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.

ACKNOWLEDGMENT

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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:

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

where the variables with bars are observed volumes and level of service before (0) and after (1) the system change. η 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:

$$V = V_0 (I/I_0)^{\eta} \qquad (2)$$

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

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

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

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

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

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

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:

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

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:

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

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:

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

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

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

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 volume$_2$ into Equation 7:

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

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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;
> γ = 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 α, β = 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 | | Transit | | Suburb | | Weekly Work Trips | | Nonwork Trips | | Number of Automobiles | Number of Workers | Number of Children |
		Time (min)	Cost ($)	Time (min)	Cost ($)	Time (min)	Cost ($)	Automobile	Transit	CBD	Suburb			
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.
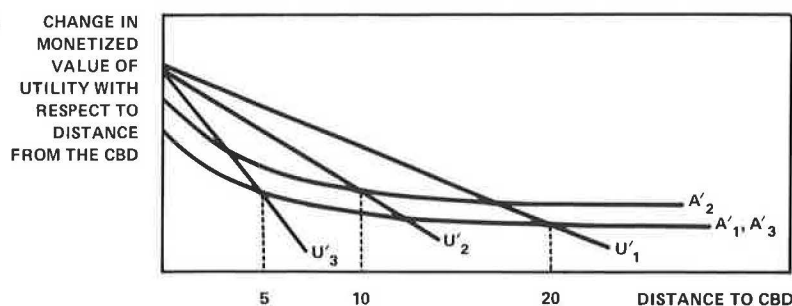
dential location is also explained.

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:

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

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

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

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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