RECEIVED

JAN 23 1981
LIBRARY

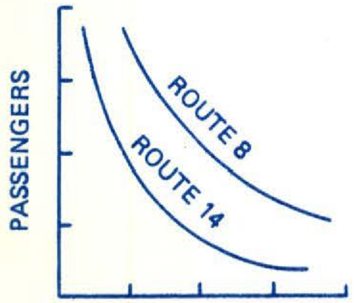
U.S. Department of Transportation
Urban Mass Transportation Administration

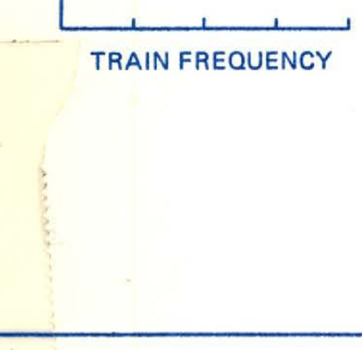
Office of Transportation Management and Demonstration

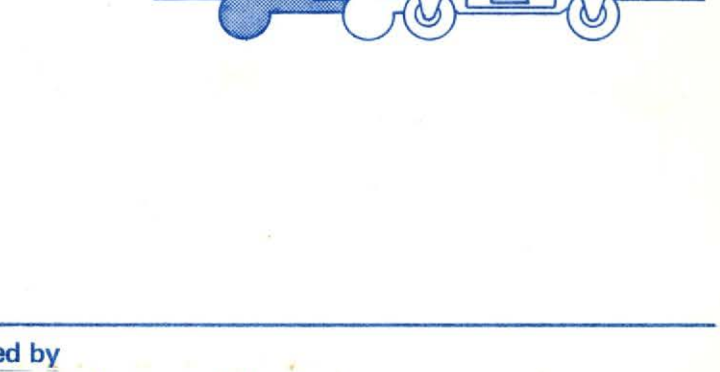
Office of Service and Demonstrations Methods

Washington, D.C. 20590

Patronage Impacts Of Changes In Transit Fares And Services







HE
305
.M29

Prepared by
Ecosometrics, Incorporated

This document is disseminated under the sponsorship of the U.S. Department of Transportation in the interest of information exchange. The United States Government does not endorse products or manufacturers. Trade or manufacturers' names appear herein solely becase they are considered essential to the object of this report.

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Patronage Impacts of Changes in Transit Fares and Services		5. Report Date September 3, 1980 6. Performing Organization Code
7. Author(s) Patrick Mayworm, Armando M. Lago, J. Matthew McEnroe		8. Performing Organization Report No. RR 135-1
9. Performing Organization Name and Address Ecosometrics, Incorporated 4715 Cordell Avenue Bethesda, Maryland 20014		10. Work Unit No. (TRAIS) 11. Contract or Grant No. DOT-UT-90014 13. Type of Report and Period Covered
12. Sponsoring Agency Name and Address U.S. Department of Transportation Urban Mass Transportation Administration 400 Seventh Street, S.W. Washington, D. C. 20590		14. Sponsoring Agency Code
15. Supplementary Notes Pricing Policy Innovations Division, UPM-33 Office of Service and Methods Demonstrations		

16. Abstract

This report presents information on public transit fare and service elasticities of demand. Data were obtained from a comprehensive review of studies performed in the United States and other countries, especially the United Kingdom. Estimates of individual fare and service elasticities were obtained from analyses of individual fare and service changes, and from direct-demand and mode-choice models based on time-series and cross-sectional data.

This report confirms the fact that transit demand is inelastic with respect to fares and services; that is, the proportional change in transit patronage in response to fare and service variations is less than the proportional change in fares and services. More importantly, the data presented in this report reveal that there is a large degree of consistency in the aggregate system-wide demand elasticities. Although there is variation in the disaggregate elasticity values, this variation is reduced and remarkable stability emerges when the analysis focuses on individual disaggregate categories. This underlying consistency, which exists across many types of cities and even countries, suggests that significant shifts in patronage could result without a deterioration in revenues from manipulations in fare and service levels.

17. Key Words	18. Distribution Statement
transit demand, elasticities, fares, services pricing, ridership, headways vehicle-miles, travel times, transfers	Available to the public through the National Technical Information Service Springfield, Virginia 22161

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	247	

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

METRIC CONVERSION FACTORS

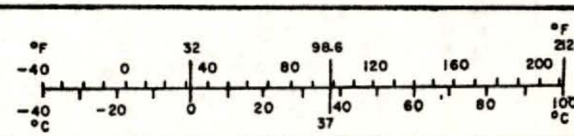
Approximate Conversions to Metric Measures

Symbol	When You Know	Multiply by	To Find	Symbol
		LENGTH		
in	inches	*2.5	centimeters	cm
ft	feet	30	centimeters	cm
yd	yards	0.9	meters	m
mi	miles	1.6	kilometers	km
		AREA		
in^2	square inches	6.5	square centimeters	cm^2
ft^2	square feet	0.09	square meters	m^2
yd^2	square yards	0.8	square meters	m^2
mi^2	square miles	2.6	square kilometers	km^2
	acres	0.4	hectares	ha
		MASS (weight)		
oz	ounces	28	grams	g
lb	pounds	0.45	kilograms	kg
	short tons (2000 lb)	0.9	tonnes	t
		VOLUME		
tsp	teaspoons	5	milliliters	ml
Tbsp	tablespoons	15	milliliters	ml
fl oz	fluid ounces	30	milliliters	ml
c	cups	0.24	liters	l
pt	pints	0.47	liters	l
qt	quarts	0.95	liters	l
gal	gallons	3.8	liters	l
ft^3	cubic feet	0.03	cubic meters	m^3
yd^3	cubic yards	0.76	cubic meters	m^3
		TEMPERATURE (exact)		
°F	Fahrenheit temperature	5/9 (after subtracting 32)	Celsius temperature	°C

*1 in = 2.54 (exactly). For other exact conversions and more detailed tables, see NBS Misc. Publ. 286, Units of Weights and Measures, Price $2.25, SD Catalog No. C13.10:286.

