of bias in the sampling and interviewing plans. Efforts were directed at reaching apartment dwellers, single-family households, mobile hard-to-reach households, and ethnic minorities, and these efforts were largely successful. However, it is believed that there are some minor sources of bias, as described below.

Households without telephones--1 percent of all California households--were not sampled. Persons who work odd hours, particularly those who work in the evenings, could have been missed, although calls were made during the afternoon as well as the evening hours. Extremely mobile individuals, especially young, single adults, are difficult to reach and are underrepresented in the survey. In fact, the average household size in the sample is higher than in the 1980 Census due to higher probability of persons being home to answer the telephone. The lack of call-backs during the last week of the survey introduces a bias against hard-to-reach households; however, since this procedure represents only 1/10 of the survey, the bias would be a minor one. Households that refused to participate in the survey (28.7 percent) may represent a bias. Data collected on some of these households and individuals show little variation when compared with data on interviewed households; there appears, however, to be a slight underrepresentation of households with low or no car ownership and of elderly persons, particularly elderly females.

## RECOMMENDATIONS AND CONCLUSIONS

The three recommendations for future surveys are (a) generate better publicity by augmenting news releases with personal visits to media staff, (b) hire quality interviewers, and (c) modify the travel card, as noted in the section on coding problems, to provide more specific location information. The experience with this survey showed that it is still possible to conduct a household-interview travel survey at reasonable cost and in a short time period. Telephone interviewing is a cost-effective technique for obtaining household travel data. The survey sample provides adequate geographic coverage and is representative of population groups in the Bay Area. It is believed that this success is due to (a) making interviewers aware at the beginning of the need to obtain responses from all population groups and (b) the use of random digit dialing to draw the sample.

## ACKNOWLEDGMENT

The work reported in this paper was financed in part through grants from the Urban Mass Transportation Administration, U.S. Department of Transportation, under the Urban Mass Transportation Act of 1964, as amended.

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Publication of this paper sponsored by Committee on Public Transportation Planning and Development.

# Simultaneous-Equations Analysis of Growth in Bus Route Patronage in San Diego

#### MICHAEL A. KEMP

An analysis of data describing 40 months' operating experience for the San Diego Transit Corporation bus system is discussed. The analysis used a simultaneous-equations model estimated by using a pooled time-series/crosssectional data base. The model relates the ridership on a specific bus route in a specific month to various influencing factors, particularly the service and fare policies adopted by the system. It also attempts to capture complex interrelations among the influencing factors. The structure of the overall model is summarized. Detailed results, however, are discussed for only one of the five equations in the system, the principal demand equation. Relatively clear bus fare and gasoline price effects were identified, but the separate influence of each of a range of service quality variables (average bus speed, average waiting time, mean stop spacing, and duration of service) was obscured by multicollinearity. Estimates of demand elasticities with respect to a range of different influencing factors are presented, along with associated confidence intervals. Several general conclusions from the analysis are discussed. The work shows that it is possible to use a transit system's time-series operating data in more sophisticated ways than have been customary: The model proved successful in identifying credible structural equations for both demand and supply relations. However, multicollinearity problems are probably intrinsic to the overall approach, and replications of the method are currently strongly constrained by the lack of appropriate computer software. Some potential uses of a model of this type are also discussed.

The San Diego Transit Corporation (SDTC) assumed operation of that city's bus system in July 1967 after purchasing it from a financially ailing private owner. Public takeover was followed by greatly increased funds for capital and operating assistance from local, state, and federal governments, and service was expanded through the introduction of new routes, extension of service periods, and increased frequencies. Between 1971 and 1975 the annual vehicle miles operated increased by 81 percent, route miles grew by 57 percent, and the fleet size and the work force expanded by 54 and 66 percent, respectively.

The service area provided a favorable setting for expansion. Compared with other cities of comparable population and land area, San Diego was growing fast and had a small bus system with relatively low ridership per capita. The large increase in supply, coupled with a major fare reduction in 1972 and a determined effort by the transit management to promote the services, produced a marked response in demand. Between 1971 and 1975, annual ridership rose by 114 percent.

