobiles, their make and model, age and sex of household members, dwelling-unit type, and household income, were also obtained. As would be expected among a sample of households that have a high level of automobile ownership, the mean household income was also high ($22 500). Every household sampled owned at least one automobile, and 72 percent owned two or more.

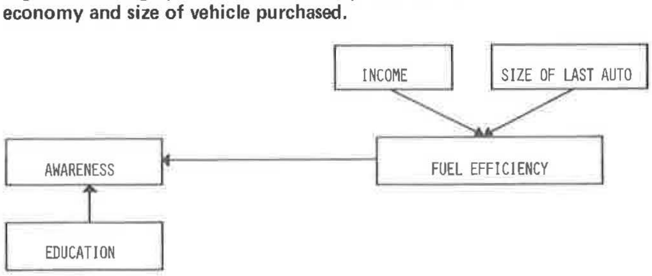
The third data set, ICPSR, was obtained from the Interuniversity Consortium for Political and Social Research. It contains data from a series of studies sponsored by FEA to examine consumers' attitudes, knowledge, and behavior regarding energy conservation (4). Data were gathered through telephone surveys of a national sample of the United States population 18 years of age and older. Information was collected from independent samples (waves) of respondents every two weeks beginning in July 1974. A total of 23 426 households was interviewed in 42 waves; each wave stressed a somewhat different issue (e.g., attitudes regarding the seriousness of the energy shortage, its probable causes, and duration). This data set also contained socioeconomic variables, such as education, income, number of automobiles per household, type of dwelling unit,and region of country, that could be correlated with an automobile size or average household automobile size.

Each of the above data sets is subject to limitations based on the initial issue being addressed. The data were insufficient in most cases to test more sophisticated causal automobile-size models; however, several salient correlates of automobile size were identified.

### Analysis Methods

A variety of analytical procedures are available to the researcher for the quantitative assessment of correlational or causal relationships. Two-stage least squares is particularly useful in the development of causal models of behavior. Two-stage least squares enables the researcher to estimate systems of simultaneous equations where the same variable may be dependent in one equation and independent in another. This methodology may be used to test interdependence between variables (for example, consumer attitudes and behavior). Estimation is dependent on the presence of exogenous variables (i.e., those completely determined outside of the system under consideration) in the equations. Socioeconomic data are often a useful source of exogenous variables. The technique first involves estimation of the endogenous (interdependent) variables in terms of the predetermined or exogenous variables. Then the original endogenous variables are replaced by the estimated endogenous variables and ordinary least squares is applied. This methodology is particularly useful when experimenting with causal models of behavior (5, 6).

Figure 1. Flowgraph of interrelationship between awareness of fuel economy and size of vehicle purchased.




## RESULTS

### Psychological Correlates

It has been hypothesized that expanding consumer awareness of fuel-efficiency ratings can increase the purchases of smaller vehicles. A prior evaluation of the FEA-EPA fuel-economy information program found that higher awareness levels of fuel-efficiency labels and guides were positively correlated with greater fuel-conserving behavior (i.e., the purchase of smaller vehicles) (2). This result was interpreted as supporting the hypothesis. Subsequently, the relationships between consumer awareness of fuel economy and automobile size were reanalyzed by using two-stage least squares to test for the mutual dependence of awareness and size of vehicle purchased, as well as for different exogenous variable inputs. Figure 1 shows all links between variables that are significant at the 0.05 level. Note that the link from awareness to size of vehicle purchased was not determined to be statistically significant as originally hypothesized. Application of the two-stage least-squares causal model identifies the direction of the link between size and awareness. This analysis found that size was a significant explanatory variable in determining level of awareness; in other words, owners of smaller, more fuel-efficient vehicles tend to be more aware of the fuel-efficiency label and guide.

The Abt data set also contained information on consumers' beliefs about the importance of various vehicle attributes in the decision to purchase a new automobile or light truck. The attributes were factor-analyzed, and the following clusters were identified:

Factor 1—Roomy interior, good warranty, superior safety features, reliable dealer, high resale value, and good service network;

Factor 2—High styling, fast acceleration, high performance;

Factor 3—Small exterior, good fuel economy, low price, had not bought this model before; and

Factor 4—Reliable model and manufacturer, ease of handling, good dependability.

The factors may be labeled value and service (factor 1), sportiness and performance (factor 2), economy and size (factor 3), and mechanical attributes (factor 4).

These factors were then used as discriminating variables to distinguish between automobile-size groups and to highlight differences in characteristics of the groups. All four factors were entered into the discriminant analysis. Two discriminant dimensions were statistically significant. The standardized coefficients of the first discriminant function indicated that factor 3 plays a predominant role in distinguishing between automobile-size groups. The second discriminant function identified factor 2 as a salient variable in differentiating between size groups.

The centroids or points about which the size groups tend to cluster are plotted in Figure 2. Dimension I may be interpreted as an economy consideration, and dimension II is essentially a sportiness consideration. Since the standardized coefficients of both factor 3 and factor 2 are negative, the more negative the centroid, the greater the importance of the factor to that size group. Thus, subcompact owners value economy more than do owners of the other size groups. Dimension II proved to be significant in differentiating owners of light trucks from the remainder of the sample. Purchasers of light trucks do not value sportiness and are only moderately concerned about economy. They are, however, more concerned about economy than are owners of standard or luxury automobiles. Figure 2 is particularly useful for making comparisons between groups.

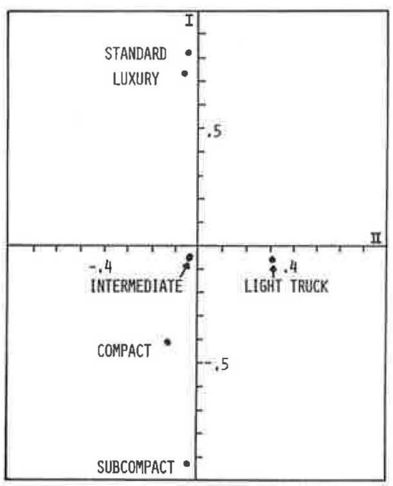
## Socioeconomic Correlates

It may also be hypothesized that certain socioeconomic variables influence automobile-size ownership and purchases. In Figure 1, for example, the link between income and automobile size is shown to be statistically significant. The sign of the estimated coefficient of income implies that people who have high incomes tend to buy larger automobiles. The coefficient for the size of the automobile replaced was also significant at the 0.05 level in determining the size of the new automobile purchased. Based on the sign of the coefficient, the implication is that the larger the size of the automobile being replaced, the larger the new vehicle will be. Consumers tend to replace automobiles with comparably sized vehicles.

Analysis of the Peskin data set uncovered some interesting socioeconomic correlates of automobile size. A cross-classification table of size and number of automobiles in households was formed by using an average automobile-size index (7). The automobile-size variable was recoded so that, as size increased, the value of the variable also went up. The following five size categories were used:

1 = U.S. subcompact, foreign subcompact, and sports automobile;
2 = U.S. compact and foreign compact automobile;
3 = intermediate automobile;
4 = luxury and full-size automobile; and
9 = other (i.e., light trucks and vans).

Figure 2. Plot of centroids of size groups in reduced space from discriminant analysis.




The average automobile-size index was then computed as the sum of the size variables divided by the number of automobiles for each household. A value greater than 4 for the average automobile-size index would imply that at least one of the household vehicles is a light truck. The index was divided into four categories: low (values 1-1.5 inclusive), medium (greater than 1.5 to 3), high (greater than 3 to 4) and other (greater than 4). This index was necessary so that each household would fall into only one cell of the classification table (i.e., two-automobile households would not be counted twice).

The cross-tabulation is given in Table 1. The chi-square value is significant at the 0.05 level, which implies that a systematic relationship exists between number of automobiles and average automobile size. More than 50 percent of the households surveyed were two-automobile families. The figures reveal that one-automobile households usually own a large automobile, and, in general, as the number of automobiles increases, the average automobile-size index tends to decline. For example, the cross-tabulation reveals that, for households that have a high automobile-size index, the row percentages decrease as the number of automobiles increases. Conversely, for households that have a medium automobile-size index, the row percentages increase as number of automobiles increases.

The ICPSR data set analysis also supported a correlation between average household automobile size and number of automobiles. A series of regressions were conducted by using average automobile size as the dependent variable and various combinations of independent variables. The value of an F-statistic indicated whether the regression formulation was significantly different from zero at the 0.05 level. If the F-test showed statistical significance, t-tests were used to assess the significance of individual coefficients. Several formulations were examined but the following one resulted in all coefficients being statistically significant and having signs that were readily interpretable:

$$\text{Average automobile size} = f\,(\text{education, region of interview, number of automobiles}) \quad (1)$$

where $R^2 = 0.075$ and $F = 2.945$ (10, 360 degrees of freedom).

It is particularly important to note the sign of the estimated coefficients. Both education and number of automobiles were found to be inversely related to average automobile size, which implies that, as the number of automobiles increases, average automobile

Table 1. Cross-tabulation of number of automobiles by automobile-size index.

| Number of Automobiles | Automobile-Size Index: Low Number | Low Percent | Medium Number | Medium Percent | High Number | High Percent | Other Number | Other Percent | Row Count | Percent |
|---|---|---|---|---|---|---|---|---|---|---|
| One | 1 | 2.3 | 11 | 25.0 | 32 | 72.7 | 0 | 0 | 44 | 27.8 |
| Two | 5 | 5.7 | 40 | 45.5 | 42 | 47.7 | 1 | 1.1 | 88 | 55.7 |
| Three + | 0 | 0 | 12 | 46.2 | 7 | 26.9 | 7 | 26.9 | 26 | 16.5 |
| Total | 6 | 3.8 | 63 | 39.9 | 81 | 51.3 | 8 | 5.1 | 158 | 100.0 |

Notes: Raw chi-squared = 42.084 26 with six degrees of freedom.
Cramer's V = 0.364 94.
Contingency coefficient = -0.458 62.

size decreases. Similarly, as education increases, average automobile size decreases. The coefficients of the dummy variables used to code possible responses to region are not to be directly interpreted. Since they were significant at the 0.05 level, an association between average automobile size and region of the country is confirmed.

To further clarify the implication of the regression findings, three cross-tabulations of automobile size with number of automobiles, education, and region were calculated. The distribution of automobile sizes by number of automobiles in household is given in the table below.

| Number of Automobiles | Subcompact or Compact Automobile (%) | Other-Sized Automobile (%) |
|---|---|---|
| One-automobile households | 24 | 76 |
| Two-automobile households | 30 | 70 |
| Three-automobile households | 32 | 68 |

Note that, as the number of automobiles owned by a household increases, the percentage of subcompacts and compacts also increases. The percentage of larger sizes displays a concomitant decrease. The table below gives the distribution of automobile size by education of the respondent.

| Education | Subcompact or Compact Automobile (%) | Other-Sized Automobile (%) |
|---|---|---|
| 8th grade or less | 19 | 81 |
| Some high school | 24 | 76 |
| High school graduate | 27 | 73 |
| Some college or college graduate | 34 | 66 |

A greater proportion of the more-educated respondents owned subcompacts or compacts than did the less-educated individuals. The results of segmentation by region of the country are illustrated in the table below.

| Region | Subcompact or Compact Automobile (%) | Other-Sized Automobile (%) |
|---|---|---|
| New England | 45 | 55 |
| Middle Atlantic | 30 | 70 |
| East North Central | 30 | 70 |
| West North Central | 32 | 68 |
| South Atlantic | 23 | 77 |
| East South Central | 24 | 76 |
| West South Central | 23 | 77 |
| Mountain states | 18 | 82 |
| Pacific states | 32 | 68 |

The highest percentage of subcompact and compact automobiles was found in New England, and the lowest percentage was found in the Mountain states. The southern regions also had lower percentages of small automobiles than did other areas of the country.

## SUMMARY AND CONCLUSIONS

This study presents a preliminary examination of the psychological and socioeconomic correlates of vehicle size. Consumer awareness of fuel-economy ratings was found to be positively correlated with vehicle size, but this does not imply that increased awareness will necessarily lead to the purchase of smaller automobiles. A causal model of behavior found that awareness level was a function of size of automobile purchased and not vice versa.

Consumers tend to group certain vehicle attributes together. These were identified as value and service, sportiness and performance, economy and size, and mechanical attributes. Economy-size considerations were determined to be the most significant in differentiating between vehicle size classes. The importance placed on sportiness and performance distinguished owners of light trucks as a distinct group from buyers of passenger automobiles.

Income and size of the automobile being replaced are correlated with the size of new automobile purchased. Higher-income households tend to purchase larger vehicles and consumers generally replace automobiles with comparably sized vehicles. Average automobile size and number of automobiles are inversely related (i.e., as the number of automobiles per household increases, the average automobile size declines). Average automobile size is also correlated with education and region of the country. In general, as education increases, average automobile size decreases. Average automobile size differs between regions of the country.

These results have a number of underlying policy implications for both automobile manufacturers and the government. For example, the original evaluation of the FEA-EPA fuel-economy information program concluded on the basis of a correlation between fuel-economy awareness and the purchase of smaller, more fuel-efficient vehicles that increasing the level of awareness of both the fuel-economy label and the fuel-efficiency guide would lead to the purchase of more fuel-efficient vehicles. Our reanalysis of the data set clarifies the relation between awareness of fuel economy and vehicle-size purchase decisions, and it shows the prior conclusions to be erroneous. Awareness was shown to be a function of size, but size was not a function of awareness. This is not to imply that awareness does not have a role in a decision to purchase an automobile or light truck. Research has indicated that there is a general lack of credibility surrounding the EPA fuel-efficiency figures (8). Consumers either do not understand or do not believe the ratings. Influencing the purchase of fuel-efficient vehicles through consumer awareness will require an improved validity for the government fuel-efficiency ratings and heightened promotional efforts that stress the consumer benefits of fuel-efficient vehicles.

Economy considerations were indeed found to be important among buyers of small automobiles. As the size of the new vehicle purchased increased, the importance of economy declined. By using discriminant analysis, buyers of light trucks may be differentiated on the basis of their attitudes toward the importance of sportiness and performance. This cluster of attributes is, on the average, much less important to purchasers of light trucks than it is to owners of passenger vehicles. A better understanding of consumer willingness to trade off attributes relating to fuel efficiency, performance, size, and costs is essential in order to promote and design fuel-efficient vehicles that will satisfy the consumer.

A negative correlation was identified between average automobile size and the number of automobiles. There is a tendency for multiple-vehicle households to have a smaller average automobile size. If the trend toward multiple-automobile households continues, this would imply a general decline in average vehicle size per household. The fuel-conservation implications of such trends cannot be determined until automobile usage patterns of multiautomobile households are more fully examined. The relationship between household size and vehicle size should also be explored.

More extensive data sources are required in order to develop a more complete understanding of consumer attitudes and behavior toward small automobiles. Data limitations forced us to use correlational methods, with one exception. The interrelationship between consumer attitudes and behavior should be studied more fully through the use of causal models (5, 6). This would necessitate the collection of new data sets that can more properly reflect consumer socioeconomic and attitudinal effects on automobile and light truck purchases.

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# Rationale for an Alternative Mathematical Approach to Movement as Complex Human Behavior

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**This paper contains arguments and data analysis for a new mathematical approach for the study of human behavior such as intraurban travel. Current disaggregate models are criticized because of their unrealistic axioms about (a) the simplicity of behavior incorporated in the concept of the dependent variable, a trip; (b) the constancy, ad hoc differentiation, or random variability of choice sets between persons; and (c) the complexity and uniformity of decision strategies and rules about how utilities for options are formed and manipulated. Arguments are advanced for more realistic approaches to movement; for inductive data analysis to specify new descriptive choice models, based on different assumptions; and hence for a consistent underlying microeconomic theory that is based on more realistic axioms for the ultimate derivation of improved analytic models of travel. The paper contains exploratory small-sample analysis to demonstrate that, by reconceiving movement as complex, hypotheses can be formulated that fit standard kinds of travel data as well as current models that have different, less realistic assumptions. Movement is thought of as (a) a sequence of events differentiated by time and space coordinates, (b) choice sets that individuals and groups find systematically limited and variant because of the spatial properties of cities, and (c) decision strategies that are simpler and more variant than currently believed because of the differences in choice sets. This paves the way for the further development of the alternative approach proposed for the study of movement as complex human behavior.**

Recent well-known criticisms of disaggregate utility-theory-based models of movement come from diverse sources (1-4). The realism of a number of different assumptions has been questioned. Specifically, it has been asserted that models of spatial and other travel choices:

1. Do not provide a realistic description of the group movements that they attempt to predict, since they ignore decisions about the sequence of a household member's activities during a given decision period (5-9);
2. Assume that limited sets of the socioeconomic characteristics of individuals and characteristics of given options (such as the travel time differences to

designated alternative destinations) are the major determinants of the demand for recurrent movement [the models thus underemphasize and do not explore the relative effects on behavior of many other possibly important variables, especially those spatial and temporal variables beyond the individual's control (institutional variables) that influence the supply (numbers and kinds) of available options] (5, 10, 11);

3. Assume that each individual confronts an identical, complicated choice situation (choice sets containing at least two alternatives for modes, destinations, activities, trip times, respectively); however, in many instances individuals have a very limited number and few kinds of alternatives in their choice sets, to the extreme of no options or missing preferred alternatives because of spatial, temporal, and other constraints (1, 12, 13); and

4. Assume that all individuals form, manipulate, and maximize utilities in the precise and complicated strict utility-maximizing way, even for simple routine behaviors like travel (9, 14).

Strict utility-maximization is an evaluation procedure whereby, given a set of alternatives, an individual, for each member of the set in turn, first, evaluates the part-utilities of each attribute of an alternative; next, sums them (or uses some other combination rule) to estimate an overall unique utility for each alternative; and then allocates choices over each pair of alternatives in accordance with the ratio of their total utilities.

## REALISTIC DESCRIPTIVE AND EXPLANATORY VERSUS CLASSIC DEDUCTIVE MODELING

The criticisms of these unrealistic assumptions in current mathematical models of movement and, by implication, of the same assumptions in the models' most widely accepted choice-theory base in microeconomics (3) seem well founded (15). No matter how well any theory or model predicts, a better alternative will always be one that might predict as well but also incorporates more realistic assumptions. The simultaneous appearance of a number of writings that reassess the realism of an established theory or a model derived therefrom is indicative of the timeliness of a search for the better alternative.

A far more interesting rationale stems from the growing recognition in the late 1970s of an apparent cleavage in the goals of, and hence the priorities accorded to, the normal criteria of realism and predictive-forecasting accuracy for the assessment of models of human social systems. It is well accepted that theories and models of human social behavior, including those of movement, inevitably reflect the personal political mores of their authors (16). One reason for this is that choices that reflect such mores exist and must be made among the typically many kinds of language terms for the same kinds of human phenomena in modeling (for example, between social classes and role-complex-related groups to describe humans in cities). The debate on value freedom in theories and models for human social behavior has therefore necessarily turned on the political and other biases built into the theories and models per se, rather than on the political and other biases in the use of results of objective research, as in the physical sciences (17).

Choice of political orientation therefore takes priority over, and precedes, scientific work on human behavior, and, given this, only the range of political perspectives directed toward major modifications of such behavior through collective action now have credibility in the so-called advanced societies that are preoccupied with crisis situations, such as energy shortages and race relations. This contrasts with the goals of physical scientists who are concerned with natural phenomena, which can generally be defined in neutral language, and whose intent is to identify the objective laws of their behavior, so that useful adaptations to such laws (rather than modifications of them) can be made by predicting the behaviors of the phenomena accurately. The effect of the primarily radical political orientation of scientific studies of human social behavior (including movement) may be argued to require the reversal of priorities of evaluation criteria for theories and models from accurate prediction to realistic explanation.

It is a truism that social systems, including cities and their movement patterns, are dynamic. Major decisions in both public and private sectors are directed toward altering current trends through changing the behaviors (manipulating the rules regulating the behaviors) of human populations. Policy issues in the urban transportation area, for example, by the late 1970s, encompassed debates on how to alter the habits of urban populations for energy conservation, the redesign of urban neighborhoods and traffic flows, the servicing of latent demand in sprawling suburban cities with paratransit, increasing the mobility of the elderly and handicapped, downtown revitalization, and adequate public service delivery, including health care. It is imperative to identify correctly the causes of, and the decision mechanisms behind, individual and group behaviors in order to be able to identify, modify, and manipulate those variables and the relations between them that could induce change most effectively. Hence, the requirement that axioms or assumptions in analytic theories and thence in derived policy-related models of human social behaviors be realistic and that such assumptions be correctly related causally to human actions. For human social systems, realistic explanatory theories and models from a variety of political perspectives will provide for a necessary diversity of potential treatments of urban and other problems. Less emphasis is desirable on classical analytical-deductive work, in which the realism of axioms or assumptions can be disregarded.

Both the progress-of-science and societal problem-solving arguments for more accurate assumptions in theories and models for movement are different from the standard arguments originally advanced for developing behavioral models in the late 1960s and early 1970s (18, 19). The original rationale for disaggregate models of movement seems to have been that, by incorporating accurate assumptions about individual decision making, theories and models would be better predictors. Although this argument still holds, the more recent arguments seem now to make the strongest case for still more behavioral approaches to the study of movement to meet inseparable scientific and political goals. Within this general perspective, the demand for new theory for, and models of, spatial and other kinds of travel behavior, without any of the key unrealistic assumptions of the present ones, seems timely and well founded.

A number of approaches to develop such new models for movement seem possible at this point. First, there is the possibility of exploring successive modifications to existing models, such as the logit and probit, with the goal of improving both their predictive accuracy and their explanatory ability by modifying one or another unrealistic assumption in turn (20-23). Since such models are basically used to forecast aggregate urban travel flows, on the assumption that, once identified through a set of coefficients that link travel to significant independent variables, current patterns of behavior and decision processes will continue at least in the immediate future. This approach can be used to furnish better numbers for the ongoing highway and transit investment decisions that must be taken now. Second, there is the possibility of developing simulation models that will isolate the reasons for individual and group responses to a specific political activity, such as staggering work hours or changing school hours in a suburban city. The household activity-travel simulator developed at Oxford and described by Jones in a paper in this Record is one such device (8, 24). This work can meet immediate policy needs for investigating how to try to modify behaviors without necessarily estimating precisely the numbers of persons who make different kinds of behavioral changes. Such research appears better oriented toward some of the newer political requirements for models of movement than simpler and earlier macro-scale forecasting approaches.

Finally, a need remains for research to explore the development of new explanatory mathematical models and a consistent, revised underlying economic theory of demand that have far less grossly unrealistic assumptions than present versions. The emphasis at the moment should not be on the predictive or forecasting accuracy of the models or of the theory produced, or on immediate policy applications at local levels, but rather on the rewriting of models of movement in a rigorous explanatory mode and, by using the insights so gained, to restructure the underlying microeconomic theory base (25). By rewriting more realistically the microeconomic theory now used to derive models not only of human responses to any transportation-related political action, but also, for example, models of housing and employment demand, the generic basis of many kinds of urban policy can be appropriately restructured. This will supplement piecemeal approaches to urban systems, which militate against obtaining conceptually or methodologically comparable findings and well-integrated and consistent results in practice. All this does not, of course, deny the urgency also of developing models of movement to meet immediate urban transportation needs.

## RESTRUCTURING THEORY

The assumptions in policy-related models that should be changed first are not just those that current work in the literature on movement suggests as the most urgently in need of revision but should also include important general axioms of microeconomic theory. Since a more detailed review of the travel literature concerning these assumptions and a critical discussion and evaluation of them is already available elsewhere (9), only a summary statement of the three principal axioms selected is provided here:

1. The individual and collective behaviors to be explained or predicted by any theory or model are simple (that is, are single, observable, recordable, and measurable events) not complex (that is, sequences of events in space and time). For example, in models of movement, the behaviors to be explained have generally been assumed to be trips by individuals, where a trip is a single movement by a person from one stop to another.
2. The individual behaves by making a choice from a set of alternatives, where the set always contains at the very least two (and usually many) alternatives for each individual and where the set is either constant between individuals or varies between them in some arbitrary way or in some random fashion, defined by an arbitrarily selected probability density function. This assumption is incorporated in both the standard strict and random utility versions of the multinomial logit model of choice behavior and some applications and modifications of them (26) (we call this the constant-choice-set axiom).
3. The individual's decision making is extremely complicated. Specifically, all individuals in a population make all decisions in the strict utility-maximizing way in all situations. This is incorporated into travel-demand models through assuming the strict utility-maximizing decision strategy for all kinds of travel choices (20).

Ongoing research, therefore, has three major goals. The first goal is to investigate human behavior as a complex phenomenon and, in particular, here, to explore the mathematical reconceptualization and measurement of the individual's travel as an example of such complex behavior, to indicate the feasibility of dependent variables defined at an increased level of complexity for modeling. The second goal is to develop a causal model of choice-set formation for the individual, assigning probabilities to any alternative included in the set, to handle the implausibility of the constant-choice-set axiom. The third goal is to identify the simpler decision strategies that different individuals might use to select alternatives in situations of different degrees of complexity, as defined by the numbers and kinds of alternatives in choice sets, and to attempt to develop mathematical choice models for them. This follows from recent advances in choice theory in psychology that emphasize the variability of decision strategies between individuals in problem-solving situations of different degrees of complexity (27).

In sum, our research is directed toward the use of data analysis to specify an explanatory and descriptive rather than a deductive and predictive model for the individual, and thence for appropriate population groups, of the general form:

$$P(j) = P(j\Sigma A), P(j/j\Sigma A) \qquad (1)$$

where

- $j$ = the individual's complex behavior (to be defined);
- $A$ = the choice set of alternatives from which j is selected for the individual;
- $P(j\Sigma A)$ = a causal model that assigns alternatives to the choice set for the individual; and
- $P(j/j\Sigma A)$ = the appropriate decision strategy for the selection of an alternative, assuming that there is more than one alternative in the choice set for the individual.

(At the moment, Equation 1 ignores possible complex interdependencies between its different right-hand side, and right-hand side and left-hand side, components.)

The relaxation of the constant-choice-set axiom and the related development of the model for the individual's choice set in Equation 1 is the most important goal for future research, as indicated by trends in the literature. [For detailed discussion of the diverse important but hitherto analytically intractable urban policy-related issues it opens up see another article (25).] Inquiry into the determinants of the individual's choice set now has a relatively long though spasmodic history; however, as yet, no satisfactory model of choice-set formation has been developed. Over a decade ago, North American geographers investigated the relations between the individual's opportunity set for spatial choice (all his or her spatial alternatives in a city), his or her cognitive opportunity set (known alternatives), and his or her choice or contact set (all those alternatives ever used) (28, 29). So-called choice-set generation problems were also noted independently in the mid-1970s in the United States, first in connection with spatial-choice modeling by both geographers and engineers (1, 30, 31) and later in connection with mode-choice modeling (32, 33). Independently, workers in Europe began inquiring into the ways in which many possible constraints limit options individuals have for decisions, in many cases reducing options to very few, one, or none (5, 8, 12, 22, 24, 34-36). At the moment, little is known about the nature, number, and relative importance of the many variables now postulated to form the choice sets for different decisions made by the different individuals in different situations.

Recent European work emphasizes the relative significance of institutional constraints. Such constraints are often encountered by the individual or group in the form of the detailed spatial distributions of activities (residences, work places, or shops) and their scheduling within the city (urban space-time or spatial constraints). Such spatial constraints need detailed definition and measurement for large population groups for all kinds of travel decision, and their relative significance vis-à-vis variables more under the individual's control in forming choice sets and influencing behaviors (such as sociodemographics influencing time and money budgets) needs to be assessed for different kinds of individuals and population groups. The development of a causal descriptive model of the individual's choice set could clearly be assisted by inductive data analysis that uses comparable sociodemographic, travel-diary, and geocoded land-use data sets for large samples of individuals in a number of areas in advanced societies (13, 25).

The development of a causal model of the individual's choice set will not only help answer some theoretical questions but could also have some immediate policy implications. The investigation of the relative importance of spatial aspects of institutional constraints and their relation to movement will distinguish those individuals and population groups whose behaviors are determined largely by institutional constraints on choices. These behaviors are best altered through collective action aimed at changing urban spatial and temporal organization, such as through changing places of employment and shopping destinations by controls on residential densities and proximities to transit lines. Alternatively, the development of a choice-set formation model will also discriminate which population groups have behaviors that could be better modified through strategies that rely on alterations by the individual of his or her behavior through manipulating personal constraints, such as time and money budgets.

From the perspective of the long-term development of theory, exploration of actual choice-set formation models for the individual, as outlined here, could permit the explicit incorporation in microeconomic theory of precise statements about important connections between institutional behaviors (that is, societal decision making at the macro level), and observable individual behaviors at the micro level (like travel), through intervening variables that define the space-time structure of the modern metropolis. In the present view, institutions create the differential distributions of activities in space and time that form the varying, tangible day-to-day environments of human beings. These distributions help form choice sets for individuals and groups, which in turn circumscribe the possibilities for their behavior by controlling their access to resources and thus affect in subtle and important ways the distribution of social costs and social benefits in urbanized societies.

The study of spatially defined choice sets, therefore, leads into the study of some special important and invisible aspects of social welfare that arise from different combinations of the relative effects of cooperative collective institutional actions (choice sets) and individual decision making (related decision strategies) for different population groups. Although, of course, this may not be the only way in which institutions affect individuals and groups, and although the operation of institutions through spatial constraints may not be relevant for all individuals in all decision situations, current research indicates that these might be fruitful questions to explore. Revised versions of microeconomic theory for these purposes could draw on descriptive choice-set formation models like the one proposed here to provide for a more rigorous treatment of the differential effects on human groups of collective action primarily directed toward changing institutions: for example, changing the housing market, changing the hiring practices of different kinds of firms in different kinds of locations, changing social roles. Current microeconomic theory assumes institutions and their reflections in the distance properties of land uses in urban systems are exogenous, and therefore, in practice, unchanging and equitable, which is especially revealed in the constant-choice-set axiom of the models of movement derived from it and outlined above. Microeconomic theory itself and derived policy-related models thus permit neither a satisfactory realistic explanation of behavior, well-informed speculation about differential impacts of institutional evolution on social access-to-opportunity costs for individuals and groups, nor the possibility of policies for some of the more radical but not necessarily undesirable social, economic, and environmental transformations that urban systems could still undergo.

Against this grand perspective, the initial tasks of the remainder of this paper appear extremely limited. Some preliminary data analysis is conducted to substantiate that some key alternative assumptions to standard ones might be feasible for future model and theory development. The alternatives are

1. The individual's behavior is complex;
2. Choice sets are restricted and might vary in a systematic way, through the effects of differential access, between persons and hence groups; and
3. Decision strategies might be both simpler than commonly conceived and also vary with differences in individuals' situations, as defined by the numbers and kinds of alternatives they confront.

The strategy of the remainder of the paper is to develop statistical hypotheses that are consistent with each and all of these assumptions and then to demonstrate that there is no acceptable grounds for rejecting them, by use of data from standard records of travel behavior. Since the latter are as well fitted by existing choice-theory-based models like the logit incorporating alternative assumptions, there is evidence of an equifinality problem, the normal resolution of which is to progress in the direction of the theory or models with the more realistic and more plausible properties. This seems clearly the direction indicated by Equation 1 and this paper.

## MATHEMATICAL RECONCEPTUALIZATION OF MOVEMENT AS COMPLEX HUMAN BEHAVIOR

### Travel as a Path in n-Dimensional Space

In both aggregate and disaggregate approaches to movement, the overt behavior to be predicted or explained, the trip, is a link between two stops, and purpose or activity, frequency, mode, time of day, and destination are the principal choices that the individual confronts for the conduct of each trip. Such choices manifest themselves, at the macro level, in the relative frequencies of trips of each kind. When choice theory is used for the modeling of movement, therefore, the trip is theoretically the unit of (derived) demand, though there are many varieties of trips from which to choose. One of the implications of treating movement and any other behavior as a complex rather than a simple phenomenon is, therefore, that it could lead to a redefinition of the unit of demand in both derived models and underlying theory.

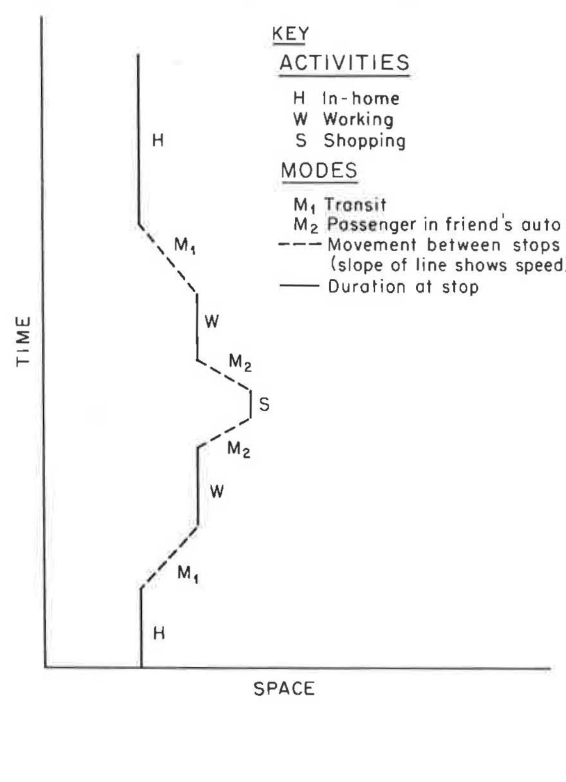
American geographers Marble, Nystuen, and Curry were the first to conceive of travel as an example of complex behavior, by considering trip making as home-to-home circuits (37). They divided movement by individuals into single-purpose (simple trip) and multiple-purpose (complex trip) travel (38, 39) and attempted to study the linkages of stops on multiple-purpose travel. Considerable emphasis was put on the statistical analysis of longitudinal travel data for individuals in order to define as rigorously and as objectively as possible the kinds of multiple-purpose trips that persons in cities tend to make (38, 40, 41). One work by Hanson and Marble in 1971 contained sophisticated statistical manipulations of a flow matrix of travel linkages between land use types. This approach enabled some patterns in the land use or activity site linkages of a sample of individuals to be determined. Patterns in the linkages of other aspects of trips (such as the linkage of modes to successive stops), were not, however, investigated. In addition, the relations of patterns of trip linkages to certain sociodemographic characteristics of individuals (such as race, class, age, culture, and sex) were explored (28, 42, 43). The contribution of this conceptualization of movement and related data analysis was its emphasis on the following:

1. That the complexity of an individual's behavior lies in the fact that it consists of a sequence of events differentiated by locations in space and time (for example, travel is a sequence of trips that link stops with space and time coordinates), and
2. That such complex behaviors of individuals linked to sociodemographic characteristics can be identified, comprising systematic behaviors that should be susceptible to normal scientific explanation through disaggregate modeling and theory-development procedures (7).

