Elasticities derived from some demand models, including the disaggregate models, do consider such cost variables. Transferability of results would be affected by the specification of these and other possibly important variables not yet identified.

The variation in elasticity data is large relative to the mean value and inversely related to the demand level and the square of the log difference in fares. The indications are that the demand weighted mean value of the cases approaches the aggregate elasticity, which may provide a better estimate of the expected response if a single value for change in demand is sought.

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Further Evidence on Aggregate and Disaggregate Transit Fare Elasticities

ARMANDO M. LAGO, PATRICK D. MAYWORM, AND J. MATTHEW McENROE

This paper presents new evidence on transit fare elasticities from experimental demonstrations and demand models. Mean values and standard deviations of fare elasticities are analyzed for both aggregate and disaggregate ridership categories. Aggregate fare elasticities for fare-free, fare prepayment versus cash payment, and promotional fare reductions are presented. Fare elasticities are also disaggregated by mode, trip length, route type, period of the day, and income and age groups. A review of the methods used in elasticities estimation is also presented.

Over the past few decades, transit operators have relied on the Simpson and Curtin formula (1) for predicting the impact of fare changes on transit ridership. The Simpson and Curtin formula, which predicts the percentage decrease in ridership as a function of the percentage increase in fares, has reverted to the rule of thumb that transit ridership will decrease (increase) 0.3 percent for every 1 percent increase (decrease) in transit fares.

Although the Simpson and Curtin rule of thumb is generally correct in highlighting the fact that transit ridership is inelastic, its indiscriminate use can lead to serious miscalculations of the ridership impacts of fare changes. This problem was brought out by two American Transit Association (ATA) studies of losses in passenger traffic due to transit fare increases between 1950 and 1967 (2,3). Both studies, while finding an average shrinkage ratio of -0.33, showed wide variances in the range of elasticities estimated, ranging from -0.004 to -0.97. Dygert, Holec, and Hill (4) have shown that in slightly more than half the cases the shrinkage ratio estimated by ATA was below Simpson and Curtin's rule of thumb.

The existence of such a wide variation in transit fare elasticities has prompted many transportation analysts to present evidence of disaggregate ridership response to fare changes (5-7). This paper presents new information on the size of aggregate and disaggregate transit fare elasticities obtained from demonstrations and demand models. In addition, this paper cautions the reader in interpreting the demand elasticity estimates from data containing no fare change.

APPROACHES TO ESTIMATING TRANSIT FARE ELASTICITIES

Nature of Approaches to Demand Estimation

Two broad approaches to estimating fare elasticities may be distinguished. These approaches include (a) monitoring fare changes or demonstration studies, or those that rely on data generated either by a practical demonstration of an actual change or by monitoring an actual change in current fares; and (b) nonexperimental approaches, or those that rely on a data base either devoid of an actual change in current fares or where actual changes are part of historical trends.

Approaches in the first category include the monitoring of transit fare demonstrations and individual fare changes such as those using monthly data series (8,9). These approaches estimate fare elasticities in current dollars. The nonexperimental approaches generally include (a) the conventional time-series analysis of annual transit operating statistics; (b) aggregate direct-demand and modal-split models based on cross-sectional data; and (c) disaggregate behavioral mode-choice models based on cross-sectional data. These last two approaches estimate fare elasticities in constant dollars. All the nonexperimental approaches have in common the facts that the data base does not contain an actual fare change in current or money terms and also that the data base is not generated with the objective of controlling for nonfare changes.