Approximate Conversions from Metric Measures

Symbol	When You Know	Multiply by	To Find	Symbol
		LENGTH		
mm	millimeters	0.04	inches	in
cm	centimeters	0.4	inches	in
m	meters	3.3	feet	ft
m	meters	1.1	yards	yd
km	kilometers	0.6	miles	mi
		AREA		
cm^2	square centimeters	0.16	square inches	in^2
m^2	square meters	1.2	square yards	yd^2
km^2	square kilometers	0.4	square miles	mi^2
ha	hectares (10,000 m^2)	2.5	acres	
		MASS (weight)		
g	grams	0.035	ounces	oz
kg	kilograms	2.2	pounds	lb
t	tonnes (1000 kg)	1.1	short tons	
		VOLUME		
ml	milliliters	0.03	fluid ounces	fl oz
l	liters	2.1	pints	pt
l	liters	1.06	quarts	qt
l	liters	0.26	gallons	gal
m^3	cubic meters	35	cubic feet	ft^3
m^3	cubic meters	1.3	cubic yards	yd^3
		TEMPERATURE (exact)		
°C	Celsius temperature	9/5 (then add 32)	Fahrenheit temperature	°F



ECOSOMETRICS

Report No. RR 135-1

PATRONAGE IMPACTS OF CHANGES IN TRANSIT FARES AND SERVICES

by

Patrick Mayworm
Armando M. Lago
J. Matthew McEnroe

September 3, 1980

S.C.R.T.D. LIBRARY

Prepared for

Office of Service and Methods Demonstrations
Urban Mass Transportation Administration
U.S. Department of Transportation

Under Contract DOT-UT-90014

00683

HE
305
.M29

ACKNOWLEDGEMENTS

The authors would like to acknowledge a number of individuals for their assistance at various stages in the research and production of this report. From the Office of Service and Methods Demonstrations (SMD) of the Urban Mass Transportation Administration, Ronald J. Fisher and Bert Arrillaga provided guidance and direction on the content of the report. Stewart McKeown, our Project Monitor, as well as Vincenzo Milione and Joseph Goodman contributed valuable information on current and past SMD demonstrations. Others contributing information to this report and to whom we are grateful include Michael Kemp, David Hartgen, Warren Somerfeld, Andrew Kilner, Anthony Hitchcock, David Quarmby, and Malcolm Fairhurst. Any errors resulting from the use of this information are our own. Special appreciation must be given to Linda Lee Jordan and Rosemarie Farinella for the professional production of this report.

ABSTRACT

This report presents information on public transit fare and service elasticities of demand. Data were obtained from a comprehensive review of studies performed in the United States and other countries, especially the United Kingdom. Estimates of individual fare and service elasticities were obtained from analyses of individual fare and service changes, and from direct-demand and mode-choice models based on time-series and cross-sectional data.

This report confirms the fact that transit demand is inelastic with respect to fares and services; that is, the proportional change in transit patronage in response to fare and service variations is less than the proportional change in fares and services. More importantly, the data presented in this report reveal that there is a large degree of consistency in the aggregate system-wide demand elasticities. Although there is variation in the disaggregate elasticity values, this variation is reduced and remarkable stability emerges when the analysis focuses on individual disaggregate categories. This underlying consistency, which exists across many types of cities and even countries, suggests that significant shifts in patronage could result without a deterioration in revenues from manipulations in fare and service levels.

TABLE OF CONTENTS

EXECUTIVE SUMMARY

BACKGROUND

During the past decade significant changes have occurred in both the economic and political environment surrounding the provision of public transportation services. On the one hand, increased operating expenses brought about by rising fuel prices and inflationary wage hikes have accelerated the rate of increase in transit deficits even though some diversion from automobile travel has occurred. On the political side, fiscal constraints spurred by national expansion of the California Proposition 13 movement have begun to check local governments' financial capability to support public transit.

The conjunction of these political and economic forces has created the need for a rational and businesslike approach to both the pricing and scheduling of public transportation services. Part of this approach calls for increased reliance on transit demand elasticities to assist transit operators in estimating passenger response to future fare and service variations. In addition, disaggregate demand elasticities can provide operators with an indication of how ridership and revenues can be increased by manipulating both fare and service levels.

The purpose of this report is to present the most reliable information available on the effects of changes in fares and services on public transportation patronage. This report does not attempt to analyze issues of pricing and service levels related to their optimality in given situations. Instead, the report concentrates on compiling estimates of transit demand elasticities and on presenting the major conclusions that may be derived from this information.

THE DEMAND ELASTICITY CONCEPT AND THE APPROACHES TO ITS ESTIMATION

The elasticity of demand is a convenient measure of the relative responsiveness of transit ridership to changes in fare and service levels. As a quantitative measure of relative change, the elasticity of demand is defined as the ratio of the percentage change in transit demand (ridership) to the percentage change in fares or service. Since the elasticity measures a ratio of percentage changes, it is therefore dimensionless and can be used to compare demand elasticity responses among different countries and time periods.

Two broad approaches to estimating fare and service elasticites may be distinguished. These approaches include:

i) quasi-experimental approaches, or those that rely on data generated either by a practical demonstration of an actual change or by monitoring an actual change in service levels or current fares, and

ii) non-experimental approaches, or those that rely on a data base either devoid of an actual change in current fares or service levels or where actual changes are part of historical trends.

The quasi-experimental approaches have in common the fact that they observe and analyze actual changes in services or in current fares (i.e., those expressed in current dollars without adjustments for inflation). The quasi-experimental approaches attempt to control -- with varying degrees of success -- for the influence of variables and factors exogenous to the measurements being taken. The two major approaches include (i) estimating from demonstrations or practical experiments, and (ii) monitoring actual changes in services or current fares.

The non-experimental approaches generally include (i) conventional time-series analysis of annual transit operating statistics, (ii) aggregate direct-demand and mode-split models based on cross-sectional data, and (iii) disaggregate behavioral mode-choice models based on cross-sectional data. These approaches have in common the fact that the data base does not focus on an actual change in fares (in terms of current dollars) or in service. The cross-sectional approaches estimate real fare and service elasticities by analyzing existing behavior and, in contrast to the quasi-experimental efforts, they do not focus on what people actually do when exposed to a fare or service change.

MAJOR FINDINGS

Fare Elasticities

Few pricing impact formulas in any major industry have achieved the same degree of overall acceptance as the Simpson and Curtin Formula 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 over the years into the rule of thumb that transit ridership will increase (decrease) 0.3 percent for every one percent decrease (increase) in fares over their previous level.

Although the Simpson and Curtin Formula is generally correct in highlighting the fact that transit ridership is inelastic (i.e., not very response to fare changes), its indiscriminate use can lead to serious miscalculations of the ridership impacts of fare changes. This problem has been brought out in several studies which have shown that there is a wide variation in the transit fare elasticities estimated. The existence of such a wide variation has prompted many transportation analysts to present evidence of disaggregate ridership response to fare changes. A summary of the principal findings on aggregate and disaggregate fare elasticities is presented below. The means and standard deviations of the fare elasticities for various market groups are consolidated and shown in Table S-1.

