pricing seemed to hold greater promise for improving the fiscal condition of the system. Of course, any pricing structure chosen should support the specific policy objectives of transit decisionmakers. Given a policy mandate to implement distance-based fares, for example, stage pricing seems most promising in terms of revenue productivity whereas graduated structures appear particularly suited to eliminating inequities. Another trade-off might involve the apparent ridership advantages of time-of-day pricing versus simplicity and user comprehensibility of flat rates. Given the almost inherent conflicts among various pricing objectives, it is imperative that the relative advantages and disadvantages of alternative pricing approaches be confronted through informed public discussion and debate.

The analytic model presented in this paper is intended to serve as a decisionmaking guide in assisting transit officials in probing the policy implications of alternative fare programs. As with any model, it represents only an abstraction of reality and must rely on managerial judgment and insight as well. Given the relative uncertainties about disaggregate fare elasticities of different ridership groups, the model is perhaps best suited for sensitivity testing and quick-response analysis. The model structure is also easily adaptable to interactive computer programming, which might prove quite useful in providing real-time output and graphic displays of the impacts of alternative fare policies. As adjustments in fare policies become more prevalent during the 1980s, such capabilities could serve to facilitate public input into the transit pricing decisionmaking process and also enhance an agency's ongoing financial planning efforts.

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

Analysis of a Fare Increase by Use of Time-Series and Before-and-After Data

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On October 1, 1978, the Jacksonville Transportation Authority (JTA) increased fares on almost all bus routes in the system. The impact of the fare increase on transit ridership is analyzed. Two complementary techniques are examined: (a) estimation of a ridership model based on time-series JTA operating data and (b) estimation of fare elasticities for market segments based on before-and-after on-board survey data. By using monthly operating data for JTA from January 1976 through June 1979 and multiple regression techniques, the elasticity of demand with respect to basic fare in real terms is estimated. The elasticity with respect to bus miles of service and the cross elasticity with respect to gasoline price are also estimated. The nonlinear, constant-elasticity model is found to best represent changes in travel behavior for the observed data. In addition, long-run elasticities are not significantly different from the one-month short-run elasticities over the time for which data were available after the fare increase (9 months). An on-board survey, administered slightly less than 6.5 months after the fare increase, is used to analyze the impact of the fare increase on market segments. Reliable estimates of market segment elasticities could not be obtained because the assumptions required for application of this method were violated. Sampling designs are required that provide more precise estimates of market segment ridership and disaggregate data by which to examine the impacts of all factors that affect transit use by market segments so that reliable estimates of market segment elasticities can be obtained.

On October 1, 1978, the Jacksonville Transit Authority (JTA) of Jacksonville, Florida, introduced a fare increase for almost all bus routes in the system. This paper presents the results of an analysis of the impact of the fare increase on transit use by the general population and by market segments. The analysis uses two approaches. Based on time-series operating data for the JTA system, a transit ridership model is estimated by using multiple regression techniques. The time-series analysis provides estimates of direct demand elasticities with respect to fare and service and the cross elasticity with respect to gasoline price. The second approach involves the use of on-board survey data collected before and after the fare increase.

Transit riders are segmented into a variety of groups, and the impact of the fare increase on each segment is examined.

This paper is organized into four sections: (a) background data on the fare increase and the JTA data collection program; (b) a description of the methodology used; (c) the time-series analysis, which describes the model specification, results, and conclusions; and (d) the market segment analysis, including the estimation procedure and conclusions.

BACKGROUND

Fare Change

The JTA bus system includes four route types (regular, flyer, downtown shuttle, and beach), three methods of payment, and five fare categories; the result is a relatively complex fare schedule. On October 1, 1978, bus fares were increased on most JTA operations. This represented the first fare change since 1973.