Moreover, SDTC generated monthly operating data that were superior in scope, detail, and quality to the norms for U.S. bus transit properties. This report derives from a study of 40 months' operating experience for the system, over a period when service and ridership were both expanding most rapidly (January 1972 through April 1975). The primary focus of the work has been to estimate a simultaneous-equations model of demand and supply by using a pooled time-series (by month) and cross-sectional (by bus route) data base. Full details of the analysis are presented elsewhere (<u>1</u>). The intent of this paper is to discuss the principal findings with respect only to the demand for rides on the system.

# OVERVIEW OF MODEL

Any serious attempt to understand the demand for public transportation services needs to take explicit account of the complex interrelations among demand, supply, and service quality. There is ample evidence that travel behavior is influenced strongly not only by the prices of the various available options but also by the characteristics of the service that each provides. Such aspects of service quality as travel times and reliability have been found to be particularly influential in the decisionmaking of travelers. But service quality is in turn affected by both the level of supply and the level of demand. Speaking broadly, changes in the quantity of transit services supplied are likely to affect such aspects as route coverage, frequency of service, the possibility of getting a seat, and so on. And, for a given level of supply, adjustments in the level of demand will imply changes in the crowding within vehicles and in the time that has to be spent picking up and dropping off passengers.

It follows that the observed long-run ridership response to a supply or fare change can be regarded as the net result of two component processes:

1. The fare or supply adjustment (the "instrumental change") itself influences demand in that it implies a change in the price or level of service experienced when traveling by transit.

2. The "direct" demand response will create additional adjustments in service quality, potentially influencing ridership volumes further. This process can be referred to as an "induced" or "secondary" effect.

Transportation analysts are not unfamiliar with interactions like these, for they apply analogously to the demand for highway travel. Both highway facilities and most passenger transportation services can be characterized broadly by the following relations. Traffic volume (q) is a function of, among other things, the level of service provided by the highway or the public transportation facility:

$$q = D(L, \ldots) \tag{1}$$

where L is a vector of level-of-service attributes, including money price. The level of service itself depends both on the design and operational characteristics of the transportation facility and on the traffic volume, through "performance function" relations of the following sort:

$$L = P(T, q, \dots, s) \tag{2}$$

where T is a vector describing the design and operation of the facility. (3)

There is also a third type of relation that influences the observed levels of demand and supply. Since transit services cannot be stored or stockpiled, there is a strong incentive for the system to anticipate temporal and spatial variations in demand and to adjust the supply accordingly. The extent to which this is done in the short run is likely to vary between different properties, but over the long run it is likely that most transit systems will be supplying most service at those times and places where the demand is greatest. In consequence, one must anticipate a third relation of the following form:

 $T = S(\hat{q}, \ldots)$ 

where  $\hat{q}$  is the transit management's expectation of q. The principal analytical problem is to specify these structural relations and to attempt to identify them from observations of equilibrium flows and service levels.

The San Diego model comprises five equations estimated stochastically, one definitional identity, and one assumed relation:

1. Demand relations--(a) The volume of passengers (on a particular route in a particular month) who do not transfer between routes (QNT) is expressed as a function of a large number of influencing factors, most significantly those describing the price and service quality of the average transit ride on the route, and (b) the volume of transfer passengers (QTR) is estimated as a function of total ridership (Q) and other factors.

 Performance functions--(a) Average bus speed
 (V) is related to, among other things, bus-stop density and the average number of riders per bus stop passed.

3. Supply relations--(a) Seat miles operated (S) are estimated as a function of the current month's patronage on the route, the short-run average variable costs, and certain financial and capacity constraints; and (b) average headway (H) is related to total seat miles operated, the average number of passengers per hour of service duration, and other factors.

 Definitional identity--The various measures of patronage are related through the identity,

$$ONT + 20TR = 0 \tag{4}$$

where QTR has a coefficient of 2 because nontransferring patronage (QNT) is measured by the difference between originating trips and transfer trips.

5. Assumed relation--Mean waiting time at a bus stop (W) is related to the mean headway on the route (H) through

 $W = A[1 - \exp(-H/2A)]$ <sup>(5)</sup>

For high-frequency services, mean waiting time is approximately half the headway; for long headways, W approaches a maximum of A, taken to be 20 min.