- Transit demand is inelastic to fare changes. Transit fare elasticities range in value from -0.04 to -0.87 with a mean of -0.28 ± 0.16 (67 cases). These results, from demonstrations and other quasi-experiments, are not appreciably different from the Simpson and Curtin rule of thumb. However the fare elasticities developed from non-experimental direct-demand and mode-choice models are noticeably higher especially for those models using cross-sectional data.

- Elasticities for fare increases do not differ from those for fare decreases. Although limited evidence from Atlanta and Madison suggests that larger fare elasticities result from fare increases than from fare decreases, the large sample of fare changes does not confirm this view.

- Fare-free elasticities are slightly smaller than comparable reduced-fare elasticities. With the exception of the fare-free elasticities for intra-CBD service, the fare-free elasticities are smaller than comparable elasticities for reduced-fare programs.

- Small cities have larger fare elasticities than large cities. Fare elasticities vary by city size and are appreciably larger in small and medium-size cities than in large cities.

Table S-1

SUMMARY OF FARE ELASTICITIES
PRESENTED IN CHAPTER 3
(Means and Standard Deviations)

AGGREGATE FARE ELASTICITIES		
<u>Estimation Method</u>		
Quasi-experimental:	-0.28 ± 0.16	(67 cases)
Time-series:	-0.42 ± 0.24	(28 cases)
Cross-sectional:	-0.53 ± 0.35	(28 cases)
<u>Type of Fare Change</u>		
Fare increase:	-0.34 ± 0.11	(14 cases)
Fare decrease:	-0.37 ± 0.11	(9 cases)
<u>Fare Change to Fare-Free</u>		
Within CBD only:	-0.52 ± 0.11	(4 cases)
System-wide:	-0.30 ± 0.17	(6 cases)
<u>City Size</u>		
Populations greater than 1 million:	-0.24 ± 0.10	(19 cases)
Populations 500,000 to 1 million:	-0.30 ± 0.12	(11 cases)
Populations less than 500,000:	-0.35 ± 0.12	(14 cases)
DISAGGREGATE FARE ELASTICITIES		
<u>Transit Mode</u>		
Bus:	-0.35 ± 0.14	(12 cases)
Rapid Rail:	-0.17 ± 0.05	(10 cases)
Commuter Rail:	-0.31	(1 case)
<u>Trip Length</u>		
London: Bus		
• trips less than 1 mile:	-0.55	(1 case)
• trips between 1 and 3 miles	-0.29	(1 case)
London: Rapid Rail		
• trips between 1 and 3 miles:	-0.25	(1 case)
• trips greater than 3 miles:	-0.60	(1 case)
<u>Route Type</u>		
Radial arterial:	-0.09 ± 0.02	(3 cases)
Intrasuburban:	-0.31 ± 0.05	(3 cases)
System-wide:	-0.24 ± 0.08	(3 cases)
CBD oriented:	-0.40 ± 0.04	(3 cases)
Non-CBD oriented:	-0.62 ± 0.09	(3 cases)
System-wide:	-0.55 ± 0.08	(3 cases)
Intra-CBD:	-0.52 ± 0.11	(4 cases)
System-wide:	-0.43 ± 0.08	(3 cases)

Table S-1 (continued)

Time Period:		
Peak:	-0.17 ± 0.09	(5 cases)
Off-peak:	-0.40 ± 0.26	(5 cases)
All hours:	-0.29 ± 0.19	(5 cases)
Trip Purpose		
Work:	-0.10 ± 0.04	(6 cases)
School:	-0.19 to -0.44	(3 cases)
Shop:	-0.23 ± 0.06	(5 cases)
Income Group		
Less than $5,000:	-0.19 ± 0.10	(2 cases)
$5,000 to $14,999:	-0.25 ± 0.11	(4 cases)
More than $15,000:	-0.28 ± 0.13	(4 cases)
Age Group		
1-16 years:	-0.32 ± 0.01	(2 cases)
17-24 years:	-0.27 ± 0.03	(2 cases)
25-44 years:	-0.18 ± 0.10	(2 cases)
45-64 years:	-0.15 ± 0.03	(2 cases)
More than 65 years:	-0.14 ± 0.02	(2 cases)

- Bus travel is more elastic than commuter- and rapid-rail travel. Bus fare elasticities are twice as large as rapid-rail fare elasticities where both modes are available. Fare elasticities for commuter-rail service appear to lie between the values observed for bus and rapid-rail service, but the limited evidence makes this claim uncertain.

- Off-peak fare elasticities are double the size of peak-fare elasticities. Regardless of the mode considered, fare elasticities for off-peak transit service are twice as large as those observed for peak-period service. Weekend fare elasticities are comparable to weekday off-peak elasticities. Cross-elasticities of demand from peak to off-peak hours are relatively small, less than +0.20 in the case of the recent off-peak fare-free demonstrations in Denver and Trenton.

- Short-distance trips are more elastic than long-distance trips. Bus trips less than one mile in length exhibit fare elasticities almost 100 percent larger than trips between one and three miles in length.

- Intrasuburban trips are four times more elastic than radial trips on arterials. The experience in London shows intrasuburban trips to be more elastic than radial trips to and from the central city. No accurate fare elasticity comparisons are possible for express and local service due to scarcity of measurements.

- Fare elasticities rise with income and fall with age. The Trenton and Denver off-peak fare-free demonstrations show that fare elasticities rise with income and fall with the age of the transit rider.

- Of all trip purposes, the work trip is the most inelastic. Shopping and school trips are two to three times more elastic than the work trip.

- Travel by the elderly is slightly more elastic than average. Although travel by the elderly is inelastic, it is more elastic than travel by the average transit rider.

- Promotional fare elasticities are slightly larger than short-term fare elasticities following permanent fare revisions. The fare elasticities estimated from ridership changes following the introduction of promotional fares are larger than those observed for permanent fare changes. Fare elasticities resulting from changes in the prices paid for fare prepayment instruments are not very different from the fare elasticities observed for permanent cash-fare changes.

Finally, the differences in fare elasticities noted above 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 American 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.

Service Elasticities

In contrast to the relative abundance of data on fare elasticities, the data on service elasticities are scarce. For example, no quasi-experimental data are available on wait- and transfer-time elasticities, and only a few cases are available on in-vehicle time elasticities. A summary of the means and standard deviations of the service elasticities is presented in Table S-2. Although the number of case studies is not large enough to support conclusions based on rigorous statistical testing, some generalizations are possible.

- Ridership response to service changes is inelastic. All services exhibit elasticities of demand with absolute values lower than 1.00. Thus, the proportional increases (decreases) in services are greater than the proportional increases (decreases) in passengers and revenues.

- Off-peak ridership is more responsive than peak ridership. Service elasticities are invariably 50 to 100 percent higher for the off-peak periods than for the peak periods.