The basic adult fare was increased 40 percent, from \$0.25 to \$0.35. All \$0.25 flyer (express) routes were increased to \$0.50 and those already charging \$0.50 remained constant. The \$0.10 downtown shuttle fare also remained the same. Cash fares for children (under 12 years) increased from \$0.15 to \$0.25. These fares can only be used on regular routes; children traveling on higher-priced routes pay the full fare. Student tickets increased from 8 for \$1 to 10 for \$2. Before the increase, higher-priced routes charged two student tickets; after the increase, students paid the full fare for these routes. The beach routes had a three-tier price structure before the increase (\$0.25, \$0.50, \$0.75); after the increase, only two fares were used on these routes (\$0.35 and \$0.85). The weekly adult pass, which can be used on all routes, increased from \$5 to \$7. The monthly pass (initiated in March 1978) increased from \$10 to \$14 [after July 1979, the price decreased to \$12 and the difference was subsidized by the Urban Mass Transportation Administration (UMTA)]. Passes for students and the elderly, which were \$2.50/week (student passes were good only Monday through Friday), were eliminated. Off-peak fares for the elderly and the handicapped (good on all routes from 9:00 a.m. to 3:30 p.m. and after 6:00 p.m. weekdays and all day on weekends and holidays) increased from \$0.10 to \$0.15.

Data Collection

JTA systemwide operating data are compiled on an annual and monthly basis. The standard JTA ridership-counting procedure involves daily counts of revenue passengers and free transfers on flyer routes and frequent counts on other routes. Revenue passengers are disaggregated by fare category and method of payment, although some groups are collapsed. Scheduled miles of service are also recorded. Separate monthly ridership and service data are available for city (regular, flyer, and shuttle) and beach routes.

In assessing the JTA data to be used in this analysis, several conditions are relevant:

1. JTA was transferred from private to public ownership in 1972. Because a change in management often brings a change in reporting procedures, only post-1972 data were considered.
2. Federal operating subsidies became a major source of funding for JTA in 1974. The infusion of these funds most likely led to a range of service changes. Because the only measure of service available, bus miles, cannot control for many of these changes (e.g., schedule adherence), pre-1974 data were excluded.
3. Finally, both ridership and service data were needed on a monthly basis. Prior to 1976, bus miles were reported only for 6-month and yearly intervals; thus pre-1976 data were excluded. The period of estimation for this study covered 42 months, from January 1976 through June 1979 (the most recent data available at the time of the analysis).

As part of a data-collection effort to evaluate a demonstration in Jacksonville of employer-based transit-fare-prepayment instruments, a before-and-after on-board survey was administered to a random sample of riders on a representative but nonrandomly selected sample of 12 routes (including regular, flyer, shuttle, and beach routes). Bus routes with only weekday service were sampled on one day. If weekend service was available, riders were also sampled during those days. The before survey was administered between September 17 and 23, 1978 (during the month before the fare increase). The after survey, administered on the same buses on the same day(s) of the week, took place six months later, between April 22 and 28, 1979.

TIME-SERIES ANALYSIS

Model Specification

By using monthly JTA operating statistics for all city and beach routes in the system from January 1976 through June 1979, the effect on ridership of relevant determining variables can be estimated by multiple regression analysis. The following model can be estimated:

$$RP_i = f(TIME_i, MILES_i, RFARE_i, RGAS_i, MONTH_k) \quad (1)$$

where

- RP_i = revenue passengers for regular, flyer, shuttle, and beach routes in month i;
- $TIME_i$ = trend variable represented by consecutively numbering the months;
- $MILES_i$ = scheduled bus miles for regular, flyer, shuttle, and beach routes in month i;
- $RFARE_i$ = basic fare in month i (\$0.25 before October 1978 and \$0.35 for October 1978 and thereafter), divided by the consumer price index (CPI) in month i (defined as CPI/100);
- $RGAS_i$ = average pump price of gasoline in Jacksonville for month i, divided by the CPI in month i (CPI/100); and
- $MONTH_k$ = set of 11 dummy variables that indicate the month of the year.