The model was estimated by using data from 21 routes that were in existence for the full 40 months of the study period. This provided a total of 840 observations. These routes accounted for 99 percent of the systemwide patronage at the start of the study period and 86 percent by the end. All five stochastic equations were estimated by the two-stage least-squares method, with a correction for first-order autocorrelation by means of a generalized least-squares procedure.

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#### DEMAND FOR NONTRANSFER RIDES

The variable QNT (nontransfer rides) represents an estimate of the number of passengers on a particular route in a particular month who do not transfer to or from any other route in the course of their journey. Whereas their numbers cannot be inferred precisely from the data set, unless the pattern of transfers between routes is markedly asymmetrical (that is, many more riders transfer from a route in a month than transfer to it), the nontransfer patrons are approximated by the difference between the originating passengers and the transfer passengers on the route; i.e.,

Q	NT = C	)R - (	)TR
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(6)

where QR is a count of originating (or "revenue") passengers--i.e., each patron is counted once only in the course of a journey, as he or she boards the first (or only) bus used in the one-way journey; and QTR is the number of transfer passengers--i.e., patrons boarding the second (or subsequent) vehicle used for the one-way journey.

QNT is preferred to QR as the dependent variable in the equation because it represents journeys that do not involve any transferring and that presumably will be made as a result of appraisal of the relative service characteristics offered by that route alone. Empirically, it was confirmed that using QNT was slightly superior to using QR. It should be noted that passenger counts must be used here for the dependent variable because typical transit operating data do not contain any origin-destination information. For the same reasons, there is no stratification by peak/off-peak or trip-length characteristics.

The range of factors that can influence the patronage on a particular bus route in a given month is obviously large. The primary focus of this analysis was on the influence of bus service characteristics in order to determine how instrumental changes made by the transit agency influenced patronage. But variations in the observed demand may be attributable to many other factors, and in order to avoid specification bias due to missing variables one should consider explicitly all possible sources of variation when specifying a demand function. In this work, the approach was to quantify as far as practical the characteristics of the bus service and alternative automobile journeys and to use dummy variables in an attempt to take account of the remaining factors, such as the characteristics of the markets served.

The estimate of the demand function for nontransfer rides is summarized below. In this equation, variables treated as endogenously determined have been identified with an asterisk. Reduced-form equations were first estimated for these variables by using the complete set of exogenous variables as regressors, and the predicted values of the variables were used in estimating the structural equations:

$$QNT = 216.7 - 81.69PB + 14.53PG + 0.7843V^* - 0.4606 \log W^*$$
(3.1) (6.1) (1.7) (1.2) (0.0)
+ 0.070 49Y - 794 4BINV + 0.3789F - 5.546L - 11.14NWD

$$(3.5)$$
  $(2.9)$   $(2.8)$   $(10.6)$   $(1.9)$ 

where

QNT = number of nontransfer patrons (000s); PB = mean bus fare (1967 dollars);

- PG = real gasoline index (January 1972 = 1.0);
- V = average scheduled bus speed (miles/h);
- W = average passenger wait time (h);
- Y = duration of service (h/month); BINV = average bus stop spacing (miles);
- E = gasoline supply shortfall (percentage of expected demand);
  - L = route length (miles);

1).

- NWD = proportion of nonworking days in the month;
- SCHL = ratio of school days to working days; and
- T = month sequencing variable (January 1972 =

The values of the t-statistic appear in parentheses beneath each coefficient value. The mean value of the dependent variable was 54.09, and that of the coefficients of the route-specific dummies was 10.65. A two-stage least-squares estimation method, autocorrelation-corrected (an asterisk denotes instrumental variables), is used;  $R^2$  (adjusted for degrees of freedom) = 0.934 and F (31 808) = 365.1.

As might be expected with such a large number of independent variables, the nontransfer patronage equation exhibited high levels of multicollinearity in all of the many specifications tested. This was most problematic for the variables that differed mostly across routes rather than over time. Unfortunately, some key aspects of service quality-bus speed, mean waiting time, and average bus-stop spacing--fall in this category, and the estimates of their effects have a relatively high level of uncertainty.