Methodological Note on Special Problems of Cross-Sectional Models

In interpreting transit demand elasticities, some problems are posed by over-reliance on elasticity estimates developed from a cross-sectional data base containing no fare change. One cannot rely on elasticity estimates from cross-sectional studies to provide accurate estimates of annual changes in patronage in response to fare changes because they reflect a different type of behavior from that implicit in time-series analysis. This difference between time-series and cross-sectional models arises because the residuals from both models cannot be assumed to belong to the same underlying population. In general, cross-sectional estimates represent behavior that, for lack of better terms, economists have labeled "long-run structural adjustments" (10-12), although it is possible that cross sections taken at a time of rapid growth or of cyclical change could also reflect short-run annual adjustments such as those characterized by time-series relations. Although cross-sectional models have advantages in forecasting structural changes in demand, dynamic annual-change-type responses cannot be estimated with any degree of confidence unless supporting time-series information is available to establish a systematic relation.

Another problem is that some recent work on disaggregate behavioral models has departed from McFadden's (13) original contribution and as a consequence, as shown by Oum (14), some of these models (a) impose many rigid a priori conditions on the elasticities and cross-elasticities of demand, (b) result in estimates of elasticities that are not invariant to the choice of the "base" or modal denominators, and (c) possess severely irregular and inconsistent underlying preference or utility structures. Moreover, an estimation problem arises whenever simultaneous mode choices concern more than two modes. Both Theil (15) and Nerlove and Press (16) argue that biased coefficients result when simultaneous choices--such as the choices involving more than two transport modes--are estimated via single-equation estimation techniques such as the maximum likelihood approaches currently used by transportation mode-choice modelers.

In spite of the alleged superiority of calibrated models relying on cross-sectional data, some studies (6,17) have shown that the approaches that rely on data generated by monitoring actual changes in current fares result in more stable elasticity estimates. The reader is therefore urged to use caution when interpreting and using elasticity estimates from calibrated cross-sectional models unless the models have been calibrated from a data base where actual fare changes have occurred.

Variable-Elasticity Models

The research and implementation issues of disaggregate behavioral models have been reviewed elsewhere (18,19) and do not have to be repeated here. One area, however, that has been overlooked concerns the need for more analysis of the interaction effects of fare and service levels. Whether from demonstrations or sophisticated mode-choice models, most demand-analysis approaches explicitly ignore the possibility of analyzing fare and service interactions by assuming constant-elasticity models (i.e., assume the interactions to be zero). These constant-elasticity models should be deemphasized in favor of variable-elasticity models with interaction effects, such as the translog models (20).

Aggregate Fare Elasticities

From an analysis of more than 60 studies of transit fare demand (6), the following aggregate fare elasticity means and standard deviations have been estimated:

Factor	Mean	SD	No. of Cases
Monitoring fare changes, demonstration studies	-0.28	±0.16	67
Nonexperimental time-series	-0.42	±0.24	28
Nonexperimental cross-sectional	-0.53	±0.35	28

The results from demonstrations and other fare-change-monitoring studies are not appreciably different from Simpson and Curtin's rule of thumb. However, the fare elasticities developed from nonexperimental direct-demand and mode-choice models are appreciably higher, especially for those models using cross-sectional data. It has been shown that the calibrated elasticities from models are almost twice as large as the empirical elasticities estimated from actual fare changes (17). The aggregate values presented in an Ecosometrics study (6) show the elasticities from studies that use cross-sectional data to be 1.89 times the elasticity values from demonstrations and studies of fare changes that use before-and-after data.

Fare-Free Elasticities

The fare-free demonstrations and case studies conducted under the sponsorship of the Urban Mass Transportation Administration (UMTA) provide information on the ridership responsiveness to maximum reductions in fare to fare-free service. The following table (6) summarizes the fare elasticities calculated from the results of these demonstrations:

	Time Period	
Service Restrictions	Off-Peak	All Hours
CBD only	-0.61 ± 0.14 (3 cases)	-0.52 ± 0.13 (3 cases)
Senior citizens	-0.33 (1 case)	NA
Students only	NA	-0.38 (1 case)
No restrictions	-0.28 ± 0.05 (4 cases)	-0.36 ± 0.28 (2 cases)

As seen from this table, the highest fare-free elasticities apply to central business district (CBD) travel where the result of the free fare is to divert a substantial number of walking trips to the free bus service. Except for the CBD fare elasticities, the fare-free elasticities are generally lower than the elasticities observed for fare increases and decreases at comparable initial fare levels. This is confirmed by the low elasticities of -0.29 and -0.19 estimated from the off-peak fare-free demonstrations in Denver and Trenton. The relatively low fare-free elasticities throw doubt on the theoretical hypothesis that the greater the relative change in fares the greater the elasticity value.

