contracts for service. In particular, small paratransit operators generally lack the resources and experience necessary to prepare detailed proposals or negotiate service contracts. Therefore, a willingness on the part of the city to offer such assistance may be desirable in order to encourage operators to bid and thus increase the competition among bidders to provide the service.

5. Administrative costs of user-side subsidy arrangements are likely to be higher than average, due to the need to monitor the ticket system, conduct contract negotiations, and oversee reimbursement procedures.

6. The system for prepurchasing tickets is costly to administer and may discourage ridership; however, such a system may be a necessary safeguard against fraud.

7. The user-side subsidy arrangement does appear to create an incentive for providers to eliminate unproductive service, although the providers generally did not initiate any major service revisions during this project.

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Elasticity Measures of Behavioral Response to Off-Peak Free-Fare Transit

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Changes in transit ridership behavior in response to the elimination of off-peak transit fares are examined. Empirically, the analysis is based on data collected for a one-year free-fare demonstration sponsored by the Urban Mass Transportation Administration in Trenton, New Jersey. Fare elasticity of demand is used as the measure of behavioral response. Important to the analysis is the clarification of distinctions among different measures of fare elasticity. In order to both illustrate the differences among types of elasticity and demonstrate the separate impact attributable to the choice of estimating technique, several techniques are applied and their results compared. It is concluded that the demand response to fare elimination is inelastic and that variations among individuals in the extent of response cannot be associated with differences in socioeconomic characteristics. Free fare is therefore judged not to be a direct means of fulfilling the transportation needs of socioeconomically defined population groups.

Between March 1, 1978, and February 28, 1979, the Office of Service and Methods Demonstration of the Urban Mass Transportation Administration (UMTA) and the New Jersey Department of Transportation sponsored the elimination of the existing 15-cent off-peak bus fare in Trenton, New Jersey, and surrounding Mercer County. The peak fare was unchanged until December 1978, when it was increased to 40 cents.

The major objective of this study was the examination of changes in transit use behavior by the Trenton area population in response to the elimination of bus fares during off-peak periods. Two major conclusions result. There was an inelastic response to the fare elimination, and little of the variation in responsiveness among individuals could be explained by socioeconomic differences. Furthermore, elasticity estimates are shown to be sensitive to the particular elasticity definition chosen, the functional form of the demand curve, the initial conditions against which changes are measured, the estimation technique applied, and the data used.

The first part of this paper reviews the concept of demand elasticity as a measure of responsiveness to fare change. A discussion of alternative measures of elasticity is presented.

The second part of the paper presents the results of estimating elasticities from data collected in Trenton. Elasticity estimates are obtained by four different procedures.

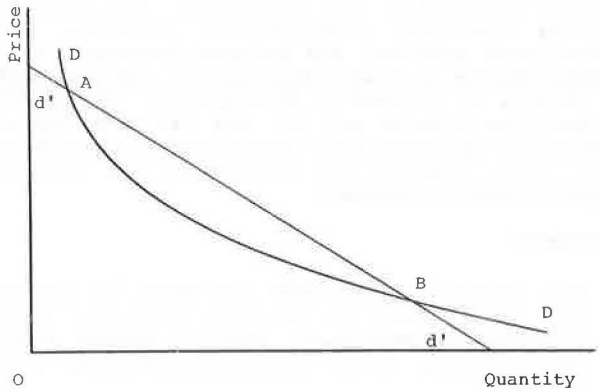
ELASTICITY MEASURES

In many studies of fare-change response, there has been inadequate recognition that there are a number of related (though nonequivalent) measures of demand elasticity. Failure to distinguish among elasticity measures results in two kinds of error. First, inferences appropriate to one type of elasticity have been drawn from estimates of another type. Second, there is a tendency for elasticities of different types to be compared directly and for conclusions to be drawn from differences or similarities in their values.

Elementary Properties of Demand Curves

To clarify the differences among alternative elasticity measures, several underlying properties

Figure 1. Linear and convex demand curves.



of demand curves should be pointed out. First, since factors other than price influence how much of a commodity people would be willing to buy, the expression of demand as a function of price alone requires either that other factors be held constant or that an explicit accounting be made of those factors.

Second, there is a distinction between the demand of an individual and that of a group of individuals. The former is a characterization of individual behavioral response; the latter is a characterization of group response and, as such, of overall market structure. While the market demand curve is simply the aggregate of individual demand curves, its shape will not in general be a scaled-up version of individual demand except in the rare circumstance where all persons in the market exhibit identical demand. Even if the individual demand curves are linear, the market demand curve is generally convex to the origin.