In the middle of the 1970s, as work in the disaggregate modeling of destination choice progressed in the United States, the question of the linking of trips by individuals, especially of nonwork trips, became important. The notions of trip chains, journeys, tours, and travel patterns appeared (23, 44, 45) and extended, although inadvertently, the earlier conceptualization of movement as complex behavior as trip linkages and multiple-purpose travel on home-to-home circuits. The appearance of the later concepts of chaining revealed not only a recognition that movement as a complex behavior is in fact a linking of events (trips) in a sequence differentiated by space and time dimensions but also that this may entail linkage and differentiation on other dimensions as well, such as trip destination (land use), activity (purpose), and mode dimensions (23, 45). Little work has been carried out on its implications, namely, that empirical research is required on longitudinal trip data for individuals (admittedly not readily available) to establish what, if any, kinds of multidimensional linkage patterns exist. So far, complex trip making has been arbitrarily divided into some simple classes, for example, trip sequences linked by purposes other than work and those not so linked or those tied to residential destinations and those not so tied (9, 20, 45).

Some well-known work in the mathematical reconceptualization of travel as complex behavior has, however, been carried out to permit this kind of empirical research, primarily at the University of Lund, Sweden (10, 34, 46), and the Transport Studies Unit at the University of Oxford, England (8, 24, 35, 36). The two-dimensional geometric representation of the individual's movement as a space-time path (Figure 1), apparently attributable originally to Hagerstrand (47) and then to Lenntorp (34) and reappearing in various guises in Thrift (46) and Dix (24), represents a first attempt to depict what an individual's movement might be, once it is granted that he or she does not make a trip but makes a sequence of trips to different places (stops) over time. However, although work at both Lund and Oxford has involved the collection of detailed individual travel data, the data have been used for different policy and modeling approaches than have been taken here, so that a still sharper mathematical reconceptualization of movement as complex behavior has not been delineated and neither has a design for related statistical analysis of longitudinal trip records to investigate repetitive patterns for individuals and population groups to demonstrate the tractability of the notion of movement as complex behavior as a dependent variable in models and theory.

**Figure 1. The individual's path in time and space dimensions.**



One of the less obvious features of the representation of the individual's movement in Figure 1 is that, by portraying it just as a line in two-dimensional space (time of day and distance), information about other aspects of travel (activities, modes, destination type, and location) is collapsed into that space. Technically, Figure 1 is a simplified geometrical representation of the individual's travel as a path in n dimensions, one

**Figure 2. Sample diagrams for representing the individual's path in n dimensions through a series of two-dimensional cross sections.**

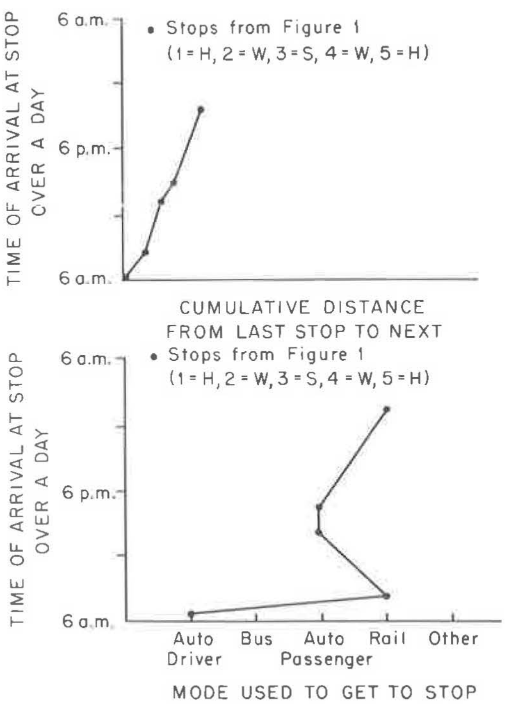



**Table 1. Distribution of sample households and individuals in Uppsala, Sweden, by life-cycle group.**

| Group Characteristics | Number of Sampled Households | Number of Sampled Individuals |
|---|---|---|
| Head of household 67 or older | 19 | 25 |
| Head of household between 50 and 66, no children living at home | 21 | 32 |
| Head of household between 18 and 49, single persons only | 23 | 26 |
| Head of household between 18 and 49, two-person household with no children | 5 | 11 |
| Head of household between 18 and 49, at least one adult, at least one child over 7 years, and no pre-school children | 11 | 24 |
| Head of household between 18 and 49, at least one adult, and at least one child less than 5 years of age | 13 | 26 |
| Total | 92 | 144 |

being time of day, another being distance from last stop to the next, and the others representing the remaining important aspects of travel as a complex behavior that have been considered, namely, mode, activity, land use type, and location of destination. The path, properly represented in the n-dimensional space, would become a line that joins a sequence of points, which represent stops, and each stop possesses a set of coordinates (or values) on a separate axis giving, at least, time of arrival at stop, distance from the last stop, location of present stop, mode used to get to stop, activity conducted at the stop, and land use at the stop. (It is clear that any other important aspects of travel could be portrayed on further dimensions, such as duration of stay at a stop.) The more rigorous geometrical representation of the individual's daily travel as a path in n dimensions is shown in Figure 2.

The immediate questions for future empirical, modeling, and theoretical work therefore become, What do individuals' trip records look like when represented in this fashion as complex behaviors, and, more importantly, is there any indication of less complex multiple-trip sequences (linking only one or two, and one or two kinds of, modes, activities, or destination types); and, are there any apparent tendencies for groups of individuals to have patterns or the same types of paths? For the purpose of this paper, it is sufficient to show that (a) paths apparently tend to be less rather than more complex; (b) individuals of the different groups tend to have different typical paths; and (c) at least some statistical methods exist to measure (classify) paths into a few classes so that complex behaviors could comprise some kind of well-behaved variables for model and theory development.

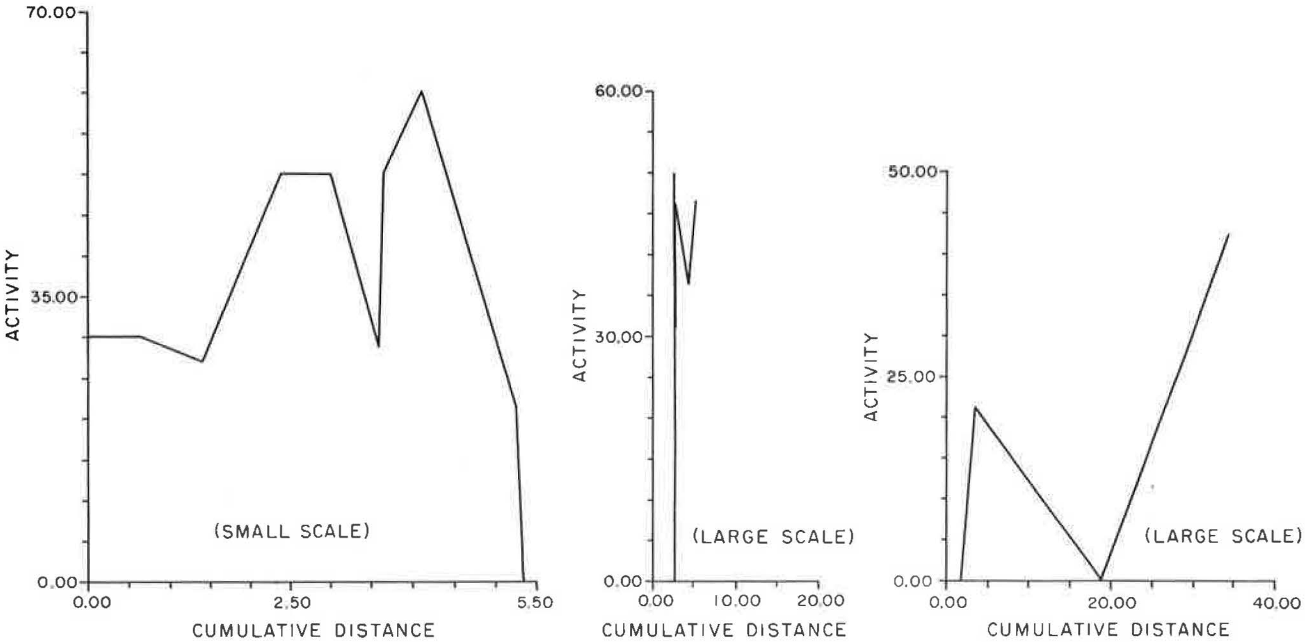
Data to document the present conceptualization of travel and to answer the questions raised should conform to the following requirements: It should consist of recent trip records for a random sample of individuals, of varying sociodemographic characteristics, where each individual's record is comprised of each stop visited in sequence over a time period, and details of the activity of the stop, times of arrival at the stop, the mode used to get to the stop, the precise point location of the stop, the land use at the stop, and the distance from the last stop. The Uppsala data set, a collection of the longitudinal travel records over 35 days for a sample of 144 individuals in 92 households in Sweden in 1971, was the only available data set that met all of these requirements.

The individuals in the set were a stratified random sample of persons by life-cycle group; Table 1 gives the definition of the group and the distribution of the sample between groups. For the exploratory purposes of this paper, an initial subsample of 40 individuals was selected randomly; each life-cycle group was represented in the subsample in the same proportion as in the complete sample. The analysis was then repeated by using a larger sample of 100 individuals to check that extremely small sample size did not influence results.

Some sample plots of the paths of the 40 individuals are shown in Figure 3. The total number of plots just for 40 persons numbered 840, so only an illustrative selection can be included. These, however, display some evidence that

1. Individuals have paths with less rather than more complex structures, that is, they use one or two modes per day, limit themselves to a few activities, generally restrict the distance traveled, and do not visit highly dispersed or a large variety of locations;
2. Some of the paths for different individuals exhibit similarity; and

Figure 3. Plots of representations of the n-dimensional paths of selected individuals in the Uppsala data set.




3. There appear to be differences in the paths for persons in different groups, although these are not necessarily simply related to life cycle.

## Classifying Paths

This preliminary data display needs to be supported by a description of some simple statistical methodology to show that the paths that represent complex behaviors could be classified rigorously, so that their associations with a number of sociodemographic descriptors could then be defined by using standard multivariate procedures (such as k-way contingency-table analysis). The illustrative approach to the classification of complex behaviors that follows refers to the early geographic work that classified travel in terms of only one possible dimension of a stop (namely the type of land use there, representing the type of destination). The extension of the discussion demonstrates how complex travel represented on additional dimensions could be classified.

The method involves manipulations of a flow matrix. For any sample of individuals, the longitudinal data of travel diaries can be summarized in a square from-to flow matrix in which the rows represent the origin stops and the columns the destination stops in the sequence of out-of-home linkages made over some time period. The initial focus is on the out-of-home linkages made over some time period. First, the analysis centers on the out-of-home land use characteristics of the origin and destination of each linkage; then cells give the number of times people traveled from land use i (e.g., bank) to land use j (e.g., barber shop) in the course of home-to-home circuits (48, 49). By next including a home-home cell to represent the frequency with which individuals ended one home-home circuit and started another one, circuits are linked together and the matrix properly represents flows over any time period (e.g., a day). The home-home cell is an artificial cell that links circuits; as it reflects no movement between two different bases, as do other cells in the flow matrix, it is omitted from subsequent analyses of travel linkages. Because the directionality of the sequence of stops is retained, the matrix is, of course, asymmetric. It is also extremely complex. Our goal is to simplify this complex matrix (a) by identifying which travel linkages occur frequently enough to be considered significant and (b) by identifying groups of land uses that tend to occur together on the same path.

In order to reduce the complexity of the matrix and to identify significant linkages, transaction flow analysis is used. Transaction flow analysis provides a way to eliminate size effects (unequal row and column marginals) that can obscure important patterns and lead to a biased interpretation of the data. The method involves specification of a null or indifference model for determining the expected number of linkages between origins and destinations and then comparison of these estimates with the observed interaction data. The null model used to estimate the number of links is normally specified as a function of the size or the relative importance of the origins and destinations (i.e., of row and column sums); therefore the residuals calculated from this model are free from the effect of different absolute flow levels among land uses. Following Slater (50), the expected flow levels, $a^*_{ij}$, are specified as:

$$a^*_{ij} = U_i V_j \; ; i = 1, \ldots, m \quad j = 1, \ldots, n \qquad (2)$$

where

$$U_i = \sum_j a_{ij} / \sum_i \sum_j a_{ij} \text{ and}$$

$$V_j = \sum_i a_{ij} / \sum_i \sum_j a_{ij}$$

and $a_{ij}$ is the observed interaction between i and j. The residuals from the indifference model are a measure of the strength or significance of the linkages among land uses and, moreover, identify for each land use the other land uses that are linked primarily as origins or primarily as destinations to the land use in question. In this manner transaction flow analysis enables us to determine which cells in the flow matrix contain significant linkages; transaction flow analysis does not, however, tease out groups of land uses that tend to occur on the same path. In order to classify paths on the basis of land use linkages, principal components analysis of the flow matrix must be performed.

Factor analysis has been used extensively as a grouping or regionalization technique (51, 52). In the analysis of directed flow matrixes a standard R-mode principal components analysis will yield factors that represent destinations that have similar patterns of linkages to the set of origins. The factor scores from an R-mode analysis provide information on the origins that tend to be identified with each factor. Groups of highly interacting land uses (complex travel patterns in one dimension) can be derived by combining sets of land uses that have high factor scores. Thus we identify destinations with similar source patterns (via the factor loadings) and the common sources associated with these destinations (via the factor scores).

An alternative grouping procedure that takes into account the indirect linkages contained in the flow matrix is to use one of the many algorithms available for grouping observations. All grouping algorithms for interaction data must address the problem of unequal row and column sums (53). In our case, this problem can be ameliorated by applying the grouping procedure to the matrix comprised of the residuals from the null independence model described above rather than to the raw linkage matrix. The groups derived from a standard hierarchical grouping procedure suffer, however, from the fact that, at any given step in the aggregation process, the previous groupings are taken as given; hence a globally optimal solution is unlikely.

The classification methods discussed thus far have considered only one aspect (dimension) of each stop in an individual's path. Since we need to be able to classify complex travel patterns in n dimensions we need to consider how these methods could be extended to encompass the dimensions of travel other than simply land use. One approach is to build a flow matrix in which each row and column is a composite of any of the limited number of dimensions of travel considered of interest. Clearly some simplification or refinement is necessary to keep the size of such a matrix manageable. As one possible solution, consider only critical dimensions of a stop: activity type (shop, recreation, work, personal business, social, and home-based activity), mode of travel (automobile, bus, bicycle, or walk), distance traveled from last stop (classified in discrete distance categories), and time of day (also classified in discrete categories). Each row and column then represents a unique combination of activity, mode, distance, and time, and the flow matrix is a record of the individual's path in four dimensions. Analysis of such a flow matrix should yield those activity-mode-distance-time bundles that occur frequently on the same path and enable the classification of paths in four dimensions similar to the typology of travel derived from analysis of the matrix of travel linkages between land uses. The same approach could be extended to paths in a larger number of dimensions, depending on the size of sample of individual daily trip records.

As can be seen from the above, the methods of analysis of the flow matrix are not complicated, given the current statistical procedures in widespread use for segmenting individuals into groups and estimating the parameters of current travel models.

The definition and measurement of travel implies, however, that the unit of demand is a set of stops that has distinguishable properties (location in time and space, mode used to get there, activity or purpose there, and land use type) and that the selection of a set of stops from a larger but still spatially constrained set generates travel as a complex behavior. Thus, the conception of distinct and excessively complicated simultaneous or sequential choices or decisions for trips (modes, destinations and times of day) (54), with simple trips of the different varieties as the unit of demand, relapses into a much less complicated and more plausible notion of what is demanded and how, once it is realized that the redefinition of travel as a complex behavior apparently entails demand for a set of stops for the accomplishment of activities from a rather larger but still spatially constrained set in a city. In urbanized societies in which increasing spatial dispersion and specialization of activities is a dominant feature, this seems an appropriate way of conceiving the origins of recurrent movement.

The implications of this for demand theory are obviously profound and beyond the scope of this paper. Some preliminary data analysis becomes even more desirable to substantiate the proposed nature of choice sets and the general contention of this paper that systematic variation of limited sets of options between individuals exists, together with resultant variability in decision procedures. It remains for future research to specify in detail a choice-set-formation model and to discover and to elaborate on precisely what are the decision strategies of individuals in different types of situations, to flesh out the explanatory model of individual and group behavior of Equation 1.

## IMPLICATIONS FOR INDIVIDUAL'S ALTERNATIVES AND DECISION MAKING

### Hypothesis 1

Hypothesis 1: Given that stops are described by a limited number of critical dimensions, the set of alternative stops for an individual to use in a day may be restricted to one or more, which are described by a limited number of values or categories and perhaps only one value or category of each aspect.

Thus, shopping for other than necessities may be associated only with regional shopping centers, the automobile mode, more than 15 min, and arrive on the way home from work; but shopping for toothpaste may be associated only with local drugstore, walk less than 5 min, and drop by from home after work. The individual might have only one regional shopping center for nonnecessities and one corner drug for necessities to choose. The kinds of associations formed for stops and the number of stops included in the choice set, however, may vary systematically between individuals in different socioeconomic groups and will be dependent on the nature of the spatial environment in which they exist. In operational terms, this implies that, in the individual's trip record, a high degree of correlation should exist between observations of the activity, distance, mode, destination type, destination location, and time of arrival aspects of stops, with repetitions of combinations increasing the degree of correlation. Moreover, the kinds of association should manifest some variation for different types of individuals.

It follows from hypothesis 1 that, if more than one stop exists in the choice set, the individual must find some means for evaluating them to select the set to use. That is, he or she must have some procedure for evaluating the cost and benefits of using the limited number of combinations of activity, destination location, destination type, distance, mode, and time of visit values or categories that describe each possible stop. This implies that some underlying common dimensions might exist in terms of which all aspects of these combinations can be described and evaluated. Since, in the literature on both the disaggregate and aggreate modeling of movement, travel time and cost have always been either plausibly argued or demonstrated to be of primary importance in regulating movement, and since recent time and money budget studies (55, 56) tend to confirm this, hypothesis 2 can be formulated as follows.

## Hypothesis 2

Hypothesis 2: Places as defined in hypothesis 1 are evaluated by each individual on two fundamental dimensions, which could be the time and cost expenditures of using them. Systematic differences could also exist between individuals in the ways places are evaluated in terms of time and cost, depending on sociodemographic characteristics, which reflect possibly varying decision strategies.

In operational terms, this means that the stops in each individual's trip record for a day, defined in terms of their six critical aspects (activity, location, land use, distance, mode, and time of arrival), should exhibit selection in accordance with a model of judgment that conforms to hypothesis 2.

The two hypotheses comprise an initial explanation of observed complex individual travel behavior, as reconceptualized here and as should be manifest, for example, in the daily trip records for the two subsamples of 40 and 100 individuals in the Uppsala data set. Statistical techniques can be used to show that the two hypotheses, by reconceptualizing behaviors as complex, options as limited and variable, and decision procedures as simple and variable too, could fit standard kinds of travel data just as well as the alternative assumptions on which current models of movement and underlying theories are based.

## Statistical Tests of Hypotheses

### Hypothesis 1

For each of the 40 individuals in each life-cycle group in subsample one, an intercorrelation matrix was prepared to show the Pearsonian simple product-moment correlation coefficient (r) between observations for each pair of aspects for each of the p stops in the individual's day. The Pearsonian simple product-moment correlation coefficient is used here as a measure of pattern (association) and not as a statistic measuring degree of explanation of a causal model, its more normal use. For this reason, no statistical tests of significance are conducted. It is recognized also that r is not strictly an appropriate measure of association between variables that are made up of mixed data (cardinal, ordinal, and ratio); however, it was the best of all measures to meet the requirements of being both a pattern measure and a measure of similarities for input into the INSCAL algorithm for the second phase of the analysis below.

The day when the individual made a maximum number of stops was selected [typically for an individual ($5 \leq p \leq 15$)]. If hypothesis 1 is correct, then the absolute value of each r in the intercorrelation matrix should tend to be high. Moreover, different kinds of association between the variables should be present for different kinds of individuals, some persons perhaps matching bus with regional shopping center and automobile with local convenience stores, and others doing the reverse. This should result in a dispersion of r's (+, -) for each pair of aspects of stops. These expectations proved to be the case when the data for the subsample of Uppsala individuals were analyzed. Tables 2-4 contain a selection of the trip records and intercorrelation matrices for selected individuals to document this. Systematic variation of choice sets between different types of individuals was tested by using multiway analysis of variance of the characteristics of individuals—stage in life cycle (rows) versus the r-values for the individuals (cells), for each possible pair of stop aspects (columns). Frequency distributions of r-values for 40 individuals in the Uppsala sample are given below. (F = relative frequency, $\bar{F}$ = mean relative frequency of r-values, and $V_F$ = the coefficient of variation.)

*All Aspect Pairs, All Individuals*

| r-Value | Number | F | $\bar{F}$ | $V_F$ |
|---|---|---|---|---|
| 0 to 0.24 | 260 | 0.36 | 0.37 | 0.45 |
| 0.25 to 0.49 | 192 | 0.27 | 0.27 | 0.47 |
| 0.50 to 0.74 | 179 | 0.25 | 0.25 | 0.51 |
| 0.25 to 0.99 | 83 | 0.12 | 0.12 | 0.83 |

*Mode and Time of Arrival*

| r-Value | Number | F | $\bar{F}$ | $V_F$ |
|---|---|---|---|---|
| -1.00 to -0.51 | 6 | 0.18 | 0.06 | 7.83 |
| -0.50 to -0.01 | 5 | 0.15 | | |
| 0.00 to 0.49 | 19 | 0.55 | | |
| 0.49 to 1.00 | 4 | 0.12 | | |

*Mode and Land Use*

| r-Value | Number | F | $\bar{F}$ | $V_F$ |
|---|---|---|---|---|
| -1.00 to -0.51 | 0 | 0 | 0.43 | 0.86 |
| -0.50 to -0.01 | 5 | 0.15 | | |
| 0.00 to 0.49 | 12 | 0.35 | | |
| 0.49 to 1.00 | 17 | 0.50 | | |

*Mode and Activity*

| r-Value | Number | F | $\bar{F}$ | $V_F$ |
|---|---|---|---|---|
| -1.00 to -0.51 | 7 | 0.21 | -0.12 | -3.52 |
| -0.50 to -0.01 | 12 | 0.35 | | |
| 0.00 to 0.49 | 14 | 0.41 | | |
| 0.49 to 1.00 | 1 | 0.02 | | |

*Mode and Distance*

| r-Value | Number | F | $\bar{F}$ | $V_F$ |
|---|---|---|---|---|
| -1.00 to -0.51 | 0 | 0 | 0.60 | 0.38 |
| -0.50 to -0.01 | 0 | 0 | | |
| 0.00 to 0.49 | 10 | 0.29 | | |
| 0.49 to 1.00 | 24 | 0.71 | | |

*Time and Land Use*

| r-Value | Number | F | $\bar{F}$ | $V_F$ |
|---|---|---|---|---|
| -1.00 to -0.51 | 2 | 0.05 | -0.03 | -11.22 |
| -0.50 to -0.01 | 16 | 0.47 | | |
| 0.00 to 0.49 | 15 | 0.44 | | |
| 0.49 to 1.00 | 1 | 0.02 | | |

*Time and Activity*

| r-Value | Number | F | $\bar{F}$ | $V_F$ |
|---|---|---|---|---|
| -1.00 to -0.51 | 15 | 0.44 | -0.38 | -1.08 |
| -0.50 to -0.01 | 15 | 0.44 | | |
| 0.00 to 0.49 | 2 | 0.06 | | |
| 0.49 to 1.00 | 2 | 0.06 | | |

**Table 2. Correlation in the individual's daily trip record between aspects of stops from the Uppsala subsample for individual 110 525 (elderly life-cycle group).**

| Stop Aspects | Mode | Time | Land Use | Activity | North-South Location | East-West Location | Distance |
|---|---|---|---|---|---|---|---|
| Mode | - | -0.70 | +0.33 | -0.66 | -0.54 | +0.67 | +0.99 |
| Time | -0.70 | - | +0.68 | +0.99 | +0.75 | -0.99 | -0.69 |
| Land use | +0.33 | +0.68 | - | -0.69 | +0.70 | -0.64 | +0.34 |
| Activity | -0.66 | +0.99 | -0.69 | - | +0.79 | -0.99 | -0.66 |
| North-South location | -0.54 | +0.75 | +0.70 | +0.79 | - | -0.77 | -0.56 |
| East-West location | +0.67 | -0.99 | -0.64 | -0.99 | -0.77 | - | +0.67 |
| Distance | +0.99 | -0.69 | +0.34 | -0.66 | -0.56 | +0.67 | - |

**Table 3. Correlation in the individual's daily trip record between aspects of stops from the Uppsala subsample for individual 130 101 (elderly life-cycle group).**

| Stop Aspects | Mode | Time | Land Use | Activity | North-South Location | East-West Location | Distance |
|---|---|---|---|---|---|---|---|
| Mode | - | -0.25 | +0.71 | +0.31 | +0.13 | -0.18 | +0.78 |
| Time | -0.25 | - | -0.38 | +0.45 | +0.64 | +0.87 | -0.46 |
| Land use | +0.71 | -0.36 | - | +0.27 | +0.04 | -0.36 | +0.74 |
| Activity | +0.31 | +0.45 | +0.27 | - | +0.96 | +0.70 | +0.34 |
| North-South location | +0.13 | +0.64 | +0.04 | +0.96 | - | +0.87 | +0.15 |
| East-West location | +0.18 | +0.87 | -0.36 | +0.70 | +0.87 | - | -0.24 |
| Distance | +0.78 | -0.46 | +0.74 | +0.34 | +0.15 | -0.24 | - |

**Table 4. Correlation in the individual's daily trip record between aspects of stops from the Uppsala subsample for individual 151 410 (middle aged with children group).**

| Stop Aspects | Mode | Time | Land Use | Activity | North-South Location | East-West Location | Distance |
|---|---|---|---|---|---|---|---|
| Mode | - | -0.48 | +0.17 | -0.73 | -0.75 | -0.83 | +0.72 |
| Time | -0.48 | - | +0.37 | -0.18 | -0.35 | -0.24 | +0.02 |
| Land use | +0.17 | +0.37 | - | +0.04 | -0.23 | -0.19 | +0.08 |
| Activity | -0.73 | -0.18 | +0.04 | - | +0.53 | +0.63 | -0.49 |
| North-South location | -0.75 | -0.35 | -0.23 | +0.53 | - | +0.90 | -0.24 |
| East-West location | -0.83 | -0.24 | -0.19 | +0.63 | +0.90 | - | -0.38 |
| Distance | +0.72 | +0.02 | +0.08 | -0.49 | -0.24 | -0.38 | - |

*Land Use and Distance*

| r-Value | Number | F | $\bar{F}$ | $V_F$ |
|---|---|---|---|---|
| -1.00 to -0.51 | 1 | 0.03 | 0.32 | 0.94 |
| -0.50 to - 0.01 | 1 | 0.03 | | |
| 0.00 to 0.49 | 24 | 0.71 | | |
| 0.50 to 1.00 | 8 | 0.24 | | |

The analysis-of-variance results were disappointing but could indicate that more, and more appropriate, sociodemographics need to be included in the analysis. The data set did not, however, contain additional sociodemographics for such an analysis. The repetition of the analysis for the larger subsample of 100 individuals showed no difference in results.

Hypothesis 2

The correlation coefficients in the matrices for individuals, such as those of Tables 2-4, comprise measures of similarity between the different aspects of stops for each person. These coefficients are the best kinds of similarities (distance or proximity) measures for input into an M D S scaling algorithm, which fits the INSCAL model of the evaluation of stimuli to data. The algorithm and the model can be used with the data for the Uppsala individual trip records to test hypothesis 2 in the following way (57).

Assume that the six critical aspects of stops in the individual's choice sets comprise stimuli for the individual. Then associations between the aspects of stops might not only reflect the restricted nature of the options in the choice sets but also the degree of similarity (proximity, discriminability) of the stimuli that define stops when they are evaluated on no more than two basic dimensions by each and every individual. The

**Table 5. Correlations between distances between stimuli (aspects of stops) in two-dimensional INSCAL configurations and input similarities (proximities) data for stimuli.**

| Individual | r-Value | Individual | r-Value |
|---|---|---|---|
| 1 | 0.881 361 | 21 | 0.550 332 |
| 2 | 0.828 531 | 22 | 0.528 632 |
| 3 | 0.691 990 | 23 | 0.646 401 |
| 4 | 0.820 661 | 24 | 0.640 377 |
| 5 | 0.820 961 | 25 | 0.734 304 |
| 6 | 0.512 941 | 26 | 0.773 128 |
| 7 | 0.733 039 | 27 | 0.567 975 |
| 8 | 0.631 778 | 28 | 0.718 454 |
| 9 | 0.617 555 | 29 | 0.849 543 |
| 10 | 0.609 835 | 30 | 0.648 269 |
| 11 | 0.358 989 | 31 | 0.816 215 |
| 12 | 0.640 775 | 32 | 0.732 914 |
| 13 | 0.840 689 | 33 | 0.621 152 |
| 14 | 0.831 145 | 34 | 0.581 234 |
| 15 | 0.764 530 | 35 | 0.851 186 |
| 16 | 0.609 176 | 36 | 0.764 260 |
| 17 | 0.619 236 | 37 | 0.812 975 |
| 18 | 0.816 674 | 38 | 0.836 420 |
| 19 | 0.874 279 | 39 | 0.795 324 |
| 20 | 0.873 872 | 40 | 0.793 309 |

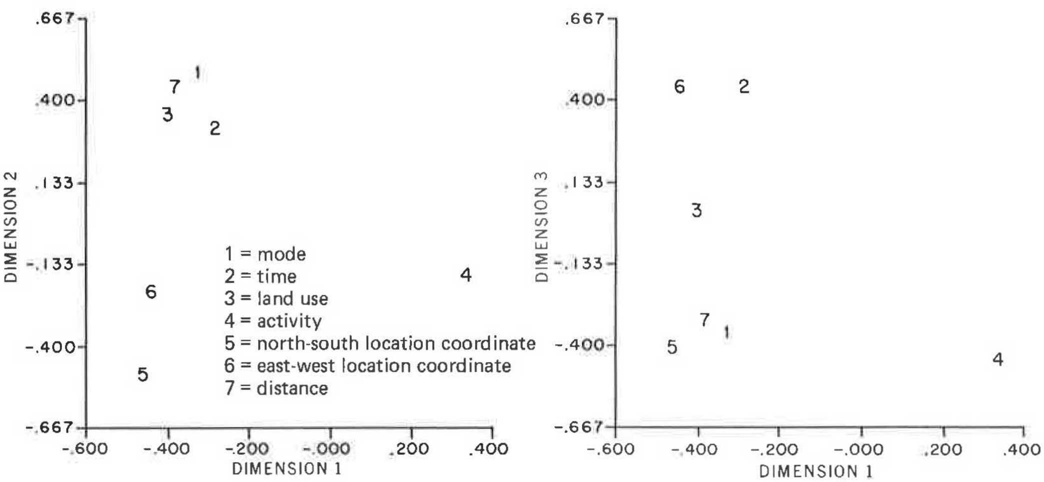
Note: Group correlation = 0.895 483.

**Table 6. Variability of weights for individuals in the Uppsala subsample on dimensions 1 and 2.**

| Individual | Dimension 1[a] | Dimension 2[b] | Individual | Dimension 1[a] | Dimension 2[b] |
|---|---|---|---|---|---|
| 1 | 126.91 | 142.35 | 21 | 102.55 | 131.60 |
| 2 | 75.09 | 76.20 | 22 | 56.03 | 65.87 |
| 3 | 113.99 | 107.46 | 23 | 58.74 | 101.31 |
| 4 | 112.12 | 131.28 | 24 | 66.04 | 110.62 |
| 5 | 73.52 | 99.78 | 25 | 77.06 | 105.54 |
| 6 | 29.82 | 86.15 | 26 | 48.05 | 62.73 |
| 7 | 49.07 | 51.40 | 27 | 112.51 | 149.58 |
| 8 | 99.98 | 135.09 | 28 | 20.21 | 78.80 |
| 9 | 62.61 | 85.81 | 29 | 38.06 | 31.88 |
| 10 | 70.73 | 125.66 | 30 | 122.07 | 101.07 |
| 11 | 20.61 | 47.17 | 31 | 38.14 | 49.10 |
| 12 | 36.40 | 47.95 | 32 | 115.23 | 108.05 |
| 13 | 48.42 | 69.13 | 33 | 59.12 | 56.31 |
| 14 | 95.78 | 124.13 | 34 | 75.15 | 72.14 |
| 15 | 67.64 | 69.07 | 35 | 112.42 | 101.32 |
| 16 | 49.44 | 59.22 | 36 | 116.85 | 86.59 |
| 17 | 67.63 | 115.13 | 37 | 79.23 | 67.21 |
| 18 | 106.92 | 129.67 | 38 | 86.31 | 88.14 |
| 19 | 87.39 | 88.68 | 39 | 54.53 | 60.49 |
| 20 | 109.44 | 108.22 | 40 | 61.52 | 70.25 |

[a] For dimension 1, t-tests of the difference between the means of weights for each pair of life-cycle groups were significant at the 5 percent level in only 3 of 21 pairs. The coefficient of variation of all weights is 30.2 percent.
[b] For dimension 2, t-tests of the difference between the means of each pair of life-cycle groups were significant at the 5 percent level in only 6 of 21 pairs. The coefficient of variation of all weights is 34.8 percent.

**Figure 4. Plot of three-dimensional group spaces and weight spaces derived from INSCAL analysis of trip records of aspects of stops used in a day.**




aspects (stimuli) that define the stops for each individual during a day should, therefore, comprise a configuration that is recoverable in a two-dimensional mental space, with each aspect (stimulus) discriminated along each dimension. However, interindividual differences should exist in recovered configurations, with systematic differences between groups of individuals, which indicate differences in evaluation procedures.