- Ridership is more responsive in lower-service areas. Service elasticities are higher in low-service areas than in high-service areas during all time periods. Thus, the proportional change in patronage is much less than the proportional change in service when frequent or fast service exists.

- Ridership response is similar across modes. Bus and commuter-rail headway elasticities are similar, as are bus and rapid-rail in-vehicle time elasticities. The limited number of cases available, however, prevents making final conclusions concerning modal differences in service elasticities.

- Headway and vehicle-miles elasticities are similar. There are no apparent numerical differences between the quasi-experimental bus headway elasticities (-0.47) and bus-miles elasticities (+0.30 to +0.85), a conclusion that is supported by comparison with the non-experimental elasticities in Table S-2.

- Ridership is more responsive to improvements in headways than in in-vehicle time. The quasi-experimental service elasticity for in-vehicle bus travel time during peak periods (-0.29) is much lower than the equivalent quasi-experimental headway elasticity (-0.42).

- Most non-experimental travel-time elasticities are questionable. There are discrepancies in the relative values of in-vehicle and out-of-vehicle travel-time elasticities from the non-experimental or mode-choice models. As a general rule, the elasticities estimated from direct-demand and mode-choice models based on non-experimental data sources are less reliable and contain more discrepancies than the elasticities obtained from quasi-experimental data.

Table S-2

SUMMARY OF SERVICE ELASTICITIES
(Means and Standard Deviations)

HEADWAY ELASTICITIES		
Bus (Quasi-Experimental)		
Peak:	-0.37 ± 0.19	(3 cases)
Off-Peak:	-0.46 ± 0.26	(9 cases)
All Hours:	-0.47 ± 0.21	(7 cases)
Commuter Rail (Quasi-Experimental)		
Peak:	-0.38 ± 0.16	(5 cases)
Off-Peak:	-0.65 ± 0.19	(5 cases)
All Hours:	-0.47 ± 0.14	(5 cases)
Commuter Rail (Non-Experimental)		
All Hours:	-0.47 ± 0.11	(4 cases)
VEHICLE-MILES ELASTICITIES		
Bus (Quasi-Experimental)		
All Hours:	$+0.63 \pm 0.24$	(3 cases)
Bus (Non-Experimental)		
Peak:	$+0.33 \pm 0.18$	(3 cases)
Off-Peak:	$+0.63 \pm 0.11$	(3 cases)
All Hours:	$+0.69 \pm 0.31$	(17 cases)
Rapid Rail (Non-Experimental)		
Peak:	+0.10	(1 case)
Off-Peak:	+0.25	(1 case)
All Hours:	+0.55	(1 case)
TOTAL TRAVEL-TIME ELASTICITIES		
Bus (Non-Experimental)		
Peak:	-1.03 ± 0.13	(2 cases)
All Hours:	-0.92 ± 0.37	(2 cases)
Bus and Rapid Rail (Non-Experimental)		
Off-Peak	-0.59	(1 case)

Table S-2 (continued)

IN-VEHICLE TIME ELASTICITIES		
Bus(Quasi-Experimental)		
Peak:	-0.29 ± 0.13	(9 cases)
Off-Peak:	-0.83	(1 case)
Bus (Non-Experimental)		
Peak:	-0.68 ± 0.32	(7 cases)
Off-Peak:	-0.12	(1 case)
Rapid Rail (Non-Experimental)		
Peak:	-0.70 ± 0.10	(2 cases)
Bus and Rapid Rail (Non-Experimental)		
Peak:	-0.30 ± 0.10	(2 cases)
All Hours:	-0.27	(1 case)
Commuter Rail (Non-Experimental)		
All Hours:	-0.59 ± 0.28	(9 cases)
TOTAL OUT-OF-VEHICLE TIME ELASTICITIES		
Bus and Rapid Rail (Non-Experimental)		
All Hours:	-0.59 ± 0.15	(3 cases)
WALK-TIME ELASTICITIES		
Bus(Non-Experimental)		
Peak:	-0.26	(1 case)
Off-Peak:	-0.14	(1 case)
WAIT-TIME ELASTICITIES		
Bus and Rapid Rail (Non-Experimental)		
Peak:	-0.20 ± 0.07	(4 cases)
Off-Peak:	-0.21	(1 case)
All Hours:	-0.54	(1 case)
TRANSFER-TIME ELASTICITIES		
Bus and Rapid Rail (Non-Experimental)		
Peak:	-0.40 ± 0.18	(3 cases)
NUMBER OF TRANSFERS ELASTICITIES		
Bus (Non-Experimental)		
Off-Peak:	-0.59	(1 case)

- Service elasticities are not available for changes in many important service variables. Although transportation analysts have confirmed the importance of other service attributes on transit ridership, demand elasticities have not been estimated for such service attributes as seat availability and service reliability. Few demand elasticities exist for number of transfers.

USE OF DISAGGREGATE DEMAND ELASTICITIES

The demand elasticity concept is particularly useful for policy analysis purposes. Although the elasticity conveys a limited amount of information about how ridership adjusts to fare and service variations, it is useful as a summary of the type of behavior -- especially possible traffic diversions -- that characterizes the demand for transit. In addition to providing the numerical values needed to assist transit operators in estimating passenger response to future fare and service variations, disaggregate demand elasticities can provide operators with an indication of how ridership and revenues can be increased by manipulating both fare and service levels. It can thus be used for transit operational and financial planning, and for the generation of general transportation policy options.

Obtaining Ridership and Revenue Impacts

The most practical use of demand elasticities is for forecasting ridership and revenue impacts resulting from fare and service variations. This report emphasizes that aggregate elasticity values, such as the Simpson and Curtin Formula, are adequate only to describe the elasticity for all trip purposes, all periods of the day, and all types of passengers. Within a particular transit system operation, however, the actual elasticities of demand may be larger or smaller depending on the characteristics of the city in question and the travel habits of the local population. To be able to estimate the impact of fare and service changes on individual market subgroups, the transit operator should use the following guidelines.

1) Analyze Past Ridership Response: Individual aggregate fare and service elasticities should be estimated from past behavior controlling as much as possible for seasonal and secular trends. Although this should be possible for fare changes, many transit agencies do not have ridership estimates following service changes. If such an analysis is not possible, the transit agency should rely on the most appropriate service elasticities presented in this report.

2) Compute Average Demand Elasticity: An average aggregate demand elasticity should be calculated from the individual cases analyzed from the previous step. This average value should be used to predict aggregate ridership changes resulting from future fare and service adjustments.

3) Compute Disaggregate Demand Elasticities: The aggregate value obtained in the previous step can now be modified so that it can be applied to individual market subgroups. To do this, multiply the aggregate elasticity by the adjustment factors presented in Chapter 5 of this report for the market in question. The resulting value will be the estimated disaggregate fare or service elasticity.