Finally, there is the problem of the time frame to which a particular demand curve applies. When a price is changed, individuals immediately begin adjusting to the new price level. Some adjustments can be made more quickly than others. Unless adequate time is allowed for full adjustment to take place, the measured response to a price change will be incomplete.

Definition of Elasticities

Having outlined some of the elementary properties of demand curves, we can now turn our attention to the definition of elasticities and their interpretation. The expression for an elasticity may be written

$$\begin{aligned} e &= (\text{percent } \Delta Q)/(\text{percent } \Delta P) \\ &= (dQ/dP)(P/Q) \\ &= \text{ratio of the marginal function } (dQ/dP) \text{ to the average function } (Q/P) \end{aligned} \tag{1}$$

where

e = price or fare elasticity of demand,
P = price or fare level, and
Q = volume of ridership per period of time.

Strictly speaking, this is the expression for point elasticity. It provides a measure of responsiveness for very small movements along a demand curve. By comparison, for measurably large price changes an arc elasticity is calculated; the arc is the segment of the demand curve that lies between the initial and the final equilibrium points. The expression for an arc elasticity can be written $(\Delta Q/\Delta P)(P/Q)$. If the demand curve is linear, the ratio dQ/dP is constant along its length and is equal to $\Delta Q/\Delta P$. Thus, with a linear demand curve it is possible to take any pair of points, to use them to determine $\Delta Q/\Delta P$, and, by multiplying the ratio of changes by the ratio of P and Q at a selected point, to find the point elasticity for any point on the demand curve. The value of the point elasticity ranges from infinite (where Q is zero) to zero (at the point where P is zero). This observation illustrates an important compromise in the use of an arc elasticity. The arc elasticity assigns a single value for the entire arc. However, since the point (or actual) elasticity varies across the range, the arc elasticity is only an approximation. The larger the range, the greater the difference between point elasticity at its upper and lower ends and hence the greater the compromise involved in using the arc elasticity.

Now consider the case in which the demand curve is not linear. Recall the earlier discussion of aggregating individual demand curves into a market demand curve. One important result was the tendency for the market demand curve to be convex to the origin. This result was obtained when the individual curves were linear. If the individual curves are themselves convex, the curvature of the market demand curve will be accentuated.

In Figure 1, DD is the actual demand curve, A and B are the two observed points, and d'd' is the linear approximation to DD implicit in the arc elasticity formula. At point A the slope of DD is greater (in absolute value) than is that of d'd'. At B the slope of DD is less than that of d'd'. Since the ratio of P to Q is the same between DD and d'd' at each of the points and since the point elasticity is the inverse of the slope times the ratio of P to Q, the arc approximation to point elasticity at A measured along d'd' is greater than that measured along DD. The reverse ranking holds at B. The arc elasticity therefore overstates the point elasticity at A. The greater the curvature is in DD or the farther apart are A and B, the greater is the distortion.

THE DATA

Over the course of the demonstration, several types of data were collected, including self-administered on-board surveys in November 1977, May 1978, and October 1978; telephone surveys in November 1977 and October 1978; and a series of six systemwide ridership counts to document overall changes. The two sets of autumn surveys were central to the original evaluation strategy. Their timing was intended to remove the effects of seasonal fluctuations. For the two telephone surveys, some individuals were selected from listings in the telephone book and others from among those who volunteered their telephone numbers during the corresponding on-board survey. The inclusion of those from the on-board survey raised the overall proportion of bus users in the sample.

The six systemwide ridership counts were made in November 1977 and in February, March, May, July, and October 1978. For each count, observers were positioned on three downtown street corners. The corners were selected so that some observer would have access to every bus that entered the downtown area.

Each of the survey types was, in a statistical sense, drawn from a different population. This has implications for either comparisons among surveys or pools of data between surveys. The sampling for each of the on-board surveys was from all trips made on Mercer Metro during the relevant survey week.

For the telephone surveys it was from the population of households, except for the on-board follow-up subgroup. As an illustration of what these differences imply, consider the following. If we assume that all trips had equal probability of being drawn in an on-board survey, an individual's probability of being drawn was directly proportional to his or her trip frequency. A person who made four trips during the survey week had twice the chance of being surveyed as did someone who made two trips. On the other hand, trip frequency did not influence the chance of being drawn in the telephone survey. Thus, the likelihood of an individual's being sampled did not have the same relationship to sample size in one type of survey as it did in the others.

ESTIMATION

For the estimation of elasticities there are two general approaches--aggregate and disaggregate. The former requires a series of at least two observations taken over time. The latter can be estimated either for a temporal series on a given set of individuals or (if different individuals face different prices) for observations on a cross section of individuals at one time. Three possibilities result: aggregate time series, disaggregate time series, and disaggregate cross section.