A brief discussion of the variables selected for this model is warranted. First, to estimate the desired fare elasticity, the relevant dependent variable is revenue passengers. Revenue passengers is preferred to other measures of ridership such as total boarding passengers because fare affects the behavior of the number of paying passengers whereas the number of free transfers is more a function of the design of the system (1). Because monthly ridership is a function of the number of days in the month, revenue passengers per day is also tested.

Fare, the independent variable of interest, is clearly an important determinant of ridership. To reflect the secular increase in all prices over the time period examined, the nominal adult basic fare is deflated to reflect the real price. The real price is the relevant measure of fare since it

reflects the fact that households must trade off consumption of different goods due to their budget constraints.

The level of bus service, a transit supply variable, also determines ridership. Scheduled bus miles on all city and beach routes is used as the measure of service. Although this is an imperfect measure of service because it does not exactly reflect important service attributes such as headways and may differ from actual bus miles provided, it is the only measure available for each month. The use of a one-equation system assumes that supply is exogenous to demand. This assumption is reasonable since the transit operator often sets the supply of service as a matter of policy given available resources (e.g., capital equipment and availability of operating subsidy money) rather than responding to variations in demand.

Demand for a transportation mode is generally assumed to be influenced by the price and level of service of substitute modes. The major competing alternative to the bus is the automobile. Average monthly gasoline prices for Jacksonville (in constant dollars) are used to reflect the price of automobile trips. Gasoline is used because of lack of data and because of its convenience as a surrogate for the price of the alternative. (Use of automobile trip cost would entail additional complications because the destinations for some trips, such as shopping or recreation trips, might change if the automobile were used rather than the bus. Thus, pricing the substitute would become more complicated.) Discussions with local officials in Jacksonville revealed that the gasoline station queues experienced during the spring and summer of 1979 in many parts of the country did not occur in Jacksonville; hence, there is no need to control for gasoline availability.

Seasonal variations in ridership are accounted for in the model by introducing a set of 11 dummy variables, one for each month of the year (December is used as the base). Because the inclusion of 11 dummy variables uses a significant number of degrees of freedom, the use of 3 dummy variables to represent seasons (winter, spring, summer, fall) is also tested.

Finally, a secular trend variable is included to account for the nonseasonal effects not explicitly included in the model. This variable is constructed by numbering the observations (months 1 through 42) consecutively.

This basic model of transit ridership is used to test two hypotheses as well as to obtain the best estimate of fare elasticity. First, alternative functional forms of the model are considered; that is, is the ridership function linear or nonlinear over the range of the data? The functional form of the model implies a given demand behavior (elasticity). The linear model implies that the fare elasticity varies with the value of the fare; the logarithmic model implies a constant elasticity. Second, the existence of long-run effects is tested; that is, does the fare elasticity increase over time as long-run adjustments are made by the transit-riding public in response to fare changes?

Elasticity Estimates

The results of this analysis indicate that the preferred model of transit ridership is the nonlinear, constant-elasticity model. The coefficients and t-statistics for the model variables are given below [DMILES = average daily bus miles and the dependent variable is LDRP (log of average daily revenue passengers)]:

Variable	Coefficient	t-Statistic
INTERCEPT	2.336	1.607
TIME	-0.0015	-2.648
LDMILES	0.7375	5.140
LRFARE	-0.2522	-7.122
LRGAS	0.1803	1.524
JAN	-0.0030	-0.237
FEB	0.0416	3.238
MAR	0.0702	4.769
APR	0.0528	4.076
MAY	0.0386	2.959
JUN	0.0084	0.549
JUL	-0.0025	-0.174
AUG	0.0107	0.743
SEP	0.0536	3.799
OCT	0.0672	4.982
NOV	0.0479	3.553

Degrees of freedom = 26, R^2 = 0.871, Durbin-Watson D-statistic = 1.946, F-ratio = 19.52, and sum of squared residuals = 0.0071. The coefficients are statistically significant at the 95 percent level of confidence.