All of the signs of the estimated coefficients for Equation 7 either conform with a priori expectations or else can be rationalized credibly. In the discussion that follows, each of the key variables appearing in the nontransfer patronage equation is reviewed in turn, and the 95 percent confidence range is indicated for the demand elasticities with respect to each variable (see Table 1). Many alternative specifications of the equation were estimated, and these generally implied elasticity values within the confidence ranges given in Table 1.

## Price Variables

Two of the variables in the equation measure prices: PB measures the real price of a complete bus trip (from joining the SDTC system to leaving it), and PG traces the real price of gasoline as a proxy for the costs of making a competitive journey by private car. The coefficient (and hence the implied elasticity value) for the bus fare variable remained relatively stable as the model specifica-

Table 1. Ninety-five percent confidence range for elasticities with respect to key variables.

	Elasticity Value at Mean of All Observations			
Variable	Expected	Lower Limit <sup>a</sup>	Upper Limit <sup>a</sup>	
Mean bus fare (PB)	-0.31	-0.21	-0.41	
Gasoline price index (PG)	+0.29	-0.05	+0.63	
Mean bus speed (V)	+0.24	-0.16	+0.63	
Mean wait time (W)	-0.01	-0,54	+0.52	
Service duration (Y)	+0.65	+0.29	+1.01	
Mean stop spacing (BINV)	-2.65	-0.85	-4.45	
Gasoline shortfall (E)	+0.01	+0.00	+0.01	
Route length (L)	-1.57	-1.28	-1.86	
Nonwork days (NWD)	-0.06	+0.00	-0.13	
School days (SCHL)	+0.10	+0.08	+0.12	

<sup>8</sup> The values given represent the 95 percent confidence limits for the elasticity estimate, assuming that the means of the dependent and independent variables are given. In other words, the standard deviation of the regression coefficient is taken as the only source of uncertainty in the elasticity value. tion was changed. Associated values of the t-statistic typically showed the variable to be significant at the 0.1 percent level. At the mean of the observations, a fare elasticity of -0.31 was implied and a 95 percent confidence range of -0.21 to -0.41. The values obtained from alternative model specifications tended to cluster in the numerically high end of the range, around -0.3 to -0.4.

The estimated equation for transfer rides (QTR) can be combined with this equation to derive fare elasticity values associated with some other definitions of patronage. For instance, the elasticity for originating (or revenue) passengers (QR) was -0.29, for transfer rides (QTR) it was -0.22, and for total ridership (Q) it was -0.27. These relative magnitudes are consistent with a hypothesis that the people who will tolerate having to transfer are more likely to be captive to the system.

Almost all of the variation in the PB variable occurred over time rather than across routes, and most of it was associated with the major fare reduction that took place in September 1972. The base fare was cut from 40¢ to 25¢, and all zonal surcharges were abolished. This meant that in some cases rides that had previously cost as much as 90¢ were reduced to 25¢. Other analyses of this fare reduction have provided independent estimates of the fare elasticity. Kemp (3) used systemwide operating data for a period of 38 months to derive point elasticity values at the mean of roughly -0.55 to -0.6, after taking account of the changes in bus miles operated. Conway  $(\underline{4})$  compared the March 1973 patronage for an aggregate of 19 routes that did not experience major service changes with the figure for March 1972 and computed an arc fare elasticity estimate of -0.72, uncorrected for the 6 percent increase in bus miles on those routes. Goodman, Green, and Beesley (5) used systemwide statistics from the same data base used in the present study to derive a point fare elasticity value at the mean of -0.51, after accounting for the effects of the growth in bus miles operated. All of these estimates are larger numerically than the estimate from this study. This is probably due to the much greater number of explanatory variables used here and in particular to the incorporation of a gasoline price variable; it is also partly due to the use of constant dollar prices in this analysis, a practice not followed in any of the three earlier studies.

Estimates of the coefficient of the gasoline price variable (PG) were also quite stable. The Equation 7 specification implies an elasticity of nontransfer patronage with respect to gasoline price of  $\pm 0.29$  and a 95 percent confidence range of  $\pm 0.05$ to  $\pm 0.63$ . Values implied by other specifications of the equation ranged from  $\pm 0.26$  to  $\pm 0.46$ .