Four estimation techniques were applied in order to illustrate both the diversity of the elasticity values derived for different types of elasticities and, for a single type of elasticity, the sensitivity of the results to variations in estimation technique.

Although the techniques used provide a fairly clear picture of both influences, they do not exhaust the estimation possibilities. Data limitations of two kinds precluded the application of further alternatives. The first involves omissions in the data as collected, which includes incomplete responses and survey questions phrased or coded in ways that prevented the retrieval of more than minimal information. There is, however, a more fundamental type of fault. In order to measure the impact of a fare change on a population, rather comprehensive information is needed on how a large number of individuals responded. Ultimately one would like to arrive at causal statements on the linkage between the fare reduction and changes in transit use. To do so requires disaggregate data, not only on descriptive characteristics and on changes in individual behavior, but also on all factors other than fare that could have contributed to the changes in travel behavior. In contrast, the existing data show travel-behavior changes only for off-peak bus use and only as individuals recall their behavior before the free fare. Furthermore, information on factors other than fare is severely limited. However, it should be pointed out that the collection of data was far richer than that generally available and that it adequately serves the set of questions for which it was originally designed.

Of the four estimation procedures used in this study, two use aggregate data. The first uses fully aggregate data and the second uses data aggregated into various population subgroups within the total market. The third procedure applies regression techniques to a disaggregate time series. The fourth procedure is a binomial logit mode-choice model that uses disaggregate data but implicitly constrains the price-change response to be reflected only in a shift of modes.

NONEMPIRICAL FACTORS THAT AFFECT ESTIMATES

This section outlines four factors, each of which tends to bias the elasticity estimates. While all can, in principle, be corrected for, it was feasible to correct only for the third in this study.

The demand for bus travel is influenced by the levels of various service characteristics as well as by fare. When the fare is reduced, ridership increases. When there is no increase in the number of bus runs, fare reductions may increase the degree of crowding. Also, especially when bus stops are close together (as they are in Trenton), the increase in ridership tends to increase the number of stops that a bus makes on a run as well as the number of people who board, which reduces the level of schedule adherence. The additional crowding and reduced reliability, even if slight, may deter some riders and thereby partly offset the rider response to the fare decrease. This results in a downward bias to the elasticities estimated as a function of price alone. The bias is large either if the change in the service characteristics is great or if the responsiveness of the market to service characteristics is high. Because of difficulties in quantifying relevant service characteristics, no attempt has been made to approach the problem with a simultaneous-equations model. There are indications that Mercer Metro's off-peak schedule adherence was less regular with the free-fare transit than it had previously been and that a greater proportion of the buses arrived downtown with all seats taken--an indication of increased crowding (1).

Second, the estimated elasticities can be interpreted only as fare elasticities, not as price elasticities. If the full price of a transit trip is taken to be the sum of the fare paid and the value of the time spent in travel, a given percentage reduction in fare is reflected as a lesser reduction in price. Thus, fare elasticities are smaller than are the associated price elasticities.

Third, when before-and-after comparisons are made, it is necessary to restrict attention in the after comparisons to those who were off-peak transit users in the before period. The total change in trip making between the before and after periods is composed of additional trips by old users and trips by new users. The result of calculating the ratio of the total percentage ridership change (inclusive of trips by new users) to the percentage fare change can be defined as a shrinkage ratio. Although the shrinkage ratio validly indicates the total impact of a fare change on the transit operator, it is not a good measure of behavioral response, since two nonequivalent groups are compared.

Finally, a problem results from having measured individual bus trip frequency but not total trip frequency. It is likely that, in response to the free-fare program, many increased both their total number of trips made and their share of total trips taken by bus. Either of these responses would increase bus trip frequency. When they occur together, the combined effect cannot be partitioned into the separate effect of each unless there is information on both the individual's total frequency and the bus modal share. It is thus impossible to determine whether a given change in bus trip frequency is largely the consequence of a mode shift with a given number of trips, an increase in total trip making with a given mode split, or a combination of the two. Since an increase in trip making and a change in mode split are different types of behavioral response, the inability to distinguish between them implies a loss of information. In the abstract, the change in bus frequency can be regarded as the combined result of two separately determined behavioral responses. Ideally, one would make separate estimates for mode split and total trip frequency. Because the data do not allow us to do so, the estimations cannot fully identify the behavioral mechanisms.