The INSCAL model and algorithm allow for interindividual differences in the evaluation of stimuli (aspects of stops) in the above ways by

1. Testing the goodness of fit to the similarities data for stimuli, for n different individuals, of n matching stimuli configurations, each in a two-dimensional space;
2. Producing a group or overall configuration for all individuals as a composite of the individual ones, providing a basis for comparison of the latter; and
3. Allowing for individual differences in configurations through variation in the weights in the function used to fit the similarities (distance) data for each individual, where the function relates the individual and group configurations in the following way:

$$d^i_{jk} = \left[\sum_{t=1}^{r} w^i_t (x_{jt} - x_{kt})^2\right]^{1/2} \tag{3}$$

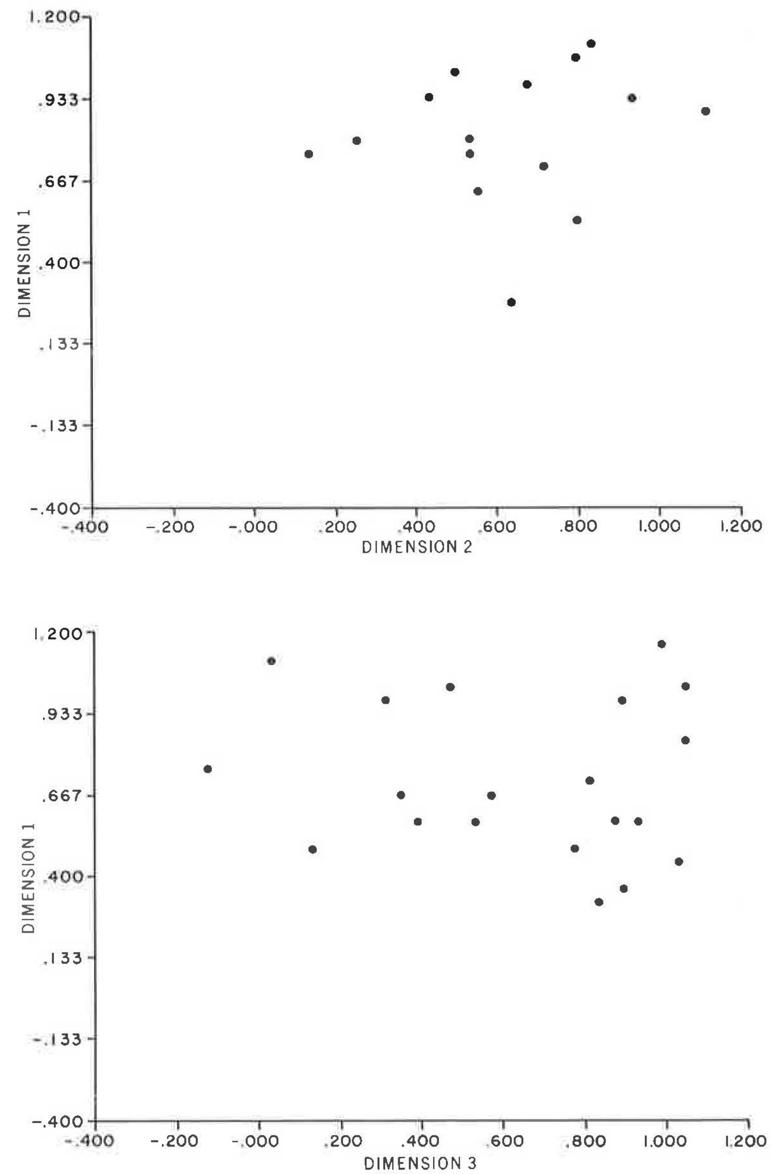
where

$d^i_{jk}$ = the distance (similarity) between the j th and the k th stimulus for the i th individual,
r = the number of underlying dimensions (here assumed to be 2),
$x_{jt}$ and $x_{kt}$ = the values of the stimulus on each dimension, and
$w^i_t$ = the weights for each dimension, specific to the individual.

On the basis of the preceding discussion, we would expect that, if hypothesis 2 is true and by using the kinds of intercorrelation matrices of Tables 2-4 for each individual as proximities input to the INSCAL algorithm:

1. Configurations of stimuli (the six critical aspects

Figure 5. Plot of three-dimensional group spaces and weight spaces derived from INSCAL analysis of trip records.




of each stop) are recoverable for each individual in a two-dimensional space, with a very good match of the distances between stimuli in each individual configuration to the input similarities (proximity) measures;

2. Stimuli are well discriminated (spaced out) on each dimension in individual and hence group configurations; and

3. There is considerable interindividual variation in weights for each dimension, with statistically significant differences in the weights (and hence configurations and evaluations) for individuals in different life-cycle groups.

The results of the data analysis for the small subsample of 40 persons conform with these expectations, as shown in Tables 5 and 6. The match of the recovered group and individual configurations to the input data is excellent, as measured by the generally high r-values in Table 5, for each individual and for the group, between the distances represented by the input data and the recovered distances for each configuration. This demonstrates that, as hypothesized, two fundamental dimensions are probably used for evaluation, most probably travel time and cost. The expected high interindividual variability in weights appears (Table 6) and, therefore, the possibility of grouping individuals in some manner to minimize intragroup and maximize between-group variance in them (and thus group configurations or evaluation functions); however, the expected association of weights simply with life-cycle group through standard multiway analysis of variance did not appear and there is no evidence as to precisely how evaluation procedures vary between groups, only that they do. Perhaps, again, some further sociodemographic variables should be included to help partition the population better (for example sex, marital status, income, and occupation) as well as life-cycle stages. These were not available in the Uppsala data set.

A repetition of the analysis by using the large 100-individual subsample yielded generally similar results, except that a third dimension of minor importance appeared (see Figures 4 and 5). This could be a dimension associated with service, also prominent in disaggregate-travel-modeling literature.

## CONCLUSION

The exploratory data analysis for both hypotheses seems sufficient to support the contention that, once it is granted that the individual's recurrent movement is an example of complex behavior and definable as a path in n-dimensional space, then it may be generated by the evaluation of a limited number of spatially defined options in terms of only several criteria, probably time and cost considerations. This is also consistent with the supposition that, although movement is complex from a researcher's point of view, it is more likely to be viewed by most persons as a routine question, not as a major decision or investment question (6). It is therefore plausible that travel options are few and decision making is simple. Choosing, as far as the individual is concerned, is not complicated problem solving in complicated situations, as our current models and theories assume. The results of the data analyses are also consistent with systematic variations in complex behaviors, spatially constrained options, and simple decision rules and strategies for population groups. It remains for further research to develop the mathematical explanatory models and theory for the analysis of human behaviors that allow behaviors to be complex and options and evaluations to be simple and permit all three to vary by population group.

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# Definition of Alternatives and Representation of Dynamic Behavior in Spatial Choice Models

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**This paper considers issues relevant to two important spatial-choice modeling problems: the definition of alternatives and the modeling of dynamic behavior. The definition of alternatives may benefit from the development of a classification scheme that consists of a reasonably small number of categories. This approach could lead to more manageable data requirements and improved model specification through the use of a larger set of alternative-specific constants. Also, spatial alternatives often have characteristics that do not vary from individual to individual. Recognition of this can lead to computational efficiencies and possibly easier use of aggregate data in model estimation. Dynamic behavior is modeled by introducing the effects of previous choices and using an error-components structure in the utility functions for choice models. Four special cases of the dynamic model are considered. It is then possible to identify the assumptions necessary to apply existing choice methodologies to dynamic choice problems and to recommend further research on methodologies that require less restrictive assumptions.**

Several features of spatial choice problems have made the conceptual and empirical development of appropriate models challenging. This paper focuses on two of the more important features: the definitions of spatial alternatives and the treatment of the dynamic aspects of spatial choice (1-3). These issues will be discussed in the context of the utility maximization approach to quantal choice problems (4, 5).

Spatial choice problems apparently differ from the more commonly modeled mode choice problems in the identifiability and number of available alternatives. Available transportation modes are easily identified and few in number. Spatial alternatives (e.g., alternative shopping destinations) can be identified in several ways, ranging from individual spatial locations to fairly large geographic zones or other aggregation schemes. Also, in many urban areas, the number of alternatives can be very large.

Another important characteristic of spatial alternatives is that many of their objective characteristics do not vary for different individuals. That is, the characteristics (such as travel times and costs of transportation modes) vary with an individual's location, but objective characteristics of spatial alternatives (such as the number of retail employees at a shopping destination) do not. This property can be used in the exploration of methods that make more efficient use of data in the estimation of spatial choice models.

Dynamic considerations are especially important for short-term spatial choices, such as shopping travel. Although repeated observations of these choices can be obtained during a reasonably short time period, these problems have often been treated empirically in the same manner as longer-range choices (i.e., only a single cross section of observations has been used). By explicit consideration of a time series of cross sections, the dynamic aspects of short-term spatial choices can be studied in detail. In addition, the consequences of improperly ignoring dynamic considerations in the development and application of spatial choice models can be identified.

## DEFINITION OF SPATIAL ALTERNATIVES

Research relevant to definition of alternatives can be divided into two categories: (a) classification of alternatives and (b) data requirements for spatial choice models. In general, the definition of spatial alternatives is of both theoretical and practical importance. The validity of the assumptions made for particular model structures [e.g., the independence from irrelevant alternatives property of the multinomial logit model (6)], is closely related to the definition of the alternatives. In addition, specification of independent variables and the resulting data requirements are influenced by the definition of alternatives.

### Classification

Choice models have been used most frequently to explain modal choice, in which the modal alternatives are fairly easily identified. For example, the classification of a particular mode as an automobile or bus is relatively easy. Also, the total number of alternatives is small; often only two alternatives (automobile and transit) are considered.

In contrast, there does not appear to be any natural method for classifying spatial alternatives, and the total number of alternatives can be quite large in many problems. Consequently, the actual definition of alternatives has been quite arbitrary and ad hoc, and often there has been no categorization of alternatives or only a very crude classification scheme. Some models, for example, have defined spatial alternatives to be the traffic zones established in metropolitan transportation studies and have made no attempt to classify alternatives, with the exception, perhaps, of the central business district (CBD) (5, 7). Examples of more developed classification systems are the classification of grocery shopping destinations by store type (8) and the classification of shopping centers by distance from home and floor area (9).

Classification is important for two reasons. First, the spatial choice problem can be made more tractable by first assigning an individual to a broad category and then assigning a specific destination within that category (9). For certain regional policy analyses where spatial detail is unnecessary, application of only the first step of this process may be sufficient. Second, even if the specific destinations are used directly, the classification approach allows the use of a fuller set of alternative-specific constants in the utility function of the choice model. The usual approach in specification of destination-choice models has been to exclude constants (5) or to include constants for only special destinations, such as the CBD (7). The classification approach allows the use of an alternative-specific constant for each category. Since the use of constants has been shown to be important in the proper specification of choice models (10), the development and use of a classification scheme is important for improved model specification as well as for problem simplification.

## Data Requirements

The most common definitions of spatial alternatives involve numerous destinations that are fairly small in geographic size. Consequently, in order to make the choice problem empirically tractable, it has been necessary to limit the size of the choice set available to each individual or household. This has been done by either assigning a restricted choice set to each individual before estimation of the model (5, 7) or by limiting the number of destinations available to all individuals by focusing on a limited geographical area. For example, the destination-choice project conducted by Northwestern University researchers (11) limited the available shopping destination to a common set. In many applications the definitions of alternative destinations involve some sort of spatial aggregation (12-14).

The necessity for limiting choice sets can be illustrated by considering the data storage requirements for estimating a choice model. When every individual has the same number of alternatives, these requirements (4) are

$$S = N(a-1)v \tag{1}$$

where

- S = the number of spaces required to store the independent variables,
- N = sample size,
- a = the number of alternatives, and
- v = the number of independent variables.

The nonlinear nature of the usual logit and probit approaches requires that all of the data be stored simultaneously.

The independent variables include characteristics of the spatial alternatives themselves, characteristics of the individual, and the spatial relationships between the individual and the alternative (e.g., distance). When objective data are used, the characteristics of the spatial alternative do not vary from individual to individual (e.g., the floor area of a shopping center is the same for everyone). In this case, if everyone has the same choice set, the actual storage requirements are

$$S = (a-1)v_1 + N(a-1)v_2 \tag{2}$$

where $v_1$ is the number of independent variables that do not vary from individual to individual and $v_2$ is the number of the remaining independent variables. A slight modification of existing logit and probit analysis computer programs would result in the smaller storage requirements of Equation 2. This would lead to greater statistical efficiency by allowing an increase in sample size and number of alternatives per individual or reduced cost for the same level of statistical efficiency.

This modification has the potential of yielding significant computational savings. For example, in a study of housing location choice, Friedman (15) developed a model that had nine communities as alternatives and nine independent variables. Of these variables, only one varied from individual to individual. Consequently, in many spatial choice problems, empirical tractability may not be as large a problem as commonly believed.

For some problems, variables that vary among individuals may not enter directly into the model. For example, a market segmentation approach may result in separate models, which correspond to various combinations of spatial separation and individual characteristics. In this case, $v_2$ is zero and the problem becomes one of estimating the effects of the characteristics of the spatial alternatives on the aggregate shares. Essentially, the situation is one of repeated observations of a single-choice situation. (Assuming each individual has the same choice set, each individual constitutes a repetition.) Although it was not used for a spatial choice problem, the random-coefficient logit model used to explain market shares of automobile models based on their characteristics is an example of the basic approach (16). Not only is there economy in computation requirements, but data requirements are drastically reduced as well. Only the aggregate shares and the characteristics of alternatives are necessary.

The ability to estimate behaviorally sound spatial choice models by using only characteristics of alternatives and aggregate shares as input data is highly desirable from a practical standpoint; however, the exclusion of independent variables, which indicate the spatial relationships between individuals and destinations and individual or household characteristics, may not be conceptually sound. In this case, it may still be possible to estimate models that have reduced data requirements by using an appropriate procedure for estimating disaggregate models from aggregate data.

Suppose a particular choice model for estimating the probability that a given individual will select a particular alternative is

$$P_i(X_2) = f_i(X_1, X_2) \tag{3}$$

where $X_1$ represents characteristics of alternatives that do not vary among individuals and $X_2$ represents independent variables that do vary among individuals. Then the aggregate share is given by

$$\text{Share}_i = \int_{X_2} f_i(X_1, X_2)\, g(X_2)\, dX_2 \tag{4}$$

where $g(X_2)$ is the probability density function.

In order to estimate the choice model by using aggregate data, it is necessary for Equation 4 to result in the shares being a function of $X_1$ and characteristics of the distributions of $X_2$ (e.g., the means and higher moments). If the choice model is multinomial probit, the results of Bouthelier and Daganzo (17) suggest that the means and the variance-covariance matrix that correspond to the variables in $X_2$ for each alternative are sufficient when $X_2$ can be approximated by a multivariate normal distribution.

For other choice models, the integral in Equation 4 can be analytically intractable. In these cases, either Monte Carlo integration techniques (18) or the approximation of $f_i$ by a polynomial expansion, such as the Taylor series (12, 19), may yield similar data requirements for the estimation of the model by using aggregate data.

There are some potential implications for current practice and future research from these characteristics of spatial alternatives. More research on the classification of alternatives into meaningful categories would be useful in the proper specification of spatial choice models and in the development of models for policy analysis at the regional level. That many of the objective characteristics of spatial alternatives do not vary from individual to individual immediately reduces the computational requirements for the estimation of choice models. Consequently, the use of much larger choice sets may be a possibility. There is also the possibility of estimating disaggregate models with aggregate data. The required data would be the aggregate shares for spatial alternatives, the nonvarying characteristics, and information such as the first and second moments of the distributions of the independent variables, which vary among individuals for each alternative. More research on the development of these procedures for models other than the probit model and on the efficiency and reliability of such methods may yield results that allow the development of practical models that have fairly moderate data requirements.

## DYNAMIC ASPECTS OF SPATIAL CHOICE

Most spatial choices are repeated. This is especially relevant for short-run destination choices, such as shopping travel. However, since most models have been estimated by using a single cross section of observations, the dynamic nature of the behavior is not emphasized.

Dynamic spatial behavior was studied by Burnett (20). However, her approach considered only one spatial alternative at a time. Modification of the usual utility maximization approach to choice behavior allows the development of models that consider more than one alternative and the exploration of the consequences of using the assumptions behind static models in dynamic contexts.

This can be seen by considering the typical approach. The utility for a given alternative can be expressed as

$$U_i = X_i \beta + \epsilon_i \tag{5}$$

where

$U_i$ = the utility of the i th alternative,
$X_i$ = the characteristics of the alternative,
$\beta$ = a vector of coefficient, and
$\epsilon_i$ = an error term.

To simplify the discussion, variables that describe individuals will not be identified. A choice model results from the utility maximization assumption and from the assumption of a distribution for the $\epsilon_i$.

The dynamic implications of Equation 5 are not clear. Certainly, if some of the independent variables change in the course of time, the resulting model will produce different selection probabilities. However, during short time periods, these variables are likely to be stable. In this case, any variation in an individual's choice over time is determined by $\epsilon_i$. If the errors are assumed to be the effects of excluded variables rather than pure randomness, then they are unlikely to vary for short time periods for a given individual, resulting in the prediction of a constant choice over time. Since this is clearly unrealistic for some types of spatial behavior (e.g., people do not necessarily limit themselves to one shopping destination), it is necessary to assume random error terms or to respecify the model to consider dynamic behavior explicitly.

A useful approach is to consider a specification analogous to the ones used in linear models that use a time series of cross-sectional data (21, 22).

A general form of such a model would be

$$U_{its} = X_{its}\beta + \sum_j \gamma_{ij} C_{j(t-1)s} + \mu_{is} + \nu_{its} \tag{6}$$

where the subscripts i and j refer to alternatives, t to a time period, and s to an individual. $C_{j(t-1)s}$ is one if individuals chose alternative j in the previous time period and zero otherwise. Although the model could be made more general by considering choices in previous time periods, in linear models a single lag term has often been used. Finally, $\mu_{is}$ is an error term that varies among individuals but not time periods and $\nu_{its}$ is an error term that varies among both individuals and time periods.

In addition to allowing the use of the time series of cross-sectional data, the revised specification introduces two additional elements. First, the possibility that the choice in one period may influence the following choice is allowed. A positive coefficient for the lag term indicates an increased choice probability in the subsequent time period, and a negative coefficient indicates the opposite influence. Second, the use of a component structure for the error term allows the possibility that some of the unobserved effects may be constant across time periods for particular individuals. An example of such a situation is when the $\mu_{is}$ represents the effects of unspecified characteristics of alternatives and the $\nu_{its}$ represents pure randomness in the choice process. For sufficiently short time periods, the unspecified characteristics would probably remain fairly constant; therefore, the error components representation would be reasonable.

The discussion in this section is confined to fixed-coefficient models. The development of dynamic choice models, analogous to the random-coefficient linear models (23), will not be considered.

In order to estimate a model that results from Equation 6, the data required are observations of the $X_{its}$ and the $C_{jts}$ for N individuals and T time periods. When one or more of the terms in the model is set equal to zero, several variations are possible.

### Case 1

Case 1 is the ordinary utility-maximization model applied to the time-series data: $\gamma_{ij} = 0$ for all i, j and $\mu_{is} = 0$ for all i, s. The basic assumption is that a static choice model can be applied directly to the dynamic problem. In estimating the model, the observations for a given individual over time would be treated as independent (i.e., in the same way as an observation of a different individual that has similar characteristics is treated). The standard static model is a special case when only one time period is observed. If the variables in X vary over time, the estimation of a choice model from the repeated observations of a single individual is another special case.

When the independent variables for the individuals do not vary over time, then the model becomes a choice experiment with repeated observations (4). Such choice problems have been treated in three ways:

1. The use of a single time period is the special case just mentioned (models estimated from data from standard transportation surveys are examples of this approach),
2. Actual observations of the repeated choices could be made (this would require travel-behavior diaries or recontact of a survey panel), and
3. Respondents could be asked to give their usual choices or the usual choice is constructed from reported choice frequencies in an attempt to capture the predominant pattern of repeated behavior (8).

If the case 1 assumptions are valid, then either of the first two data collection procedures will allow the estimation of consistent model coefficients. However, it is conjectured that the use of the usual choice as the dependent variable does not result in consistent estimation. This is based on an empirical example (24) in which models that used the usual behavior were quite different from those that used actual choice behavior. In addition, simulated data can be used to show that for some simple binary-choice models, when usual choice is the dependent variable, coefficient estimates do not converge to finite values when the data were constructed by assuming a model with finite coefficients. More research on the consequences of using the usual rather than actual choices would be useful in the determination of whether the apparent inconsistency is generally the case and the magnitude and direction of the bias if it is a problem.

### Case 2

The key assumption in case 2 is that previous choices affect current choices: $\mu_{is} = 0$ for all i, s. However, there is no constant component to the error term for a given individual. The effects of factors not explicitly included in the model are treated as completely random.

Since previous behavior is explicitly considered, observations of more than one time period are necessary. However, since the error terms are independent across time periods, existing models (such as the multinomial logit model) could be used directly.

A special case of this model occurs when the $X\beta$ term is zero (i.e., current choice is only a function of previous choices). The model then yields the transition probabilities of a Markov model of spatial choice (25, 26). In general, the model can be viewed as incorporating the effects of learning (27).

### Case 3

Case 3 introduces the possibility that there may be unspecified effects that are constant for individuals over time: $\nu_{ij} = 0$ for all i, j. Since it is impossible to distinguish empirically between the two error components when only a single cross section of observations is made, the identification of the variance components specific to individuals requires more than one period of observation. Most of the research on linear models has been concerned with the development of estimates for models analogous to the case 3 model (28-33).

This particular model illustrates the ambiguity of interpreting the selection probabilities estimated from a static model in a dynamic context. If the $\mu$ terms are zero (case 1 model), then each individual has a probability of selecting a particular alternative for each time period as determined by the model. At the other extreme, if the $\nu$ component is zero, each individual makes a constant deterministic choice. The selection probabilities from the model are the probabilities that individuals who have the same choice situation will make a particular constant choice. For example, in the mode choice case, the case 1 model gives a probability that an individual will use the bus on a particular day, and the extreme version of the case 3 model gives the probability that an individual who faces a particular choice situation will always choose the bus. The intermediate case is when both $\mu$ and $\nu$ are nonzero, in which case the selection probabilities for an individual lie between those estimated from the model and the deterministic situation.

Estimation of case 3 models introduces correlations in individual behavior over time. Therefore, each time period does not constitute a completely independent observation. As a result, estimation of the model, as in case 1, does not appear to be valid.

A possible estimation approach, which is analogous to that used in linear models, would be to explicitly identify the $u$ terms. This is referred to as the fixed-effect approach. This would result in a set of alternative-specific constants for each individual. Since this is undoubtedly unwieldy in practice, it may be possible to first classify the sample and have one set of constants for each category. Also, it might be necessary to classify the alternatives, as suggested earlier, in the specification of manageable sets of constants. When this is done, standard choice models can be used directly.

A conceptually more appealing approach is to deal directly with the more complex variance structure, the random-effects approach. This approach would be analogous to the work on correlated error terms among alternatives (34, 35) (e.g., the development of the multinomial probit model). Further, simulation and empirical work with linear models has indicated that models that deal directly with variance components perform better in small samples than do those that identify constant terms (22, 36). This suggests that research on the estimation of case 3 models may be very important.

### Case 4

Case 4—the full model—does not appear to introduce any new considerations. However, note that, for linear models, this case is the most sensitive to incorrect assumptions. That is, when a case 4 model is estimated as a case 2 model, inconsistent coefficients result. On the other hand, when a case 3 model is estimated as a case 1 model, the coefficient estimates are consistent but inefficient (21, 22). Further research could be useful in the determination of whether an analogous situation exists with respect to choice models. It could be the case that explicit consideration of the error components is especially important for case 4 models.

This approach to dynamic spatial choice models is similar to the methodology developed by Heckman (37) to explain dynamic labor-force-participation decisions. The models tested the effects of personal, household, and economic characteristics as well as previous participation in the labor force on women's decisions to work. Two variations of a generalization of the case 4 model were used. The first explicitly considered the variance structure (random effects) and the second directly identified the error components that corresponded to individuals (fixed effects). The models described here involve a generalization of Heckman's approach from the binary to the multinomial case and also shift the emphasis to independent variables that describe the characteristics of alternatives.

The specification of models that satisfy Equation 6 can be viewed as a special case of specification analysis that involves the possible exclusion of independent variables (33). That is, the $\mu_{is}$ can be treated as independent variables and the consequences of considering or not considering these components can be examined. In this regard, the recent work in specification analysis for choice models is relevant (38, 39). This analysis indicates that exclusion of the $u_{is}$ component can result in two sources of bias in the coefficient estimates: bias resulting from possible correlations between the error component and the other independent variables and bias resulting from changes in the distribution of the random component of the utility functions.

The bias resulting from excluding $\mu_{is}$ can be illustrated by a special case of the binary probit model. Assume that $\mu_{is}$ is not correlated with the independent variables, which are further assumed not to vary over time for the individuals. In this case, Equation 6 applies to two alternatives and the $\mu$ and $\nu$ are independent normal variables that have expected values equal to zero. Let the variance of $\mu$ be $\sigma^2$ and the variance of $\nu$ be one-half. If the inverse standard normal function is applied to the observed proportion that each individual selects the first alternative, and this variable is used as the dependent variable and X is the independent variable, then it can be shown that consistent estimates of $\beta$ are obtained when ordinary or generalized least squares is applied (38). On the other hand, if the maximum-likelihood method is used, the resulting coefficients converge to

$$b = \beta/\sqrt{1 + 2\sigma^2} \quad (7)$$

Therefore, the ratio of the regression estimators and the maximum-likelihood estimators yields information on $\sigma^2$, the variance of the error component that corresponds to individuals. This result follows from the fact that the $\mu$ are left-out variables that are uncorrelated with the observed variables and from the fact that uncorrelated, left-out variables result in the above differences between the regression and maximum-likelihood estimators (38, 39).

Further, the specification analysis approach allows explicit consideration of the distribution of $\mu_{is}$ in the development of random-effects models. Therefore, initial research on the development of dynamic choice models can be guided by the approach used in the analysis of specification problems.

The four cases of the dynamic choice model have presented a framework for discussing dynamic choice problems. It was noted that certain cases allow the use of existing choice models. In addition, further research on choice models to explicitly consider the variance structure in Equation 6 appears to be important to the development of dynamic choice models.

## SUMMARY AND CONCLUSIONS

The definition of spatial alternatives, the efficient use of both disaggregate and aggregate data sources, and the proper specification of models of dynamic behavior have been recognized as important issues. As in the case of mode-choice modeling, the ability to classify alternatives into a reasonably small number of categories would lead to models that are empirically more tractable. Further, classification allows the use of a larger set of alternative-specific constants, which may be important in the proper specification of choice models. Unlike the mode-choice case, however, many spatial choice models have subsets of independent variables that do not vary from individual to individual. Modification of existing programs to account for this feature and exploration of techniques for estimating choice models by using aggregate data would allow greater efficiencies in data collection, computation, and statistical accuracy.

Dynamic choice behavior was considered by modifying the utility function in the choice model to include effects of past behavior and by introducing an error component that is constant for a given individual over time. Several cases were considered. These are useful in understanding how previous models of spatial choice fit into a dynamic context, in exploring the consequences of improper dynamic assumptions, and in indicating necessary research to develop dynamic choice methodology.

Some of the cases allow direct use of existing choice methodology. The use of such methodology, which requires the most careful consideration, is the case in which the error components that are constant for a given individual over time are explicitly specified as constant terms (fixed-effect approach). In order for such an approach to be empirically manageable, both individuals and alternatives should be classified into a reasonably small number of categories. Investigation of the statistical reliability of this approach in small samples by use of empirical and simulated data is an important area for further investigation.

The analytical development of dynamic models that are derived from direct consideration of the components of the variance structure (random-effects approach) is an area for longer-term research activity. In the development of such models, the special features of spatial alternatives, which were discussed earlier, would have to be considered. Based on experience with linear models, this is the most desirable approach to the development of dynamic spatial choice models. Investigation of the small sample properties of such models is also important.

Finally, the prediction accuracies of the dynamic choice models derived from future research should be assessed. This assessment would indicate the extent to which models that have less-restrictive assumptions improve on the prediction accuracies of existing choice models used in dynamic contexts.

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# Analysis of the Metropolitan Boston Transportation System During the Postblizzard Week–February 13-17, 1978

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On February 6 and 7, 1978, a major blizzard crippled transportation services in the Boston metropolitan area. The disruption was so great that all but emergency vehicles were banned from the streets and highways in most eastern Massachusetts communities during the week after the blizzard. Not until midnight on Monday, February 13, was the ban completely lifted in the densely populated activity centers of the region. In some of these communities an on-street parking ban remained in effect through Tuesday, February 14. In addition to these legal restrictions, large quantities of snow presented additional obstacles to vehicular travel. Because of these legal and physical impedances, state and regional transportation agencies encouraged the use of transit or ride sharing for work trips in the region. In addition, the state recommended staggered work hours for employees in downtown Boston. This paper analyzes the effects of the driving and parking bans on travel in the region. Data pertaining to the volumes and temporal distribution of the various modes of travel during the week after the blizzard were collected and analyzed. These data were compared with travel data from a more typical time period. The analysis indicates that a significant shift to public transportation took place for the commute-to-work trip and that, through a combination of staggered work hours and special suburban transit services, the public transportation system was able to accommodate the great increase in demand. This shift to public transportation was only temporary in nature, however; normal preblizzard travel patterns returned when restrictions on vehicular travel were removed.

On February 6 and 7, 1978, a major snowstorm struck the Boston metropolitan area and dropped from 66 to 81 cm (26 to 32 in) of snow in less than 24 h. This blizzard came only two weeks after another record-breaking storm. Most of the snow from that storm had not melted, although the streets and roads were cleared and public transportation service had returned to normal. The February 6 storm caused such disruption of transportation services, including both public and private transportation, that the governor banned all but emergency vehicles from state highways and local streets in most of the communities in eastern Massachusetts. This was done to enable snowplows to proceed unhampered in their efforts to clear the roads.

The driving ban was lifted in some communities as early as February 10. It was not until midnight on Monday, February 13, that the ban was lifted in the core communities of Boston, Cambridge, Somerville, Medford, Brookline, Chelsea, Revere, and Winthrop (shown in Figure 1). Nearly half of the employment in the Boston region is located in this area. While the driving ban was still in effect in these areas, an attempt was made to enable people to return to work on Monday, February 13, and to resume normal activities. Some means of transportation other than the automobile had to be used by the approximately 750 000 persons who work or reside in the areas where the driving ban was in effect. Normally approximately 60 percent of the peak-period trips to the Boston central business district (CBD) and approximately 50 percent of the trips to the remainder of the regional core area, which includes Cambridge, Somerville, Everett, and Chelsea, are made by public transportation. Although many of these persons normally use a public transportation mode, many others had to temporarily switch modes from automobile to transit.

The cities of Cambridge and Boston imposed an on-street parking ban for Tuesday, February 14. This discouraged automobile commuters from entering downtown Boston and Cambridge for an additional day after the driving ban had been lifted.

To enable the transit system to handle the higher-than-usual demand, a system of staggered work hours was implemented. Different categories of employment were allocated to different work shifts, ranging from a 7:00 a.m. to 3:00 p.m. early shift to an 11:00 a.m. to 7:00 p.m. late shift. Although compliance was voluntary, the lieutenant governor appeared on television to urge adherence to the staggered shifts. In addition, a large number of major employers were contacted by the Massachusetts Bay Transportation Authority (MBTA) to request their support in encouraging employees to comply with the schedule. The Executive Office of Transportation and Construction urged suburban cities and towns to establish emergency bus routes to rapid transit stations or to downtown Boston and organized temporary downtown terminal areas for these routes.

Travel restrictions during the poststorm week provided an incomparable opportunity to address the following questions:

1. Would people manage to utilize the transit system successfully as an alternative mode of travel?
2. Would the transit system be able to handle the vastly increased demand?
3. Would people voluntarily stagger their work hours to enable the transit system to expand its capacity successfully? and
4. Would the reduction in automobile travel have a major impact on air quality?

These questions are part of the larger issue of whether or not the transit system could successfully attract and absorb vastly increased patronage with little if any modification of existing facilities and thus provide an alternative to the automobile during an emergency situation. The questions are dealt with in this report by examining the following data:

1. Work attendance in impacted areas during the postblizzard week versus that for a typical week,
2. Systemwide transit ridership during the postblizzard week versus that for a typical week,
3. Distribution by time of transit alightments and boardings at the four transit stations in the high-density central area and two terminal stations,
4. Highway volumes at selected counting stations on the first two days of the poststorm week versus that for a typical weekday, and

Figure 1. Communities that lifted the driving ban at midnight, February 13.


5. Air quality data for the postblizzard week versus that for the rest of the month.

Because the contingency plan for enabling people to return to work while the driving ban was still in effect was hastily organized one day before it was to go into effect, the data collection efforts were also hampered by lack of sufficient planning. Even so, boardings and alightments were counted manually at selected stations, and further data were contributed by the MBTA, private carriers, and the municipalities that provided their own transit services, which resulted in enough data to form the basis for the analysis presented below.

## PUBLIC TRANSPORTATION

Public transportation for 79 cities and towns in the Boston metropolitan region is provided primarily by the MBTA, which operates a system of rapid transit, trolleys, surface buses, and trackless trolleys. In addition, it subsidizes commuter-rail services operated by the Boston and Maine Railroad (B&M). Additional transportation service, mainly express bus service for commuters, is provided by numerous private carriers. The MBTA currently operates approximately 65 route-km (40 route miles) of rapid transit, 70 route-km (43 route miles) of streetcar lines, 5715 route-km (3550 route miles) of bus service, 13 route-km (8 route miles) of trackless trolley, and 385 route-km (240 route miles) of commuter rail. The MBTA operates approximately 1300 vehicles and the B&M operates approximately 200 vehicles.

Throughout this analysis of travel behavior during the postblizzard week, comparisons will be made to typical travel behavior. Typical MBTA 24-h ridership (based on 1978 revenue data) and typical peak-period ridership (based on factors derived from various MBTA ridership surveys) are given in the table below. Because transit travel shows seasonal variations, ridership on the postblizzard weekdays of February 1978 is compared with ridership on a typical February weekday.

| Mode | 24-h Regional Ridership (round-trip) | 3-h Peak-Period Inbound Ridership to Boston CBD |
|---|---|---|
| MBTA rapid transit—including Green Line central subway | 303 600 | 80 000 |
| MBTA surface transit—bus, trolley, and trackless trolley | 268 500 | 28 000 |
| Private carrier | 15 000 | 5 700 |
| Commuter rail | 31 000 | 12 000 |
| Total | 618 100 | 125 700 |

### Work Attendance

To evaluate the ability of the transit system to transport persons to work when commuting by automobile is banned, it is helpful to compare work attendance during the postblizzard week (February 13-17) with that of a typical weekday. The table below presents this information and indicates that, except for the very first day of the week (February 13), attendance was nearly normal.

| Date | Attendance (%) | Percentage Below Normal |
|---|---|---|
| Typical weekday | 93-96 | - |
| February 13 | 86-90 | 6-7 |
| February 14 | 91-93 | 2-3 |
| February 15 | 91-93 | 2-3 |

| Date | Attendance (%) | Percentage Below Normal |
|---|---|---|
| February 16 | 93-96 | - |
| February 17 | 93-96 | - |

The first question to be addressed is whether or not commuters were able to successfully utilize the transit system as an alternative mode of travel. If major ridership increases occurred during the postblizzard week, this would indicate an affirmative answer to the question.

## Rapid Transit

Table 1 compares daily rapid transit ridership during the postblizzard week with daily ridership on a typical weekday in late February. As is obvious from the table, ridership was significantly greater on the first three days of the week, but the differences were smaller on Thursday and Friday.