Fare Prepayment Versus Cash Payment

The knowledge of fare elasticities of demand for transit fare prepayment is limited. The scant information available from Europe shows pass riders to be more fare-inelastic than cash-fare or ticket riders, reflecting the fact that pass users are frequent riders who, like commuters, exhibit low fare elasticities. In Paris, the fare elasticity of demand for passes is -0.14 in contrast to -0.20 for single-ride tickets (21). The Midland Red Bus Company in Warwickshire County, England, shows fare elasticities of -0.10 for passes and -0.32 for single-ride tickets (21).

There have only been a few attempts to calculate fare prepayment demand elasticities by using U.S. data. In Jacksonville, Florida, the adult cash fare elasticity of -0.31 is lower than the demand elasticity for passes (-0.36) (22). The systemwide fare elasticity is -0.38. Demand elasticities for pass users participating in the employer-promoted fare prepayment demonstration in Sacramento (23) were calculated by Ecosometrics to be -0.41 for work trips, -0.27 for nonwork trips, and -0.39 overall. The higher fare elasticity for work trips compared with that for nonwork trips is indicative of the limitations on nonwork travel for individuals working every day.

By using a maximum-likelihood disaggregate choice model, Page (24) estimated fare elasticities of the probability of purchasing a pass ranging from -0.18 to -0.38 for the Sacramento employer-promoted monthly-pass program. Although the elasticity estimates are reasonable, the econometric-demand work conducted here and elsewhere on pass programs has failed to analyze passes as rate structures. The result of this improper reflection of the econometrics of rate structures is to confuse the price-and-income effects of passes on demand (25).

Fare Elasticities from Promotional Fare Reductions

Although transit properties across the country are continuously offering "bargain fares", "Sunday specials", and "fare-free days," few of these programs are monitored closely for their short-term and long-term ridership and revenue impacts. Caruolo and Roess (26), however, have identified two fare-free projects from which fare elasticities could be calculated.

An Auburn, New York, experiment involved the all-day elimination of a 25-cent fare for one month. Although ridership increased more than 300 percent during the fare-free month (fare elasticity of -0.63), there is no mention of the level-of-ridership attrition after the experiment. In Madison, Wisconsin, fares were abolished during off-peak hours for one week. Total weekly ridership increased 93.5 percent, resulting in a fare elasticity of -0.32.

In 1975, Madison conducted a demonstration project to test the effects of reduced fares and more frequent headways on weekend ridership (27). Although some data discrepancies exist, the demonstration is one of the only documented efforts in the United States to sequentially vary transit fares and headways. The results of the short-term weekend fare reduction and subsequent fare increase are presented below (6,27):

Fare Change	Date of Fare Change	Fare Elasticities Saturday	Fare Elasticities Sunday
Decrease	January 18, 1975	-0.28	-0.20
Increase	May 10, 1975	-0.51	-0.64

Caruolo and Roess (26) also reviewed the 1974 "Save-on-Sunday" program sponsored by the Metropolitan Transit Authority in New York City. Under the two-rides-for-the-price-of-one program, ridership increased by approximately 37 percent overall. The Sunday price promotion lasted six months and resulted in an overall fare elasticity of -0.47 (6). As in Auburn and Madison, the price promotion in New York City resulted in a net revenue loss for the operator.

DISAGGREGATE FARE ELASTICITIES

Recently, transit operators have begun to target fare programs to meet the needs of specific user groups, and aggregate fare elasticities do not provide reliable estimates of the ridership and revenue impacts of individual programs. This section presents evidence of disaggregate fare elasticities for different types of trips and user groups.