Two other preliminary conclusions can be drawn:

1. The constant-elasticity model suggests that ridership responds to changes in real fare rather than nominal fare.
2. Tests for lagged effects indicate that the long-run elasticities are not significantly different from the short-run elasticities over the observed range of data.

The best estimates obtained for the arc elasticities are quite reasonable. The elasticity estimated for bus trips with respect to real fare is -0.252, the arc elasticity with respect to bus miles is +0.738, and the cross elasticity with respect to real gasoline price is +0.180. Note that for the constant-elasticity model the arc and point elasticities are equal.

In comparing these elasticity estimates with other estimates, differences due to variable definition (nominal fare versus real fare) and measurement (arc elasticity versus shrinkage ratio and aggregate versus disaggregate elasticities) must be considered. Moreover, elasticities estimated for real-fare increases typically appear to be larger than elasticities estimated for real-fare decreases, all other things being equal. Similarly, service elasticities for bus systems with low levels of service appear to be larger than elasticities for systems with high levels of service. In light of these differences, the fare elasticity estimated in this analysis lies in the range of arc elasticity estimates obtained in comparable studies of the aggregate response to real-fare changes, clustered between -0.20 and -0.45. The estimated elasticity with respect to bus miles also falls within the range established by other studies of bus systems with levels of service similar to that of JTA; these estimates are concentrated between +0.65 and +0.90 (2,3).

Alternative Functional Form

The first step in the analysis involved selecting the best functional form of the model. By using monthly revenue passengers as the dependent variable, both the linear equation and the log equation (using logarithmic transformations of RP_i, $MILES_i$, $RFARE_i$, and $RGAS_i$) were estimated.

The results of the two models indicated that both fit the data well. In both cases, the coefficient of determination (R^2) was relatively high, 0.89, and the coefficients had the expected signs. The

Durbin-Watson D-statistic, nearly 2 in both equations, suggests that there is no significant first-order automobile correlation. Because transit demand is commonly believed to be nonlinear, the log model (implying a constant elasticity) was retained for further testing.

Further Estimation of Model

The second step in the analysis included two tests. First, because the number of (total) days in the month is expected to influence monthly ridership, the dependent variable was changed to the log of average revenue passengers per day in month i ($LDRP_i$). The values for $LDRP_i$ were calculated by taking the log of the ratio of RP_i to the number of days in month i. The log of $MILES_i$ was also converted to reflect average daily bus miles, $LDMILES_i$.

Both revenue passengers and average daily revenue passengers result in satisfactory models. The latter model was retained because it is intuitively more reasonable.

The second test involved substituting three dummy variables to represent the seasons for the monthly dummy variables. The use of dummy variables to represent seasons rather than months significantly degraded the explanatory power of the model. Because the number of degrees of freedom with the set of 11 dummy variables appeared to pose no problems and resulted in a better model, the full model (Equation 1 in the text table above) was retained.

Change in Fare Elasticity Over Time

In time-series models, the coefficient reflects the periodicity of the data; that is, the elasticities estimated with this model reveal the magnitude of response over a period of one month. Several studies of fare elasticity suggest that the elasticity for bus trips increases over time (1,4). On the other hand, there is evidence that long-run fare (and service) elasticities are not significantly different from short-run elasticities (5). In this final step of the analysis, the existence of increasing behavioral adjustments over time was examined.

One of the most flexible lag models is the partial-adjustment model (6). The partial-adjustment model assumes that there is a desired level of ridership in month i, DRP_i*, which is a function of the explanatory variables in month i. The values of DRP_i* are not directly observable. However, it is assumed that an attempt is being made to bring the observed DRP_i to its desired level and that this attempt is only partly successful during any one period. A complete adjustment of DRP_i is not achieved in a single period due to the persistence of travel habits and the inability of travelers to adjust their travel behavior in a short period of time. The rate of adjustment of DRP_i to DRP_i* is calculated by estimating the coefficient for the lagged dependent variable.