Rapid transit boardings were counted for the four downtown stations that have the largest transit volumes (Washington, Park, State, and Government Center) and two terminal stations (Harvard and Forest Hills). These volumes were compared with those for a typical weekday in February, as given in Table 2. Boardings at these stations were only slightly higher than those of a typical weekday.

There are several possible explanations for this phenomenon. One is that the four downtown stations are located in an area that normally has a high mode split to transit. Another explanation may lie in the work attendance figures presented in the table above. Although these figures did not indicate a large drop in work attendance, it may be hypothesized that lower attendance rates may have been concentrated downtown, where companies and agencies that employ large numbers of people could afford to allow the employees whose access was particularly difficult to stay home. Another factor that could help account for the relatively low ridership figures at the downtown stations is a possible decrease in the number of discretionary trips, which may have been caused by expectations that the transit system would be overcrowded. The problem with all but the first of these reasons is that systemwide data indicate an increase in ridership; however, these reasons relate to reductions in ridership.

The usefulness of using systemwide data to predict ridership in the downtown stations is limited in that many persons who used the transit system during the post-blizzard week were former automobile drivers who (a) do not work downtown where transit access is good or (b) live at such distances from their work locations that they would have unreasonably long trips if they chose to use transit. In the first case, the new riders would not make radial trips and, thus, the increase would be reflected in the outlying stations rather than in the downtown stations. In the second case, the proportion that board at the outlying stations would be higher than usual, thereby increasing revenue and leading to an overestimate of boardings based on revenue data. The absence of school children and probable reduction in the number of elderly patrons could have the same result.

The two terminal stations for which data are presented (Harvard and Forest Hills), on the other hand, show significant increases in boardings. These terminal stations attract riders from the northwest and southwest areas of the Boston region, including passengers who are making through trips as well as downtown trips.

All legal restrictions, including the Boston and Cambridge parking ban, were lifted by Tuesday night. Station boardings began to decrease on Tuesday and the return to near-normal driving conditions on Wednesday apparently diverted many of the new transit riders back to their automobiles. Nevertheless, the analysis of travel behavior on Monday indicates that commuters were able to successfully use transit as an alternative mode of travel during emergency conditions.

## Commuter Rail

Systemwide counts for all B&M and special Amtrak commuter services that operated during the week of February 13 are presented in Table 3, along with an average count for a more typical operating day.

The increase in ridership on the commuter rail lines was proportionately the largest increase of any part of the public transportation system and persisted the most strongly through the second week after the storm. This may be in part because commuter rail serves outlying suburban towns where the road conditions may have discouraged travel by automobile longer than they did elsewhere. As with rapid transit, the data indicate a successful mode shift to public transportation.

## MBTA Surface Lines

Ridership information for surface lines of the MBTA, including buses, trackless trolleys, and the surface stations of the Green Line, is presented for the system as a whole, both for a typical day (February 28) and for the postblizzard week, in Table 4.

As with the other transit modes, ridership was much higher on Monday and Tuesday than on a typical day and

**Table 1. Comparison of round-trip rapid transit ridership.**

| Date | Ridership[a] | Difference from Typical Weekday (%) |
|---|---|---|
| Tuesday, February 28[b] | 303 600 | - |
| Monday, February 13 | 421 150 | +39 |
| Tuesday, February 14 | 391 250 | +29 |
| Wednesday, February 15 | 361 300 | +19 |
| Thursday, February 16 | 352 300 | +16 |
| Friday, February 17 | 380 500 | +25 |

[a]These figures show estimated total round-trip ridership (excluding passholders) on the Red, Blue, and Orange Lines and on the Green Line central subway for the dates indicated.
[b]Typical weekday example.

**Table 2. Comparison of rapid transit boardings.**

| Date | Four CBD Stations | Difference from Typical Weekday (%) | Two Terminal Stations | Difference from Typical Weekday (%) |
|---|---|---|---|---|
| Tuesday, February 28[a] | 66 000 | - | 30 150 | - |
| Monday, February 13 | 80 000 | +21.0 | 45 280 | +50.0 |
| Tuesday, February 14 | 76 000 | +15.0 | 32 943 | +9.0 |
| Wednesday, February 15 | 70 000 | +6.0 | 35 919 | +19.0 |
| Thursday, February 16 | 71 000 | +7.5 | 31 267 | +4.0 |
| Friday, February 17 | 76 000 | +15.0 | 35 676 | +18.0 |

[a]Typical weekday example.

declined as the week proceeded. It is interesting to note that the midweek decline was steeper for surface transit than for rapid rail. This is probably due in part to road conditions, which gave rail service a greater advantage over private vehicles than that of surface transit.

### Private Carriers

A number of private carriers provide regular commuter service by express bus into Boston from outlying suburban communities. During the postblizzard week, many of these companies provided additional service in combination with the special services put together by some of the communities in the Boston region; others simply added to their regular service. Ridership data from three of the larger private carriers for the week of February 13 along with data for a typical day are presented in Table 5. As shown, the private carriers carried substantially more passengers during the postblizzard week. As with other transit services, the difference decreased as the week proceeded.

### Emergency City and Town Bus Service

Twenty of the region's 101 cities and towns responded to the transportation problems of the snow emergency by organizing special bus services (with either school buses or contracted private carriers) to transport commuters either to major distribution points in downtown Boston or to nearby commuter-rail and rapid-transit stations. Fares on these services ranged from no charge to $2.00, depending on whether or not the municipality subsidized the service. The majority of these services operated only on Monday and Tuesday of the postblizzard week, although six towns continued service through Friday, February 17.

These services ranged in size from a pair of operations that carried more than 2000 bus passengers on Monday to a small suburb's operation of a single bus that carried 43 passengers. More than 13 000 passengers commuted to Boston via these emergency services on Monday, February 13. Detailed ridership information for the remainder of the week was difficult to obtain, but it is known that the six services that continued still carried more than 1000 commuters to and from Boston on Friday, February 17. The reason for the sudden decline in ridership is obvious. As restrictions on driving private automobiles were removed, the incentive to use special bus services weakened. Nevertheless, the level of patronage of these operations points to the existence of a potential market for such services—particularly for express bus service to downtown Boston.

**Table 3. Comparison of daily commuter rail ridership.**

| Date | Number of Passengers | Difference from Typical Weekday (%) |
|---|---|---|
| Tuesday, February 28[a] | 31 000 | - |
| Monday, February 13 | 59 925 | +93.0 |
| Tuesday, February 14 | 45 600 | +47.0 |
| Wednesday, February 15 | 42 275 | +36.0 |
| Thursday, February 16 | 39 570 | +27.0 |
| Friday, February 17 | 37 445 | +21.0 |

[a]Typical weekday example.

**Table 4. Comparison of daily ridership on MBTA surface lines.**

| Date | Number of Passengers | Difference from Typical Weekday (%) |
|---|---|---|
| Tuesday, February 28[a] | 268 500 | - |
| Monday, February 13 | 391 000 | +45 |
| Tuesday, February 14 | 322 500 | +20 |
| Wednesday, February 15 | 318 000 | +19 |
| Thursday, February 16 | 311 000 | +16 |
| Friday, February 17 | 265 000 | -1 |

[a]Typical weekday example.

**Table 5. Comparison of daily ridership on private-carrier express bus service.**

| Date | Riders[a] | Difference from Typical Weekday (%) |
|---|---|---|
| Typical weekday | 7 300 | - |
| Monday, February 13 | 12 500 | +71 |
| Tuesday, February 14 | 10 200 | +40 |
| Wednesday, February 15 | 9 500 | +30 |
| Thursday, February 16 | 9 250 | +27 |
| Friday, February 17 | 9 300 | +27 |

[a]These figures include only service provided by three of the largest private carriers in the region.

### Other Public Transportation Services

Two other public transportation or related services showed increases during the postblizzard week. These were the commuter boat, which operates from Hingham to Boston, and fringe parking lots (after they were plowed). The rise in patronage of the commuter boat was quite dramatic, from a typical ridership of 60 riders to 1000 riders on Monday, February 13. Even at the end of the week ridership was still 50 percent greater than on a typical weekday. Fringe parking lots showed only minimal increases.

### Summary of Public Transit Ridership

As is evident from the preceding sections, a significantly larger than usual number of people used public transit during the postblizzard week. The total number of persons who used public transportation on Monday, February 13 was nearly 900 000, an increase of almost 50 percent above that for a typical day in February, and on February 14 ridership was over 775 000, an increase of 28 percent. As stated previously, commuters in the Boston region successfully utilized the transit system as an alternative form of travel.

## HIGHWAY TRAFFIC VOLUMES

As a corollary to the data on public transit ridership, vehicle counts for selected highway locations are presented in Table 6. The traffic volumes for Monday, February 13, on the highway links shown are from 20 to 68 percent lower than the typical average daily traffic (ADT) volumes for those links and show an average drop of more than 50 percent. Traffic had stabilized somewhat by Tuesday but was still lower in most cases. The drops were more pronounced, generally, for CBD-oriented highways, such as the Northeast and Southeast Expressways, than for highways that have a more suburban orientation, such as MA-128; this holds true more for February 14 than for February 13. On February 14, the driving ban was lifted, but the city of Boston's parking ban was still in effect.

Unfortunately, the data on which the analysis is based are a bit spotty. A number of counting stations (automatic traffic recorders) were disrupted by the storm or the snowplows and had not been repaired by the following week. Manual counts were not possible and, thus, valuable automobile-occupancy data were not collected. However, we can assume that automobile occupancies did

Table 6. Comparison of selected highway volumes.

| Date | CBD Oriented (Sumner-Callahan Tunnel) ADT | CBD Oriented (Sumner-Callahan Tunnel) Difference from Typical Weekday (%) | Non-CBD Oriented (MA-128) ADT | Non-CBD Oriented (MA-128) Difference from Typical Weekday (%) |
|---|---|---|---|---|
| Typical weekday | 70 000 | - | 57 900 | - |
| Monday, February 13 | 27 100 | -61 | 46 300 | -20 |
| Tuesday, February 14 | 47 700 | -32 | 53 700 | -8 |
| Wednesday, February 15 | 58 400 | -17 | NA | - |
| Thursday, February 16 | 66 900 | -4 | 57 500 | -1 |
| Friday, February 17 | 76 100 | +9 | 61 800 | +7 |

Table 7. System supply and demand characteristics.

| Mode | Tuesday, February 28 | Monday, February 13 | Tuesday, February 14 | Wednesday, February 15 |
|---|---|---|---|---|
| Bus and trackless trolley | | | | |
| Vehicle trips | 7 660 | 7 924 | 7 806 | 8 113 |
| Passengers | 294 400 | 202 500 | 215 100 | 180 850 |
| Passengers per bus | 38 | 26 | 28 | 22 |
| Rapid transit | | | | |
| Vehicle trips | 2 987 | 2 452 | 2 450 | 2 955 |
| Passengers | 303 600 | 421 150 | 391 255 | 361 313 |
| Passengers per vehicle trip | 102 | 172 | 160 | 122 |
| Commuter railroad | | | | |
| Vehicle trips | 773 | 564 | 564 | 564 |
| Train passengers | 33 105 | 59 926 | 47 995 | 42 281 |
| Passengers per vehicle trip | 43 | 106 | 85 | 75 |

increase on Monday and Tuesday of the postblizzard week because of the driving and parking bans.

## CAPACITY OF THE TRANSIT SYSTEM

The information on transit ridership that has been presented reveals only one aspect of the change in transit usage that took place during the week of February 13. The aspect discussed so far is the change in demand. The change in supply (the degree to which the capacity was changed) must be determined in order to analyze how the vastly increased demand was handled. If capacity was not in fact increased, then changes in riders' behavior, such as the staggering of work hours, must have facilitated the accommodation of the demand.

Table 7 presents the number of passengers and vehicle trips and the vehicle loads for February 13, 14, and 15 and for a typical day—February 28. February 28 appears to be a typical day with regard to supply as well as ridership, according to data available from the MBTA.

As can be seen in the table, capacity (measured in daily vehicle trips) was in fact reduced during the postblizzard week. This was caused primarily by equipment shortages caused by storm-related damage. Therefore, as the table indicates, vehicle loads were significantly greater than on a typical weekday. The obvious conclusion is that the postblizzard surge in transit travel was not handled by an increase in capacity.

Ordinarily, peak-hour transit vehicles operate at greater than 75 percent capacity on a typical weekday and on some lines at greater than 100 percent capacity. Therefore, given the postblizzard reduction in capacity, the system's ability to absorb the greatly increased demand must be attributed to a combination of the extremely high number of passengers per vehicle and the effectiveness of the staggered work hours program, which is discussed in the next section.

It should be pointed out that most schools in the region were closed for the entire week of February 13-17. One exception to this was private schools, which had already begun to open. In the MBTA region, approximately 65 000 students rely on the MBTA for transportation to and from school. In addition, many colleges and universities in the core area (which have a total enrollment of approximately 150 000) did not hold classes on February 13 and 14, which also must have had an effect on the regional transportation system. The effect of these school closings was to create some additional capacity in the transit system, although much of it was off-peak capacity and therefore did not directly affect most commuter trips.

## STAGGERED WORK HOURS POLICY

One of the problems faced in financing and operating transportation systems, both highways and mass transit, is peaking characteristics. A transportation system is usually built and operated to accommodate approximately the maximum demand expected on a typical weekday. To increase the capacity of the system, physical expansion is usually required. Particular attention has been drawn in the past few years to the short duration of the peak, which is more characteristic of transit systems than other modes. Two effects of this short peak are (a) the necessity of a much larger vehicle fleet and labor force than would be needed if this travel occurred over a longer time period and (b) uncomfortably crowded conditions that may discourage some travelers from using transit.

During the week of February 13, in which both legal restrictions and physical impedances reduced the number of work trips made by automobile, we expected that the shift to transit would place an enormous strain on transit service during the already overburdened peak period. Therefore, the governor's office recommended that a policy of staggered work hours be in effect during the week. Different categories of workers were assigned to different arrival and departure times in an effort to spread out the peak period and thereby increase the capacity of the transit system for that week.

Figure 2 shows the percentage of morning-peak-period transit alightments that occurred in each 0.5-h interval at four of the central stations (Government Center, State, Park, and Washington) on February 13, 14, and 28. Figure 3 shows these distributions for two terminal transit stations (Harvard and Forest Hills). We would expect that both graphical depiction and statistical analysis would show more pronounced peaking on February 28 than on February 13 and 14, the peaking distributions of which would be similar. We might expect

Figure 2. Rapid transit alightments at four stations in the Boston CBD during the morning peak period.

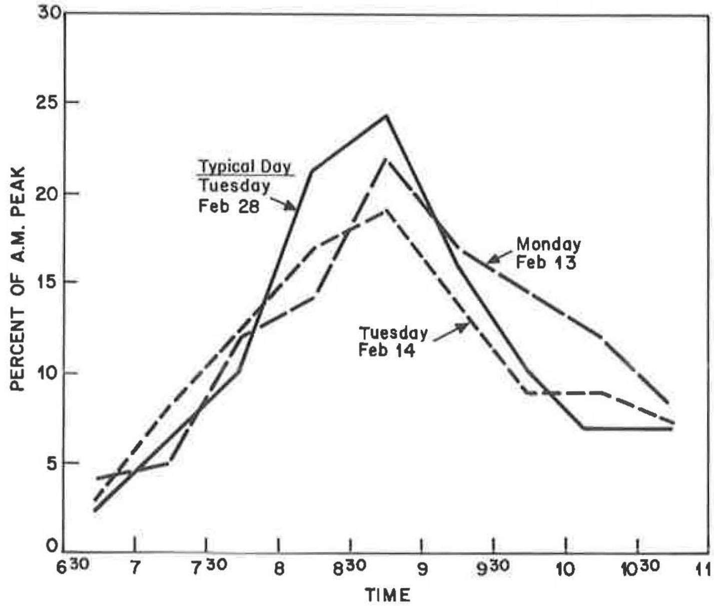



Figure 3. Rapid transit boardings at two terminal stations during the morning peak period.

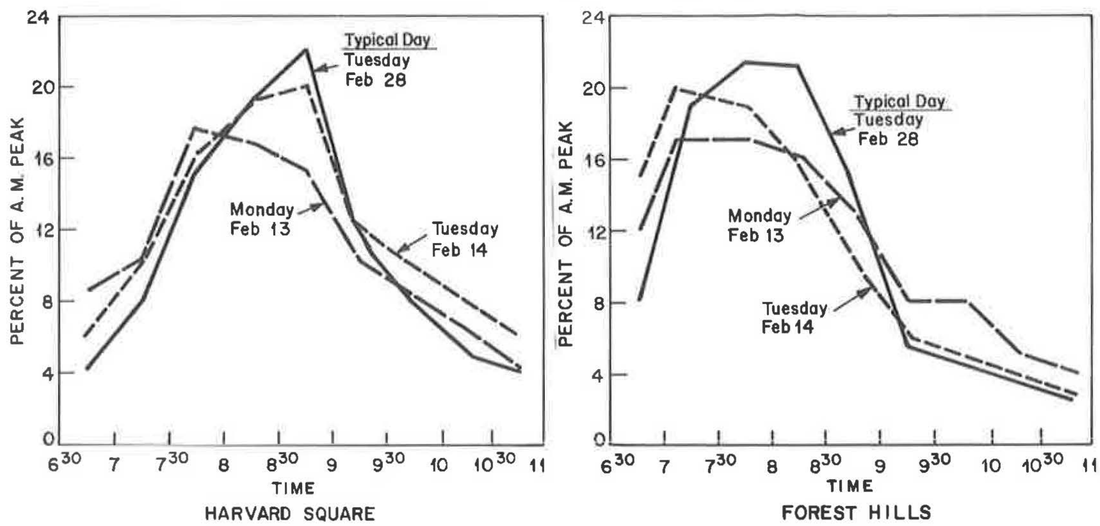
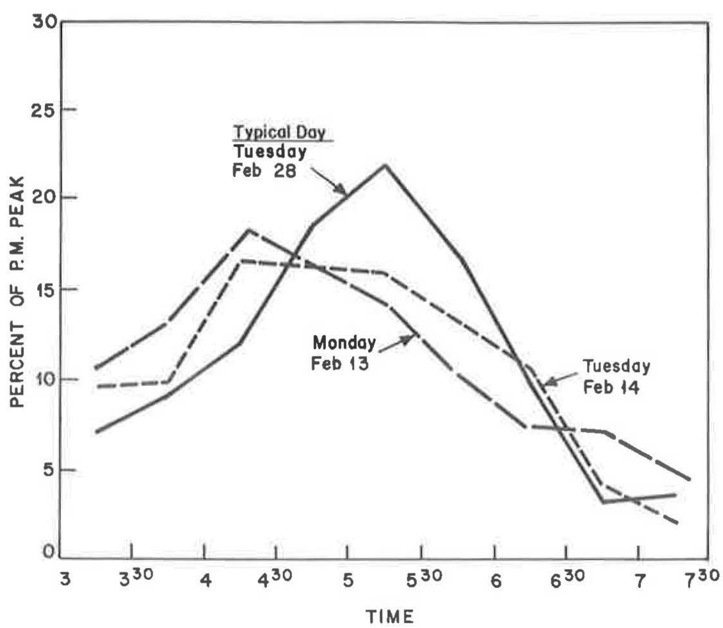



Figure 4. Rapid transit boardings at four stations in the Boston CBD during the evening peak period.



that the peak would be more spread out on Monday than on Tuesday because commuters might have had higher expectations of crowding on that day and, therefore, shifted their boarding times. On the other hand, even more shifting of boarding times might have been expected on Tuesday as a response to the experience of overcrowding on Monday. This is what, in fact, occurred. A further explanation of why peak-period travel was more spread out on Tuesday is that more travelers may have understood how to comply with the staggered work hours program. Another possible factor is that persons who had attempted to arrive at work at their usual time on Monday, by using transit, may have switched to automobile on Tuesday, when there was, in fact, a shift from transit to automobile for peak-period travel.

Figure 4 depicts the evening peak-period boardings at the four central stations. Commuters departed earlier than usual on February 13 and 14 to try to avoid congestion and to compensate for longer travel times. The evening peak period was more spread out on Tuesday than on Monday, perhaps for the reasons given above regarding the morning peak period.

Two different statistical tests were performed to corroborate the conclusions reached through graphical depiction. The first was the chi-square test, which evaluates whether or not observed frequencies differ significantly from normally expected frequencies. The second was the Wilcoxon matched-pairs test, which ranks differences between two distributions to determine if they are statistically different from one another. In all cases the chi-square test corroborated our graphical depiction: The distributions of boardings on February 13 and 14 were significantly different from those of the typical weekday and were also significantly different from each other. This was true for both morning and evening periods and for both the central and the terminal stations. The Wilcoxon test was slightly less conclusive but generally supported the results of the chi-square analysis.

In order to see if the recommended staggering of work hours had any effect on the peaking characteristics of the roadways, hourly traffic volumes at a number of locations on February 2, 13, and 14 were graphed and analyzed. A graph that typifies the pattern found is presented in Figure 5. A chi-square test shows that these distributions of highway volumes are significantly different from one another.

The major differences between the three days is in magnitude (as also shown in Table 6), although, as Figure 5 indicates, some differences in peaking are apparent. On February 13, the morning peak retains a large portion of the travel but is less pronounced than usual; on February 14, the pattern is similar but the peak is slightly more pronounced. On both February 13 and 14, the morning peak hour occurred somewhat earlier than usual as commuters attempted to compensate for longer travel times.

The analysis of highway travel, as well as that of transit travel, shows that a staggering of work hours did occur, although significant peaking still existed on both February 13 and 14.

## AIR QUALITY IMPACTS

One of the important objectives of transportation planning in recent years has been to improve air quality by reducing mobile-source emissions. This can be achieved by restricting travel by automobile, controlling the availability of parking spaces, and staggering work hours. Figure 6 depicts the levels of carbon monoxide

Figure 5. Hourly traffic counts on a Boston expressway.

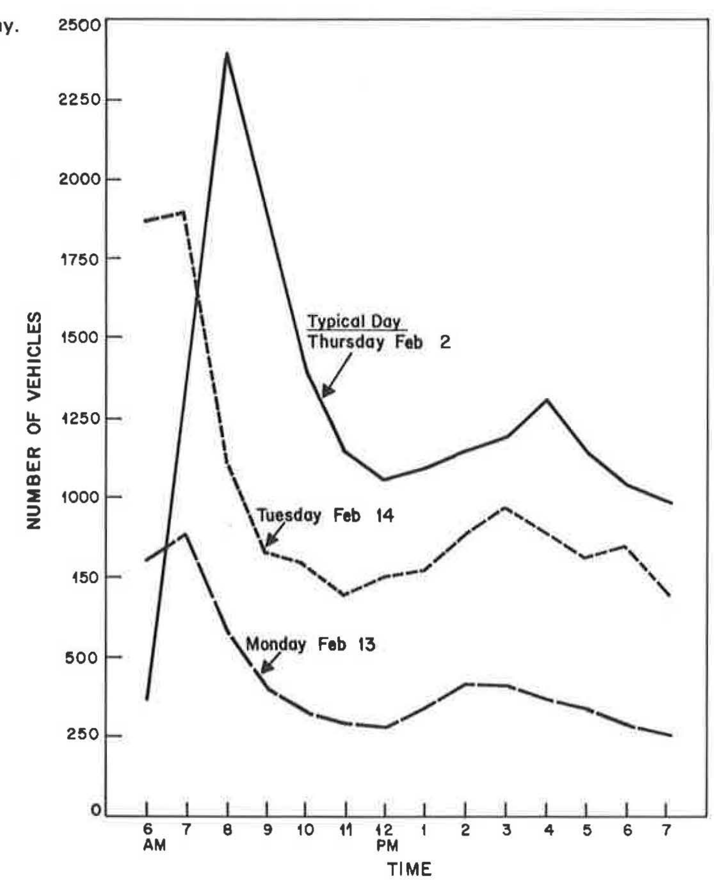
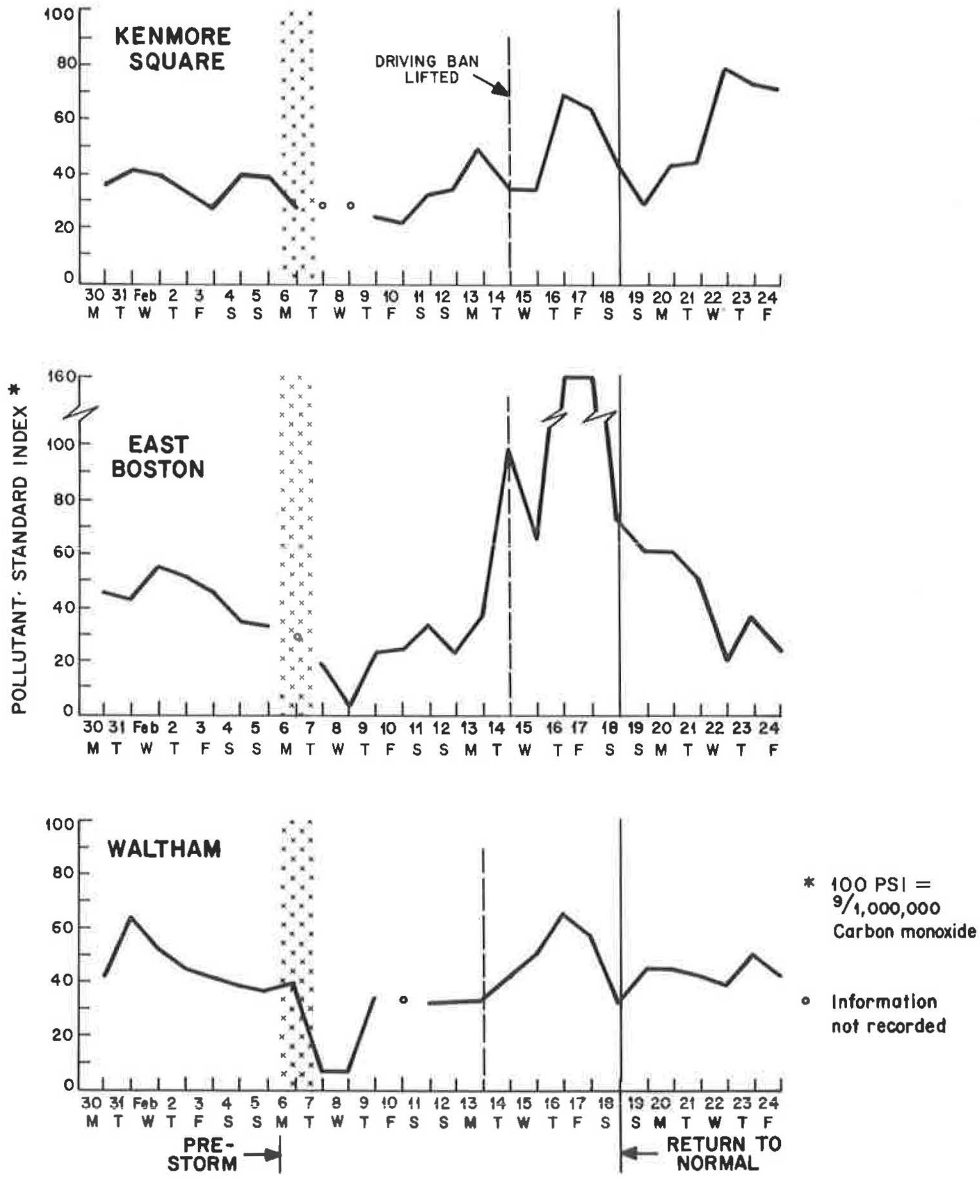


Figure 6. CO measurements at three locations.




(CO) in the atmosphere at three locations in the region during the week of February 6, when the blizzard occurred and an areawide driving ban was in effect. For comparison, data for the following week, during which a partial driving ban was in effect, are presented, as are data for two more typical weeks.

A comparison based only on the postblizzard week would be misleading because pollution levels were higher than normal that week. Many automobiles were used for the first time after being unused for up to a week. Therefore, many drivers tended to idle longer than usual after starting their automobiles, which resulted in higher than average emissions. Impedances created by the blizzard and the postblizzard cleanup forced some automobiles to take more circuitous routes than usual and to travel more slowly, which also caused higher emissions. In fact, emissions for this week were about 70 percent higher than those for the two typical weeks presented in Figure 6. A comparison between the week of the driving ban and these two weeks shows that during the ban, CO levels were 50 percent lower than average. This conclusion is not surprising since approximately 90 percent of CO emissions in the region are produced by automobiles.

## CONCLUSIONS

The four major questions posed earlier in the paper can be answered as follows:

1. Commuters forced to travel by means other than private automobile were able to successfully utilize the region's public transit system;
2. The transit system was able to handle the vastly increased demand, though not without some uncomfortable crowding of passengers;
3. People voluntarily staggered their work hours, which helped the transit system to cope with the increased demand; and
4. The reduction in automobile travel resulted in vastly improved air quality.

In addition, the postblizzard week introduced the transit system to people who previously may have considered the automobile to be the only reasonable mode for their work trips. Another important ramification of the postblizzard week was the organization of successful emergency transportation services by cities and towns in the Boston region. Some of these communities operated a subsidized service; others apparently covered their costs from farebox revenues. It has long been thought that one of the largest untapped markets for transit in the Boston region is in express services for commuters who reside in suburban communities and work in downtown Boston. In line with this theory and as a result of the satisfaction of many of the commuters with the temporary express bus services of February 13 and 14, officials and citizens in a number of these communities have begun to examine their feasibility or to plan and develop permanent express bus services for commuters.

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# Use of Before-and-After Data To Improve Travel Forecasting Methods

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**Most practitioners think that disaggregate probability choice models are a theoretical advance over traditional methods. The accuracy of these models remains in doubt, however, given the conflicting, often aggregate, findings from time-series research and before-and-after studies, which may have more validity than disaggregate demand studies. This paper evaluates various travel-demand research methods to uncover a consistent explanation for variations in their findings. The results of before-and-after studies can be used to infer first-order approximations to travel-demand relations. It is shown how these results, by using demand elasticities, can be integrated into a system for predicting travel behavior responses to system changes. We argue that the observed differences between quasi-experimental and disaggregate model results can be attributed to differences in the types of data being used. Without a priori information or a formal specification of long-run household decisions, the cross-sectional data used in estimation of disaggregate models will not typically reveal short-run traveler preferences. Future research should concentrate on isolating short- and long-run behavior. This may require merging data from cross-sectional surveys and before-and-after quasi experiments. If only cross-sectional data are used, attention should be given to the effects of long-run residential decisions in interpretation of the data.**

Volumes along a transportation link that connects an origin and destination (arbitrarily defined) are the result of the interaction between two separate relationships. The first of these, labeled supply, assumes a fixed capacity for this transportation service; consequently, as the volume on this link increases past a certain point, its level of service will decline. Prior to any change in the system, it is a knowable relationship within tolerable error limits. Short-run demand for travel is premised to be a separate relationship that increases as the level of service for the link improves.

The major problem for an analyst in the evaluation of a change in the transportation system is that the effects of level of service on demand are not known within acceptable limits of certainty. Prior to a system change, the analyst knows equilibrium volumes, level of service, and the system performance relationships. A system improvement is depicted by a translation of the supply curve. If we assume short-run stability and equilibrium in the network, a new level of service and volume along the link will result. To evaluate whether this improvement should be made, the analyst needs to forecast the new volumes and level of service. This requires an approximation of a segment of the demand curve.

Consideration of long-run demand increases the complexity of forecasting the effects of system changes. Sometimes we can assume that the locational impacts of system change are negligible. However, often long-run demand cannot be ignored, even if the analyst is only interested in predicting short-run effects.

How can an analyst predict equilibrium volumes and level of service? Traditionally, there are two procedures: (a) previous experience with similar system changes can be used to infer the potential impacts or (b) two or more existing situations where there are variations in the level of service can be compared to infer how these variations affect trip making. We will call the former quasi-experimental design and the latter cross-sectional data analysis.

## QUASI-EXPERIMENTAL DESIGN

Much of our knowledge about transit and highway impacts comes from quasi-experimental findings. Some recent summaries of before-and-after studies have validated that (a) short-run transit fare elasticities are substantially less than unity in absolute value, which implies that increases in fares will increase revenues and decrease deficits (1); (b) land values around new highways increase, which implies that transferred user benefits exceed immediate disamenities (2); and (c) rail rapid transit will not, by itself, cause an increase in residential density (3). A recent handbook for planners (4) also gives more tentative, quantitative results on a variety of potential transportation control instruments, such as priority lanes, automobile-restricted zones, transit operating and marketing, and shared-ride modes.

The major problem is that findings from a single before-and-after study are not typically generalizable. It is useful to distinguish two types of problems: internal validity and external validity (5). A study of the relation between a transportation system change and traveler response must have internal validity (by definition) in order to isolate cause and effect. During the past decade, transportation impact studies have increasingly shown internal validity. Thus, this is no longer a major problem, except in the interpretation of earlier impact studies where a large amount of research, especially on highway impacts, yielded relatively few valid findings (6).

External validity remains a major problem, both conceptually and practically. A cause-and-effect relation observed in a study of traveler responses lacks external validity if it cannot be generalized. One reason is simply that base conditions will differ; another is that the magnitude of system change will differ. Thus, instead of merely transferring the observed volumes, estimated elasticities from before-and-after studies are more often used to formulate a first-order approximation to the unknown demand curve.

Observed elasticities will vary among experiments. This finding can be interpreted as indicating that an elasticity is a function rather than a number. It can also be interpreted that the response to a system change will itself vary, depending on a number of other variables not explicitly considered in the approximation of the demand function. This means that the functional form of the approximation may be inaccurate. Also, the function or parameters may be different for various market segments affected by the same system change—the aggregation problem. Probably the major sources of variation in elasticities (or traveler response) estimated from quasi-experimental designs stem from variations in the timing of the response and differences in base conditions.

## FORECASTING SYSTEM THAT USES ELASTICITIES

A useful interpretation of the data from a before-and-after quasi experiment is that the slope of the demand curve is revealed. This is summarized by the following computation:

$$\eta \equiv (\ln\bar{V}_0 - \ln\bar{V}_1)/(\ln\bar{I}_0 - \ln\bar{I}_1) \quad (1)$$

where the variables with bars are observed volumes and level of service before (0) and after (1) the system change. $\eta$ is by definition the arc elasticity of demand with respect to the level of service variable I.

The analyst can then approximate a demand function as follows:

$$V = V_0(I/I_0)^\eta \quad (2)$$

In conjunction with the known system performance relationship, I = S(V), this gives the analyst two equations with two unknowns, which can be solved for the forecasts of equilibrium volume and level of service, $\hat{V}_1$ and $\hat{I}_1$.