Fare Elasticities by Mode

Several studies have confirmed that bus fare elasticities (8 cases) are two times greater than rapid-rail fare elasticities (8 cases), as shown below (6,21,28,29):

City	Bus Service	Rapid-Rail Service
New York	-0.32 ± 0.11	-0.16 ± 0.04
London	-0.33	-0.16
Paris	-0.20	-0.12
Mean and SD	-0.30 ± 0.10	-0.15 ± 0.13

For six independent fare changes in New York City between 1948 and 1977, the mean bus fare elasticity is -0.32 ± 0.011 while the value for subway service is -0.16 ± 0.004. This larger elasticity for bus transit than for rapid rail can be explained by the more numerous substitutes for bus transit. Automobile, taxi, and even walking modes of travel share the same right-of-way and serve the same routes as buses. In contrast, rail transit has fewer modal substitutes, is faster than bus transit operating on surface streets, and occupies its own right-of-way.

Although it can be said for certain that bus fare elasticities are, on the average, twice as large as rapid-rail elasticities, the relation between bus and commuter-rail fare elasticities is inconclusive. Although it is our belief that commuter-rail fare elasticities are lower than those for buses, the few observations available show inconsistencies that make it impossible to formulate definite conclusions. The most reliable of the fare-elasticity estimates are those from London (30) and from the Boston 1963 demonstration (31), which show commuter-rail elasticities lower than bus fare elasticities (6).

Long- and Short-Distance Fare Elasticities

The demand for very short transit trips appears to be more elastic with respect to fares than is the demand for long trips. The London Transport Review Board's 1968 mathematical analysis (32) shows that bus trips of less than 1 mile exhibit higher fare elasticities (-0.55) than trips of 1-3 miles (-0.29). Bly (21) reports that in Essen, Germany, the fare elasticity for short- and long-distance trips was found to be -0.32 and -0.12, respectively.

Fare Elasticities by Route Type

Differences in fare elasticities have been observed for various types of transit services and routes in urban areas. The general consensus has been that on routes in which the preponderance of travel is for work purposes, such as radial arterials and express routes, the fare elasticities are lower than those observed on routes with a large proportion of discretionary travel, such as on intrasuburban and local routes.

Table 1 presents data from the London Transport experience that tends to support this. The results show that weekday intrasuburban trips are more elastic than radial trips between central London and the suburbs. The relatively large intrasuburban fare elasticities suggest that the intrasuburban trips are either less important or have more modal substitutes than radial trips.

Peak and Off-Peak Fare Elasticities

In nearly every study where peak and off-peak fare elasticities have been estimated, off-peak elasticities are two to three times larger than the values observed for peak travel. The off-peak fare elasticities for New York and London presented in Table 2 (6) are 2.5 times larger than corresponding peak-period values. Moreover, this factor applies equally to bus and rapid-rail travel. For subway service in New York City and bus service in St. Louis, afternoon peak-period ridership is more elastic than morning peak-hour ridership indicating that a greater degree of nonwork or nonessential travel takes place during the evening rush hour.

Table 1. Fare elasticities by route type and transport mode.

	Route Type		
Transport Mode	Radial Arterial	Intrasuburban	All
Bus	-0.09	-0.38	-0.32
Rapid rail	-0.11	-0.28	-0.26
Commuter rail	-0.06	-0.26	-0.13
Mean	-0.09	-0.31	-0.24

Note: Because own-price elasticities were not presented in Fairhurst and Smith (30) and could not be estimated, the elasticity values presented in this table were calculated from simulations of a 10 percent fare increase across all public transportation modes.

Evening, late night, and weekend fare elasticities are not much different from the values observed for midday services, although the results obtained from a 1968 study for New York City (28) show Sunday ridership to be less elastic than Saturday ridership (6).