4) Estimate Ridership Impact: The disaggregate demand elasticity can now be used for estimating the ridership impacts of alternative pricing and service level policies. The following formula should be used for this purpose:

$$\text{RIDERSHIP GENERATED OR LOST} = \left(\frac{\text{Change in Fare (Service)}}{\text{Existing Fare (Service)}}\right) \times \left(\begin{array}{c}\text{Disaggregate}\\ \text{Market}\\ \text{Elasticity}\end{array}\right) \times \left(\begin{array}{c}\text{Existing}\\ \text{Market}\\ \text{Ridership}\end{array}\right)$$

5) Estimate Revenue Impact: The final step in the analysis of an individual fare or service change is to estimate the revenue impact. The revenue generated or lost can be estimated using the following formulas.

For fare change:

$$\text{REVENUE GENERATED OR LOST} = \left(\text{Change in Fare}\right) \times \left(\begin{array}{c}\text{Disaggregate}\\ \text{Market}\\ \text{Elasticity}\end{array} + 1\right) \times \left(\begin{array}{c}\text{Existing}\\ \text{Market}\\ \text{Ridership}\end{array}\right)$$

For service change:

$$\text{REVENUE GENERATED OR LOST} = \left(\frac{\text{Change in Service}}{\text{Existing Service}}\right) \times \left(\text{Existing Fare}\right) \times \left(\begin{array}{c}\text{Disaggregate}\\ \text{Market}\\ \text{Elasticity}\end{array}\right) \times \left(\begin{array}{c}\text{Existing}\\ \text{Market}\\ \text{Ridership}\end{array}\right)$$

Joint Consideration of Transit Fare and Service Levels

The aggregate fare and service elasticities presented in this report indicate that transit demand is inelastic to both fares and services. Consequently, independent variations of fares and services will not by themselves increase both revenues and patronage at the same time. For example, an increase in service -- without a corresponding fare change -- will probably not result in revenue increases large enough to cover the extra costs of the service improvement because the proportional change in patronage is less than the proportional change in service.

However, the collection of data indicates that there is a large degree of variation of the disaggregate elasticity values suggesting that significant shifts in patronage could result without a deterioration in revenues from manipulations in fare and service levels. For example, using the data presented in Chapters 3 and 4, the mean bus headway elasticity on routes with less than ten-minute headways is -0.19 during off-peak hours. The average off-peak fare elasticity for bus service, however, is -0.37. Since the service elasticity is so low, a transit agency cannot hope to increase ridership and revenues substantially by further headway improvements. If anything, headways should be reduced with the operating cost savings applied either to other corridors with relatively poor service or to the same route in the form of a fare reduction.

Patronage losses associated with attempts to increase revenue can be minimized by increasing fares only for users exhibiting small demand elasticities, such as commuters. The service saved as a result of reduced demand, albeit little during the peak period, could be applied to routes with relatively poor service and result in further revenue increases if the patronage gained by the service adjustment is greater than the patronage lost due to the fare increase.

The above examples suggest that if the disaggregate fare and service elasticities are known for a particular transit market, the ridership or revenues generated by a particular action or set of actions could be improved by manipulating both the fare and service levels. Planners at the London Transport use estimates of fare and vehicle-miles elasticities derived from experimental and modeling studies along with other factors to assess the effectiveness of alternative fare, service, and equipment investment policies. Although the British planners are still some distance away from joint fare and service planning decisions, the theoretical and analytical apparatus that would enable them to expand into joint comprehensive planning of fares and services is indeed in place.

Here in the United States, performance indicators provide transit managers with quantitative information form which many service-level decisions are made. Joint fare and service planning decisions, however, are seldom taken since techniques for assessing alternative fare and service levels are not immediately available. In addition, most transit systems have flat-fare structures or rigid zone systems which do not provide transit managers with the opportunities to explore discriminant pricing policies. Nevertheless, in the near future national demonstrations of joint fare and service level variations will be performed to provide the transit industry with more information on fare and service demand elasticities, on their interactions, and on their use for policy planning purposes.

1

BACKGROUND AND OBJECTIVES

The decade of the 1970's has witnessed significant changes in both the political and the economic environment surrounding the provision of public transportation services. On the one hand, increased operating expenses brought about by increased fuel prices -- a consequence of the so-called 1973 "energy crisis" -- and inflationary wage hikes have accelerated the rate of increase in transit deficits even though some diversion from automobile travel has occurred. On the political side, fiscal constraints spurred by national expansion of the California Proposition 13 movement have begun to check local governments' financial capability to support public transit.

The conjunction of these political and economic forces has created the need for a rational and businesslike approach to both the pricing and scheduling of public transportation services. As a significant proportion of city residents depend on these services, their financial viability must be ensured.

REPORT OBJECTIVES

The purpose of this report is to present the most reliable information available on the effects of changes in fares and services on public transportation patronage. The information collected on passenger responses to fare and service changes has been synthesized to assist transit operators in estimating their possible effects. Guidelines on the use of this information are presented. This report does not attempt to analyze issues of pricing and service levels related to their optimality in given situations. Instead, the report concentrates on compiling estimates of passenger responses and on presenting the major conclusions that may be derived from this information.

COVERAGE OF DATA AND STUDIES

The report emphasizes the American experience with passenger responses to changes in fares and services. In some instances where the American experience is insufficient, data from studies and demonstrations performed in Canada and, especially, the United Kingdom have been utilized. Let the reader be assured that no bias is introduced by the limited reliance on British data. Comparisons of British and American experiences in passenger responses to changes in fares conducted by Bly (1976) have shown no significant differences between the two countries.

Although a considerable number of studies and reports have been reviewed in the process of developing a comprehensive compilation of passenger response data, not all of them are quoted in the text or in the Appendices. This is the result of a conscious process of quality control. Some studies were rejected because they used flawed methodologies that resulted in inadmissible estimates. In other instances, however, questionable estimates have been retained only because better estimates are not available in this very limited data base. Moreover, the reader will note that the text explores differences in opinions among several authors and studies, thereby documenting proper and reasonable conflicts on unresolved issues.

2

ELASTICITY OF DEMAND AND ITS MEASUREMENT

The demand for public transportation is influenced by many factors, including the level of transit fares and the quality and quantity of service provided. In an attempt to understand and compare the relative responsiveness of transit ridership levels to changes in transit fares and service levels, transportation planners have adopted the concept of elasticity, which is widely used by economists to indicate the proportional change in the consumption of a good resulting from a change in its price. This chapter explores the concept of demand elasticity as applied in the transportation field. The methods of measuring demand elasticities are reviewed first, followed by a discussion of methods of estimating ridership demand.