A common simplification is that the system performance does not vary in the range of considered volumes. This allows computation of $\hat{V}$ directly as

$$\hat{V}_1 = V_0(I_1/I_0)^\eta \quad (3)$$

Another common simplification is to use percentage differences from the base volumes and level of service:

$$\hat{V}_1 = V_0 + \eta V_0[(I_0 - I_1)/I_0] \quad (4)$$

This approximation is usually worse than the logarithmic approximation and can lead to counterintuitive results, especially for large system changes or numbers close to zero.

### Example of Use of Quasi-Experimental Findings: Short-Run Response to Reserved Bus Lane

Consider the case of reserving an existing expressway lane for peak-period bus service as a means of reducing automobile emissions. In order to evaluate the effectiveness of this transportation control strategy, we need to predict the reduction in private automobile use that would result. The method for finding an approximate change in automobile volumes on the expressway is described below. (Our example was designed for U.S. customary units only; therefore the values are not given in SI units.)

#### Base System Data

The existing expressway has four lanes that carry 6800 vehicles/h during the peak period. Average speed is 35 mph and average distance of a commute for the freeway link is known to be 8.77 miles. Average time on the expressway link for a peak journey is then 15 min.

#### Base System Supply Relationship

The speed-volume curve of expressways of this type, estimated from the Highway Capacity Manual (7), is as follows

$$\text{speed} = 225(\text{volume/lanes})^{-1/4} \quad (5)$$

where

speed = average miles per hour along the expressway,
volume = vehicles per hour during the peak, and
lanes = number of lanes serving traffic during the peak.

In order to transform Equation 5 into a relationship between travel time and volume, we convert speed to miles per minutes, invert both sides of the equation, enter the number of lanes, and multiply through the average distance. These operations yield the base system supply curve for automobile level of service on the expressway:

$$\text{expressway min} = (8.77 \times 60/225)(\text{volume}/4)^{1/4} = 1.65\,(\text{volume})^{1/4} \quad (6)$$

Supply Changes

Two supply changes need to be considered: (a) the reduction in expressway capacity for private automobiles and (b) the increase in level of service for transit. The reduction in freeway capacity by one lane changes the supply curve (Equation 6) to the following:

$$\text{expressway min} = (8.77 \times 60/225)(\text{volume}/3)^{1/4} = 1.78\,(\text{volume})^{1/4} \qquad (7)$$

Comparison of Equations 6 and 7 shows that the reduction in lanes causes an average trip-link time increase of approximately 8 percent.

For transit supply, level of service will improve as a result of the exclusive right-of-way. We assume that transit commute trip time for the market served by the expressway is reduced to 80 percent of the base system transit commute trip time. We further assume that mode diversion will not change the performance of transit. Thus, the transit supply change is approximated by a single number rather than by a function:

$$\text{transit min}_1/\text{transit min}_0 = 0.8 \qquad (8)$$

where transit min = average transit line-haul and wait time for commute trips in the expressway market, and 0, 1 = indices where 0 denotes time period before system change and 1 denotes time period after system change. We further assume that no change in transit coverage will be made, so that access time changes can be ignored.

Data from Quasi-Experimental Studies

For the demand analysis we need to have some notion of the sensitivity of automobile travelers to trip times by various modes. Let us assume that highway impact studies exist from which we can infer that the short-run own-elasticity of peak automobile travel on a similar freeway link with respect to time on the link is equal to -0.5. In addition, assume that a number of transit studies indicate that the short-run cross-elasticity of automobile travel with respect to transit line-haul time is 0.15.

Demand Curve Approximation

The implied demand curve (Equation 3) from these findings is as follows:

$$\text{volume}_1 = \text{volume}_0\,(\text{expressway min}_1/\text{expressway min}_0)^{-0.5} \times (\text{transit min}_1/\text{transit min}_0)^{0.15} \qquad (9)$$

Substituting into Equation 9 the base system and transit change data (Equations 7 and 8) yields the following analytic approximation:

$$\text{volume} = 25\,470\,(\text{expressway min})^{-0.5} \qquad (10)$$

Equilibrium Flow and Level of Service

The equilibrium private automobile travel volumes on the expressway shortly after the system change can be determined by substituting Equation 7 into Equation 10:

$$\text{volume}_1 = 25\,470(1.78\ \text{volume}_1{}^{1/4})^{-1/2} = (19\,090)^{1/1.125} = 6385 \qquad (11)$$

The equilibrium average trip time can be computed by substituting the equilibrium volume into Equation 7:

$$\text{expressway min}_1 = 1.78(\text{volume}_1)^{1/4} = 15.91 \qquad (12)$$

Extension to Long-Run Response

It is conceptually possible to apply long-run elasticities from various sources to develop a long-run demand function approximation. To see how this is done, we take the above example of a reserved bus lane and expanded transit service to estimate long-run volumes and level of service on the remaining highway lanes.

Base System Data and Supply Relationship

These are the same as in the short-run case.

Supply Changes

The reduction in freeway capacity and increase in transit line-haul speeds are assumed to be the same as in the short-run case. Thus, Equations 7 and 8 are relevant to the forecasting of long-run response.

We assume that in the long run, the transit operating authority increases its route coverage in response to the increased demand for transit. This increase in transit level of service is approximated by the following measure:

$$\text{transit coverage}_0/\text{transit coverage}_2 = 1.2 \qquad (13)$$

where the subscript 2 indicates some period defined as the long run.

Data from Quasi-Experimental Studies

Let us assume that highway impact studies indicate that the long-run own-elasticity of peak automobile travel on a similar freeway link with respect to line on the link is equal to -0.75. In addition, findings indicate that the long-run cross-elasticity of automobile travel with respect to transit line-haul time is 0.30 and that the long-run cross-elasticity of automobile travel with respect to transit coverage is -0.40.

Demand Curve Approximation

The implied long-run demand curve from these findings is as follows:

$$\text{volume}_2 = \text{volume}_0(\text{expressway min}_2/\text{expressway min}_0)^{-0.75} \times (\text{transit min}_2/\text{transit min}_0)^{0.30} \times (\text{transit coverage}_2/\text{transit coverage}_0)^{-0.4} \qquad (14)$$

Substitution into Equation 14 of the base system data and the long-run transit level-of-service changes gives the following analytic approximation:

$$\text{volume}_2 = 45\,064\,(\text{expressway min}_2)^{-0.75} \qquad (15)$$

Equilibrium Flow and Level of Service

The long-run equilibrium private automobile travel volumes on the expressway can be determined by substituting Equation 7 into Equation 15:

$$\text{volume}_2 = 45\,064\,(1.78\ \text{volume}_2{}^{0.25})^{-0.75} = (29\,243)^{1/1.1875} = 5766 \qquad (16)$$

The long-run equilibrium average trip time can be computed by substituting $\text{volume}_2$ into Equation 7:

$$\text{expressway min}_2 = 1.78(\text{volume}_2)^{1/4} = 15.51 \qquad (17)$$

Information Gained from Elasticities

A comparison of the estimated volumes and travel times with two assumptions bracketing the range of effects reveals the value of information gained from quasi-experimental data. If no change in volume is assumed, then emissions are overforecast by 6 percent in the short run and 18 percent in the long run. If, as is more likely in practice, we assume that volumes will decrease proportionate to the reduction in highway capacity, then emissions would be underestimated by 20 percent in the short run and by 13 percent in the long run. These results are summarized as follows:

| Data | Volume (vehicles/h) | Level of Service (min/trip) |
|---|---|---|
| Using estimated elasticities | | |
| Short run | 6385 | 15.91 |
| Long run | 5766 | 15.51 |
| Using assumption | | |
| No change in volume | 6800 | 16.14 |
| 25 percent reduction in volume | 5100 | 15.00 |

## CROSS-SECTIONAL DATA ANALYSIS

Cross-sectional data analysis treats each unit of observation as a separate quasi experiment. Because there is a large amount of variation in the data from traditional interview travel surveys of large homes, there is the potential for observing a wide range of transportation system conditions and associated household behaviors.

The key assumption in demand modeling of cross-sectional data is that correlations between level of service and observed behavior are short-run cause-and-effect relations. This assumption can be stated in terms of elasticities. Let us suppose that one group of households must pay $1.00 for transit round trips and they are observed to make 1 transit trip/day; another group of households pays $0.50 for equivalent service and they make an average of 1.5 trips/day. A simple fare elasticity would then be computed as

$$n = (\ln 1 - \ln 1.5)/(\ln 1 - \ln 0.50) = -0.58.$$

If this simple model were applied to analyzing the effects of reducing the fare to $0.50 for group one, we could conclude that this group would increase its transit travel from 1 to 1.5 trips/day.

Obviously, actual travel-demand models are much more complex than the elasticity computation presented above. Many other factors besides fare are usually included in the models to explain the observed response, including the level of service of all modes available and demographic descriptors of the household. However, the basic interpretation of the data remains the same: After controlling for the factors for which data are available, the model isolates the short-run effect of level-of-service variations on travel behavior.

A key question, which has not been adequately addressed, is, How valid is this assumption? We argue below that the assumption leads to potentially large errors in model application, especially in trip-distribution models and possibly in mode-split models.

## CROSS-SECTIONAL BIAS

Cross-sectional data reveal residential and job location preferences. Households will have considered accessibility to various activities in making these decisions. Thus, their travel behavior will be largely predetermined by the factors that went into the location decisions.

Households tend to cluster in homogeneous groups. Housing location for a family is determined in large part by the family's choice of an area where other people like themselves are located. They will prefer neighbors who are similar in status, life cycle, and preferences toward neighborhood amenities, such as public transportation.

As a consequence, households that a priori have a preference for transit will locate in areas that have good access to transit, and a second group of households that have few proclivities toward transit will locate where transit access is poor. The cross-sectional data will closely correlate transit use and transit access. A mode-split model estimated on these data will find that if transit access is improved for the second group to the level of service of the first group, then the second group will travel by transit as much as the first group. This finding, however, would be wrong because the second group has revealed poor intentions of using transit as a result of its housing location decision. What the mode-split model has picked up is that transit access can be used to discriminate groups in their location preferences by using transit access; it has not isolated a short-run cause-and-effect relationship between transit access and transit use.

Another example, which is conceptually more difficult to analyze, is trip distribution. Let us consider two sets of destination alternatives: the downtown and the suburbs. Some activities that serve as nonwork trip ends are available in both the downtown and the suburbs. Alternatively, some activities in downtowns are not available in the suburbs because they require a large market area. Preferences between ubiquitous versus unique downtown activities will vary among households. Those households that prefer activities unique to the downtown will, as a consequence, have a higher demand for residential locations that are more accessible to the downtown. Households that have low preferences for downtown activities will care less about their accessibility to the downtown and will have other criteria that matter more in their choice of residence.

A trip-distribution, or destination-choice, model will correlate distance to the downtown with travel to the downtown. This can be specified by relating the frequency of home-based trips to the downtown versus those to suburban destinations as a function of the relative times and costs of travel from home to the alternative destinations. It would then be inferred from the model that, if accessibility to the downtown were improved, there would be a higher frequency of trips to the downtown. This conclusion would be specious: The correlations in the data have revealed preferences for downtown versus suburban activities as indicated by location decisions. As in the case of mode split, accessibility is being used to discriminate among groups of households rather than to determine short-run choice decisions.

Example of Competing Hypotheses About Trip Distribution

A stylized example will demonstrate the problem of cross-sectional bias. For this exercise, we assume that there is a well-developed urban core with suburban rings. Trip time to the downtown is proportional to distance from the downtown. Ubiquitous population-serving activities follow residential settlements such that they are equally accessible to every location in terms of travel time.

Household location preferences can be described, in reduced form, as a function of distance from the downtown. We consider three prototypical households: outer suburban, inner suburban, and inner city and their round-trip levels of service to the central business district

(CBD). We assume that each household earns $20 000/year and has identical value of travel time at $4.00/h. All workers commute to the CBD. The data on these households are presented in Table 1. Clearly, there are unexplained preferences for location from the data. Some differences among the households in life cycle, status, and life-style may explain the various locational preferences.

A simple model of residential location based on distance from the downtown can be formulated as follows

$$W(D) = U(D) - \gamma t_c f_c - \gamma t_s f_s \qquad (18)$$

where

- $W(D)$ = utility over an arbitrary period, say one week, of the location including disutility of travel expressed in monetary terms;
- $U(D)$ = utility of the location over one week, including neighborhood and residual income after housing expense expressed in monetary terms;
- $\gamma$ = value of travel time;
- $t_c, t_s$ = travel time to the downtown (c) and suburbs (s); and
- $f_c, f_s$ = frequency of travel over one week to the city center (c) and suburbs (s).

We assume for suburban locations that $t_s$ is constant. We also assume a true short-run destination probability choice relation of the following form:

$$P_c = 1 - P_s = 1/[1 + e^{\alpha+\beta(t_s-t_c)}] \qquad (19)$$

where $P_c, P_s$ = probability of a home-based nonwork trip going to the downtown (c) or to the suburbs (s), and $\alpha$, $\beta$ = unobserved constants.

This can be interpreted as a disaggregate logit model or as the friction factor component ($F_{ij}$) of a gravity model. Several definitions complete the model:

$$f_c = f_{nc} + f_w \qquad (20a)$$

$$f_{nc} = f_n(P_c) \qquad (20b)$$

where $f_{nc}, f_w$ = frequency of travel over a week to the CBD for nonwork (nc) and work (w) purposes.

If the family is in long-run equilibrium, it will have maximum utility with respect to distance

$$W'(D) = 0 \qquad (21)$$

which implies the following two equivalent relationships:

$$U'(D) = (\gamma/m)[f_w + f_n(P_c)] - (\gamma/m)f_n\beta(1 - P_c)P_c(t_s - t_c) \qquad (22)$$

$$t_s - t_c = \{(m/\gamma)U'(D) - [f_w + f_n(P_c)]\}/[f_n\beta(1 - P_c)P_c] \qquad (23)$$

where $m = (\partial t/\partial D)^{-1}$ = speed for travel to the downtown at the point of residence.

Figure 1 shows the interpretation to be given to the equilibrium location decision. Households equate the marginal utility of the residential distance from the city to the marginal utility of traveling a shorter distance to the CBD. We assumed that households 1 and 3 have the same disutility of travel (A') to the CBD and that household 2 has a higher disutility because of more frequent work trips to the CBD. The major variations in location with respect to the CBD are the result of differing locational preferences, however. This is indicated in Figure 1 by variations in the marginal utility of location curves (U′).

Let us return to the problem of estimating a short-run destination choice model. This would involve estimating the following log odds function from Equation 19:

$$\ln[(1 - P_c)/P_c] = \alpha + \beta(t_s - t_c) \qquad (24)$$

The data that are available are the relative times for trips to the CBD and suburbs and the frequencies for each. Variations in the observed frequencies among households will be correlated with variations in relative times.

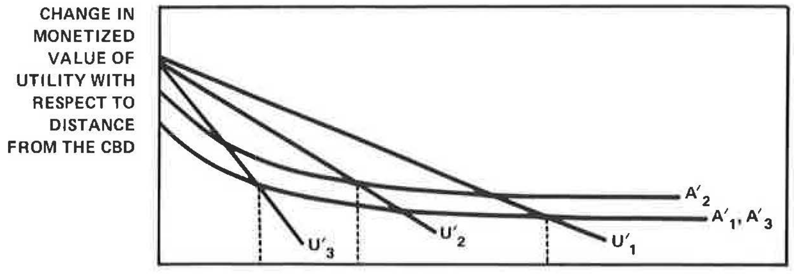
However, the most important determinant of observed variations in relative time ($t_s - t_c$) will be due to variations in U′(D), which are unobservable from the cross-sectional data. This can be seen by referring to Equation 23. The relative time to the CBD versus the suburbs is a function of the marginal utility of the housing location and the fixed schedules of trips for work and nonwork purposes. The short-run probabilities cannot be isolated from the data unless preference for resi-

Table 1. Data on three prototypical households.

| Household Location | CBD Distance (km) | Automobile Time (min) | Automobile Cost ($) | Transit Time (min) | Transit Cost ($) | Suburb Time (min) | Suburb Cost ($) | Weekly Work Trips Automobile | Weekly Work Trips Transit | Nonwork Trips CBD | Nonwork Trips Suburb | Number of Automobiles | Number of Workers | Number of Children |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Outer suburb | 32 | 60 | 6.00 | 120 | 2.00 | 10 | 0.75 | 5 | 0 | 2 | 14 | 2 | 1 | 3 |
| Inner suburb | 16 | 40 | 3.00 | 80 | 1.00 | 10 | 0.75 | 10 | 0 | 2 | 9 | 2 | 2 | 3 |
| City | 8 | 20 | 2.00 | 40 | 0.50 | 60 | 6.00 | 0 | 5 | 14 | 2 | 1 | 1 | 1 |

Note: 1 km = 0.62 mile.

Figure 1. Equilibrium residential location.



dential location is also explained.

Let us suppose that short-run experiments have shown that the aggregate elasticity of travel from the suburbs to the CBD with respect to improvements in travel time is 0.2. This allows us to infer the true short-run destination choice model (Equation 24) for households 2 and 3:

$$\ln[(1 - P_c)/P_c] = 1.68 - 0.005\,(t_s - t_c) \tag{25}$$

However, a model estimated by regressions of the observed times and frequencies would have the following parameters:

$$\ln[(1 - P_c)/P_c] = 0.10 - 0.04\,(t_s - t_c) \tag{26}$$

That is, in this synthesized example, the estimated elasticity would be in error by a factor of 8.

## Existing Evidence on Demand Models

There is some evidence in the literature to support the contention that demand models estimated from cross-sectional data do not adequately isolate short-run behavior. Though these results may not be overly compelling when viewed individually, there appears to be a consistent pattern.

### Comparisons of Level-of-Service Elasticities

Chan and Ou (1) compared level-of-service elasticities estimated from demand models with those observed from before-and-after data. It appears that demand-model elasticities (typically from mode-split models) are about twice observed elasticities. This finding must be qualified because different cities were being compared. Some attempts were made to control for factors (urban form, city size, level of service of competing modes) that affect elasticities, but the estimates are still not strictly comparable. Nonetheless, the results are provocative and supportive of the hypothesis that demand models are picking up long-run effects.

### Specification of Time in Demand Models

One problem with estimating the effects of the marginal value of time from cross-sectional data is that people who give time a low value will take longer journeys and, therefore, create a negative statistical correlation between marginal value of time and length of the trip. However, this correlation does not tell us that any given individual has decreasing marginal value of time when choosing among alternative destinations. In fact, decreasing marginal value of time is inconsistent with the notion that people have fixed time constraints for travel and other activities.

Recently, two separate disaggregate destination-frequency choice models have been estimated that use the logarithm of travel time as an argument in the probability of choice function (8, 9). Thus, the observed marginal value of time is inversely proportional to the amount of travel time between an origin and destination; that is, marginal value of time is observed to decline with respect to distance of a trip.

It can be presumed that these models are not measuring short-run travel response. Rather, they are distinguishing groups of people who have different preferences for time spent in travel. As such, the models are internally inconsistent—their structure assumes everyone has the same value of time as a function of trip distance but the correlations in the data reflect differences among individuals in value of time.

### Commute Fields and Time Budgets

Aggregate data analysis by Zahavi (10) indicates that the average time spent in travel by households has shown historical stability. This is consistent with expanding commute fields for urban areas as a result of improved accessibility, a trend well documented by Berry and Gillard (11). This is also consistent with the results of the Bay Area Rapid Transit (BART) impact study, which showed increased residential dispersion as a result of BART (12).

An interpretation of these findings is that transportation improvements open up opportunities for residential location. In time, transportation improvements will extend the definition of the urban area. A mobile society, one where the average duration at a residence is only five years, will take advantage of these opportunities by dispersing in terms of distance but, perhaps, showing temporal stability in time spent on commute trips.

This argues that travel schedules and preferred time spent on trips are relatively inflexible across time for an observed aggregate, though they may vary widely within the aggregate. Consequently, observed correlations from a disaggregate one-shot survey would not be transferable for forecasting purposes unless location decisions are also considered explicitly.

### Temporal Stability of Gravity Model

A review of experience with travel-demand procedures indicates that the gravity model has demonstrated temporal stability in regional planning.

Experience with the gravity model in Boston and San Francisco has indicated that k-factors are remarkably stable over time and contribute substantially to the overall accuracy of the model. The San Francisco experience is especially noteworthy because the friction factor was a disaggregate destination choice model that showed considerable temporal instability (Equation 13). K-factors were added to improve forecasting accuracy. In Boston, k-factors estimated in 1963 are still being used.

This experience implies that communities are relatively stable in terms of the preferences for residential location. Households that have like preferences for activities will be similar along other dimensions and will cluster into homogeneous travel-analysis zones. As the transportation level of service changes, their travel behavior will be relatively unaffected; if the demographics of a community change, then travel behavior would be affected more. However, the demographic composition should be relatively stable even if the population in the zone increases. Immigrants would tend to be similar to existing residents.

# RECOMMENDATIONS FOR DEMAND-FORECASTING PROCEDURES

Based on the above observations, we propose several recommendations for future development of demand-forecasting methods. The key notion is to integrate quasi-experimental designs and cross-sectional demand model estimation so as to draw on the strengths of each approach.

## Disaggregate Data Analysis in Quasi Experiments

A major review of before-and-after research in transportation advocated the use of disaggregate models in future impact evaluations and transit demonstration program evaluation (6). This recommendation is now being implemented in the Urban Mass Transportation Administration (UMTA)-funded service and method demonstration evaluations now being monitored by the Transportation Systems Center. This should result in estimated short-run demand relationships that show more external validity than previous attempts. It will also yield experience in estimating models and relationships.

### Uses of A Priori Information in Disaggregate-Demand Models

At least two travel-demand research projects have analyzed the problem of using a priori information in demand model estimation. The first of these (14) put inequality constraints on estimated coefficients to ensure that time and cost variables would have elasticities with the right sign. The other effort (15) considers a Bayesian framework for disaggregate model estimation with nonrandom samples. Neither of these consider explicitly the problem of using a priori information on observed short-run elasticities to condition or restrain the parameter estimates of a model estimated on a separate cross-sectional sample of observations.

We make the following conjecture: the likelihood functions used in estimating disaggregate demand model parameters can be modified in a straightforward way with a priori aggregate information from before-and-after experiments. If this conjecture is true, and if software modifications for existing model estimation programs can be made easily, then the isolation of short-run and long-run responses to transportation changes may be achieved with cross-sectional data.

### Full Specification of Household Behavior

An important conclusion of the above analysis is that cross-sectional data alone could not isolate short-run travel behavior without consideration of location preferences. This argues for the use of a model specification that incorporates residential location behavior in order to determine short-run travel demand. This argument has already been advanced by Brand (16) in the context of improving existing urban transportation travel-forecasting procedures. Some recent research along these lines is now being performed by Gillen and Westin (17).

## CONCLUSION

The purpose of this paper has been to show a direction for travel forecasting methodological research that has the potential to have a high payoff in improving travel prediction accuracy. We are mindful that there are probably as many research recommendations about travel demand as there are researchers of travel demand. However, scarce research and development resources should be allocated to topics that will provide more accurate estimates of policy impacts. We have argued that the gain in accuracy obtained by using before-and-after information in travel-demand modeling could be quite large. It remains to be argued whether other directions for research into travel demand would have an equivalent payoff in forecasting accuracy and improved policy evaluation.

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# Comparison of Observed and Coded Network Travel Time and Cost Measurements

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The paper compares two types of measurements of trip times: those provided by the standard network algorithms are compared with trip-time components observed along the traveler's path from home to work and back. The two types of measurements are found to be different. The root mean square errors of the network measurements with respect to observed values are very large (75-135 percent of the mean value) for the non-line-haul travel time components. The means and the variances of the network measured variables, as a rule, are much smaller than the variances or means of the manually coded observed-travel times. Coefficients estimated by using the two types of data are not numerically similar. Statistical tests show that at least the alternative-specific constants' and the level-of-service variables' coefficients are different in the models developed by using the two types of data. Finally, the effect of substantial errors in level-of-service measurements on travel forecasts is discussed. It is also shown that good (short-run) travel forecasts can be obtained from the network-based models provided that consistent network coding conventions are followed and incremental forecasts are avoided.

For several reasons the development and use of disaggregate travel-demand models, and this does not mean logit and probit models only, has increased substantially in recent years. Disaggregate travel-demand models are based on information of individual traveler's choice rather than on percentage choices of groups of travelers. The transportation level-of-service attributes (e.g., travel time and cost components) that enter these travel-demand models have normally been obtained in one of two ways. Either the times and costs have been those that the respondent reported in the interview (often called perceived travel times and costs) or the travel times and costs have been obtained from the coded transportation network by using network models such as the urban transportation planning system (UTPS). These are often termed the network or aggregate travel times and costs because they are in the zone-to-zone values. In a few studies the travel times and costs have been those experienced by the travelers as measured by observation along the paths and the times of day used by the travelers.

In this paper the observed travel time and cost measurements are compared with those obtained from the coded networks. Statistical tests are then conducted to examine whether the coefficients of a mode choice estimated by using the types of data are equal.

Two sets of data were used to conduct the analyses. A subset of home-interview data collected before the opening of the Bay Area Rapid Transit System (BART) in 1972, which contained 142 observations, were originally used to conduct the analyses. The results of this work were reported earlier (1). Since some of the results of this earlier work were statistically inconclusive, a new set of data, collected in 1975, after the opening of BART, were prepared. These data contain approximately 700 observations.

The experienced values of travel times and costs would appear to be preferable to the network-based values. This is because the person included in the sample may not have the same travel characteristics as the average person does and because individual travel behavior is presumably a derivative of one's own rather than the zone's transportation circumstances. However, to obtain observed travel-time and cost components is a time-consuming and expensive process; few researchers have the resources available and the patience to do that. It is far easier to use existing networks to calculate the travel-time components and hope that the errors, if any, are minor.

Given that all the current models used in production planning are based on network information, it is important that the networks yield information on service levels and result in models that are equivalent to the service levels and models obtained by using the observed values of service variables. This assumption of equivalency, now made, needs verification.

## COMPARISON OF THE EXPERIENCED AND NETWORK TRAVEL-TIME MEASUREMENTS

The way in which the two types of values were obtained needs to be defined. In the pre-BART data the observed transit travel times were obtained by asking the transit agency's information service to route travelers as if an inquiry call for a transit route was made by the traveler. The observed automobile travel times were based on travel-time runs (moving-vehicle method) made at various times of day and by routing travelers at the minimum time path at their time of travel. In the post-BART data the observed transit travel times were measured along the route travelers reportedly chose or would choose for their transit trip. The observed automobile travel times were obtained as in the pre-BART data.

The network values were obtained through standard network models and associate either peak or off-peak values with the travelers, depending on when the trip took place.

The pre-BART data were prepared independently of the present research. The post-BART data were prepared later under the supervision of Talvitie. Round-trip travel time and cost values are used in both sets of data.

The comparison of the observed (O) and network (N) travel times may be started by listing the means and variances of the travel-time components of interest. These appear in Table 1 for the post-BART data. Examination of the values in Table 1 reveals interesting differences. The variances and the means in the observed data cells appear to be consistently higher than those in the network data. The greatest concern, on the basis of the values in Table 1, appears to be with the out-of-vehicle time components. The average coded walk time to BART is 28.7 min; however, the observed value is more than fourfold, 123.0 min. (Note that this average pertains to all travelers, not just those who chose to use BART with walk access.)

In order to gain more knowledge of the similarities

Table 1. Means and SD of travel time and cost components by mode and type of measurement—post-BART data.

| Time or Cost Component (min) | Type | Automobile | | Bus with Walk Access | | BART with Walk Access | | BART with Bus Access | | BART with Drive-Park Access | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| On-vehicle time | N | 45.2* | 24.6* | 68.5* | 34.7* | 44.2 | 21.4 | 45.0 | 20.1 | 41.3 | 24.9 |
| | O | 50.5* | 28.7* | 77.3* | 35.8* | 37.3 | 22.5 | 48.1 | 24.1 | 48.1 | 25.4 |
| Walk time | N | NA | NA | 18.4 | 5.1 | 28.7 | 8.6 | 25.3 | 8.3 | 13.5 | 5.7 |
| | O | 8.6 | 25.2 | 23.0 | 24.8 | 123.0 | 109.0 | 19.6 | 18.3 | 25.3 | 31.9 |
| Headway | N | NA | NA | 29.0 | 18.5 | 18.5 | 8.0 | 20.4 | 15.5 | 18.5 | 8.0 |
| | O | NA | NA | 29.0 | 18.1 | 20.7 | 9.1 | 30.4 | 18.8 | 20.7 | 9.1 |
| Transfer time | N | NA | NA | 19.1 | 13.4 | 12.8 | 6.9 | 23.1 | 16.7 | 12.8 | 6.9 |
| | O | NA | NA | 35.4 | 23.4 | 26.8 | 15.7 | 37.2 | 20.1 | 26.8 | 15.7 |
| Number of transfers | N | NA | NA | 2.7 | 1.1 | 2.9 | 1.4 | 4.6 | 1.3 | 2.9 | 1.4 |
| | O | NA | NA | 2.6 | 0.9 | 2.3 | 0.7 | 2.6 | 0.9 | 2.9 | 0.7 |
| Cost per wage | N | 37.3 | 33.5 | 14.8 | 14.4 | 16.7 | 10.3 | 21.7 | 14.3 | 17.3 | 10.5 |
| | O | 31.9 | 29.4 | 14.8 | 14.4 | 17.4 | 10.3 | 20.8 | 11.4 | 24.3 | 13.9 |

*Pre-BART data value.

Table 2. Correlation coefficients, intercepts, and slopes for regressions between the observed and network measurements—post-BART data.

| Travel Time Component and Mode | Correlation Coefficient | Intercept a | SE | Slope b | SE |
|---|---|---|---|---|---|
| On-vehicle time, BART and walk | 0.74 | 3.1 | 0.77 | 0.77 | 0.04 |
| On-vehicle time, BART and bus | 0.77 | 5.8 | 3.0 | 0.92 | 0.06 |
| On-vehicle time, BART and park | 0.61 | 22.4 | 2.0 | 0.62 | 0.04 |
| Walk time, bus | 0.22 | 3.5 | 1.1 | 1.06 | 0.26 |
| Walk time, BART and walk | 0.31 | 10.0 | 20.3 | 3.94 | 0.68 |
| Walk time, BART and bus | 0.24 | 6.0 | 4.6 | 0.54 | 0.17 |
| Walk time, BART and park | 0.26 | 5.3 | 4.4 | 1.48 | 0.30 |
| Headway, bus | 0.39 | 18.0 | 1.6 | 0.38 | 0.05 |
| Headway, BART and walk | 0.40 | 12.3 | 1.1 | 0.45 | 0.06 |
| Headway, BART and bus | 0.27 | 23.7 | 2.4 | 0.32 | 0.09 |
| Headway, BART and park | 0.40 | 12.3 | 1.1 | 0.45 | 0.06 |
| Transfer time, bus | 0.28 | 25.9 | 2.8 | 0.49 | 0.12 |
| Transfer time, BART and walk | 0.28 | 18.8 | 3.3 | 0.63 | 0.22 |
| Transfer time, BART and bus | 0.36 | 27.4 | 2.6 | 0.43 | 0.09 |
| Transfer time, BART and park | 0.28 | 18.8 | 3.3 | 0.63 | 0.22 |

between the experienced and network travel-time values, regressions were run to obtain correlation coefficients, intercepts, and slopes. Ideally, we would like to obtain a correlation coefficient of one, an intercept of zero, and a slope of unity. The more we deviate from these values the less equal are the two sets of data. The correlation coefficients, intercepts, and slopes are given in Table 2 for post-BART data.

Examination of the numbers in Table 2 shows that, except for some isolated time components, the desired values for correlation, intercepts, and slope are not achieved. Statistically speaking, the hypotheses that the slopes should equal unity and the intercepts are zero must be soundly rejected for all variables, except in two or three isolated cases. In fact, the numbers of Table 2 do not appear to represent regressions between two types of measurements of the same variable.

The information produced so far about the similarities and dissimilarities of observed and network measurements of travel times can be conveniently summarized by using two measures: the root mean square error (RMSE) and Theil's U-coefficient. The former is often used as an all-around measure of goodness of fit; the latter measure is zero for perfect measurements (or forecasts) and has an upper bound of one. Furthermore, Theil's U-coefficient can be decomposed to three components (denoted $U^M$, $U^S$, and $U^C$), which indicate the proportional loss in accuracy due to differences in means, standard deviations, and covariances, respectively. These useful summary measures are given in Table 3 for the post-BART data.

The results in Table 3 are interesting. Except for the line-haul travel times, BART and walk or park headways, and the cost variables, the RMSEs are roughly equal in magnitude to the means of the observed times and costs, which indicates large errors in measurement. The same result is conveyed by the Theil's U-coefficient; the U-coefficient obtains very large values for out-of-vehicle time components. If we impose an arbitrary but reasonable U-coefficient value of 0.20-0.25 for acceptably accurate measurements, then even some on-vehicle and travel-cost measurements fail to meet the standard. The components of the U-coefficient indicate that, with some exceptions, the largest share of the error comes from the covariances between the network and observed values.

As a final item before actually estimating choice models by using the two types of measurement, it is instructive to examine typical frequency plots of some of the travel variables. The analysis performed by McFadden and Reid (2) tells that zonal averages will yield consistent estimates for coefficients, given that the distributions of variables are not skewed. Thus, the distribution of the variables for the entire sample (one can envision it to be one large zone) ought not to be skewed either if good coefficients are to result from using zonal averages. In examining the frequency plots it is good to keep in mind that most of the difference between the two types of measurements is due to covariances. Thus, the frequency plots for the two measurements can look similar without the measurements being similar because measurements in any given interval may not pertain to the same individuals.

It is natural to start with the plots of on-vehicle times. An automobile on-vehicle time plot is shown in Figure 1. An examination of the plot in Figure 1 suggests that there is a great deal of similarity between the two types of measurement; the only noticeable difference is the fat tail of the observed automobile on-vehicle time distribution. One might suspect that the lack of fat tail in the network times distribution is due to improper accounting of congestion effects. A $\chi^2$ test against the null hypothesis (that the distributions of the two measurements are the same) was, however, rejected at the 0.95 level of confidence.