ESTIMATION PROCEDURES AND RESULTS

The first of the four estimation procedures uses only the data from the six ridership counts made from street corners. Because trips by old users are indistinguishable from those by new users, the procedure estimates a shrinkage ratio. The total ridership level from each of the counts was regressed on time and on a dummy variable that takes the value of 1 for the free-fare period and 0 for the 15-cent fare period. The time variable isolates trend effects. There were too few observations to attempt seasonal adjustment. Two equations were estimated, one for the peak period and one for the off-peak period. For each, the coefficient on the dummy variable represents the effect of free fare. The results are reported below (the t-statistics are in brackets after each coefficient; ridership is expressed in thousands of trips per week and time is measured in months):

Trips = 85.25 [10.92] + 1.22 [0.72] * time − 7.58 [−0.60] * dummy (R^2 = 0.15).
Trips = 45.22 [10.95] − 0.73 [−0.82] * time + 29.04 [4.37] * dummy (R^2 = 0.92).

The coefficients on the time variables reflect the changes that would have occurred without free fare. The estimated impact of fare removal can be read from the coefficients on the dummy variables. The coefficient on the dummy in the second equation (off-peak period) indicates an increase of 29 000 weekly off-peak trips as a result of the free fare. This coefficient is statistically significant at a 95 percent level. The constant term is an estimate of the base level of ridership. A shrinkage ratio of 0.64 obtains by taking the change in ridership due to free fare (29 000) as a percentage of the base ridership (45 000) and dividing by the percentage change in fare (100 percent); a 90 percent confidence interval places it between 0.24 and 1.26.

The second estimation procedure combines data from the two autumn on-board surveys with the data from the corner counts. From these, total before-and-after ridership estimates were calculated for each socioeconomic group into which the respondents could be divided. The elasticity estimates were determined by algebraically fitting a demand curve through the observed before-and-after pair of demand points. To illustrate the importance of the demand curve's functional form, each of two specifications was fitted. In order to base the before-and-after comparisons on a common set of individuals, respondents who reported a prior off-peak trip rate of 0 were eliminated from the after survey when the elasticities were calculated. However, to compare the influence on the specification of including new users, the calculations were repeated by using the entire after sample. These last calculations can be thought of as population-group-specific shrinkage ratios, since they include the impact not only of the changes in ridership by old users, but also of the ridership of new users.

Table 1 contains the results of the estimations. The first four columns show the results of fitting a linear demand curve by the arc elasticity formula. Of these four, the first two columns present the elasticities calculated at the demand curve's midpoint between 15 and 0 cents. The third and fourth columns have results computed at 15 cents. The estimates in the fifth and sixth columns are the result of fitting an exponential demand function, as explained below. The elasticities in these columns are calculated at 15 cents. To illustrate the importance of restricting before-and-after comparisons to a common group, the first, third, and fifth columns use the data from all respondents to the second survey. The second, fourth, and sixth columns include only those respondents to the second survey who reported positive prior frequency. The elasticities are for the group aggregates, not for individuals or even typical individuals within each group. That is, they apply to the entire group of, say, elderly people and lend no insight into the behavior of a typical elderly person.

The linear demand function can be written $Q = a - bP$, where a = constant and b = slope of the demand curve. The price elasticity can be written $e = (\Delta Q/\Delta P)(P/Q) = -b(P/Q)$, where b = inverse of the slope of the demand curve. Given b, an elasticity can be estimated for any P,Q-pair.

Although the linear demand curve is simple and commonly used, many alternative specifications are possible, and often another is more suitable. As pointed out earlier, the elasticity estimates may be quite sensitive to the particular form chosen. An exponential demand curve underlies the fifth and sixth columns in Table 1. It is written $Q = Q_0 \exp[b(P_0 - P)]$, where Q_0 = initial quantity level and P_0 = initial price level. The elasticity is again computed as $(dQ/dP)(P/Q)$. In this instance it equals $-bP$. Thus, the elasticity is linear in P, whereas with the linear form the quantity demanded is linear in P/Q.

Table 1 allows comparisons both between columns that show estimation differences and among groups within a category. With regard to the former, the following discussion suggests the more-important comparisons.

Comparisons Between Columns 1 and 2, 3 and 4, or 5 and 6

These comparisons illustrate the differences between shrinkage ratios (columns 1, 3, and 5) and elasticities (columns 2, 4, and 6). The shrinkage ratios, since they include new users, have smaller values than the elasticities. Since all columns are calculated with the same base values, comparison also shows the variation among groups in the contribution made to the total change by increases on the part of old users and the addition of new users. When the second column is small in relation to the first (or the fourth in relation to the third or the sixth in relation to the fifth), the major contribution is from new users; when it is relatively large, most of the change is attributable to old users. For instance, for the groupings by trip purpose, new users are responsible for all the additional recreation trips and most of the new shopping trips but few of the new medical trips.