MEASURING THE ELASTICITY OF DEMAND

The elasticity of demand is a convenient measure of the relative responsiveness of transit ridership to changes in individual factors influencing demand. As a quantitative measure of relative change, the elasticity of demand is defined as the ratio of the proportional change in transit demand (ridership) to the proportional change in the factor being observed.[1] Thus, a transit fare elasticity

---

[1]A concept also used in this report is the cross-elasticity that measures the sensitivity of the demand for product i due to a change in the price (or other factor) of product j. For example, a peak/off-peak cross-elasticity may be defined as the percent change in peak transit demand due to a one-percent change in off-peak fares.

will indicate the percentage change in transit ridership resulting from a one-percent change in fares. Since the percentage change in ridership, fares, and services is independent of the units in which each is measured, the ratio of percentage changes -- the elasticity -- is also dimensionless. Therefore, one may compare, for example, the fare elasticities observed in the United Kingdom with those observed in the United States.

Transportation analysts have used several methods for calculating the elasticity of demand, each resulting in slightly different numerical values. Since this report focuses on the comparison of these values, it is important to present at least a cursory review of the formulas used to calculate the principal demand elasticity measures.[1] For convenience, the following paragraphs will describe only fare elasticities. Obviously, other factors influencing transit demand, such as headways and travel time, can be substituted.

Point Elasticity

The point elasticity is a measure of the ratio of an infinitesimal proportional change in demand to an infinitesimal proportional change in the fare, all other influencing variables held constant. Mathematically, the point elasticity is described as:

$$\varepsilon_{pt} = \frac{dQ}{dF} \cdot \frac{F_1}{Q_1}$$

where ε_{pt} is the point elasticity defined at ridership level Q_1, and fare level F_1. In this equation dQ and dF represent the derivatives of the respective variable.

Without information on the functional relationship between F and Q (i.e., on the shape of the demand curve), one cannot calculate the point elasticity at different ridership and fare-level combinations. Moreover, the formula only expresses the elasticity value at a point (Q_1, F_1) and, therefore, cannot be used to measure the relationship between finite changes in ridership and fare. As a practical matter, certain assumptions on the shape of the demand curve have to be made and then, with two sets of points available, an elasticity measure can be calculated.

---

[1]For a more comprehensive review of elasticity measures, see Grey (1975).

Shrinkage Ratio

The shrinkage ratio, also referred to as the loss ratio and line elasticity, is the measure most familiar to U.S. transit operators. Mathematically, the shrinkage ratio is calculated as the percent change in ridership divided by the percent change in fare. Thus:

$$\varepsilon_{sr} = \frac{Q_2 - Q_1}{Q_1} \div \frac{F_2 - F_1}{F_1} = \frac{\Delta Q/Q_1}{\Delta F/F_1}$$

where ε_{sr} is the shrinkage ratio calculated for the change in ridership and fare levels from (Q_1, F_1) to (Q_2, F_2).

The shrinkage ratio is a simple measure to calculate and provides an accurate approximation of the point elasticity for very small ridership and fare-level changes. Grey (1975) uses the term "line elasticity" to describe the shrinkage ratio, because over the range of fare and ridership changes being considered, the demand curve is assumed to be a straight line. Theoretically, the demand elasticity resulting from a fare increase from F_1 to F_2 should be identical to the elasticity measured for a fare reduction from F_2 to F_1. In the case of the shrinkage ratio, however, this is not so, especially for large fare changes, since the percentage change is calculated from the original fare and ridership levels.

Midpoint Elasticity

The difference between demand elasticities measured in the two directions can be eliminated by taking the effective fare and ridership levels at the midpoint between the two observations. The midpoint elasticity, therefore, is a convenient measure for use with large fare changes. Mathematically, the midpoint elasticity is described as:

$$\varepsilon_{mid} = \frac{(Q_2 - Q_1)}{(Q_2 + Q_1)/2} \div \frac{(F_2 - F_1)}{(F_2 + F_1)/2} = \frac{(Q_2 - Q_1)\ (F_2 + F_1)}{(Q_2 + Q_1)\ (F_2 - F_1)}$$

where $_{mid}$ is the midpoint elasticity calculated for the change in ridership and fare levels from (Q_1, F_1) to (Q_2, F_2).

Unlike the shrinkage ratio, the midpoint elasticity is a convex curve at a constant value of the fare elasticity.[1] The midpoint elasticity is also commonly referred to as the arc elasticity.

Arc Elasticity

In this report, the arc elasticity is defined by the logarithmic definition of elasticity. Mathematically, the arc elasticity is described as:

$$\varepsilon_{arc} = \frac{\log Q_2 - \log Q_1}{\log F_2 - \log F_1}$$

where ε_{arc} is the arc elasticity calculated for the change in ridership and fare levels from (Q_1, F_1) to (Q_2, F_2).

At constant elasticity values, the arc elasticity also represents a convex demand curve, although slightly different from the curve represented by the midpoint formula.

With the exception of the point elasticity, which requires information on the actual form of the demand curve, each of the elasticity measures discussed above assumes a unique functional form. Figure 2-1 presents the demand curves for the shrinkage ratio and midpoint and arc elasticities based on an initial point elasticity [at (1,1)] of -0.30.

---

[1]Although the shape of the demand curve depends on how the consumer ranks one good with respect to another, it is generally assumed that demand curves are negatively sloped and convex to the origin: the lower the price, the greater the quantity demanded.