The walk time (bus with walk access) frequency distribution in Figure 2 indicates that the network-coded walk time has a highly peaked distribution; however, the

Table 3. RMSE and Theil U-coefficients of travel time components—post-BART data.

| Variable | Mean (Observed) | RMSE | Theil U U | $U^M$ | $U^S$ | $U^C$ |
|---|---|---|---|---|---|---|
| On-vehicle time | | | | | | |
| BART and walk | 37.2 | 17.4 | 0.26 | 0.16 | 0.00 | 0.84 |
| BART and park | 48.1 | 23.2 | 0.32 | 0.09 | 0.00 | 0.91 |
| Automobile (pre-BART) | 50.5 | 13.1 | 0.17 | 0.16 | 0.10 | 0.74 |
| Bus (pre-BART) | 77.2 | 18.8 | 0.16 | 0.22 | 0.00 | 0.78 |
| Walk time | | | | | | |
| Bus | 23.0 | 24.5 | 0.63 | 0.03 | 0.64 | 0.33 |
| BART and walk | 123.0 | 143.1 | 0.85 | 0.43 | 0.50 | 0.07 |
| BART and bus | 19.6 | 19.1 | 0.50 | 0.09 | 0.27 | 0.64 |
| BART and park | 25.3 | 33.1 | 0.77 | 0.13 | 0.63 | 0.25 |
| Headway | | | | | | |
| Bus | 29.0 | 20.3 | 0.42 | 0.00 | 0.00 | 1.00 |
| BART and walk | 20.7 | 9.7 | 0.32 | 0.05 | 0.01 | 0.94 |
| BART and bus | 30.4 | 23.2 | 0.53 | 0.18 | 0.02 | 0.80 |
| BART and park | 20.7 | 9.7 | 0.32 | 0.05 | 0.01 | 0.94 |
| Transfer time | | | | | | |
| Bus | 35.4 | 28.6 | 0.59 | 0.33 | 0.12 | 0.55 |
| BART and walk | 26.8 | 20.8 | 0.60 | 0.45 | 0.18 | 0.37 |
| BART and bus | 37.2 | 25.4 | 0.50 | 0.31 | 0.24 | 0.45 |
| BART and park | 26.8 | 20.8 | 0.60 | 0.45 | 0.18 | 0.37 |
| Cost per wage | | | | | | |
| Automobile | 31.9 | 19.2 | 0.30 | 0.08 | 0.05 | 0.87 |
| BART and walk | 17.4 | 4.6 | 0.16 | 0.03 | 0.00 | 0.97 |
| BART and bus | 20.8 | 8.0 | 0.23 | 0.01 | 0.13 | 0.86 |
| BART and park | 24.3 | 11.3 | 0.33 | 0.38 | 0.09 | 0.53 |

Figure 1. Frequency plot—automobile in-vehicle time.

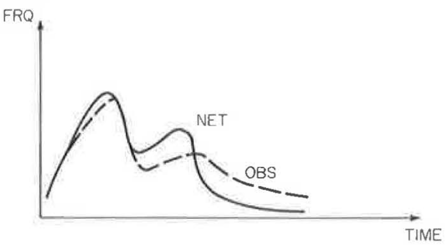
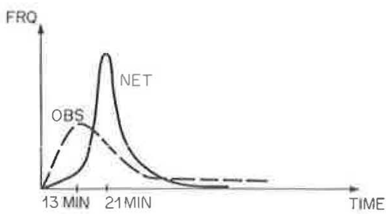



Figure 2. Frequency plot—walk time.




distribution of the observed walk times both peaks earlier and is much fatter. The appearance of the two distributions is as expected. Traffic zones are connected to network with relatively few common values and the observed values show a scatter, which relates to the location of individuals with respect to the bus-line configuration.

The frequency plot for bus headways (round trip, directional headway summed) appears in Figure 3. Note that the network headways are shorter in duration; their distribution also has a noticeably thinner tail than that of the observed headways. The apparent reason for this is that zones have been connected to trunk-line streets on which many bus lines operate and have low headway for consecutive buses. In actuality the travelers' origins and destinations are dispersed within the zones, and by taking note of schedules the travelers can gain the advantage of nearer bus lines in spite of their lower service frequency.

The frequency plot for transfer time in Figure 4 shows similar characteristics on the distribution of headways. Again, it appears that the majority of network paths use trunk-line streets that have frequent bus service and, where transfers are necessary, the transfer times are quite short. The observed transfer times show, in contrast, that travelers use routes that are convenient for them on some other grounds besides the headways of transfer buses. The distributions of transfer times also show that paths built by network algorithms do not coincide with paths actually taken by travelers—a fact well known to most transportation planners.

The two types of measurements (observation and network) of travel-time variables are certainly different. On the basis of the correlation analysis and the frequency plots we would not expect to obtain similar models with the two types of data. This is because there were large differences in the measurement and because the frequency distributions were not normal but were highly skewed. This latter result also enables the conclusion that the coefficients obtained with the aggregate network data are biased.

## COMPARISON OF MODE CHOICE MODELS DEVELOPED WITH SERVICE MEASUREMENTS

The model specifications used in the tests reported in this section is a minor variant of the model specification developed by the urban travel demand forecasting project (UTDFP) at the University of California, Berkeley (3). The larger post-BART sample of 700 observations will be used. The earlier paper (1), which used only the small pre-BART data set, resulted in inconclusive answers. Even so, the main hypotheses seemed to be supported by the previous analyses.

First, the coefficients of both system and socioeconomic variables were found to be numerically different, though the statistical evidence to support the existence of such differences was inconclusive. The reason for these differences was ascribed to the correlations between the socioeconomic and service attributes, which correlations were taken to be manifestations of people's travel and other choices. It was then concluded that the observed service-level calculations preserve these correlations and are likely to yield unbiased coefficients and demand elasticities (given a good model specification) while the network calculations do not appear to preserve these correlations and, by simple logic, must yield coefficients that are statistical artifacts. An example clarifies this. Assume that two

Figure 3. Frequency plot—headway.

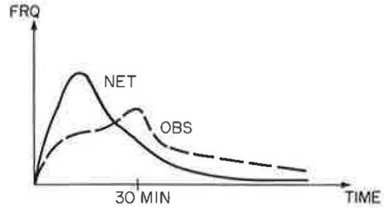



Figure 4. Frequency plot—transfer time.

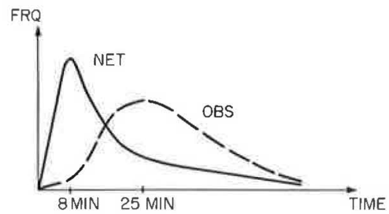



Table 4. Chi-square statistics for various tests of coefficient equality in models developed by using observed and coded network-based service attribute data.

| Hypothesis | $\chi^2$-statistic | Critical $\chi^{2a}$ | Accept or Reject |
|---|---|---|---|
| 1. Equality of alternative specific constants | 35.4 | 12.6 | Reject |
| 2. Equality of coefficients of service variables | 53.0 | 12.6 | Reject |
| 3. Equality of coefficients of socioeconomic variables | 33.0 | 14.1 | Reject[b] |
| 4. Equality of coefficients of service variables given unequal alternative specific constants | 29.0 | 12.6 | Reject |
| 5. Equality of coefficients of socioeconomic variables given unequal alternative | 5.2 | 14.1 | Accept[b] |

[a]At 0.05 level.
[b]For these tests the assumption of statistically independent samples may not have been strictly met.

travelers who have different socioeconomic attributes reside in the same zone and go to work in the same destination zone. The network algorithms assign these two people identical values for the service attributes. The choice model in turn attributes the choice to the different socioeconomic attributes (because the service attributes are equal) even though the service levels may contribute to the choice.

Second, the models that were developed by using travel times and costs from networks were observed to have coefficients whose relative values were approximately equal to those used in building the network paths. For example, if walk and wait times were weighed two in building the paths, then this same ratio (two to one) was observed in the choice model. Variable specification also seemed to have an effect; the arguments to support it are lengthy and not repeated here. The obvious hypothesis then was that the conventions used to build the paths and create the variables procreate the choice models based on coded network service data. We conjectured that if (a) networks in two or more cities are coded by using similar conventions, (b) paths are built by using similar weights, and (c) variables are created by using same type of rules (e.g., wait time is one-half of the headway up to 10 min of headway and one-fourth thereafter) then, with normal low percentage of transit users, the resulting choice models for those cities should indeed be identical. The models so obtained are not, of course, really behavioral or transferable travel-demand models, but only reflections of the coding procedures.

Third, the socioeconomic and system attributes were found to increase the predictive power of the models only slightly.

The more ample post-BART data support these hypotheses, which were arrived at by use of the small pre-BART data set. The appropriate statistical test for many of the hypotheses presented in this paper is a nested (Chow-like) likelihood ratio test. McFadden (4) has shown that if we have two independent samples (A and B), a test for the equality of the coefficients is possible. Let $L_A$ and $L_B$ be the maximum log likelihood levels attained for the samples A and B and $L_{AB}$ be the maximum log likelihood for the combined sample, then $\chi^2 = -2(L_{AB} - L_A - L_B)$ is distributed $\chi^2$ with K degrees of freedom, where K is the number of parameters. The same test can be used to test the equality of a subset of coefficients (e.g., coefficients of the service attributes).

The results of the various tests are shown in Table 4, and the models are estimated by using the observed and network variables that appear in Table 5. In Table 4 the tests on subsets of coefficients all lead to rejection of equality of coefficients (tests 1-3). Tests 4 and 5 follow orthodox statistical testing of hypothesis. That is, given the inequality of alternative-specific dummies (test 1), a test is made about whether the system variables have equal coefficients (test 4) with negative results. Finally, given the inequality of alternative-specific dummies and system variable coefficients, a test is made for the equality of socioeconomic variables' coefficients (test 5) with affirmative results. Thus, the tests unequivocally show that the models developed by using the observed and coded network service data are different. This is not a surprising finding, given the large discrepancies in the two types of measurements found in the first section.

Turning then to the model coefficients, we were unable to reproduce the coefficients of the UTDFP model, which was developed by using the network measurements. The greatest discrepancy is in the automobile and driver and drivers variables. In the UTDFP model these coefficients were between 3.0 and 5.0 and 1.0 and 2.0, respectively; coefficients of this magnitude were also estimated by Atherton and Ben-Akiva (5). On the other hand, models developed observed service-level attributes that seem consistently to produce coefficients similar to those in our study, which are substantially smaller (6, 7). This discrepancy was not investigated in depth at this time. It is suspected that one of the chief reasons for discrepancies is the possibility of having choice-based samples. Network coding and manual coding exclude different travelers from the sample. Another reason may be the use of different rules to exclude alternatives. A third reason may be the use of different model specification. How these three causes affect model coefficients will be investigated later.

Note that, by using the observed data, the out-of-vehicle time components do not seem to be valued more dearly than the in-vehicle time components. In contrast, when the network data are used the ratio of walk time to in-vehicle time is 1.9. This is approximately the same as used in building the paths in the network, where this ratio was 2.0. These same ratios are not observed for the wait times. However, there were substantial perturbations to these data after the paths were run, which makes the analysis of the effect of coding and pathbuilding conventions to model impossible with the present data (8, 9, 10).

Third and finally, the models have a low explanatory power over and above the explanatory power contained in the alternative-specific dummies. The overall proportion of successful predictions increased little more than 10 percent, or from 54 to 67 with observed service

Table 5. Model specification, coefficients, and t-values.

| Variable | Alternative Entered, Zero Otherwise[a] | Observed Service | | Network Service | |
|---|---|---|---|---|---|
| | | Coefficients | t-value | Coefficients | t-value |
| Income | 1 | -0.0000674 | 2.5 | -0.0000246 | 1.0 |
| Drivers in household | 1,3,6 | 0.788 | 4.5 | 0.929 | 5.1 |
| Drivers in household | 7 | 0.717 | 3.6 | 0.854 | 4.8 |
| Head of household | 1 | 0.192 | 0.9 | 0.658 | 3.5 |
| Employment density | 1 | -0.00144 | 3.1 | -0.00166 | 3.8 |
| Automobiles per driver | 1,3,6 | 1.781 | 3.9 | 1.976 | 4.3 |
| Automobiles per driver | 7 | 1.021 | 2.0 | 1.340 | 3.1 |
| Cost per wage (min) | 1-7 | -0.0469 | 6.4 | -0.0304 | 5.2 |
| In-vehicle time (min) | 1-7 | -0.0122 | 1.7 | -0.0329 | 4.4 |
| Walk time (min) | 1-7 | -0.0170 | 4.3 | -0.0634 | 3.6 |
| Headway (min) | 3-6 | 0.00735 | 0.7 | -0.0186 | 2.3 |
| Transfer time (min) | 3-6 | -0.0173 | 1.3 | -0.00039 | 0.03 |
| Number of transfers | 3-6 | -0.393 | 2.1 | 0.0288 | 0.3 |
| Alt 1 dummy | 1 | -1.116 | 1.6 | -2.910 | 3.4 |
| Alt 3 dummy | 3 | -5.206 | 7.7 | -5.502 | 8.5 |
| Alt 4 dummy | 4 | -0.579 | 1.7 | -1.154 | 3.1 |
| Alt 5 dummy | 5 | 0.0842 | 0.3 | -1.285 | 4.1 |
| Alt 6 dummy | 6 | -2.744 | 4.9 | -3.769 | 6.5 |
| Alt 7 dummy | 7 | -2.993 | 4.6 | -3.690 | 6.1 |
| Number of observations | | 676 | | 700 | |
| Log likelihood at zero | | -904.95 | | -1134.2 | |
| Log likelihood at maximum | | -614.50 | | - 711.58 | |
| Proportion successfully predicted | | 0.67 | | 0.61 | |

[a]Alternatives: 1 = drive alone, 2 = bus with walk access, 3 = bus with automobile access, 4 = BART with walk access, 5 = BART with bus access, 6 = BART with automobile access, and 7 = shared ride.

variables and from 54 to 61 network measurements when both the socioeconomic and the service variables were added to the model. This has to be considered a low payoff—too much of the behavior is explained by the unobserved variables.

## CONCLUSIONS

The conclusions of this paper are obvious. On the level-of-service side, substantial errors are possible and can result both in inaccurate forecasts and biased model coefficients. On the demand side, incremental forecasts should be avoided by using models based on network information because of biased coefficients. However, it is not concluded that ball-park travel prognoses cannot be made by using current network-based model systems.

The forecasting accuracy of the models is nearly identical, regardless of the type of data used. The saying "data do not matter" has, apparently with justification, circulated among travel-demand modelers. The network-based models seem to have simple aggregation properties. Koppelman's (11) careful in-depth study on aggregation shows that predictions with zonal averages seem to perform remarkably well. There are two reasons that cause this to be the case. First, networks ignore the within-zone variances, the source of aggregation bias. Table 1 shows that between-zone variance (network data) accounts for 10-60 percent of the total variance (observed data) for the excess time components and about 70-90 percent of the on-vehicle time variances. Thus, by using the networks there is not much left to aggregate as far as the service variables are concerned. Second, assume that the network travel times and costs are errors-in-variables-type variables or

$$Z = X + v \tag{1}$$

where

$Z$ = the network values,
$X$ = the true values, and
$v$ = a (random) error.

Let us then assume that $X$ and $v$ are independently and normally distributed with means $m_x$ and zero and variances of $\sigma_x^2$ and $\sigma_v^2$. These are reasonable assumptions. Any time a trip is taken but the trip time is not known exactly, it is a random variable; and this random variable is independent of the traveler's location within the traffic zone. The hypothesis in disaggregate travel-demand models is that the choices of travelers depend on the true values or, in a regression sense,

$$Y = \alpha + \beta X + e \tag{2}$$

The use of linear regression is justified because of the clarity of the result and because of the fact that the logit curve is nearly linear for small coefficient values, or over the relevant range (due to both the small variances in the networks and variable defintions, e.g., automobile and drivers varies between 0 and 1; however, variable number of drivers may introduce a serious nonlinearity).

In predicting, we do not know the true value $X$ but the network value $Z$, and thus, we need to obtain $E(X|Z)$, but this is equal to

$$E(X|Z) = (\sigma_v^2 m_x + \sigma_x^2 Z)/(\sigma_v^2 + \sigma_x^2) \tag{3}$$

and

$$E(Y|Z) = \alpha + \beta[(\sigma_v^2 m_x + \sigma_x^2 Z)/(\sigma_v^2 + \sigma_x^2)] \tag{4}$$

where $\alpha$ and $\beta$ are the consistent errors-in-variables estimators for $\alpha$ and $\beta$. On the other hand, the least-squares predictor is

$$Y = \bar{Y} + b(Z - \bar{Z}) \tag{5}$$

where $b$ is just an ordinary least-squares (OLS) estimator of $Y$ on $Z$. It can be shown that

$$b = \beta/(1 + \sigma_v^2/\sigma_x^2) \tag{6}$$

or

$$Y = \bar{Y} + b(Z - \bar{Z}) \tag{7}$$

$$Y = \alpha + \beta m_x + \beta(Z - \bar{Z})/(1 + \sigma_v^2/\sigma_x^2) \tag{8}$$

Because $E(v) = 0$, $\bar{Z}$ is an unbiased estimate for $m_x$, and

$$Y = \alpha + \beta[(\sigma_v^2 m_x + \sigma_x^2 Z)/(\sigma_v^2 + \sigma_x^2)] \tag{9}$$

But this is exactly what was obtained by using the consistent errors-in-variables coefficients $\alpha$ and $\beta$, Equation 4.

Even though the OLS coefficients b in Equation 7 are not unbiased they yield unbiased forecasts. Thus, for prediction purposes the network-based models, whether aggregated or disaggregated, can be used with success, provided that conventions for network coding and path building are not changed and out-of-range predictions not made. Note that incremental forecasts cannot be made because the demand elasticities are not unbiased.

A good example of how poorly done network coding results in wrong travel forecasts is provided by the BART patronage predictions. In the UTDFP sample the following shares were observed for BART patronage, and predicted by using the network information; in the third line revised predicted shares are shown by using the average observed service levels where they differ from the network values by more than 5 min.

| Share | Drive | Shared Ride | Bus | BART |
|---|---|---|---|---|
| Observed | 0.595 | 0.22 | 0.12 | 0.065 |
| Predicted (network service variables) | 0.53 | 0.21 | 0.135 | 0.125 |
| Revised (observed service variables) | 0.60 | 0.24 | 0.11 | 0.05 |

The error in prediction is almost totally due to network coding; the remainder can be attributed to unforeseen land-use changes and other highly unpredictable items, such as reliability; aggregation error may also be present.

Discussions of the difficulties in validating demand models, of which the Metropolitan Transportation Commission (MTC) model system discussion serves as a good example, are exclusively directed to the problems associated with the demand models to the total neglect of the service side. Webber (12) discusses at length the mistakes made by planners for not knowing that supposedly out-of-vehicle time is valued in people's minds two to three times more than the in-vehicle time and attributes, among other things, the 100-percent mistake in BART patronage forecasts to this lack of knowledge about travel behavior.

Given that (a) the bulk of the explanatory power is in the constant terms of the demand model, (b) presumably the unobserved attributes that underlie these constants change only slowly, and (c) travelers do not seem to be very sensitive to travel times and costs (and, hence, minor errors in service variables, say 5 min, do not substantially affect the predictions), it should be hard to make a bad prediction in the short run—provided, of course, that the service levels are not predicted wrongly.

Although networks can be used to give adequate ballpark travel forecasts in many planning situations, their usefulness is limited. We mentioned that incremental forecasts could not be made by using network-based models because of their biased coefficients. Careful coding of networks is also costly and time consuming and depends on good human judgment. This heavy reliance on human judgment in network coding can be a two-edged sword. On one hand it can be used to guard against foolish mistakes, often attendant with the blind use of models, but on the other hand human judgment lends itself too easily to errors of commission. Planners who want demand figures to justify, for example, a rail transit link should code short-access links and weigh them heavily in building network paths and also in travel-demand models. In case of BART, the access walk times were underestimated more than fourfold (123 min versus 28 min). Such errors are going to show up in predictions even if the behavioral weights are not guessed correctly. Furthermore, there is evidence that no mistake was made by using equal weights for the travel-time components.

It seems to us that academicians and planners alike have been too attracted to debating and estimating statistically the mysteries of human behavior (with little success one might add) to pay attention to the obvious, which is directly observable and requires really no insight to human behavior—the level of service provided by the transportation system. A good effort to improve our capabilities in the entire supply side of transportation is desirable.

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# Methodology for Assessing Transportation Policy Impacts

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**Travel-demand models may make a variety of assumptions about the way in which people respond to transportation policies. It is important to choose an appropriately specified model for a particular impact study. Full impacts cannot always be anticipated, however, or they may be too complex to be handled by a mathematical model. This paper describes a survey technique, the household activity-travel simulator (HATS), that is able to examine both the direct and secondary effects of policies on different types of household. The methodology uses display equipment in a household in-depth interview in a way that makes explicit the role of travel in daily life and the constraints and options that influence behavior; household members use the equipment to simulate their responses to policy proposals. HATS thus provides a guide to model selection and development and, where no appropriate model exists, may itself be used as a crude predictor. Several studies have now been completed and it seems possible to relate response patterns to three factors: (a) severity of the policy change, (b) whether the change is forced or permissive, and (c) the types of households affected. Case study findings are presented. The technique provides a useful indication of public opinion and appears more intelligible to both the public and politicians than does a more conventional methodology. The insights obtained from HATS studies also appear to be of wider value to policymakers, since they can help to identify problems clearly, generate a range of policy solutions, and encourage a comprehensive evaluation of the options. HATS also has a more academic role as a research and educational tool.**

Transportation planners have a range of disaggregate and aggregate models to use in the assessment of the impacts of various transportation policies. Experience suggests, however, that correct prediction of people's responses to a policy is not always possible, even in very general terms. The third (lunchtime) rush hour on the newly opened downtown sections of the Washington, D.C., Metro subway apparently came as a complete surprise to officials (1). Many British planners were equally unprepared for the secondary effects of traffic restraint in city centers (2).

The unanticipated effects of transportation policies are cited as evidence of the failure of transportation modeling techniques. However, this is often incorrect—the disparity between prediction and outcome may be a symptom of the misapplication of the model, beyond the range of the validity of its assumptions, rather than a basic fault in the model itself. All models make simplifying assumptions about human behavior—by the way they characterize the decision process (i.e., model structure), by the selection of a small set of independent variables to explain behavior, and by the limitations on the range of possible behavioral adjustments (via the model outputs). The important point is to ensure that the representation of behavior embodied in the model is appropriate to the application. This requires that the modeler understand the response pattern that a policy is likely to evoke.

A recent paper (3) has proposed a tentative fourfold classification of response patterns, based on the degree of interaction (or strength of linkage) between individual travel decisions. These model domains assume

1. Independence between successive travel decisions made by one individual and between decisions made by different people (except at an aggregate level where congestion levels, for example, may be affected);
2. Spatiotemporal linkages where the individual is also an independent decision maker, but his or her travel decisions are interdependent in space and time (e.g., shopping travel linked to the work trip);
3. Interpersonal linkages where a travel decision is taken jointly by members of a group (e.g., the household), or where decisions taken by one person will directly affect the behavior of others; and
4. Full interdependence where strong interpersonal and spatiotemporal linkages operate.

A second level of complexity is introduced by the nature of the policy and the degree of compulsion involved. We may distinguish between policies that lead to forced and permissive responses (3). The former might involve the withdrawal of a bus service or change in school hours and the latter might involve the introduction of an additional facility (e.g., new shopping center or road improvement). Impacts of permissive policies are more difficult to anticipate because of uncertainty about who will hear of or take advantage of the change.

In the physical and applied sciences, empirical relationships are recognized to apply within defined limits (e.g., certain ranges of temperature or pressure), but a similar notion is not prevalent in the social sciences. Most operational travel-demand models make domain 1 assumptions about behavior, but the outcomes observed in Washington and the United Kingdom represent responses to policy that lie outside of this domain. Transportation researchers are not yet able to define domains precisely nor to provide models that operate satisfactorily in the more complex domains (although disaggregate modelers are beginning to consider a wider range of linkages).

This paper describes a survey technique that may be used to explore likely responses to a policy and, by identifying the relevant response domains, to provide a means for selection of an appropriate travel-demand model. In cases where the policy appears to have major direct and secondary effects that cannot be handled by available models, the technique itself may be used as a crude predictor by using a larger sample of respondents. Insights gained from applying the technique can aid policy generation and evaluation and provide a basis for the development of formal models that are designed to operate in the more complex domains.

## STUDY METHODOLOGY

The full range of potential responses to policy measures (both direct and secondary impacts) can be accommodated by working at the domain 4 level. In this way we can establish whether certain linkages remain undisturbed by a proposed change and hence the extent to which impact assessment can confidently proceed, by using techniques that assume simplified response patterns.

Domain 4 level linkages can be studied by viewing travel behavior as part of a daily pattern of human activities—the things people do in time and space (4). Instead of being represented as discrete, independent entities, trips are viewed as part of a continuous pattern of events in time and space. Trip making is but one of many daily activities, but it has the special characteristic that it represents the means by which people move through space in order to use facilities for activity participation at different locations. Figure 1 contrasts the traditional conception of travel embodied in domain 1 models with that implied by the human-activity framework. A review of the literature and discussion of some of the implications of the approach for travel-demand modeling may be found in another article (5).

By using this theoretical approach, the Transport Studies Unit has developed a survey technique, the household activity-travel simulator (HATS), to examine the daily structure of household activity and travel patterns and to explore the ways in which people respond to policy changes.

## The HATS Interview

HATS is composed of a set of display equipment that is used by household members in a carefully designed group in-depth interview. The survey procedure used in HATS policy studies is shown in Figure 2. Prior to the main interview, sampled households are asked to provide basic sociodemographic information and to keep a record of behavior, which indicates the timing and location of each activity, for a specified number of days.

At the beginning of the main interview each participant constructs a physical representation of a selected diary day on a display board, by using colored blocks and markers to represent an activity pattern. A completed HATS display board is shown in Figure 3. The lower part is used to represent the temporal pattern of the person's day. Appropriately placed colored blocks indicate how time is spent on different activities throughout the day and whether this is at home, away from home, or in traveling. The upper part of the board uses a map or some other spatial representation to indicate where the activities took place and to record the travel modes and routes that link them. In most studies between 10 and 12 activity groups are distinguished by color. A comparison of Figures 1 and 3 demonstrates how the theoretical framework is clearly translated into the HATS board representation.

Once this exercise has been completed the interviewer asks respondents to describe and account for existing behavior patterns, and in this way the group identifies existing interpersonal linkages, spatiotemporal constraints, and activity opportunities.

The interviewer next introduces the proposed policy change (e.g., revised work hours or changes in transit service) and asks the group to consider how it might affect their existing behavior. Where respondents consider making adjustments or rearrangements to their day, they test them on their boards to see if they are feasible (see Figure 4). The HATS representation imposes a number of logical checks on the spatio-temporal feasibility of suggested responses and helps to make explicit the interpersonal linkages that may be affected (e.g., chauffeuring arrangements or meal-times).

As an example of the way these checks operate, consider the reaction of households to an improved transit service. Many people appear to be in favor of the system at the time of survey but fail to use it once implemented. The technique largely removes this effect by imposing a series of built-in checks on responses (through the boards and group discussion):

1. Is the system accessible to the respondent and does it serve destinations that he or she would wish to visit? Are activities there that the respondent would wish to pursue?
2. Does the service run at times when the respondent would be able, or would wish, to use it for both outward and return journeys?
3. Is the respondent prepared, or able, to commit a sufficient block of time to allow for the return journey and the time spent at the destination?
4. If use of the service involves extra travel, or a change in activity or destination, what will the respondent give up in its place (since more time on one activity can only be at the expense of another)? and
5. Are linkages with other people affected? How do they react? What indirect problems might it cause?

By using an in-depth interview format, it is also possible to probe other factors that are not directly shown

Figure 1. Alternative representations of travel in different domains.

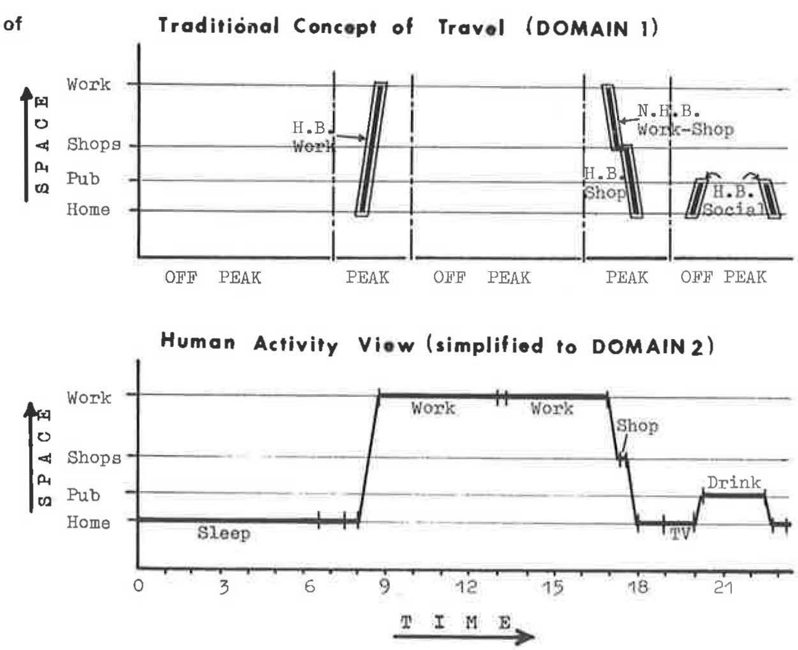


**Figure 2. HATS survey procedure.**

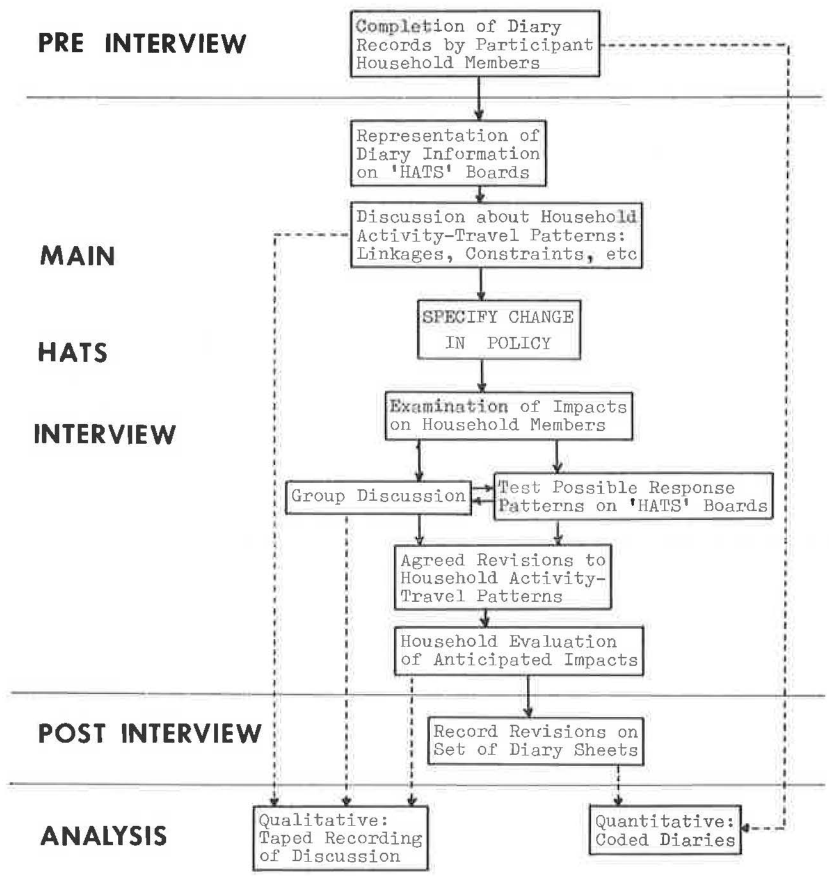



**Figure 3. A completed HATS display board.**

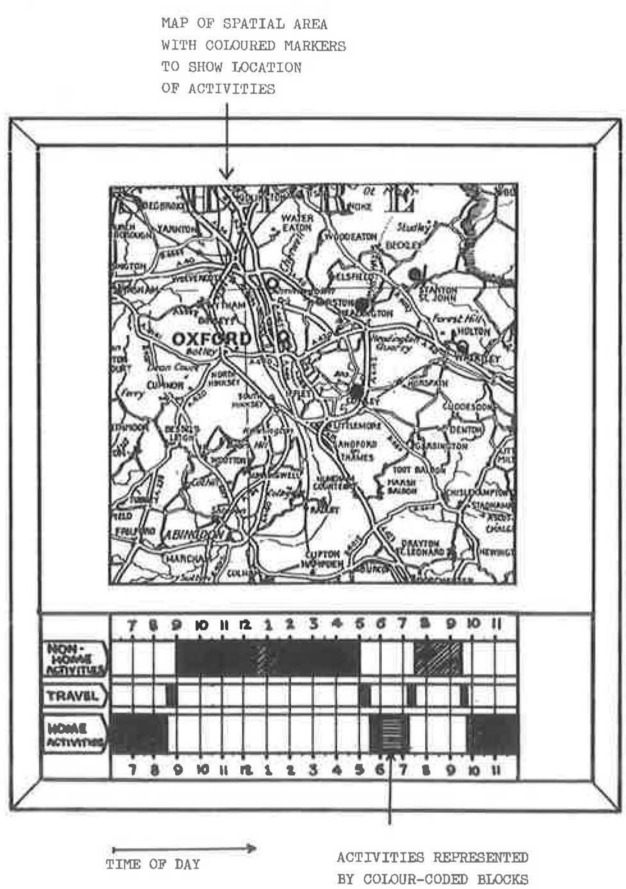
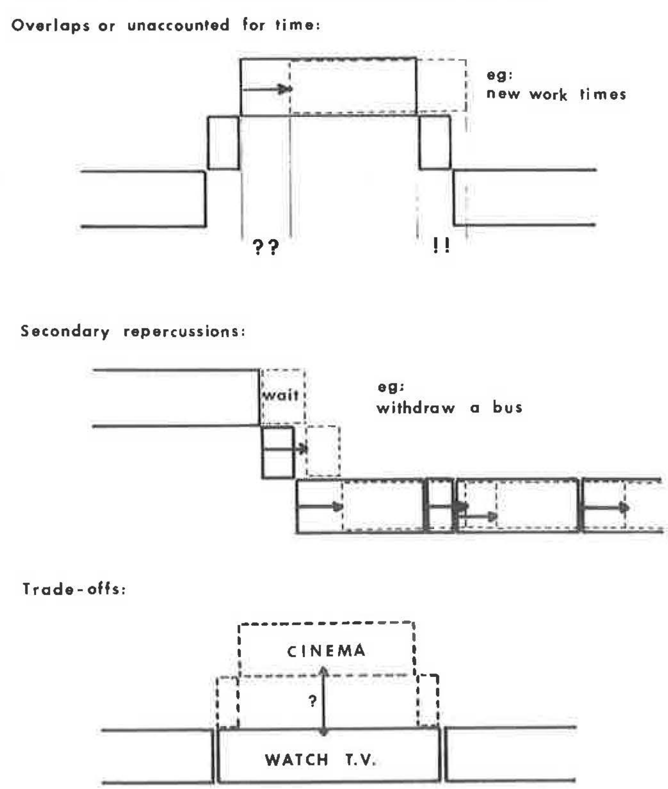



**Figure 4. Examples of checks built into the HATS interview.**



on the boards, such as comfort, safety, and cost and to get the reactions of other household members as to the realism of the responses of each member.