Comparisons Between Columns 3 and 5 or 4 and 6

Here the differences due to the choice of functional form are evident. With the two functional forms chosen, the differences are most noticeable for elasticities of higher absolute value. It should again be noted that the underlying data are identical and that all differences in results are due to the functional form. Without grounds for believing one form to be correct, the lesson is to

Table 1. Algebraic elasticity estimates.

Data Type	Linear Demand Function				Exponential Demand Function	
	At Midpoint		At 15 Cents			
	All Users	Old Users	All Users	Old Users	All Users	Old Users
Aggregate	0.17	0.10	0.41	0.24	0.34	0.21
Group aggregate						
Household size						
1	0.16	0.08	0.37	0.17	0.32	0.16
2	0.14	0.06	0.32	0.12	0.28	0.11
3	0.11	0.07	0.26	0.15	0.23	0.14
4	0.19	0.12	0.48	0.28	0.39	0.25
5	0.13	0.08	0.30	0.16	0.26	0.15
6+	0.24	0.19	0.63	0.47	0.49	0.39
Automobiles						
0	0.14	0.03	0.33	0.06	0.28	0.06
1	0.16	0.13	0.37	0.30	0.31	0.26
2	0.21	0.16	0.52	0.40	0.42	0.33
3+	0.24	0.20	0.62	0.49	0.48	0.40
Sex						
Female	0.15	0.08	0.35	0.17	0.30	0.16
Male	0.20	0.15	0.50	0.35	0.41	0.30
Age						
Less than 17	0.16	0.09	0.38	0.21	0.32	0.19
17-24	0.19	0.14	0.46	0.33	0.38	0.28
25-44	0.22	0.15	0.55	0.35	0.44	0.30
45-64	0.10	0.02	0.22	0.04	0.22	0.04
65+	0.11	0.03	0.26	0.06	0.23	0.06
Income						
$0-5000	0.05	0.01	0.10	0.01	0.10	0.01
$5000-10 000	0.14	0.09	0.32	0.19	0.28	0.17
$10 000-15 000	0.35	0.29	1.10	0.82	0.74	0.60
$15 000-25 000	0.10	0.02	0.21	0.04	0.19	0.04
$25 000+	0.31	0.23	0.91	0.60	0.65	0.47
Trip purpose						
Work	0.14	0.09	0.34	0.20	0.29	0.19
School	0.12	0.04	0.26	0.09	0.23	0.08
Shopping	0.11	0.06	0.24	0.12	0.21	0.11
Medical	0.14	0.13	0.32	0.29	0.28	0.26
Recreation	0.08	0.02	0.18	0.04	0.17	0.04
Social	0.09	0.04	0.21	0.07	0.19	0.07
Other	0.64	0.57	3.52	2.64	1.51	1.29

be cautious about accepting either as the correct elasticity.

Comparisons Between Columns 1 and 3 or 2 and 4

All four of these are for the linear demand curve. The comparison is between evaluating the elasticity at the original point and evaluating it at the midpoint. Recall that, along a linear demand curve, elasticity rises with price. Therefore elasticities calculated at the original point are higher than those calculated at the midpoint. It is evident that the selection of a point at which to compute an arc elasticity can have strong bearing on its value.

Comparison Among Population Groups Within a Category

For any categorization, groups with higher values increased their share of total trips in response to free fares. For instance, taken as a group, persons with more cars were more responsive and gained in ridership in relation to persons with fewer cars. This ranking holds both for old users and for all users. Similarly, men gained in relation to women, persons aged 25-44 gained in relation to those older and younger, and the $10 000-$15 000 income group gained in relation to other income groups.

As noted above, the on-board surveys sampled trips, not persons. A given number of trips may be composed of either a large number of individuals who each take a few trips or a small number who each take many trips. Similarly, a change in the number of trips may result from either many more trips by a few people or a few more trips by many people. The inability to distinguish between the two explanations is a consequence of the estimating group rather than the individual elasticities. In interpreting the results, it should be remembered that, since either explanation may hold, no inference can be drawn about the behavior of members of a group.

Categorizing the population by a single characteristic at a time loses much information. Even without the introduction of questions of causality, there is no way to determine whether the indicated response of, say, the high-income group would or would not vary if that group were further broken down by automobile ownership or some other variable.