The results of this test reveal that there is no lagged effect. The statistical insignificance of the coefficient for the lagged dependent variable suggests that there is a complete adjustment to the desired level of ridership in any single period. This indicates that the long-run elasticities are not significantly different from the short-run elasticities over the observed range of data. Perhaps one explanation for this finding is that, because the change in real fare was small for most observations, due to secular inflation, only marginal changes in travel behavior are made. Therefore, a complete adjustment could be achieved in a single period.

The arc elasticity estimates obtained from the preferred model, Equation 1, are as follows: fare arc elasticity is equal to -0.252, service arc elasticity is equal to +0.738, and gasoline price arc cross elasticity is equal to +0.180. These elasticities were quite stable over the different specifications tested. The fare elasticity ranged from -0.23 to -0.27, the service elasticity ranged from +0.74 to +1.00, and the gasoline price elasticity ranged from +0.11 to +0.18. Because average fare in Jacksonville increased 24 percent compared with the 40 percent increase in the basic fare, the fare elasticity estimate represents an underestimate of the true elasticity. However, real fare was decreasing over the range of most of the data. Because the percentage change due to inflation is equal regardless of the measure of fare, the degree of bias in the elasticity estimate is likely to be small.

Findings

The analysis presented here constitutes a preliminary investigation of the travel response to fare changes in the JTA system. The findings suggest a number of directions for further research.

1. The available data provide the opportunity to estimate separate elasticities for different route types (regular, flyer, etc.) and for different fare category segments (adult cash, student tickets, pass users, half-fare for the elderly and the handicapped, etc.).
2. The use of basic fare represents a relatively crude measure of price; calculation of average fare based on the proportion of users facing each fare provides a more precise measure.
3. The elasticity estimates obtained in this study refer to the total number of transit trips. Data for the changes in number of users and number of trips per user would be more revealing. For example, the adjustments to system changes may have been completed in a single period because the aggregate response may have been dominated by changes in trip frequency that are more quickly achieved than attracting new users or losing old users.
4. The findings concerning ridership response since the increase in basic fare were based on only nine observations (October 1978 through June 1979). More recent operating data are needed to explore the response in greater detail.
5. Finally, a number of factors relevant to ridership were excluded from the model--for example, measures of comfort and more precise measures of service such as wait time and reliability. Measures of these variables need to be developed and included in ridership models.

ANALYSIS OF MARKET SEGMENTS

Elasticity Function

By using before-and-after survey data, the impact of the fare increase on market segments can be estimated. However, simple comparison of the number of bus trips made by a given market segment in the before and after periods will lead to spurious results. This is because factors other than fare affected ridership during this period. Therefore, attributing the entire change in ridership to the fare increase results in biased estimates of the impact of fare. To control for the effects of exogenous factors, the survey data are used in conjunction with the time-series model.

The before-and-after survey data are used to estimate the share of each market segment in each

period. The after-period share is multiplied by the number of daily revenue passengers predicted for April 1979 by using Equation 1 as presented earlier in the text table. The before-period share is multiplied by the number of daily revenue passengers expected in April 1979 if the fare had not increased; the expected ridership is predicted by using Equation 1. The predicted and expected April 1979 ridership is 40 751 and 44 354, respectively. The difference between the predicted and expected April 1979 trips can then be attributed to the change in (nominal) fare faced by the market segment. Based on the previous finding that the relation between fare and ridership is multiplicative, the multiplicative forecasting formula is used to estimate the elasticity with respect to fare for each market segment (the subscript for each market segment is dropped from these equations). Because the multiplicative model yields a constant elasticity, the point estimation formulas below can be used to estimate the required elasticities, as follows:

$$Q_0 = Q_e(F_1^e/F_0) \tag{2}$$

$$e = \log(Q_0/Q_e)/\log(F_1/F_0) \tag{3}$$

where

- Q_0 = predicted number of April 1979 trips,
- Q_e = predicted number of expected April 1979 trips,
- e = elasticity,
- F_0 = average fare in the before period, and
- F_1 = average fare in the after period.