Once household members have agreed on likely revisions to their activity-travel patterns they are asked to give their opinions as to whether they regard the impacts as beneficial or adverse and in what way. This concludes the main interview, which normally takes from 1 to 1.5 h. The interviewer subsequently notes any revisions that were made to the boards on a second set of diary sheets. A more detailed description of the HATS interview procedure may be found elsewhere (6).

### Data Analysis

The interviews produce a tape recording of discussion and comment and diary records of current behavior and HATS-simulated modifications.

Tape analysis usually begins with the preparation of formal transcripts from a sample of interviews. These are subject to a detailed content analysis to select themes around which reports of each interview can be prepared. This is preferable to the specification of a report structure a priori, since part of the value of a HATS study is to reveal the unexpected. Each report contains a mixture of notes and quotations, which may be supplemented by tables and diagrams. Where possible the report is prepared directly following the interview, so that any unexpected points that do emerge can be probed more fully in subsequent interviews.

The diary records perform three functions during analysis:

1. Quantitative descriptions of the behavior patterns that are discussed in the tape reports,
2. Data base for examining hypotheses and relationships that result from the tape analysis (this may be supplemented with data from a local transportation study), and
3. A measure of the quantitative impact of a policy change, in conjunction with simulated after records of behavior.

A detailed description of the analysis of HATS diaries is given in Clarke (7).

The relative importance of the diary and tape data depends on the nature of the policy change that is being considered. For forced changes, the paired diary records are usually the main source of data, and the tapes provide additional insight in the form of qualification, understanding, and evaluation. For permissive policy changes, however, many households do not modify their boards during the interview and the primary emphasis rests on the tape output and on obtaining an indication of the relevance of the proposed changes to existing household activity patterns. Here the diary data are used to examine insights (formulated as hypotheses) that emerge from the tape analysis.

## APPLICATIONS

HATS was conceived early in 1975 as an adaptable means for examining existing household behavior and exploring response to change. It has undergone two field trials, which involved before-and-after studies into the effects of school-hour changes (8) and the impacts of reductions in frequency of rural buses (9). The latter was based on an independent assessment of the technique by consultants, who reported favorably on its use and potential. Although sample sizes in both studies were small, HATS appears to give realistic indications of probable policy impacts and works particularly well in larger households, which are composed of parents and children. Such groups have complex interpersonal linkages that currently are not clearly understood and their members are directly or indirectly affected by a wide range of policy proposals.

HATS is developing into a useful and sophisticated social survey technique and is being used or considered by several British local authorities as a means of assessing transportation policy impacts. Two studies currently under way are using HATS to investigate the likely effects of improved transit services (both bus and rail) and projects now being discussed include policies to change work or school hours, the impact of a new mass transit system, and the optimum scheduling of low-frequency bus services. The technique not only provides general insights into policy impacts; it also makes clear the particular advantages and disadvantages of proposals (such as improved transit) for potential users. This information can be used in the design of publicity material.

In one application, a county council is using the technique to validate or adjust the behavioral assumptions of its conventional four-stage travel-demand model. The model is being used to examine the effects of a policy to upgrade a local commuter rail service (more stations, greater frequency, and feeder buses). They are concerned that their model is unable to allow for certain perceived attributes of the service (e.g., comfort or reliability) or to incorporate possible secondary effects, such as the reallocation of the household automobile.

Where possible, local staff are trained to conduct a proportion of the HATS interviews themselves, so that local authorities can have the full benefit of the knowledge gained—not all of which is in a form that could be incorporated into a study report. Interview and analysis manuals are prepared for each application, but the unstructured nature of most studies requires a series of skilled training sessions. An educational version of HATS enables interviewers to take on the role of household members responding to a particular policy change. This is proving to be a useful training aid.

### Understanding Response Patterns

The studies completed to date have provided valuable insights into the ways in which people respond to policy changes (both hypothetical and real) and the nature and extent of any linkage effects. Response to a policy seems to relate to three factors:

1. The severity of the policy change,
2. Whether change is forced or permissive, and
3. The types of household affected.

The more severe a policy change, the more likely it is to have a significant impact on households. This is intuitively obvious, but the HATS technique provides a means of quantifying reaction to specific policies and makes clear the mechanisms that are involved. Other things being equal, the more a policy affects the location or timing (or cost) of activity or travel facilities, the less likely it is that the overall activity pattern will remain unchanged and the more likely that nonusers will be indirectly affected. In some respects an activity pattern is analogous to a kaleidoscope. A small policy change usually has only a minor impact (taking up some slack in a person's day or reducing the pressure they find themselves under), but as the change increases in magnitude a point may be reached where a fundamentally different pattern is formed.

The distinction between forced and permissive change lies not so much in the nature of the response pattern but in the certainty of the reaction. The group affected by a forced change can usually be readily identified; it can be assumed that they have perfect knowledge of the change and that they will adjust to the new situation in some way. By their nature, permissive changes tend to increase choice and invite, rather than demand, a response. As a result, identification of the groups who might benefit is more difficult, and it is hard to be sure of the extent to which individuals will become aware of the change. When the magnitude of a policy change is small, forced changes are usually more effective at modifying behavior than are permissive ones. Increased parking difficulty is more likely to change the mode or destination of trips than will a transit improvement. When the improvement is perceived to be substantial, however, a permissive change may lead to as radical a response as a forced one. The opening of a new shopping center, for example, may affect the destination, mode, timing, frequency, and travel group for household shopping trips and so significantly change daily activity patterns.

Household and personal characteristics are a third important factor that affects reaction to a policy. They determine whether a policy is relevant to a person, how much scope for marginal adjustment they have, and whether other people are likely to become involved. Retired people, for example, have less tightly constrained activity patterns and so are usually able to absorb changes by taking up slack and, because they are home-centered, spatiotemporal linkage effects are usually few. Conversely, children are closely tied to their parents and the clock, and the whole family is usually involved in any policy that affects them. As the children grow up they become more independent until, once they have their own automobile, they have few daily links with other household members and respond to many policies as though they were embryonic one-person households. Thus, it may be necessary in some cases to disaggregate policy effects by household type and use differently structured models that reflect the different response patterns of each group.

### Case Studies

An example of the effect of a forced change is provided by a study of school-hour changes, which was performed in West Oxfordshire. In this instance the policy varied in its consequences for different families because it involved both a 0.5-h change in school hours and a revised pattern of statutory school transport. As a result, children left or arrived home as much as an hour earlier. This provided the opportunity to examine the importance of the magnitude of a change in timing.

The study found that a small adjustment in timing in the morning could disrupt established household routines and cause some resentment. There appeared to be more slack in the afternoon, but when children arrived home at least 0.5 h earlier, fundamental changes in activity patterns occurred. The extra time between arrival home and the evening meal enabled the generation of late afternoon trips (for shopping or personal business activities) or their transfer from nonschool days. Alternatively, children now had enough time to complete homework before the evening meal and to leave the evening free for a range of outside activities (hence leading to increased trip rates). In families where children traveled to school by automobile (instead of by school bus) interpersonal linkages were more likely to be affected by the timing changes. Further findings and a full account of the study are available elsewhere (6, 8).

Transit improvements are a good example of a permissive change and two studies are currently examining the effect of such changes on household activity patterns. The first is being conducted in Basildon new town, Essex. As part of a general improvement in bus services in the town, the service headway from one new residential development to the town center was decreased from 2 h to 0.5 h. This was chosen for a before, HATS, and after study. A half-hourly rail service to the town center was available from a station 1-1.5 km away in a valley and was both faster and cheaper than bus service. The authority was interested in how the improved service would be received, whether it would attract former rail users (because of its greater door-to-door convenience), how useful it would be for intermediate journeys not served by rail, and whether a substantial number of new trips would be generated.

HATS interviews suggested that local residents would welcome the service but that few trips would be generated. A few would switch from rail to bus, but the main effect would be a shift from walking to bus for trips in the 1-2 km range. Activity patterns would not be significantly affected by the service improvement and there would be no major linkage effects; a standard mode-choice model, which included walking trips, would capture the main impact. Preliminary analysis of the after survey data supports this conclusion.

The second study was conducted in the suburbs of a larger urban area (10), where many local facilities were not within walking distance and intersuburban bus services were poor. Husbands in one-automobile households commonly used the automobile for the journey to work, which caused considerable accessibility and scheduling problems for wives, especially if they had young children. Given an improved transit service to work, husbands seemed willing to relinquish their use of the automobile so that the spouse could use it for shopping, child-chauffeuring activities, or commuting to a part-time job. In some situations, therefore, an improvement in transit service may invoke both interpersonal and spatiotemporal linkage effects and thus enable the adoption of a more complex or less tense daily household routine.

## MODELING IMPLICATIONS

Most operational travel-demand models implicitly operate within domain 1 (see Figure 1); that is, they treat trips as separate entities and predict a person's demand for travel without reference to their other trips or to other decision makers. In some instances this may be a reasonable simplification, as when the policy change is small or the affected individuals have very simple travel patterns, but on other occasions this is an oversimplification.

The HATS studies demonstrate how, under certain conditions, linkages between events and people are brought into play and significantly modify the simple response pattern that would result from domain 1 assumptions. Take, for example, an individual's choice of travel mode. Standard domain 1 models account for mode choice as the outcome of trade-offs between the attributes of competing modes for the trip in question. From findings to date, a rational choice may take account of a wider set of interrelationships:

1. Characteristics of the trips to and from the destination (such as mode choice for the journey to work, depending in part on the alternatives available for the journey home),
2. Characteristics of more complex trip sequences on one excursion away from the home base (thus an auto-

mobile may be chosen for the journey to work because of the need to use it for business or to run errands during the lunch hour), and

3. Interdependencies between household members (a husband may forego use of the family automobile for his journey to work so that the wife can use it to chauffeur the children during the day).

If a model is used that assumes the independence of trips when in fact significant linkages operate, the resulting misspecification may lead to incomplete and biased forecasts of policy impacts.

It seems intuitively likely that, the more linkages a model incorporates, the more complex will be its structure and the more expensive it will be to operate. Traditional domain 1 models will thus continue to have an important role to play in cases where their assumptions are appropriate. In other instances, however, there is an urgent need for operational models at the higher-order (domain 2-4) levels (3). There are as yet no models that fully incorporate domain 4 linkages. However, when policies are considered that invoke such linkages, HATS may be used as a crude predictive device, by using a larger sample of households.

A limited validation of the predictions from a HATS study was carried out as part of an assessment of the technique for the United Kingdom Transport and Road Research Laboratory (9). The study examined the effects on 22 rural households that use buses of a severe reduction in off-peak service frequency (from 8 buses/day to 2 buses/week). Table 1 (9) summarizes trips made before the change, those predicted in the HATS study, and trips reported in an after study. When allowance is made for seasonal variations, the results are encouraging; a much larger validation exercise is planned for 1979-1980.

Used predictively, HATS seems to offer one advantage over a conventional model: It makes clear the degree of uncertainty in forecasting. In some applications (particularly those that relate to permissive changes) it is not always possible to arrive at a single most likely household response pattern but rather a range of responses (e.g., which reflect different levels of anticipated service reliability). A conventional modeler might interpret this as a failing of the technique, because it gives uncertain answers, but it probably reflects a real variability in response.

## ASSESSMENT

The HATS technique seems to be particularly relevant to the assessment of the effects of transportation policy. It is able to examine both the likely direct and secondary repercussions of a policy and to provide a guide as to the public acceptability of the proposals. Experience in the United Kingdom also suggests that the study methodology and findings are readily assimilated by local politicians, who find it more intelligible than conventional assessment procedures.

By its nature, HATS is primarily an exploratory device, to be used when policy impacts are uncertain or as an aid to policy generation. HATS might be a cheaper technique to use for forecasting than a conventional model in a small local study, but it would normally only be sensible to use it as a formal predictive device on a larger scale when strong linkage effects were anticipated that could not be handled by an existing operational model. Costs of using the technique depend on the type of application (in particular the importance of the very skilled, in-depth component of the interview and analysis), but have been estimated at between 5 and 15 times that of a standard home-interview survey, which collects only one-day travel diary and demographic information (9); the higher cost is comparable with that of a typical group, in-depth interview. The HATS interviews provide a much wider range of qualitative and quantitative information than do conventional studies, and the higher costs are offset by the use of much smaller sample sizes. Any direct comparison is invalid, however, since the two procedures have very different objectives.

Although this paper has emphasized the role of HATS in impact studies, the technique is very flexible and adaptable and has a wide range of potential policy applications—particularly if used in conjunction with other survey or analysis techniques. In the Basildon study, for example, the study team found that the insights from the HATS interviews helped considerably in the subsequent design of a transit attitude and use survey in the town. In other instances, authorities have used the findings in a transit-marketing exercise. Where possible, a conscious effort is made to link HATS findings with outputs from traditional planning and travel surveys.

In a research context, the technique has obvious value as an aid to theory and model development, and is particularly useful at eliciting the decision rules that should be built into behavioral models. The notion of constrained trade-offs is basic to the HATS interview procedure (i.e., more time on one activity is gained at the expense of less time on another), and this opens up possibilities for developing more realistic evaluation procedures. Finally, HATS has been proven to be useful as an educational aid, both as a means of illustrating the role of travel in daily life and in a more sophisticated way as a gaming device, where students take on the role of household members and simulate the impact of alternative policies on the household's daily routine.

Table 1. Change in travel behavior caused by a village bus service reduction.

| | Total Trips per Day[a] | | |
|---|---|---|---|
| Travel Mode | Behavior Before | HATS Response | Behavior After |
| Village bus | 29 | 9 | 8 |
| Walk and other bus | 5 | 9 | 9 |
| Bicycle and other bus | 0 | 2 | 1 |
| Automobile passenger and bus | 0 | 1 | 0 |
| Automobile passenger | 14 | 10 | 12 |
| Automobile driver | 4 | 4 | 12[b] |
| Bicycle | 0 | 2 | 2 |
| Walk | 34 | 31 | 37[b] |

[a] Based on 22 interviews.
[b] Increases due to unusual trips on sampled after days plus seasonal effects.

## POLICY IMPLICATIONS

HATS findings also have more general implications for the evaluation and formulation of transportation policies. Individuals often evaluate transportation policies in terms of their indirect effects on activities, rather than on the travel rearrangements per se, which may include changes to in-home activities (6, 11). The recording procedure used in HATS interviews provides a means of quantifying change in these terms, but there does not always seem to be a simple relationship between degree of change (as measured in time budget terms) and strength of feeling for or against a proposal. This needs further investigation.

The approach also brings out much more clearly the links between transportation and land-use policies—since every travel change affects the timing or location of activities and hence has indirect effects on the usage of facilities and, in the longer term, on the land-use patterns themselves. Some interviews have also demonstrated one mechanism by which longer-term mobility decisions are triggered. If people are physically unable to adapt to a policy change, given their role requirements and the space and time constraints of their daily activity pattern (or find it very difficult or stressful), they start to consider more basic decisions, such as a change in automobile ownership or a new workplace or residential location. A similar process often occurs naturally in a person's life as circumstances change (e.g., need for a second household automobile or need for a larger dwelling unit as children grow older).

## SUMMARY AND CONCLUSION

HATS is a new social survey technique that enables the analyst to examine the role of travel in daily life and the ways in which households respond to change. This knowledge may be used by policymakers to anticipate the impacts of their policies or by the researcher as a basis for the development of theory or more behavioral models. The technique is particularly suited to the identification of the spatiotemporal and interpersonal effects of change and, where complex responses are anticipated, HATS may be used as a crude predictive device.

The incorporation of in-home activities is a key element in the HATS procedure. They have direct relevance to travel decisions (e.g., need to be home by a certain time for a family meal or inability to go out because of young children) and their inclusion completes the picture of daily behavior, and thus enables the systematic examination of secondary policy repercussions. Collecting information on daily activity patterns also seems to result in higher recorded trip rates (7). As more policies are proposed that invoke complex or unanticipated responses, the grounds are stronger for including in-home activities in the impact assessment.

The understanding obtained from HATS interviews also has wider policy value and may provide guidance as to the nature of the problem, the policy options to be considered, and the ways in which their impact might be evaluated. In the longer term the concepts embodied in HATS (even if not the technique itself) are likely to have a strong influence on transportation planning in both the United Kingdom and the United States.

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# Perceptions of Comfort, Convenience, and Reliability for the Work Trip

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**This research uses perceptual mapping techniques to examine the influence of comfort, convenience, and reliability on the travel behavior of work travelers. Several studies have examined these variables individually, but no research has yet been performed that considers the use of all three notions in the context of one study so that the joint effect of these variables can be analyzed. A self-administered survey was distributed among work commuters in the northern suburbs of Chicago to collect the perceptual data needed to perform this analysis. By use of factor analysis, preference regression, and first-preference logit models, several conclusions were reached: (a) People do not perceive comfort, convenience, and reliability as independent variables in selecting their mode of travel to work. Significant overlapping of these variables occurs in the public's perception of these notions. (b) Travelers do not perceive the comfort, convenience, and reliability of access and main modes in the same fashion. Each mode was perceived differently by the respondents. Thus, the use of a combined perceptual space to represent the underlying dimension for line-haul and access modes may lead to erroneous results. (c) Preference regression and first-preference logit modeling lead to almost identical results. Despite slightly higher estimation costs, the use of first-preference logit is recommended because of more efficient estimation properties.**

Considerable ongoing research effort has been in the area of mode-choice analysis in the field of travel-demand forecasting. Large strides have been made to improve modeling and forecasting procedures. As the drive for better understanding and improved models progresses, the need for inclusion of qualitative variables in travel-demand models has become evident. In recent years, researchers have examined work in the modeling of the choice processes performed by psychologists, sociologists, and marketing researchers in order to incorporate their results into travel-choice modeling efforts. One approach that has shown great promise is the use of perceptual data and analytical techniques from experimental psychology and marketing methods. These techniques allow the model builder to use qualitative, nonmetric information in a quantitative, metric context and allow the use of subjective variables such as comfort, convenience, and reliability in travel-behavior models.

This research uses perceptual mapping techniques to examine the influence of various aspects of comfort, convenience, and reliability on the travel-to-work behavior of commuters. The major focus of this study is the way in which individuals perceive these aspects for their work trips. Several studies have used those aspects that relate to one of these dimensions individually, but no research has yet been performed that considers the use of all three notions in the context of one study so that the joint effect of these variables can be examined.

A self-administered survey was distributed among work commuters in the northern suburbs of Chicago to collect the perceptual data needed to perform this analysis. By use of factor analysis, preference regression, and first-preference logit models, it was discovered that people do not perceive comfort, convenience, and reliability as independent variables in the selection of their mode of travel to work. Significant overlapping of these attributes occurs in the public's perception of these abstract concepts.

## BACKGROUND

Several recent research efforts have employed attitude-scaling techniques in an attempt to quantify the notions of comfort, convenience, and reliability for use in travel-behavior models. Nicolaidis investigated the influence of comfort in individual mode-choice models of the work trip (1). By use of psychometric scaling procedures, a comfort index was derived and used, along with travel time and cost, in the models. These models were found to be statistically significant, and the comfort index added to the explanatory power of the models.

At the same time, Spear studied the effect of a generalized convenience variable in a mode-choice model of the work trip (2). Binary (automobile versus transit) logit models were developed, by using travel time, travel cost, and the convenience variable. The convenience variable was highly significant in all models.

The most recent work was performed by Prashker (3). He investigated the effect of a reliability variable in mode-choice models of the work trip. Multinomial logit mode-choice models were constructed by using travel time, travel cost, and reliability performance measures, which were derived by using psychometric scaling techniques. In all models, the reliability performance measures were statistically significant. The explanatory power of the models was increased by using the reliability variable.

The results from these studies demonstrate the need to include qualitative variables in travel-behavior models. Individually, comfort, convenience, and reliability add to the explanatory power of the models; however, no study has been performed that examines the joint effect of these concepts. This study hopes to fill in some of this gap.

## METHODOLOGY

To most individuals, the terms comfort, convenience, and reliability are ambiguous. It is, therefore, necessary to collect less ambiguous information about service characteristics. One method that enables this to be done is to represent each qualitative concept by a small set of nonambiguous attributes, each of which describes some facet of the concept.

Our research uses attributes to define the concepts of comfort, convenience, and reliability.

| Variable | Attribute |
|---|---|
| Comfort | Protection from weather |
| | Cleanliness of vehicle and station |
| | Fatigue felt when traveling |
| | Control of immediate surroundings |
| | Feeling of personal safety |
| | Feeling of privacy |

| Variable | Attribute |
|---|---|
| Convenience | Transfers required |
| | Stops required |
| | Frequency of service |
| | Accessibility to means of travel |
| Reliability | Variability of travel time |
| | Waiting required |
| | Likelihood of accident or breakdown |
| | Influence of weather on travel time |
| Performance | Speed of vehicle |
| | Total travel time |
| | Cost of use means of travel |

The small number chosen for each variable represents an attempt to keep the length of the questionnaire reasonable. In addition, three attributes that deal with objective performance measures were included to complete the set of attributes considered important for an individual's travel behavior.

This research was designed to obtain individual ratings of the various stimuli (modes) on each of 17 attributes. The use of semantic scales to gain the information proved effective in two of the recent projects (1, 3) and was adopted for use in this research.

Two techniques were considered for analysis of the responses—multidimensional scaling and principal components factor analysis with rotation. Two recent studies that compared multidimensional scaling methods (INDSCAL) and factor analysis as techniques for analyzing perceptual data (3, 4) indicate that both approaches yield consistent results. However, factor analysis did so more easily and at a lesser cost in computer time. Also, in one study, factor analysis provided better interpretation of the dimensions of the perceptual space (4). Hence, factor analysis, with rotation of the factors, was used in this research.

The definition of the attitudinal variables is similar to that used in the earlier studies. Three perceptual spaces were constructed, one for access modes, one for main modes, and the last for all modes together. This is done to test the assumption made by earlier researchers that individuals perceive access and main modes in the same way. Preference models are constructed in two ways. One uses variables from the separate main- and access-mode spaces, and the other represents both main and access modes in a single perception space.

Factor analysis provides a set of factor scores for each stimulus for each individual. These factor scores are the coordinates of an individual's rating of the stimulus in the perceptual space. In this study, the coordinates of the stimuli in the perceptual space are included as separate variables in the models. Values are assigned to each perceptual dimension of each mode (both access and line-haul) for each individual.

These variables were used as input to a set of preference models in an attempt to uncover the importance associated with the dimensions in the perceptual spaces. Two types of models were estimated: preference regression and first-preference logit (4). Comparisons were made between the spaces of the separate and combined modes for both model types. Further details of the methodology may be found elsewhere (5).

Table 1. Distribution and response characteristics.

| Mode | Distribution Number | Distribution Percent | Usable Returns Number | Usable Returns Percent |
|---|---|---|---|---|
| Commuter rail | 649 | 45 | 76 | 43.7 |
| El or subway | 497 | 35 | 71 | 40.7 |
| Automobile | 294 | 20 | 27 | 15.6 |
| Total | 1440 | 100 | 174 | 100.0 |

## SURVEY DESIGN AND SAMPLE STATISTICS

The survey was conducted in the cities of Evanston and Wilmette among commuters to downtown Chicago. Although this area is biased toward the higher levels of education and income, these biases were not thought to be harmful to this study since the research is exploratory in nature and not intended for policy formulation or total generalization, so that a representative sample is not required.

Three major modes exist for travel from Evanston and Wilmette to downtown Chicago: commuter rail, elevated rapid transit, and automobile. To ensure that each of these alternatives was represented in the sample, the surveys were distributed at commuter rail and elevated train stations in the Evanston and Wilmette areas in proportion to their morning peak-period demand, and at parking garages in the Chicago central business district (CBD). The survey was distributed in December 1976. The number and percentage of usable returns by each of the alternative main modes are presented in Table 1. The distribution procedure allowed a good representation of all three main modes in the sample. Thirty-six percent of the 484 surveys returned were usable. Only 12 percent of the 1440 surveys sent out were returned and usable.

The survey form consisted of four parts. The first part deals with the actual behavior of the respondent: time of travel, mode used, and a carpool question. The second part constituted the attitudinal portion of the survey. Three types of questions are asked in this section. The first type deals with the individual's preferences for a travel mode to work. The preference data are used to develop the preference model that provides the importances of the dimensions of the perceptual space. The second type deals with the importance of each attribute in the choice of travel mode to work. The last type is the most important in the entire survey, and also the most complicated. The respondent is asked to rate each access and main mode on each of the attributes on a seven-point scale. The modes are divided into the access and line-haul segments because it was felt that these portions of a trip to work might be perceived differently and that their importance in preference and choice might also be different.

The third part of the questionnaire deals with the collection of disaggregate travel times and travel costs. This part is divided into three sections, one for each of the main modes of travel to downtown Chicago: automobile, commuter train, and elevated rapid transit. For each mode of travel, the respondent is requested to answer the questions in that section as if he or she used that mode of travel for the work trip. In this way, everyone answers the questions in the same context. The fourth part collects the standard demographic data used in most transportation-planning studies, including age, sex, income, and automobile ownership.

The demographic statistics of the total sample are presented in Table 2. It can be seen that the expected representation of higher levels of education and income is obtained. In addition, the majority of the respondents report high-status occupations.

## ANALYSIS

By use of the 174 usable observations, various perceptual spaces were constructed and evaluated by use of factor analysis, preference regression, and first-

Table 2. Demographic characteristics.

| Characteristic | Percent | Characteristic | Percent |
|---|---|---|---|
| Sex | | Occupation | |
| Male | 75.6 | Professional or technical | 52.3 |
| Female | 24.4 | Manage or administrate | 22.6 |
| Age | | Sales | 6.6 |
| <20 | 0.9 | Clerical | 5.5 |
| 20-29 | 27.0 | Service | 2.1 |
| 30-39 | 24.0 | Other | 10.9 |
| 40-49 | 19.6 | Length of residency | |
| 50-59 | 17.8 | <1 year | 14.0 |
| ≥60 | 10.7 | 1-5 years | 37.1 |
| Education | | 6-10 years | 15.6 |
| High school | 4.4 | >10 years | 33.3 |
| College | 54.7 | Marital status | |
| Graduate level | 32.6 | Married | 72.6 |
| Other | 8.3 | Not married | 27.4 |
| Income | | Automobile ownership | |
| <$5000 | 3.5 | 0 per household | 4.4 |
| $5000-$15 000 | 28.4 | 1 per household | 57.8 |
| $15 000-$25 000 | 36.5 | 2+ per household | 37.8 |
| $25 000-$35 000 | 17.1 | Driver's license | |
| >$35 000 | 14.6 | Yes | 96.6 |
| | | No | 3.4 |

preference logit. This section discusses the steps followed in each phase of the analysis and the conclusions reached in each step.

Data were collected about each individual's rating of each of the 17 attributes for each of 11 mode segments, for both the access and line-haul modes. Factor analysis was used to construct the three perceptual spaces. Various dimensionalities were attempted, ranging from a two-factor solution to a five-factor solution. The appropriate dimensionality for each space was selected based primarily on clarity of interpretation of the factor space. The four-factor solution was selected for all three perceptual spaces. Table 3 presents the attributes that load onto each factor.

One objective of this research was to test the assumption that individuals perceive main and access modes differently. To test the assumption, the three perceptual spaces were constructed. In examining the attributes' loading on each dimension for each perceptual space, it can be seen that in no case are the dimensions comparable between the access- and main-mode types. This result is true as the dimensionality is increased from the two- to four-factor solution. Therefore, it is concluded that these individuals do not perceive the comfort, convenience, and reliability of access and main modes in the same fashion, so the use of only one perceptual space to represent the underlying perceptual dimensions may lead to erroneous results. This is a significant departure from the three earlier works described previously.

Labels were developed for the dimensions of each of the three perceptual spaces and are presented in Table 3 along with the attribute loadings on each dimension. For the access-mode space, the dimensions were labeled reliability, on-time performance; time and effort; comfort; and personal autonomy. For the main-mode space, the dimensions are given different labels, which reflect the different attribute loadings. The dimensions in the combined-modes space are labeled as on-time performance, time and effort, amenities, and service measures. Although some dimensions of the three spaces are similar, the spaces are not similar overall.

As stated earlier, one objective of this research was to investigate whether people perceive comfort, convenience, and reliability as separate concepts. In the results obtained, none of the dimensions can be labeled strictly as a comfort dimension, a convenience dimension, or a reliability dimension. Elements of each concept appear on more than one dimension. Therefore, based on this analysis, people do not appear to perceive

Table 3. Four-factor perceptual space.

| Measure | Attribute |
|---|---|
| Access mode | |
| 1. Reliability, on-time performance | Number of stops required |
| | Frequency of service |
| | Accessibility to means of travel |
| | Cost to use means of travel |
| | Variability of travel time |
| | Waiting required |
| | Influence of weather on travel time |
| | Number of transfers required |
| 2. Time and effort | Protection from weather |
| | Fatigue felt when traveling |
| | Total travel time |
| | Speed of vehicle |
| 3. Comfort | Cleanliness of vehicle and station |
| | Feeling of personal safety |
| | Likelihood of accident or breakdown |
| 4. Personal autonomy | Control of immediate surroundings |
| | Feeling of privacy |
| Main mode | |
| 1. On-time performance | Fatigue felt when traveling |
| | Total travel time |
| | Number of stops required |
| | Speed of vehicle |
| | Feeling of personal safety |
| | Variability of travel time |
| | Likelihood of accident or breakdown |
| | Influence of weather on travel time |
| 2. Amenities | Cleanliness of vehicle and station |
| | Control of immediate surroundings |
| | Feeling of privacy |
| | Cost to use means of travel |
| 3. Service measures | Frequency of service |
| | Accessibility to means of travel |
| | Waiting required |
| 4. Waiting measures | Protection from weather |
| | Number of transfers required |
| Combined modes | |
| 1. On-time performance | Number of stops required |
| | Cost to use means of travel |
| | Feeling of personal safety |
| | Variability of travel time |
| | Likelihood of accident or breakdown |
| | Influence of weather on travel time |
| 2. Time and effort | Protection from weather |
| | Fatigue felt when traveling |
| | Total travel time |
| | Speed of vehicle |
| 3. Amenities | Cleanliness of vehicle and station |
| | Control of immediate surroundings |
| | Feeling of privacy |
| | Number of transfers required |
| 4. Service measures | Accessibility to means of travel |
| | Frequency of service |
| | Waiting required |

comfort, convenience, and reliability as independent attributes when they choose a travel mode for their journeys to work. Although the attributes of these qualitative variables play a role in the choice process, travelers appear to consider them in a different manner than was previously believed.

Given the respondent's stated preferences for nine combined travel modes, and factor scores for each dimension of the mode-perception spaces, preference models were estimated to test how effectively the derived perception spaces predict the stated preferences. Two techniques were used to estimate these models: preference regression and first-preference logit.

The general definition of the preference model is as follows:

$$P_{ij} = \sum_k \alpha_k a_{ijk} + \sum_k \mu_k m_{ijk} + \text{automobile dummy} \tag{1}$$

where

$P_{ij}$ = preference rank of alternative j by individual i,
$\alpha_k$ = access-mode parameter for dimension k,
$\mu_k$ = main-mode parameter for dimension k,
$a_{ijk}$ = access-mode factor score for dimension k, and
$m_{ijk}$ = main-mode factor score for dimension k.

Several points must be made about the definition of the model. First, the preference ratings were solicited with respect to the nine alternative travel modes that consist of access-mode and main-mode segments. The factor scores are defined for each mode segment separately. Thus, the factor scores for both the access and line-haul portions of the trip must be included in the model. Second, special consideration must be made for the automobile-all-the-way alternative. Unlike the other modes, this alternative consists of only one mode segment; it has no access portion. An automobile dummy variable is included to represent the absence of any access mode.

Preference ratings include ties, and some respondents did not use the entire seven-point scale in the ranking. Therefore, the respondent's preference ratings were normalized so that the sum of the ratings is constant and ties were defined as the mean value of their ranks.

Two preference-regression models were constructed by using separate access-mode and main-mode spaces versus a combined-mode space. The goodness-of-fit statistics for these models are presented in Table 4. The models were able to predict 49.4 percent of the first preferences for the separate-modes space and 52.3 percent for the combined-modes spaces.

The models all have highly significant F values, although the $R^2$ values are low. However, previous uses of preference regression show that $R^2$ values are usually low (3), and so these values are acceptable for this research. In addition, the first-preference recovery percentages compare favorably to the results obtained in other studies (3, 4). The large and significant automobile dummy-variable parameter indicates that the variable is picking up the effect of the absence of the need to use an access-mode for automobile-all-the-way.

Table 4. Preference regression results.

| | Separate-Modes Space | | Combined-Modes Space | |
|---|---|---|---|---|
| Dimension | Coefficient | Significance | Coefficient | Significance |
| Access 1 | 0.714 | 0.000* | 0.540 | 0.000* |
| Access 2 | 0.080 | 0.262 | 0.051 | 0.477 |
| Access 3 | 0.075 | 0.390 | -0.051 | 0.554 |
| Access 4 | 0.086 | 0.271 | 0.492 | 0.000* |
| Main 1 | 0.665 | 0.000* | 0.049 | 0.630 |
| Main 2 | 0.201 | 0.076* | 0.770 | 0.000* |
| Main 3 | 0.014 | 0.869 | 0.208 | 0.032* |
| Main 4 | -0.003 | 0.972 | -0.147 | 0.122 |
| Automobile dummy | -2.309 | 0.000* | -2.534 | 0.000* |
| Constant | 4.941 | 0.000* | 5.135 | 0.000* |

Notes: F = 33.57 for the separate-modes space and 33.63 for the combined-modes space and was significant at the 0.10 level; $R^2$ = 0.163 for the separate-modes space and 0.171 for the combined-modes space.
*Significant at 0.10 level.

Table 5. First-preference logit results.

| | Separate-Modes Space | | Combined-Modes Space | |
|---|---|---|---|---|
| Dimension | Coefficient | t | Coefficient | t |
| Access 1 | -1.045 | -6.96* | -1.273 | -6.37* |
| Access 2 | 0.097 | 0.88 | 0.027 | 0.24 |
| Access 3 | -0.958 | -4.26* | -0.631 | -3.56* |
| Access 4 | -0.464 | -3.12* | -0.342 | -2.04* |
| Main 1 | -1.032 | -5.46* | 0.190 | 0.78 |
| Main 2 | 0.002 | 0.01 | -1.649 | -5.46* |
| Main 3 | -0.917 | -3.88* | 0.029 | 0.12 |
| Main 4 | 0.170 | 0.67 | -0.625 | -2.57* |
| Automobile dummy | 9.011 | 6.16* | 7.868 | 6.16* |

Notes: Pseudo $R^2$ = 0.2744 for the separate-modes space and 0.2809 for the combined-modes space; $-2\,[L(B^*) - L(B^0)]$ = 209.8 for the separate-modes space and 218.8 for the combined-modes space.
*Significant at 0.10 level.