This difficulty serves to introduce the third estimation procedure. By using data in disaggregate form, multiple-regression analysis circumvents the limitations of diminishing cell size. In the regressions that follow, all data are from the autumn 1978 on-board survey. The individual's percentage change in off-peak bus trips, evaluated at the midpoint, was used as the dependent variable. The independent variables are listed below (the estimating technique was ordinary least squares):

1. Age dummies for four or five age categories,
2. Dummy for men,
3. Dummies for four or five men-age interaction categories,
4. Dummy for Trenton residence,
5. Number of automobiles in household,
6. Dummies for four or five income categories, and
7. Income per household member (an imputed income level for each income category divided by the number of household members).

Table 2. Regression estimate results.

Variable	Coefficient	Coefficient ÷ SE
Constant	0.045	1.05
Household automobiles	0.049	2.05
Dummies for age		
17-24	0.093	2.31
25-44	0.022	0.505
45-64	0.049	0.979
65+	-0.034	-0.474
Dummy for men	0.048	2.05
Dummies for men and age		
Men 17-24	-0.121	-2.17
Men 25-44	-0.029	-0.471
Men 45-64	-0.168	-2.25
Men 65+	-0.089	-0.833
Dummies for income		
$5000-10 000	0.017	0.546
$10 000-15 000	-0.010	-0.318
$15 000-25 000	-0.019	-0.507
$25 000+	0.049	1.11
Income per household members if at least $1000	-0.0024	-0.525
Dummy for city residence	0.006	0.266

Note: R^2 = 0.020; N = 1133.

The results are presented in Table 2. Note first that only about 2 percent of the variation in responsiveness has been explained. On the other hand, a number of the individual coefficients are significantly different from zero at a 95 percent confidence level. Ignoring for the moment the fact that the remaining coefficients are not significant, we can infer that, although most of the variation in response to free fare is determined by factors not included in the equations, the contribution of the significant included variables has been determined. Thus, although the extent of differences across age groups, income groups, and so forth is indicated by the coefficient values and since some conclusions about the variations in group responsiveness can be drawn from them, the most important conclusion is that these are not the important factors in determining variations in individual responsiveness. From a policy point of view, recognition of the relative unimportance of socioeconomic and related variables argues against free fare as an instrument to reach groups defined by socioeconomic characteristics.

The elasticities used for the regressions are arc elasticities for typical individuals. A predicted value of the elasticity for an individual can be found by substituting the appropriate values for all the independent variables and by applying the estimated coefficients.

In interpreting the results it should be recalled that bus trip frequency is the product of overall trip making and bus mode share. For example, people who travel frequently but use the bus infrequently will exhibit large percentage changes in bus use by shifting a small share of their trips to the bus. Because the bus trip percentage increase is large, this shift would be interpreted as a relatively dramatic change in travel behavior. However, since there are no data to extract the two-component bus trip frequency, this case is impossible to distinguish from that of a person who travels only by bus and likewise exhibits a sharp increase in trip making. It is important to note that the inability to distinguish between these cases greatly reduces the usefulness of the estimates for identifying variations in behavioral response. It no doubt also contributes to the low R^2-values.

Aggregate elasticity estimates are derived by applying the estimated coefficient values to data on the individuals in the sample and taking a weighted average of the results. This procedure links the aggregate elasticity to the explained portion of the individual elasticities. If the explained portion had been substantial, this could be argued as a netting out of random components in individual response. However, it is difficult to argue that 98 percent of the individual variation is random. Consequently, the aggregate elasticities are subject to large error. The individual elasticities were weighted by the respondent's share of all trips collectively taken by the respondents during a typical week; the resulting value was 0.528.

The final estimation technique applies binominal logit to the choice of mode between automobile and bus. The data source is the 1977 telephone survey. Estimation was sharply constrained by data limitations: There were too few observations to include any modes but automobile and bus or to distinguish between automobile passengers and drivers. Furthermore, only estimation of mode choice was possible, due largely to the omission of variables that might contribute to distinguishing over more-complex choice dimensions. The overall explanatory power of the model indicates this less than does the statistical significance of individual coefficients.

In all, the results here are not comparable with those of the other approaches. This is especially unfortunate since the logit estimation procedure has an important inherent advantage over the other techniques. By using cross-sectional rather than time-series data, the results are influenced by exogenous interperiod changes. Use of cross-sectional data also serves to offset the simultaneous-equations bias that results when responses to fare and service changes interact over time.

The first two of the independent variables included in the estimate are travel time for automobile and for bus, both in minutes. The third variable, bus wait time, was specified as the minimum of one-half the headway plus 15 min. The results were insensitive to the assumption made. Bus cost depended on the time the trip began. If it began during the off-peak hours, the cost was 15 cents; for trips that began during the peak, it was 30 cents. Automobile cost was estimated as 9 cents/mile plus parking cost. The 9-cent figure lies between the per-mile cost of gasoline and the total per-mile vehicle operating cost. It was used on the assumption that individuals perceive fuel costs and are partially aware of additional operating costs. There is no way to determine how many persons traveled together on the automobile trips, and hence the vehicle cost is taken to be the individual's cost. However, in the results, variations in the assumption on automobile cost were reflected almost entirely in the coefficient on that variable.