There are scant data available on accurate estimates of the cross-elasticity between peak and off-peak periods. Ecosometrics (6) presented evidence that showed the mean elasticity of peak demand to off-peak fare changes to be +0.15 ± 0.14 (6 cases) and the mean elasticity of off-peak demand to peak period fare adjustments to be +0.03 ± 0.01 (2 cases). Clearly, the reason for the extremely low peak demand cross-elasticities is that workers have little choice in deciding their home-to-work travel time. In cities with differential time-of-day pricing and well-organized variable work hours programs (such as in Duluth, Minnesota), peak to off-peak fare cross-elasticities may be larger.

Fare Elasticities by Income and Age

One would expect high-income groups to have a larger fare elasticity than low-income groups. The analyses of both the Denver and Trenton off-peak fare-free demonstrations provide partial support for this general hypothesis, as shown in the table below (33,34):

	Off-Peak Fare Elasticities	
Household Income ($)	Denver	Trenton
Under 5 000	-0.28	-0.09
5 000-9 999	-0.24	-0.10
10 000-14 999	-0.25	-0.41
15 000-24 999	-0.28	-0.08
25 000 or more	-0.31	-0.43

Although the Denver demonstration shows only slight differences in off-peak elasticities by income group, Trenton's fare elasticities generally rise as household incomes increase. The elasticities calculated in these demonstrations refer to off-peak hours when most nonwork trips are taken. Whereas most of the new transit trips in the Denver case came from the more-affluent groups, the largest increase in temporal shifts from the peak came from the lowest-income groups.

The Denver and Trenton off-peak fare-free demonstrations have provided some evidence to suggest that there is an inverse relation between age and ridership response during the off-peak hours. In both demonstrations, young people were most responsive to the off-peak fare elimination, as shown in the following table:

Age Category	Demonstration		Mean
(years)	Denver	Trenton	Value
1-16	-0.32	-0.31	-0.32

Table 2. Disaggregated fare elasticities by time of day and week.

	Peak Period									
City	A.M.	P.M.	Average	Off-Peak Period	Midday	Evening	Late Night	Saturday	Sunday	All Hours
New York										
Rapid rail	-0.03	-0.06		-0.11	-0.10	-0.18	-0.04	-0.15	-0.04	-0.09
St. Louis	-0.13	-0.17			-0.40	-0.38				-0.24
Madison				-0.32				-0.28	-0.20	
								-0.51	-0.64	
Denver				-0.29	-0.28			-0.28	-0.45	
Trenton				-0.19	-0.18	-0.22		-0.13	-0.26	
London										
Bus		-0.27	-0.27	-0.37						-0.33
Rapid rail		-0.10	-0.10	-0.25						-0.16
Stevenage, England		-0.32	-0.32	-0.84						-0.67

Age Category (years)	Demonstration Denver	Demonstration Trenton	Mean Value
17-24	-0.30	-0.24	-0.27
25-44	-0.28	-0.08	-0.18
45-64	-0.18	-0.12	-0.15
65 or older	-0.16	-0.12	-0.14

CONCLUSION

The principal focus of this paper has been on identifying the differences in fare elasticities of transit demand among market groups. Although systemwide elasticity values, such as the Simpson and Curtin formula, have been useful for predicting aggregate ridership changes resulting from changes in fares, these values do not provide reliable estimates of the ridership and revenue impacts of individually targeted fare programs. Thus, the evidence currently available on disaggregated fare elasticities of demand was presented.

Also, the differences in fare elasticities noted in this paper highlight the futility of using flat-fare systems as revenue-producing agents. Not only do flat fares provide more subsidy to the more-affluent suburbanites and other long-distance riders, but they also result in significant losses of opportunities for increasing ridership and revenues. If U.S. transit companies are going to take advantage of the increased revenue and ridership opportunities afforded by the differences in fare elasticities across transit markets, the reliance on flat fares will have to be abandoned.