The two different perceptual spaces do not perform significantly differently. However, based on intuitive reasoning and the differences in perception structure, the use of separate access-mode and main-mode perceptual spaces is recommended instead of the combined-modes space.

The implied importance rankings of the dimensions of the separate-modes space derived from the model are intuitively more appealing than those derived from the combined-modes space. The three most important factors from the separate-modes model are access-mode reliability, main-mode on-time performance, and main-mode amenities. The other dimensions are much less important. The combined-modes model has as its most important dimension main-mode amenities, followed by access-mode reliability. The results from the separate-modes space present a ranking that seems more reasonable. A priori, we would expect that access-mode reliability would be one of the most important factors in the choice of travel mode to work. That is, if the access mode is not reliable, the probability of arriving at the main mode on time would be small, thus causing the traveler to miss his or her connection. That the main-mode's reliability was more important than main-mode amenities is also no surprise. In general, the importance rankings of the dimensions adds further support to the recommendation that the separate access-mode and main-mode space be used in future research efforts.

Two first-preference logit models were constructed; one for each type of perceptual space. The coefficients and goodness-of-fit statistics are presented in Table 5. The models were able to predict 43.1 percent of the first preferences for the separate-modes space and 44.25 percent for the combined-modes space.

As before, the automobile dummy variable is highly significant and accounts for the absence of the automobile access-mode segment. The goodness-of-fit statistics are low, but this is expected based on previous studies and the preference-regression results. The pseudo-$R^2$ values are low, but the likelihood-ratio statistics are significant in both cases.

The implied importance rankings are similar to those derived from the preference-regression models. The rankings for the models from the separate-mode space are identical in the first two positions, as are the rankings for the models from the combined-mode space. The first-preference logit models have a greater number of significant variables than do the preference-regression models. This result is important and justifies the higher cost of using logit estimation. Therefore, based on the similarity of the rankings between the two different preference models, differences in parameter significance, and considering cost, first-preference logit modeling is recommended to identify relative importance of dimensions of service perceptions.

The first-preference logit analysis also supports the use of the separate-mode spaces over the combined-mode space. The results, which are similar to the ones from preference regression, are more intuitively pleasing and seem to be more meaningful.

## CONCLUSIONS AND EXTENSIONS

The relative importance of dimensions in these perceptual spaces was estimated by using preference-regression and first-preference logit models. From this analysis, several conclusions are reached.

1. The use of a single perceptual space to represent both access-mode and main-mode segments is not acceptable. There is no basis for an assumption that travelers perceive these two mode types in the same

fashion. Perceptual spaces were built to examine the differences between a single perceptual space for both mode segments and separate perceptual spaces for each mode segment. The results indicate that individuals perceive these two segments differently. Hence, the use of separate perceptual spaces for access and main modes is recommended for future research efforts. The results obtained by using the separate-mode spaces were more understandable than those for the combined-modes space and support the hypotheses of this research.

2. Examination of the attributes that loaded onto the dimensions of the perceptual spaces indicates that individuals probably do not perceive comfort, convenience, and reliability as independent factors when they select a means of travel for their work trips. There is significant overlapping of the attributes of each concept across all dimensions.

3. The use of preference regression and first-preference logit lead to almost identical results in the preference-modeling phase of the analysis. However, due to better estimation properties, the use of first-preference logit is preferred.

Several extensions can now be discussed. In conducting this research, only 14 attributes of the three qualitative concepts were used. Those 14 attributes were chosen because they were the most important ones in the previous studies. A large share of the convenience and reliability attributes are time related, so that it is possible that little information was gained about those variables; the comfort attribute does not seem to suffer from this problem. Further research to identify an appropriate set of attributes is needed. Specifically, an investigation of the attributes of convenience and reliability must be undertaken in an attempt to identify a well-defined, mutually exclusive set of attributes for these concepts.

Another issue to be considered concerns the validity of questioning individuals about abstract concepts, such as high travel time or low variability of travel time. The use of a set of attributes eliminated some problems of ambiguity; however, the use of the abstract ranges introduces some confusion. One study (3), which considered this problem in dealing with time variations, found that specification of actual ranges greatly aided the respondents in answering those questions.

Another problem with the abstract ranges arises in the mapping of perceptual data into the objective performance space. Each respondent determines his or her own values for those ranges, so it is quite plausible for two individuals to have the same perception of some attribute on some mode when the performance characteristics are vastly different. For example, one individual may consider a wait of 5 min to be an extremely long wait, but another may consider an extremely long wait time to be on the order of an hour or more. These individuals would have identical perceptions for vastly different cases. The ranges must be explicitly specified with actual values when the information will be used to attempt a mapping of the perceptual data into reality.

The use of the reported preferences as the dependent variable in the preference modeling to derive the importances of the dimensions provides one approach to understanding travel-choice behavior. Because data were collected on observed behavior, the use of these actual choices as the dependent variable would also uncover revealed importances of the individuals. Since the link between preference and behavior is complex, this extension is warranted.

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# Traveler Attitude-Behavior Implications for the Operation and Promotion of Transport Systems

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**Alternative hypotheses on how traveler attitudes relate to system usage are examined to infer strategies for the operation and promotion of transport systems. Two different transport modes (carpools and buses) and two different data sets are analyzed. The analyses highlight the differential roles of perceptions of system attributes and modal affect in accounting for traveler behavior. In addition, the mutual dependence of attitudes and behavior on each other is confirmed. After these relationships are empirically demonstrated, some practical operational and promotional implications are developed. It is noted, for example, that system improvements by themselves can be insufficient to produce desired changes in system usage. Two specific promotional strategies that can complement system improvements and help increase system usage are described and linked back to the analysis of traveler attitude-behavior relationships.**

Despite an abundance of research on attitudes toward transportation systems (1), there is no widely accepted theory of traveler behavior that incorporates traveler attitudes and allows specific predictions about the effects of changes in transportation systems. This has hindered attempts by designers of transportation systems to make cost-effective trade-offs between system attributes. It has also retarded the development of effective transportation marketing programs that encourage travelers to use existing transportation facilities in ways that minimize the need for new facilities.

Previous research has verified that attitudes are correlated with traveler behavior and sociodemographic characteristics (2, 3). The need for improved theory is reflected, in part, by the emerging interest in whether attitudes are determinants of traveler patterns or whether traveler behavior causes attitudes (4, 5). The latter issue is important because if attitudes cause behavior, then mode choice can be influenced by changing traveler viewpoints toward public transit, carpools, and single-occupant automobiles. By studying consumer preferences for transit attributes, for example, it is possible to specify one or more mixes of comfort, convenience, and safety that give optimum consumer satisfaction within given cost constraints. A modeling framework can be developed that links subjective reactions to objective features of the system.

Even if attitudes do not determine behavior, they can still be used in a number of transportation policy and planning contexts, such as the identification of perceived user benefits. In order to determine the proper role for attitudinal research in transport analysis, it is essential to determine the nature of the interrelationships between traveler attitudes and traveler behavior.

## DEFINITION OF ATTITUDINAL COMPONENTS

It is important to clarify what is meant by attitudes, since transportation researchers have used the term rather loosely (6). Social psychologists accept the structuring of attitudes into the following three components: cognitions, feelings (affect), and behavioral intentions (7). However, there is much controversy about the relationships among these components.

The results presented in this paper refer exclusively to cognitions and affect. Behavioral intentions are important, but they form the focus of attention of other research summaries (8). The cognitive or perceptual components represent a person's information about a tangible or intangible object. Each piece of information can be broadly classified as either a belief in the existence of an object (awareness) or an evaluative belief about an object (perceptions or comparative judgments of specific attributes). The affective or feeling component deals with the person's overall feelings of like or dislike for an object, such as a bus. Affective (preference) judgments may be said to combine information about product evaluation and the individual's ideal product.

## MODELING PERSPECTIVES

Several modeling perspectives from social psychology and marketing can be merged and extended to form the basis for a widely accepted theory of traveler behavior. These modeling perspectives can be adapted so that they yield benefits to transportation system designers and marketers. Multiattribute models help us to appreciate the combined effects of different kinds of perceptions; hierarchical models direct attention to linkages among different kinds of attitudinal components and behavior. Cognitive balance concepts identify the possibility that attitude-discrepant behavior can cause attitudes to change. That is, attitudes and behavior complement one another with respect to cognitive balance.

### Multiattribute Models

Rosenberg and Fishbein have asserted that liking an object, such as a bus, is a function of perceptions about the attributes of the object and the importance of those attributes to individuals (9, 10). The functional relation between preference for an object and attribute perceptions and importance is frequently assumed to be linear and additive (11).

Beliefs pertain to object attributes. Some attributes may be very important and yet not influence consumer preference because the traveler does not believe that the bus possesses those attributes. Alternatively, a transport mode may be very high on an attribute (e.g., low cost), but not be liked to a commensurate degree.

In the latter case, multiattribute models presume that consumers simply do not believe that attribute is important. Multiattribute models are known to correlate with consumer preference; however, their chief value to consumer research is in the area of diagnosis, not prediction. Aggregate measures, such as satisfaction with the product and consumer purchase or usage intentions, perform better than measurements of beliefs as predictors of buyer behavior (12). However, these aggregate measures of consumer attitudes (i.e., satisfaction and usage intentions) fail to reveal the relative significance of product attributes as determinants of consumer preference. Furthermore, policy implications largely emerge from an understanding of those factors that can be adjusted to change consumer preference and behavior.

### Hierarchical Models

Some behavioral theorists have suggested that several attitudinal constructs feed into one another before they ultimately influence behavior (13). Typically, three attitudinal concepts are differentiated: cognition, affect, and conation (see Figure 1). It is often argued in hierarchical models that affect toward a service is a function of cognitions about that service. This is compatible with the multiattribute models mentioned above. Hierarchical models are structured as they are because it is presumed that cognitions and affect do not influence behavior directly. Instead, these models presume that cognitions and affect influence behavior through their position in the hierarchy, which has the structure: cognition-affect-conation-behavior.

At the Second International Conference on Behavioral Travel Demand, the basic hierarchical model of cognition-affect-conation-behavior was suggested as an explanation of mode choice by travelers (14). Subsequent empirical research by Tischer and Dobson has shown that parts of the overall model are compatible with traveler judgments (8).

### Cognitive Balance

Another basic approach to analysis of attitudes is cognitive balance or consistency theories (15, 16). This theoretical perspective uses drive-reduction principles to explain why people change their attitudes or behavior to avoid cognitive inconsistency, a noxious state. Festinger developed one of the most widely studied balance theories with his cognitive dissonance model (18-21). When relevant attitudes and behavior are the obverse of each other, then cognitive dissonance is generated. The degree of dissonance arousal depends on the importance of the cognitive elements (i.e., behavior and attitudes).

Cognitive balance is important in the present context because it implies that behavior can cause attitudes. Attitudes will be modified when they are at variance with behavior. This occurs because it is frequently easier to change attitudes than behavior. Horowitz and his associates (2, 5) have pioneered in the application of cognitive dissonance theory to travel behavior. Multiattribute models generally assume that attitudes influence behavior without acknowledging that behavior can concurrently affect attitudes. The formulations considered below are based on hierarchical multiattribute notions, and they permit attitudes and behavior to be mutually dependent on each other.

### Research Objectives

This paper attempts to build on and extend prior efforts at theory construction and validation for attitudinally based models of travel behavior. Structural equations and flowgraphs are used to quantify and assess hypotheses about traveler attitude-behavior interrelationships. Our modeling orientation references multiattribute, hierarchical, and cognitive-balance notions. Two data sets are used to analyze assumptions about traveler behavior mechanisms with respect to two different transport modes—buses and carpools.

## STUDY DESIGN

### Data Sets

The analyses reported here were performed on attitudinal data collected by the Federal Highway Administration (FHWA) and General Motors Research Laboratories (GM). The FHWA data set was assembled from an attitudinal transportation survey conducted in the Los Angeles area in 1977. For the purposes of our analysis, the sample is composed of approximately 800 individuals who work in the downtown area and who live within 3.2 km (2 miles) of a freeway, which feeds radially into that area. Crisscross telephone directories were used to select households randomly that surrounded the freeways from census tracts with a high incidence of downtown workers. Only commuters who worked in this downtown area were eligible for the interview. When a household contained more than one downtown worker, the person taking the less frequently used mode was chosen to be interviewed.

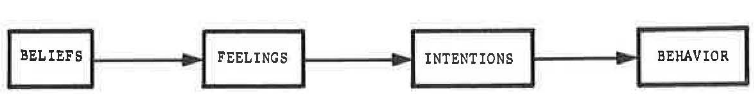
The GM data set, the carpooling questionnaire, includes 1010 respondents from the Chicago area, not all of whom were instructed to complete the entire questionnaire (2). Respondent selection was dependent on modal status and place of employment. Enterprises that employed at least 100 people were randomly chosen from a list of Chicago firms and those firms agreeable to participation distributed the questionnaire to their employees. Because of the unique requirements of this analysis, the eventual sample for the results reported here is based on approximately 400 respondents.

### Variables

Three types of variables are used in our analyses. These are attitudes, behavior, and sociodemographic characteristics. The attitudes and behavior are examined for their mutual dependence on each other as conditioned by sociodemographic characteristics.

Two types of attitudinal measure are included in the analysis. The first of these attitudinal variables is the perception of system attributes, a cognitive attitudinal component. A previous analysis of these data derived factors that corresponded to convenience and comfort perceptions for buses (22). Bus convenience was defined with respect to specific consumer evaluations of ease of use, reliability, on-time arrival, ease of getting from the bus to the final destination, wait time for the bus, and convenience. The specific attributes that

Figure 1. Simple, hierarchical attitude-behavior model.



define bus comfort were crowding, relaxing experience, space for packages, and comfort. The second type of attitudinal variable was overall affect toward buses. It was defined by responses to a seven-point scale, from completely satisfied to completely dissatisfied.

Respondents were asked to state the way they traveled to work. The frequency of bus and carpool usage (the behavioral variables) were designated on a category scale that ranged from never through five or more times per week. This response was converted to a monthly frequency prior to analysis.

Sociodemographic characteristics were used as background variables for studying the interrelationships of attitudes and behavior. Characteristics used to identify interrelationships were income, number of automobiles available, number in household, number of driver's licenses in a household, number of blocks from bus to final destination, and a quantity called impedance, based on the travel times of buses and automobiles.

## Analysis Method

The primary analytical tool is structual equations estimated by two-stage least squares. The general topic is discussed from a broad social-science perspective by Heise (23) and Hanushek and Jackson (24). Flowgraphs, which are discussed extensively by Heise, are used to represent structural equations and to display estimated t-values for structural equation coefficients.

Figure 2 depicts, in flowgraph form, a simple example in which attitudes (A) and behavior (B) are mutually dependent. This sort of feedback is referred to as a nonrecursive relationship. The variables $EX_1$ and $EX_2$ are exogenous variables because their values are determined by factors outside of the system of equations depicted by the relationships shown in Figure 2.

In this research, exogenous variables are demographic, objective, or transport system variables (e.g., $EX_1$ = income and $EX_2$ = automobile availability). The variables A and B are called endogenous variables because their values are determined by the system of equations. The structural equations for Figure 2 have the following representation:

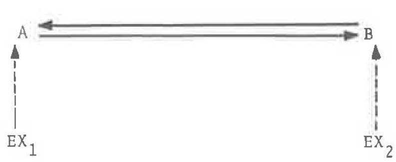
$$B = f_a\,(A, EX_2) \tag{1}$$

and

$$A = f_b\,(B, EX_1) \tag{2}$$

Since attitudes and behavior are on both sides of the system of equations, ordinary least squares is not an appropriate estimation procedure. Ordinary least squares requires that right-hand variables be independent of residuals, which will be violated when any variable appears on both sides of a system of equations. However, unbiased estimates can be obtained by using two-stage least squares. The first step is to estimate the endogenous variables as a linear function of the exogenous variables. The least-squares representation of this step is

Figure 2. Mutual dependence of attitudes and behavior on each other.




$$B \simeq f_1\,(EX_1, EX_2) = \hat{B} \tag{3}$$

and

$$A \simeq f_2\,(EX_1, EX_2) = \hat{A} \tag{4}$$

The estimates of the endogenous variables ($\hat{B}$ and $\hat{A}$) are substituted into the structural equations to estimate the coefficients of the structural equations. The second stage can be denoted by

$$B \simeq f_3\,(\hat{A}, EX_2) \tag{5}$$

and

$$A \simeq f_4\,(\hat{B}, EX_1) \tag{6}$$

The results of the second stage can be used to test hypotheses about the relation between attitudes and behavior. For example, the interpretation of mutual dependence can be based on the statistical significance of the coefficients for A and B in Equations 5 and 6. If the coefficients for both estimated endogenous variables are statistically significant, then mutual dependence is supported.

## A Hierarchical Model

Figure 3 shows a flowgraph and a set of structural equations similar to the ones that will be discussed here. The flowgraph depicts a model in which cognitions (CONV and COMF for convenience and comfort perceptions, respectively) act as determinants of feelings (MA for modal affect). It is hierarchical because CONV and COMF indirectly influence behavior (BEH) through MA. Since there is an isomorphism between flowgraphs and structural equations, the flowgraphs provide an overall view of an interconnected set of structural relationships. Figure 3 draws the analogy for a system of Equations 7-10. The exogenous variables $EX_1$-$EX_5$ designate demographic and transport system variables.

Each structural equation defines a part of the flowgraph. For example, Equation 7 denotes BEH and the two arrows that go into it from MA and $EX_5$. The coefficients of the structural equations correspond to the arrows that link the variables in the flowgraph. It is possible to indicate the statistical significance of the equation coefficients and the corresponding linkages by placing t-statistic values on the arrows. As with the simpler model above, the computation of the coefficients and the relevant t-statistics can be achieved through two-stage least squares.

# RESULTS

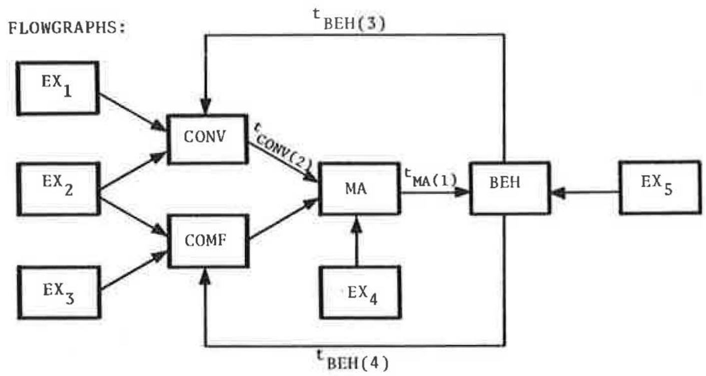
The top flowgraph of Figure 4 shows a hierarchical model derived from the FHWA bus data. The exogenous variables in the model are defined at the bottom of the figure; they will not be explicitly discussed since our focus is on the interrelations among endogenous variables. The flowgraph shows convenience and comfort perceptions that feed into modal affect. Modal affect corresponds to overall satisfaction with the bus. Behavior, namely frequency of commuting by bus, is pictured as being directly influenced by modal affect; convenience and comfort perceptions are shown to contribute indirectly to behavior through modal affect. The t-statistics for this model show that the link from convenience to modal affect is significant but the link from comfort to modal affect is not. However, this does not mean that perceptions of comfort are unrelated to modal affect; rather, when comfort is combined with convenience to predict modal affect, comfort does not add any predictive power over that obtained from convenience. The link from modal affect to behavior is highly significant.

The bottom flowgraph of Figure 4 shows a model that is identical to that in the top flowgraph except for the addition of behavioral feedback. The links from behavior back to perceptions of convenience and comfort are both significant. This confirms the findings of a previous report (4) that cognitions are influenced by behavior.

These two flowgraphs represent two alternative hypotheses about the influence of feedback on cognitions.

**Figure 3. Equivalence between structural equations and flowgraphs.**

FLOWGRAPHS:




STRUCTURAL EQUATIONS:

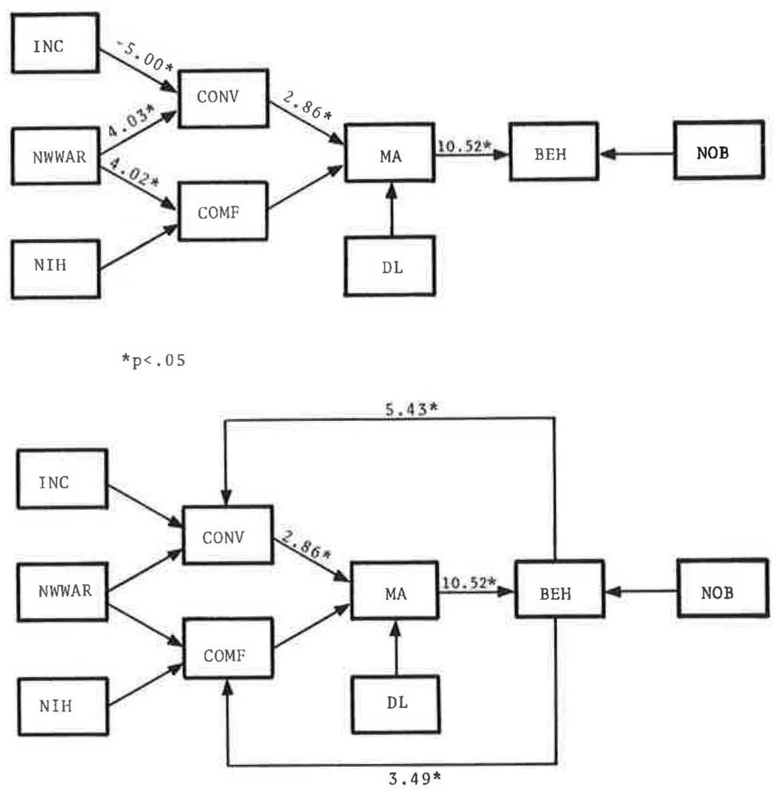
(1) BEH = f(MA, $EX_5$)

(2) MA = f(CONV, COMF, $EX_4$)

(3) CONV = f(BEH, $EX_1$, $EX_2$)

(4) COMF = f(BEH, $EX_2$, $EX_3$)

**Figure 4. Behavioral feedback in a simple attitude-behavior model.**




EXOGENOUS VARIABLES:

INC = Income

NWWAR = Number of autos in household divided by number workers in household

NIH = Number of residents in household

DL = Number of drivers licenses in household

NOB = Number of blocks

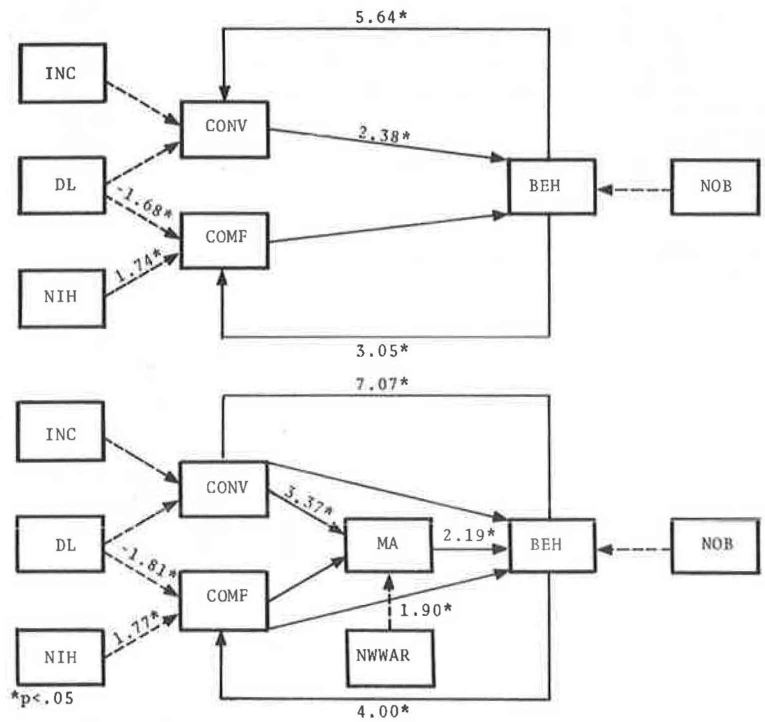



**Figure 5. Role of affect for bus attitude-behavior relationships.**

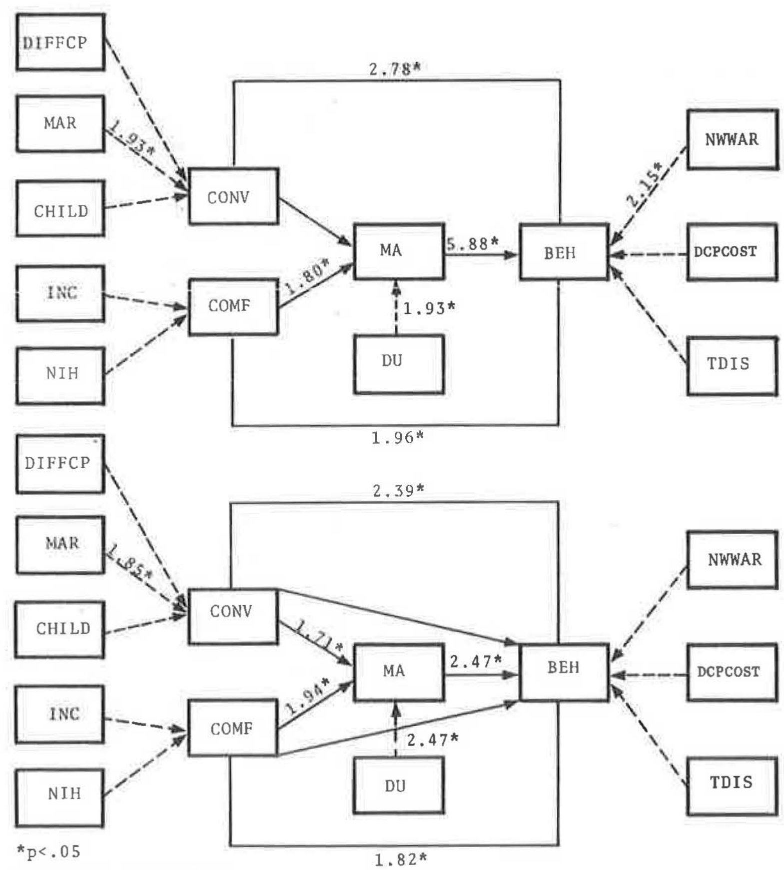


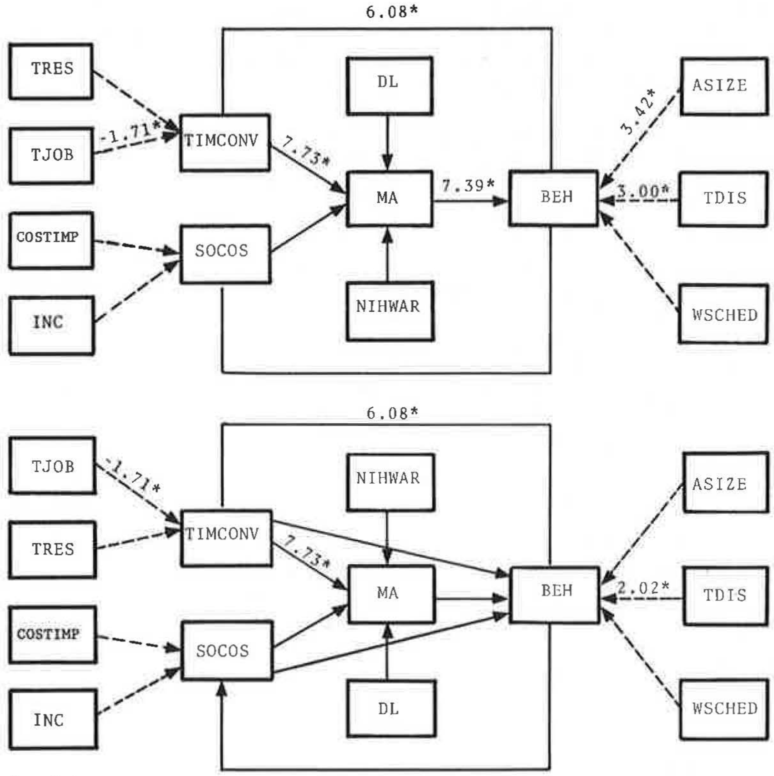

**Figure 6. Hierarchical model for FHWA carpool data.**

EXOGENOUS VARIABLES:

DIFFCP = Difficulty obtaining carpools
MAR = Marital status
CHILD = Children under 18
INC = Income
NIH = Number of household members

NWWAR = Workers-autos divided by workers
DCPCOST = Auto-carpool costs
TDIS = Trip distance
DU = Type of dweling

**Figure 7. Hierarchical model for GM carpool data.**




*p<.05

EXOGENOUS VARIABLES:

TJOB = Years at job
TRES = Years at residence
COSTIMP = Cost of carpooling
INC = Income
NIHWAR = Number in household-autos divided by number in household

DL = Regular drivers
ASIZE = Auto size
TOIS = Trip distance
WSCHED = Work schedule

A comparison of the two hypotheses permits an evaluation of the role of behavioral feedback in traveler attitude-behavior interrelationships.

Both flowgraphs verify that the attitude-to-behavior links are statistically significant. These flowgraphs support a hierarchical relationship in which perceptions influence affect and affect, in turn, contributes to behavior. When behavioral feedback is introduced into the set of relationships, the t-values of the exogenous variable antecedent of perceptions become statistically nonsignificant, but the attitude-to-behavior links remain unchanged. Behavioral feedback is highly significant with respect to cognitions, but the feedback of behavior on attitudes does not require changes in attitude-to-behavior relationships.

Figure 5 shows two flowgraphs that clarify the role of modal affect in the hierarchical model. The exogenous variables in these flowgraphs are the same as those in Figure 4 and their influence is similar. The top flowgraph in the figure shows that when modal affect is taken out of the equations, the link from convenience to behavior is significant. The link does not have as large a t-statistic as that from modal affect to behavior in Figure 4. But behavior can be predicted from beliefs on a statistically significant basis. This is the kind of link that researchers depend on when they look at the relationship between perceptions of system attributes and behavior.

However, the bottom flowgraph shows how important modal affect is in predicting behavior. The direct links from convenience and comfort to behavior are not significant when modal affect is included with them as a predictor of behavior. On the other hand, the link from modal affect to behavior is still significant. It is, perhaps, an overstatement of the case to say that all of the predictive power of convenience comes from its relationship with modal affect. However, these flowgraphs clearly show that modal affect predicts frequency of use over and above the effect of beliefs on behavior.

Figure 6 shows two flowgraphs derived from the FHWA carpool data. The endogenous variables in this model are the same ones as in the previous models. The exogenous variables are demographic and system variables that would be expected to be related to carpool usage. The link from comfort to modal affect is significant in both flowgraphs. This indicates that, relative to convenience, perceived comfort is a more important factor for carpools than it is for buses. However, our analyses of a large number of models for carpools show that comfort is not always significant. It is not a consistent predictor of modal affect. Notice also that convenience is significant in the bottom flowgraph but not in the top one. In general, perceptions of system attributes are not strong predictors of modal affect for these carpool data.

The feedback links from behavior to perceived convenience and comfort are both significant. This shows that behavior influences attitudes toward carpools as well as toward buses.

The top flowgraph shows that the largest t-statistic is from modal affect to behavior. The bottom flowgraph shows that modal affect influences behavior over and above the influence of convenience and comfort on behavior. However, the links from convenience to comfort are not significant when the influence of modal affect is included with them. These findings show that modal affect is an important predictor of behavior for carpools as well as for buses.

Figure 7 shows two flowgraphs from the GM carpool data. As noted above, the attributes rated here are different from those included in the FHWA survey. TIMCONV is a combination of the perceived convenience and perceived time savings of carpools. SOCOS is a combination of judgments of the social costs of automobiles. The measures of modal affect and behavior are similar to those used in the FHWA survey.

The top flowgraph shows that, in general, the relations are similar to those in the FHWA data. The bottom flowgraph shows that the links from convenience and social cost to behavior are not significant when the influence of modal affect is included with them. However, unlike the FHWA data, modal affect is not a significant predictor of behavior when the influence of perceived convenience and social costs is included. For this data set then, modal affect is a strong predictor of behavior but does not add any additional predictive power over perceived convenience.

## DISCUSSION OF RESULTS

This paper presents structural-equation modeling analyses of traveler attitude-behavior interrelationships. The results provide information on three topics that relate to bus and carpool usage:

1. Behavioral feedback influences perceptions of system features,
2. Convenience perceptions are more important than comfort perceptions for buses and more important than perceived social costs for carpools, and
3. Affect has incremental explanatory power over cognitions in describing bus usage.

The impact of behavioral feedback on traveler attitude-behavior interrelationships is important for several reasons. Our findings suggest that travel attitudes and behavior mutually influence each other, and it is for this reason that the exclusive study of either one by transport analysts will lead to an incomplete understanding of traveler behavior and potentially faulty policy implications for the design and operation of transportation systems. Self-reports of feature ratings do predict behavior, but behavior also changes the rating of features. From a theoretical perspective these results show that a behavioral feedback mechanism that is consistent with cognitive dissonance theory can concurrently exist with attitudinal influence on behavior. From a marketing viewpoint these findings suggest a promotional strategy that transit operators might use to increase patronage. Our results suggest that experience with a system improves users' perceptions of its features, which are in turn related to usage. Therefore, offering potential patrons free or reduced-fare rides to give them experience with a system should enhance their evaluation of it, and this in turn should increase the frequency of use.

A second promotional strategy is suggested by the links from perceptions of attributes to behavior. It would emphasize those features of a system that are most strongly related to usage. For the data sets we have analyzed, convenience perceptions stand out as an extremely important factor, which underlies traveler behavior. Perceptions about social costs of automobile driving and comfort have a weaker association with travel behavior. A promotional campaign that emphasizes convenience is likely to be more successful than one that emphasizes comfort or social costs. There may also be other features that we have not analyzed that are important to transit usage. In addition, analyses of these data reported elsewhere (22) have shown that the strength of the links between attitudes and behavior vary for different subgroups or market segments. An effective promotional strategy should, then, emphasize not only the important features but should also be targeted to specific market segments for which that factor is especially important.

Our analyses also showed that, at least for buses, the relation between perceptions of system features and behavior is mediated by their relations to modal affect. Modal affect was found to be not only the strongest predictor of behavior but also to add predictive power over and above the influence of perceived convenience and comfort. This suggests that favorable evaluations of transit attributes are necessary but not sufficient to attain transit ridership. Perceptions of attributes do influence affect, but there appears to be a component of it that is independent of the perceived attributes of a system. It may be necessary, therefore, to change a potential user's image or overall evaluation of a mode before favorable perceptions of features can lead to increased usage.

We need to achieve a better understanding of modal affect, its determinants, and what can be done to manipulate it. It may be determined by such factors as peer group norms and social class variables. We also need to know more about how market segmentation influences the interrelationships among cognitions, affect, and behavior.

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