# Bus Service Characteristics

Equation 7 contains four variables that are aspects of transit service quality: average bus speed, average passenger wait time, average bus-stop spacing, and monthly duration of service. The lion's share of the variation in all of these variables was caused by differences across routes rather than over time. Multicollinearity presented a problem in identifying the individual effect of each variable, and the elasticity estimates consequently have a higher level of uncertainty than was found for the price variables.

Duration of service (Y) was the most significant of the four service characteristics. In Equation 7 the coefficient is significantly different from zero at the 0.04 percent level. This variable captures three sources of variation: differences in month lengths, changes in the operating hours on certain routes, and (most important) differences in operating hours across routes. The implied demand elasticity at the mean with respect to Y was +0.65, and the 95 percent confidence interval was +0.29 to +1.01. Estimates derived from other specifications ranged from roughly +0.30 to +1.69.

The next service characteristic in order of explanatory power was average bus-stop spacing (BINV), which served as a proxy for mean walking time to and from the bus. The negative coefficient value was significantly different from zero at the 0.4 percent level. The implied elasticity value at the mean of the observations was -2.65.

The best available supply-oriented descriptor relating to bus travel time was average operating speed, if it is assumed that journey distances were determined independently of speed. According to the model, there are two ways in which ridership is expected to be associated with bus speed. In the demand equation, higher average speeds are associated with shorter travel times, and this should help to boost ridership. But on the supply side, increased demand at a fixed level of supply tends to slow down the buses. The two effects work in opposing directions, and a negative correlation coefficient between QNT and V (-0.24, significantly different from zero at the 0.1 percent level) suggests that the supply-side process was the stronger of the two.

It says a great deal for the overall specification of the model, therefore, that in all of the demand functions tested the speed variable emerged with a positive sign, after correction for autocorrelation. In other words, despite a net negative correlation between demand and speed, the model structure was able to separate out credible demand- and supply-side components of the overall association. The coefficient of V in Equation 7 implies an elasticity of +0.24 at the mean of the observations.

If it is assumed that the reciprocal of the speed variable is proportional to the average travel time in the bus, the elasticity of demand with respect to in-vehicle time is -0.23 at the mean of the observations. The extent to which the inverse of speed is a good indicator of travel times, however, depends on how much passenger trip lengths vary across routes. If trip lengths do vary significantly (and there is circumstantial evidence to suggest that they do), then the elasticity with respect to the reciprocal of V will provide a biased estimate of the in-vehicle time elasticity.

The fourth characteristic of bus service appearing in the nontransfer patronage equation is mean passenger waiting time (W). But, despite its strongly negative correlation with nontransferring rides, the multicollinearity problem led to a wide range of different coefficient estimates, many with anomalously positive signs. This is despite the fact that demand- and supply-side forces in this instance are likely to be mutually reinforcing: Shorter wait times should spur demand, and increased ridership will create a reason to reduce headways. But the coefficient value in Equation 7 is barely negative, implying an elasticity value with respect to W of -0.009 at the mean of the observations.

The findings from this equation suggest that, in comparing the various components of passengers' door-to-door travel times, demand was most sensitive to walking time and least sensitive to waiting time and the sensitivity to in-vehicle time was intermediate between the two. This general hierarchy was sustained for most alternative formulations of the equation. The relatively low elasticity for waiting time is somewhat out of line with the consensus of previous research findings, most of which are derived from cross-sectional analyses of tripmaking and might, therefore, be expected to produce numerically higher absolute values for the elasticities. Waiting-time elasticities are generally believed to be greater than elasticities for in-vehicle time, although a number of studies have produced values in the same hierarchy found here.

# Other Explanatory Variables in the Equation

Of the remaining variables appearing in the equation, the length of the bus route (L) was clearly the most influential. This variable had a high explanatory power and relatively stable negative coefficient, significant at the 0.1 percent level, in every specification of the nontransfer patronage equation in which it was included. The elasticity value at the mean with respect to L was -1.57.