Market Segment Elasticities

Equation 3 was used to estimate the elasticities for each market segment. The estimates obtained were, for the most part, quite implausible. Several values were positive. (The impact of a fare change on ridership cannot be positive.) Similarly, several estimates that were negative appear to be quite large (in absolute value) in relation to other evidence.

To estimate the market segment elasticities, the sample proportions of each segment were used. The proportions estimated for each market segment in the before and after samples are associated with a degree of sampling error. To evaluate the uncertainty imposed by the sampling error, confidence intervals can be constructed for the estimated proportions to determine the likely range of values for each market segment proportion. By using 95 percent confidence intervals for the proportions in the before and after periods, the range of values for elasticities of each market segment is determined. The resulting ranges for the market segment elasticities indicate two important facts: (a) that the range is wider for smaller segments than for larger ones and (b) that the range is quite large for most segments, which suggests that the degree of uncertainty surrounding the point estimates of elasticities is too large to permit conclusions concerning the value of each market segment elasticity. This last point is particularly important since the level of precision obtained in the Jacksonville surveys is typical of on-board transit surveys. Generally, on-board surveys also fail to provide reliable estimates of total ridership. Because daily fluctuations in ridership are large, boarding count data based on one or two days result in imprecise measures of ridership and lead to inefficient estimates of the change in both aggregate ridership and ridership by market segment.

Assumptions

Given the implausible results obtained, a review of the assumptions required by this approach and why the procedure failed to yield reliable estimates of market segment elasticities is useful.

A number of assumptions are implicit in this method:

1. It must be assumed that the routes sampled and those not sampled are used by each market segment at the same rate. Because the routes selected are representative of all JTA routes, this assumption is reasonable.
2. Because the ridership predictions used are those of a single equation estimated for the entire JTA system, it is assumed that all factors included in the model and excluded from the model affect all market segments equally. Similarly, the error in the model is assumed to be distributed among the segments in proportion to their estimated market shares. This assumption is less reasonable and may lead to biased results.
3. It is assumed that nonrespondents are distributed across market segments in the same way as respondents. This assumption may lead to a wide variety of biases. For example, riders taking short trips may have been less likely to respond to the survey questions than other riders. To the extent that some market segments take more short bus trips and because certain market segments are more likely to substitute walking for these trips after the fare increase, both the magnitude and the relative size of the market segment elasticities will be biased.
4. Finally, it is assumed that had fares not changed the market segment shares would remain constant.

The variables used to estimate the elasticities merit additional discussion. Ridership on the 12 selected bus routes was sampled at different rates. Because the characteristics of riders are expected to vary by route, the sample observations must be weighted in order to obtain unbiased estimates of the population proportions on the entire system for each market segment. The observations for each route are weighted in inverse proportion to their probability of being selected.

The following variables were used to segment the market: means of payment, household income, age, automobile availability, occupation, trip purpose, sex, race, and fare category. Automobile availability refers to the traveler's access to an automobile as a driver or passenger for the bus trip taken at the time of the survey. Home-based and non-home-based work and school trips are designated as work trips. Shopping, personal business, and other trips are defined as nonwork trips. Social and recreational trips are defined as recreational trips. Because the after sample included no observations in the children's fare category, an elasticity could not be estimated for that segment.

Market segmentation involves developing segments composed of members with similar behavior. Because the sample size of most on-board surveys prohibits segmentation along more than one or two variables (i.e., with very limited or no cross classification), it is very likely that the groups defined are heterogeneous. The group-specific elasticities represent the aggregate response of that group and may hide significant differences among the members of the group. To the extent that Jacksonville riders in each group may differ in relevant ways from transit riders in other areas that share the single characteristic, market segment elasticities

estimated for Jacksonville may not be transferable to other areas.