Socioeconomic data included a set of dummies for age, a dummy for men, the number of household members, and the number of automobiles owned by the household.

In the estimation, since the drawing for the sample was partly random and partly based on choice, a correction was necessary. Entries from the choice-based on-board follow-up portion were weighted according to the bus trip proportion in the random section (2). The bus trip share in the random portion was thus used as an estimate of the share in the overall population. The reported version of the equation follows (the t-statistics are in brackets after each coefficient):

$$\ln[\Pr(\text{bus})/1 - \Pr(\text{bus})] = 0.0656\ [0.0319]$$
$$+\ 0.000\ 001\ 74\ [1.33]\ (\text{time}_{\text{auto}} - \text{time}_{\text{bus}})$$

- 5.44 [-1.26] (bus cost) - 0.116 [-0.122]
(auto cost) - 0.247 [-0.272] (transfers)
- 1.07 [-0.189] (bus wait time)
+ 0.632 [0.887] (Trenton residence dummy)
+ 0.469 [1.249] (automobiles per household)
- 0.0262 [-0.123] (household size)
- 0.866 [-1.10] (dummy for men)
- 1.02 [-1.03] (dummy for ages 17-24)
- 0.515 [-0.557] (dummy for ages 25-44)
- 1.35 [-1.76] (dummy for age 45+).

As can be seen from the t-statistics, none of the coefficients is significant at the 95 percent level, that on the dummy for age 45+ is significant at the 90 percent level, and those on bus cost, number of family automobiles, and travel time are significant at the 75 percent level.

The summary fit statistics appear at first to be quite good. The log likelihood (with all coefficients but that on the bus constant set to zero) takes a value of -92.65. With the estimated coefficients it is -39.37. Thus, -2 log (likelihood ratio) = 106.56 and $\rho^2 = 0.58$. Although both these summary statistics are quite good, all 213 trips are predicted as automobile trips with the estimated coefficients and measured variable values. Against this, the sum of the individual choice probabilities suggests that, on an expected-value basis, 28 of the trips would be taken by bus. The aggregate point elasticity at the original fare level for off-peak trips alone is 0.58.

Since the approach does not allow either for a shift according to the time of day (i.e., drawing riders from the peak period to the off-peak period) or for an increase in total trip making, the value as estimated is high in comparison with those of the other estimation procedures.

SUMMARY OF ESTIMATION RESULTS

A summary of the estimates is shown below. All values are for elasticities calculated at 15 cents. Since all estimates are substantially below 1, the conclusion that the demand is inelastic is a firm one. This conclusion holds for the shrinkage ratio estimates as well.

Type of Estimate	Aggregate Elasticity Value	Shrinkage Ratio	Data Used
Regression		0.64	Corner counts
Algebraic			1977 and 1978 on-board surveys
Linear	0.24	0.41	
Exponential	0.21	0.34	
Regression	0.51		1978 on-board survey
Logit	0.58		1977 telephone survey

The differences among the estimates from the four procedures are attributable to three factors: (a) use of different portions of the data for different estimates, (b) estimation of different types of elasticity, and (c) influences of the estimating techniques themselves. Although it is not possible to fully separate the influences of the three factors, several conclusions about the direction of their influence can be drawn.

The first comparison is between types of elasticity. Because shrinkage ratios include the influence of trips by people newly introduced to the system, they are of higher value than aggregate elasticities. The second set of estimates allows a comparison between shrinkage ratios and aggregate elasticities, which is unaffected by data source or differences in estimating technique. The shrinkage ratios are about 50 percent larger than the elasticities. While this should in no way be taken as a rule regarding the relative difference, it confirms the importance of distinguishing between the two concepts.

There is no similarly simple ranking between individual and market elasticities. However, in any market there are some individuals with elasticities larger than the aggregate market elasticity and others with values smaller than the market value. This must be true, since the market elasticity is a weighted average of the individual elasticities. An important point implicit in this is that much information on the diversity of individual responses is embodied in the individual elasticities. Estimation of only aggregate elasticities loses all this information.