The clearly negative effect of bus-route length on demand merits discussion. One might expect that this variable most strongly represents the size of the population of the catchment area, which would presumably imply a positive effect on patronage. This expectation is reinforced by a highly significant positive correlation coefficient between L and QNT (+0.59). In the presence of the set of routespecific dummy variables, however, some underlying factor causes the variable to appear in the demand equation with an unambiguously negative sign and a relatively sharp coefficient value. The most likely explanation is that all of the "market-size" effects have been (as hoped for) loaded onto the route dummies and that the route length is standing proxy for a journey-length variable. If, as seems credible considering the high proportion of transit trips that are typically for commuting, longer routes imply longer average trip distances, then L is probably characterizing the effects of competition with travel by private automobile. The travel time, comfort, and convenience advantages of car travel will increase guite markedly with trip length, particularly on a reasonably free-flowing highway network such as that in the San Diego area. The longer the trip, the more attractive it appears for potential patrons to choose the private automobile in preference to transit, all other factors remaining constant. Such a rationale is consistent with a great deal of the empirical evidence and analysis of modal-choice behavior, and it is a quite credible explanation for the strength of the effect observed in the model.

The variable E measures the percentage shortfall in gasoline supplies in the State of California for a period of seven months as a result of the 1973-1974 oil embargo by the Organization of Petroleum Exporting Countries. During this period there was a national surge in transit ridership. The positive coefficient for the E variable, significant at the 0.6 percent level, suggests that the SDTC system shared in this temporary surge in ridership. Part of the effect is, presumably, captured by the gasoline price variable. The patronage elasticity with respect to the nonprice aspects of the shortage, as characterized by E, was +0.006, which denotes a small but nevertheless statistically significant effect.

#### GENERAL CONCLUSIONS FROM SAN DIEGO STUDY

The San Diego analysis provided substantial evidence on many of the questions that were identified as objectives of the study. These questions can be broadly grouped as either "methodological"--concerned with the value and practicalities of using this type of method to analyze transit demand and supply--or "substantive"--concerned with the actual findings from the San Diego experience. The methodological issues are the more important of the two categories in the scope of their implications.

First, this work shows that it is possible to use the time-series operating data of a transit system in somewhat more sophisticated ways than have been customary in the past. Although the problems and deficiencies of the approach must be acknowledged, overall the exercise was judged to be quite successful. In particular, the ability to identify meaningful demand and supply functions is impressive, especially so in the case of those variables (such as average bus speed) for which it has proved possible to separate out different demand- and supplyside relations with ridership. Also remarkable is the extent to which guite simple model formulations produced coefficients and signs substantially in line with theory and consensus evidence from other empirical studies.

Second, beyond the scope of the one model equation reviewed in this paper, it was also encouraging that some of the effects that, a priori, one might expect to be fairly subtle in nature and magnitude appear to be detectable by this method despite the level of aggregation of the data, difficulties in measurement, and the need to characterize certain influences very imperfectly. Since a large number of previous studies have been able quite easily to identify simple yet credible transit demand relations from time-series operating data, the success of this study in doing so is not remarkable; what is more innovative and notable is the ability to identify both an average-bus-speed equation and a meanheadway equation.

A third general conclusion from the San Diego study is that multicollinearity problems are likely to make it difficult to fine-tune the demand equation sufficiently to provide precise estimates of service elasticities by using this method. The multicollinearity problems encountered in the San Diego analysis are unlikely to be unique to this data set but are probably intrinsic to the overall approach. They appear to be the result of several factors: the large number of causal variables included in the demand equation, the need to use route-specific dummy variables to take account of market-size variations across routes, the practice of concentrating service changes into a small number of points in time, and intercorrelations between service variables caused by operating policies. Investigations suggested that one standard approach to alleviating multicollinearity--adding more observations--would not be likely to provide much relief in the San Diego case despite a greatly increased variability in key service variables as data on express and feeder routes were added. The time-series transit demand model estimated by Gaudry (6), which also incorporated a large number of independent variables, suffered from a similar multicollinearity problem.