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Abridgment

Free-Fare Transit: Some Empirical Findings

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This paper presents comparative results from two free transit demonstrations funded by the Urban Mass Transportation Administration. In Denver and Trenton, one-year experiments with off-peak free transit began early in 1977. The analysis here is based on survey and ridership-count data collected as part of the demonstration evaluation process. Aggregate ridership increases of about 50 percent were observed at both sites following the elimination of fares. The majority of the additional trips would have otherwise been made by non-bus modes, though roughly 15-25 percent would not have been made at all without free fare. Transit-dependent groups, including the elderly, the poor, and the carless, were less responsive to fare elimination than were nondependent groups. Neither demonstration had a measurable impact on automobile use. At both sites increased ridership led to modest and generally localized deteriorations in service quality.

This paper summarizes the results of two off-peak free-fare demonstrations sponsored by the Office of Service and Methods Demonstrations, Urban Mass Transportation Administration (UMTA). One took place in Denver and the other in Trenton. Each lasted for one year. Restriction of free fare to off-peak periods served to reduce the overall cost of the demonstrations since peak-period ridership continued to generate revenue. Furthermore, continued collection of peak-period fares focused ridership gains on the excess capacity of the off-peak periods.

Although the basic approach to fare elimination was identical in Denver and Trenton, the two demonstrations had several important contextual differences. These included predemonstration site-and-transit service characteristics, underlying local objectives for the demonstration, the manner in which fare elimination was implemented, and external events that influenced the observed impacts of the demonstrations. Perhaps the most significant differences between the two demonstrations were in the circumstances under which they originated. Whereas the Trenton demonstration was planned from the beginning as a one-year experiment, the Denver demonstration evolved out of what was initially planned as a one-month, locally sponsored transit promotion effort. One consequence of the more spontaneous origin of the Denver demonstration is that there was little opportunity to develop either a comprehensive implementation procedure or an evaluation plan.

Also, during the course of the demonstration Denver restructured its bus routes from a radial pattern, focused on Denver's central business district (CBD), to a grid pattern. The route restructuring probably had both temporary and longer-term negative impacts on free-fare ridership levels (1).

AGGREGATE CHANGES IN TRANSIT RIDERSHIP

With the introduction of off-peak free fares, each site experienced a large increase in aggregate system ridership that was sustained throughout the demonstration period. In Trenton, average weekly off-peak ridership rose by 46 percent; in Denver, the increase was 52 percent. Figure 1 presents monthly ridership estimates for the two sites from January 1977 through June 1979.

Although ridership peaked early in each demonstration, it is evident from the figures that much of these ridership gains were sustained throughout the year of free fare. This suggests that even after the novelty of free bus service wore off, free fare continued to make transit an attractive travel alternative. Following the reinstitution of off-peak fares early in 1979, ridership remained above projections based on predemonstration levels, suggesting that some of the ridership induced by the free fares was retained after fares were reimposed. However, several exogenous events also influenced post-demonstration ridership in ways that were probably significant but cannot be easily quantified. Perhaps the most significant influence came from the nationwide gasoline crisis that occurred in 1979. The long-term impacts of the free-fare promotion are therefore uncertain at best, but are probably not of sufficient magnitude to offset the revenue loss associated with the year-long free-fare promotion.

TRAVEL-RELATED BENEFITS

The benefits ascribed to free-fare-induced transit derive from three sources: (a) increased mobility for transit dependents, (b) reduction of car travel through diversion of car trips to transit, and (c) economic stimulation of commercial areas through increased trip making for shopping.

One of the principal benefits attributed to free-fare transit is an increase in the mobility of transit-dependent segments of the population. By eliminating cost as a barrier to travel, proponents argue (2,3) that such groups as the poor, the elderly, or the young will have greater access to activities and opportunities throughout the urban area.

It was found that 12 percent of all free-fare trips in Trenton and 7 percent of those in Denver