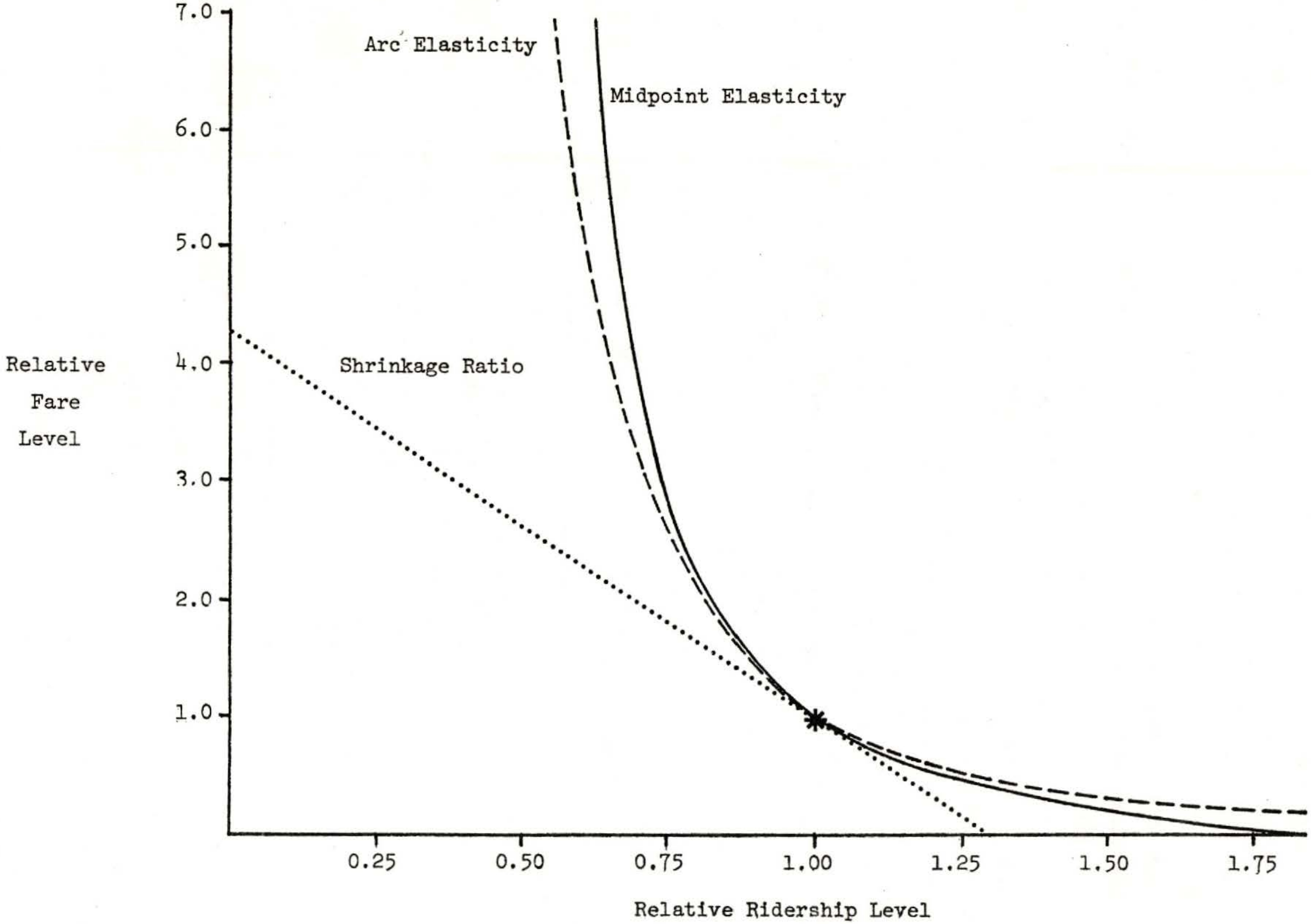


Figure 2-1: ELASTICITY OF DEMAND CURVES BASED ON AN INITIAL POINT ELASTICITY OF -0.30

Source: Grey (1975), p. 80.

Several important observations can be made from the demand curves presented in Figure 2-1. First, for very small fare changes [i.e., for very small movements from point (1,1)], all three measures produce similar values. When the fare change is large, however, the shrinkage ratio differs considerably from both the midpoint and arc elasticities. Moreover, for large fare increases, the midpoint and arc elasticities are numerically larger than the shrinkage ratio, and numerically smaller for fare decreases.

Consider the hypothetical situation presented in Table 2-1 where several fare increases and decreases occur. Based on a constant midpoint elasticity of -0.30 for comparative purposes, a shrinkage ratio and arc elasticity are calculated for each case. As the table shows, the shrinkage ratio differs considerably from the constant midpoint elasticity as the size of the fare change increases. However, notice how close the arc elasticity is to the midpoint value of -0.30 except for large fare decreases.

Table 2-1

SHRINKAGE RATIO AND ARC ELASTICITY VALUES FOR VARIOUS FARE CHANGES BASED ON A CONSTANT MIDPOINT ELASTICITY OF -0.30

Type of Fare Change	Percent Fare Change	Shrinkage Ratio	Arc Elasticity
Fare Increase	+90	-0.189	-0.291
	+50	-0.226	-0.296
	+10	-0.282	-0.300
Fare Decrease	-10	-0.321	-0.300
	-50	-0.444	-0.290
	-90	-0.723	-0.218

Another important observation from Figure 2-1 concerns the point at which the curves cross the horizontal axis, indicating the point of fare-free service. Whereas both the midpoint elasticity and shrinkage ratio will measure a change to fare-free service, the arc elasticity never meets the axis (it approaches the axis asymptotically) and, therefore, is undefined at zero fare. In addition, only the midpoint elasticity is defined when measuring ridership response for a fare increase from free fares as shown in Table 2-2.

Table 2-2

DEMAND ELASTICITY VALUES IN FARE-FREE SITUATIONS BASED ON A MIDPOINT ELASTICITY OF -0.30

Type of Fare Change	Midpoint Elasticity	Shrinkage Ratio	Arc Elasticity
To Fare-Free	-0.30	-0.86	Undefined
From Fare-Free	-0.30	Undefined	Undefined

The last important difference among the demand elasticity measures presented here concerns the relation between the numerical value of the elasticity and the effect on revenues. For arc and midpoint elasticity values numerically less than -1.00,[1] the demand response is said to be inelastic since a reduction in fares will lead to only a slight increase in ridership and, therefore, a reduction in total revenue; similarly, an increase in fares will lead to only a slight decrease in ridership and, therefore, a net increase in revenue. For elasticity values numerically greater than -1.00, the demand response is said to be elastic and the fare and revenue changes are inversely related. Thus, a midpoint and arc elasticity of -1.00 corresponds to the situation where the proportional change in fares produces the same proportional change in ridership and, thus, no change in revenue. This is not true, however, of the shrinkage ratio, which may be numerically greater than -1.00 when estimated from a fare reduction program resulting in a revenue loss.

[1]Demand elasticities are generally negative numbers, since there is an inverse relation between the price of a good and its consumption.

Without information on the demand curve, it is impossible to determine which demand elasticity measure best represents the transit market being observed. The linear form of the shrinkage ratio has been widely used due to its simplicity even though it has serious drawbacks during large fare changes. The midpoint and arc elasticities are now considered the dominant methods for expressing transit ridership response, and in this report both forms are used interchangeably. Wherever possible, shrinkage ratios have been converted to midpoint elasticities for comparative purposes. In addition, all demand-response estimates made by Ecosometrics, Inc. are based on the midpoint formula, because it can be used for changes to free fares and because it performs well "when considering falling rather than rising prices,"[1] a common occurrence in many transit systems during the past decade. However, whatever demand elasticity measure is used, one must be cautious about interpreting the results as definitive.