CONCLUSIONS

Two conclusions arise from the empirical results. The first is that fare elimination provokes an inelastic ridership response. The second is that the differences in response among individuals cannot be explained by their socioeconomic characteristics. For policy purposes, the first conclusion implies that a fare reduction will lead to a revenue loss, which thus requires a subsidy increase. With zero fare, the revenue loss is obvious; however, the implication is that, even with a small fare reduction, Mercer Metro would have experienced a drop in revenue. The second result implies that general fare policy has very little leverage as a tool for reaching particular user groups. If, for instance, a policy goal is to provide mobility to the poor, free fare is only an indirect way of doing so, since large numbers of riders other than the poor will also participate. The spillover from target to non-target groups is great.

For research purposes there is a more-fundamental set of conclusions. The original research design for evaluation of the Trenton free-fare demonstration placed strong emphasis on recording what happened: There was little emphasis on learning why it happened. The data collection program reflected this bias. It should be noted that at a level of generalization that is not too broad the answers to the question "Why?" are self-evident: The changes occurred because the fare was reduced to zero. However, for several important purposes this explanation is inadequate. The fact of a diversity of responses among individuals suggests that the link between fare change and ridership response has complexities that are not easily identified. Without a more complete understanding of why individuals responded as they did, we can estimate neither how the Trenton population would respond to an alternative policy nor (except in general terms) how the population of another city would respond to an off-peak free fare.

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Abridgment

Factors That Influence Local Support for Public Transit Expenditures

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Survey data collected in Ann Arbor, Michigan, are used to assess the importance of various types of motivation to support a property-tax millage earmarked for public transit. A key finding is that user benefits are relatively less important than nonuser benefits in garnering local support. Concern over fuel depletion and overuse of automobiles, stimulation of business within the city, ability to use the service should one wish to, and a perception that the service offered is of high quality are major factors in transit support.

Faced with skyrocketing prices and uncertain supplies of fuel, urban travelers are increasingly turning to public transportation. Since transit users rarely pay their full costs, however, the operating deficits of many systems are increasing sharply with this added demand for service. Transit managers and local public officials are understandably hesitant to ask for higher taxes to finance transit during a period when real or spendable income is on the decline.

An incentive to generate local funds for transit service is provided by legislation passed at the federal level during the 1970s. Since 1974, each local dollar spent on operating a public transit system in larger cities is eligible to be matched by a federal dollar, up to the city's allocation limit (which is based on its population and density). In 1978, federal operating assistance was extended to small urban (population less than 50 000) and rural areas. Even with the substantial price reduction in transit brought about by the federal matching funds, many communities have garnered only a limited local share. As a consequence, they are receiving only a fraction of their full allocation of operating assistance funds.

The research reported here indicates that many public officials have been overly cautious in their hesitancy to place transit-financing referenda on the ballot. It may in fact be possible to obtain rather widespread support for a local tax if it is earmarked for provision of public transit. The results of the analysis to be summarized in this paper indicate that transit's constituency is potentially quite broad--supporters of transit are unusually diverse.

CASE-STUDY CITY

Ann Arbor, Michigan, has proved to be an excellent site to research the issue of local support for public transit expenditures. As is true of many states, Michigan law enables its cities to place referenda on the ballot that propose special property tax assessments to raise revenues for specific urban services. In 1973, a proposal was placed on the ballot in Ann Arbor to increase the property tax by $0.0025 which is equal to approximately $50 for the average-valued single-family house within the city. The assessment was to be used to provide a transit service of considerably higher quality than existed at the time. It is worth noting that, because the referendum was placed on the ballot in 1973, the prospect of federal matching funds did not yet exist.

The millage proposal passed by a margin of almost 2:1 (61 percent). Late in 1976, the new transit system was fully operational in all sectors of the city; implementation was carried out incrementally over a three-year period. A propitious opportunity to study local support for transit financing developed at this time. City residents could see what their tax dollars were buying; it was decided to study how many residents would favor continuation of the millage and why.

DATA USED IN THE ANALYSIS

The city of Ann Arbor obtained a technical assistance grant from the Urban Mass Transportation Administration to evaluate public response to the improved transit system. A telephone survey of 1175 randomly selected Ann Arbor residents was administered in March and April of 1977 by the University of Michigan's Survey Research Center. The questionnaire was quite detailed; numerous attitudinal, behavioral, and situational measures were included.

To measure willingness to pay the property tax for transit, the following question was asked:

> In April 1973, Ann Arbor voters approved a proposal to finance the public transportation system. This costs about $25 per year for a family living in a house worth $20 000, or about $50 per year for a family living in a house worth $40 000. Suppose the question of continuing this tax were on the ballot again; would you vote to continue the tax or would you vote against it?

It is noteworthy that respondents were informed how much the transit system costs them. (In the case of renters, a cost estimate was furnished based on an assumed monthly rental rate of 1 percent of the assessed value.)

In the analysis of responses to the support question, a number of measures were used as