Average fare in the before and after periods for each market segment is used to estimate elasticities. Although basic fare was used in the time-series analysis, it is believed that analysis of market segments requires a more precise measure of fare.

Average fare is often calculated by dividing revenues by number of revenue passengers. However, because different segments of the population are charged different fares and different bus routes are priced differently in Jacksonville, the average fare defined in this way can change as the composition of ridership or choice of destination varies. Unfortunately, changes in average fare due to changes in the composition of ridership or destination choice do not explain variation in total ridership (they are a result of changes in ridership). Therefore, a method for calculating average fare that reflects only changes in the fare structure (i.e., a pure supply-side change not contaminated by changes in riders confronting various fares) is needed.

The problem of calculating average fare so that the change in fare reflects change in prices is analogous to the problem of determining whether an individual's welfare has changed given changes in his or her total expenditure. Economists use index numbers to measure the actual change in welfare. Two index numbers are commonly used. The Laspeyre index measures the cost of purchasing the base-year quantities at the current-year prices, relative to both quantities at the base period. The Paasche index measures the cost of purchasing the given-year quantities at given-year prices relative to the cost of those same quantities at base-year prices.

In the context of transit fares, the price is the fare charged an individual; the quantity consumed is the proportion of riders who are charged that fare. To calculate average fares for the sample of riders surveyed before and after the fare change, the Laspeyre index can be applied as follows. Average fare in the before period is equal to

$$\mathrm{FARE}_L^0 = \Sigma p^0 S^0 \qquad (4)$$

where p^0 is the before fare charged a group of individuals and S^0 is the share of riders sampled in the before period who face a given fare change (e.g., from \$0.25 to \$0.35). Average fare in the after period is equal to

$$\mathrm{FARE}_L^1 = \Sigma p^1 S^0 \qquad (5)$$

where p^1 is the fare paid in the after period by the share of riders S^0 sampled in the before period. By using the Paasche index, average fare in the before period is equal to

$$\mathrm{FARE}_p^0 = \Sigma p^0 S^1 \qquad (6)$$

where S^1 is the share of riders in the after sample who face a given fare change. Average fare in the after period is equal to

$$\mathrm{FARE}_p^1 = \Sigma p^1 S^1 \qquad (7)$$

Average fare is calculated by using the geometric mean of the two index numbers to develop an unbiased estimate of average fare. The average fares for each market segment before and after the increase are given in Table 1.

As mentioned previously, it is assumed that all market segments are affected by other factors in the same way. This assumption may impose a serious degree of bias in many cases. For example, the group without an automobile available decreased their tripmaking significantly more than the group with an automobile available. It is likely, however, that riders with an automobile are more responsive than the average to gasoline price increases. Therefore, the increase in bus trips attributable to the gasoline price increase is underestimated for this group and part of the increase attributed to the fare change. Conversely, if the no-automobile group is actually less responsive than the average to the gasoline price increase, the decrease in bus trips attributable to the fare change is underestimated.

A related issue is the bias imposed by the implicit assumption that all factors that affect ridership are accounted for. If publicity and public

Table 1. Average fare by market segment.