The final methodological conclusion is that both this work and any attempted replications of the method with other data sets are strongly constrained by the lack of appropriate software packages able to cope flexibly with pooled time-series/cross-sec-tional data. Despite an initial concern to keep costs low by restricting the study to using readily available data and off-the-shelf software, the exercise proved to be quite costly in terms of both analyst time and computer time. In part, this was because of the large number of variables considered, but it was also largely because of the cumbersome and inflexible method that had to be devised to manipulate the data and to estimate the model by using available programs. Although the development of similar models for other transit systems could have considerable value for short-range planning purposes (as discussed below), the benefits of doing so will probably not outweigh the costs until more appropriate software is available.

USES OF THE MODEL

How might a model of the San Diego type be used productively? What are its advantages and limitations? First, the model can make a valuable shortrange planning tool for forecasting the outcomes of fare and service changes on an existing route network. If the structural equations have been estimated over a fairly wide variety of service conditions or service changes (as in the San Diego case), they can be used to produce predictions of, say, the patronage response to adjustments in headway or average speed or to changes in fare level or structure or duration of service. With the exception of forecasting the demand response to a systemwide fare change, transit planners generally do not have the tools available to allow them to make good ex ante assessments of a range of possible operating policies. The San Diego type of model could be particularly valuable for this type of planning and management application; once estimated, the model could be updated periodically at a quite low level of effort and cost to incorporate the most recent operating experience.

For short-range planning purposes, the multicollinearity in the demand equation should not present any serious problems, unless perhaps a proposed service change contravened previously established operating policies. The restriction of the model to appraising service changes on the existing route network only is caused, of course, by the decision not to include variables that describe the size and structure of the catchment area of each route. Because of this, the model does not take account of the varying propensities of different types of people to use transit services. In theory, these types of effects could easily be incorporated into the model by making the effort necessary to add data on, say, the numbers of residents and jobs located within a given distance of each route and the types of people in those homes and workplaces. In practice, this extension to the demand equation might prove to be problematic, for it would be impossible to obtain monthly time-series data for these variables and it would therefore be necessary either to change the structure of the data base or to interpolate the demographic and socioeconomic data from the 1970 and 1975 censuses.

So, as the model currently stands it cannot provide strong guidance as to the likely performance of alternative new route alignments or indicate which of the existing routes may have the demographic and socioeconomic conditions most conducive to service expansion. The same constraint also limits the transferability of the demand elasticity findings to other areas or systems, although the usual robustness of transit elasticity values and the fact that the values obtained in the San Diego analysis lie invariably within the ranges established in the most comprehensive surveys suggest that the findings may have some wider transferability.

These limitations aside, the most valuable use of a San Diego-type model would be to simulate a set of possible service or fare policy changes in order to forecast the near-term patronage (and hence gross revenue) implications of each. If the estimation period for the model were up to date, then predicting the monthly ridership and farebox revenues for each of the policy options over the next full fiscal year should be a relatively simple exercise. Coupled with some improved operating cost models that would allow one to project the cost implications of the various policies under investigation, such a model would provide a very valuable tool for operational planning. It would be particularly suitable to assessing which routes stand to show the largest ridership gains from spending a given sum on service enhancement or, conversely, where costs might be reduced for the minimal loss in patronage.

The second major application of a model of this type lies in the interpretation of the ridership data generated by, say, an experiment that involves significant fare and service changes. A good example of the type of demonstration that would probably benefit from using a similar analysis approach is provided by the series of UMTA-sponsored experiments with various forms of fare reduction or fare abolition carried out in the late 1970s. In these demonstrations, a major focus was on identifying the patronage response ascribable to the fare change alone in order to provide a basis for predicting the ridership implications of more extensive or more radical fare-reduction policies contemplated for other cities. Insofar as the demonstrations created significant ridership gains, the possible interactions between the operating policies, the patronage volume, and the resultant service quality need to be considered if the effects of the fare change per se are to be correctly identified. An analysis scheme of the type developed for the San Diego bus system offers a means of doing this without extravagant data requirements.

#### ACKNOW LED GMENT

The work reported in this paper was supported by funds from the UMTA Office of Service and Methods Demonstrations. Gershon Alperovich and Keith Goodman contributed importantly to the work, and Vincenzo Milione, the UMTA contract monitor, provided valuable advice. The opinions are mine and do not necessarily reflect the views of the Urban Institute or the research sponsor.

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Publication of this paper sponsored by Committee on Public Transportation Planning and Development.