Market Segment	Average Fare[a] Before	Average Fare[a] After	Market Segment	Average Fare[a] Before	Average Fare[a] After
Means of payment			Occupation		
Pass	0.3885	0.4600	Student	0.2380	0.3451
Ticket	0.2300	0.2975	Homemaker	0.2380	0.3451
Cash	0.2763	0.3456	Clerical-sales	0.3445	0.3767
Income (\$)			Skilled laborer	0.2907	0.3724
<5000	0.2553	0.3457	Houseworker	0.3211	0.3885
5000 to 9999	0.2948	0.3671	Other	0.2901	0.3658
10 000 to 14 999	0.3230	0.3714	Trip purpose		
15 000 to 24 999	0.3504	0.3722	Work	0.3185	0.3728
>25 000	0.3371	0.3733	Nonwork	0.2471	0.3422
Age			Recreational	0.2586	0.3497
<16	0.2161	0.3215	Sex		
16-24	0.2856	0.3653	Female	0.2806	0.3593
25-39	0.3183	0.3729	Male	0.2965	0.3622
40-59	0.3221	0.3730	Race		
60-64	0.2825	0.3613	White	0.3163	0.3607
>65	0.1984	0.2947	Black	0.2723	0.3619
Automobile availability			Other	0.2500	0.3500
Automobile	0.3339	0.3701	Fare category		
No automobile	0.2688	0.3562	Adult	0.3087	0.3719
Occupation			Student	0.2114	0.3234
Professional	0.3327	0.3727	Senior citizen and handicapped	0.1324	0.2299
Retired	0.1834	0.2860			
Unemployed	0.2446	0.3428	Total	0.2910	0.3610

[a]Average fare is defined as the geometric mean of the Laspeyre and Paasche indices: Geometric mean $_i^j$ = $[\text{Laspeyre index}_i^j \times \text{Paasche index}_i^j]^{1/2}$, where i is the market segment and j is the before or after period.

information campaigns accompanied the fare increase, then certain market segments may have increased their ridership more than others due to these promotion efforts. The decrease in bus trips attributable to the fare increase alone would be underestimated for these segments. Similarly, quality-of-service characteristics such as the level of crowding may affect different market segments differently. By failing to account for the impact of changes in crowding, the elasticities and relative magnitudes across segments may be biased.

Therefore, the failure to obtain reliable estimates of market segment elasticities appears to be derived from two major sources:

1. The survey data do not provide sufficiently accurate estimates of market segment proportions.
2. The assumption that all market segments are affected by other factors in the same way is inevitably violated, which leads to biased estimates of the impact of fare on each segment.

CONCLUSIONS

The results of this analysis of the impact of the fare increase on market segments lead to the conclusion that it is very difficult, if not impossible, to estimate market segment elasticities with data from typical on-board surveys. At the least, estimates of elasticities for different groups must be based on more precise estimates of the proportions of each group than are typically obtained in on-board transit surveys. A preferred approach would use actual ridership by market segments rather than estimates of proportions. However, the resources required to obtain precise measures of ridership are large due to the high variability in transit ridership and the relatively small size of many segments.

The problems encountered in this analysis of market segments could be mitigated or overcome in the following ways:

1. An analysis of the effect of the fare increase on former users, including those individuals who stopped using the transit system, should be carried out so that the demand elasticity for a single population can be measured.
2. The sources of the decrease in trips should be evaluated.
3. To measure the impact of fare changes on market segments, sampling designs that provide more precise estimates of population proportions or estimates of market segment ridership should be used. Both larger simple random samples and disproportionate random sampling to ensure that relatively small groups are adequately represented would lead to more accurate results.
4. Market segments based on more than one segmentation variable should be developed so that homogeneous groups can be examined.
5. Finally, a disaggregate analysis should be undertaken so that the impacts of all factors that affect transit use can be accurately measured and more precise estimates of the fare elasticity for different groups can be made.

ACKNOWLEDGMENT

The material presented in this paper is based on a study funded by the Transportation Systems Center (TSC) under the Service and Methods Demonstration program of the Urban Mass Transportation Administration. I would like to thank Lawrence Doxey of TSC for his helpful comments and observations and Daniel Brand of Charles River Associates, who provided many insights and suggestions. The assistance of Thomas Parody of Charles River Associates, who designed the on-board survey and supplied critical information on JTA, and the contribution of Lawrence Levin, who conducted the data processing, are also gratefully acknowledged.

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