APPROACHES TO ESTIMATING DEMAND ELASTICITIES

Two broad approaches to estimating fare and service elasticities may be distinguished. These approaches include: (1) quasi-experimental approaches, or those that rely on data generated either by a practical demonstration of an actual change or by monitoring an actual change in service levels or current fares, and (2) non-experimental approaches, or those that rely on a data base either devoid of an actual change in current fares or service levels or where actual changes are part of historical trends. Time-series demand studies which do not focus on specific fare or service level changes, as well as all modeling efforts based on cross-sectional data, are classified as non-experimental approaches. The time-series analyses by Kemp (1974) and Goodman, Green, and Beesley (1977), however, are considered quasi-experimental approaches because they concentrate on individual fare and service changes with the careful monitoring of monthly data.

The distinction presented in this report between the two approaches is crucial because the quasi-experimental approaches yield estimates that are more reliable and more realistic than the estimates produced from non-experimental approaches, particularly those that rely on cross-sectional analysis.

The elasticities from quasi-experimental and non-experimental time-series approaches discussed in this report denote short-run patronage adjustments -- of

---

[1]Grey (1975) p. 76.

a year or less -- to changes in fares and services. This time period is not long enough to permit changes in residential location and other adjustments on the part of the transit clientele. The non-experimental cross-sectional approaches, whose elasticities are usually larger in value, are devoid of time connotations in the pattern of patronage adjustments to changes in fares and services. Although the cross-sectional approaches do not consider the effect of time, and since there are difficulties in explaining what type of behavioral adjustments they represent, the elasticities from cross-sectional models are called "structural" or "long-run" elasticities.

Quasi-Experimental Approaches

Quasi-experimental approaches have in common the fact that they observe and analyze actual changes in services or in current fares (i.e., those expressed in current dollars without adjustments for inflation). The quasi-experimental approaches attempt to control -- with varying degrees of success -- for the influence of variables and factors exogenous to the measurements being taken. The two major approaches included:

a) Estimating from Demonstrations or Practical Experiments. These approaches rely on exposing an experimental group to an actual change in current fares (or in services as the case may be) while controlling or keeping constant to the extent possible other, unmeasured influences. In some of these cases, random samples of the experimental group and a control group are chosen to compare the effects with and without the change or treatment.

The estimation methods for these demonstrations vary from simple computations of average elasticities to more sophisticated probit and logit models of choice behavior. Biases will result, however, unless the latter modeling approaches specifically analyze the change in travel by pooling cross-sections through at least two time periods (i.e., the before and after), and provide proper control for the individual traveller "taste" effect by using some of the statistical methods available for analyzing pooled cross-sections over time.

b) Monitoring Actual Changes in Services or in Current Fares. A second approach consists of carefully monitoring actual fare or service changes, either by using before-and-after surveys or by using a monthly time series of bus patronage figures. An example is Kemp's monitoring of fare changes in San

Diego and Atlanta.[1] In these studies, Kemp analyzed a time series of monthly patronage figures using regression analysis. The regression analysis estimated bus patronage as a function of fares and vehicle miles. Time trend and seasonal dummy variables were also included to control for other influences. Although there are uncertainties whether this approach suffers from the simultaneous-equation or identification bias in the estimation of the vehicle-miles coefficient, Kemp's careful studies of fare changes stand in contrast to other comparable but less serious efforts.

Non-Experimental Approaches

This category includes a series of approaches which, while different in estimation techniques, have one element in common, namely that the data base does not focus on either an actual change in fares (in terms of current dollars) or a change in service. The cross-sectional approaches estimate real fare and service elasticities by analyzing existing behavior and, in contrast to the quasi-experimental efforts, they do not focus (because the data base is devoid of these notions) on what people actually do when exposed to a fare or service change. This category includes most of the cross-sectional approaches used in the disaggregated or behavioral-choice models and in the aggregated transportation direct-demand models. The main approaches used in conjunction with non-experimental data include:

a) Time-Series Analysis of Transit Company Patronage Data not Related to a Specific Fare or Service Change. Most time-series analyses involve an annual data series in which several fare and service changes occur over a fairly long period of time (i.e., five to ten years). Generally using least-squares regression, the analyst is able to estimate the effect such changes have on transit patronage. Usually, the greater the variation in the variables over time, the better the explanatory power of the model, resulting in more reliable demand elasticity estimates. Most of these approaches estimate elasticities in terms of current fares.

Occasionally a data series will not include actual fare changes. In this situation the analyst bases his estimation of demand elasticities on the fact that while the fares have remained constant in monetary value, in real terms they have decreased due to the general inflation reflected in the consumer price index. Thus the analyst comes to depend on a data base which contains solely real changes (no monetary changes) in fares. This approach relies on time-series analysis with transit patronage estimated as a function of real fares (after

[1] See Kemp (July 1974 and March 1974).

adjustment for changes in the consumer price index), total vehicle mileage, time trend, and seasonal dummy variables. These approaches are subject to the same simultaneous-equation or identification bias noted earlier.

b) Aggregate Direct-Demand and Modal-Split Models Based on Cross-Sectional Data. This category refers to aggregate models in which the dependent variable represents a grouping of observations into traffic zones or other classification. In the aggregate direct-demand models, an internal structure of the Cobb-Douglas type is postulated. These models may be estimated through simple regression analysis or through constrained least squares as in the case of Kraft and Domencich's (1970) Free Transit study. These models have been criticized because of their statistical inefficiency, in that they require more data than the disaggregated models to obtain a fixed confidence level. However, as will be seen later, they also have basic problems in predicting patronage changes.

c) Disaggregate Behavioral-Mode-Choice Models Based on Cross-Sectional Data. In the disaggregate models, the dependent variable is a quantal variable representing a single trip. These have been labelled "behavioral" models because their behavior pattern corresponds to household utility-maximizing behavior. The household is pictured as estimating the potential net utility from making trips (a trade-off of the disutility from the effort and cost involved versus the utility derived from making the trip) and examining the full range of alternate choices before actually making a decision. The behavioral-mode-choice models estimate -- using logit or probit analysis -- the probability of choosing a mode as a function of the service attributes of that mode, the attributes of the competing modes, and the socio-economic characteristics of the person in question.

The mode-choice elasticities are not easily comparable to the time-series elasticities from quasi-experimental approaches. In the first place, the mode-choice elasticities are cross-sectional elasticities, much higher than their comparable time-series elasticity values, as explained below. Second, as shown by Koppelman (1975), the disaggregate elasticity at the sample mean is not necessarily equal to the aggregate elasticity of the population, where the latter is defined as the weighted average of the individual disaggregate elasticities using the individual probabilities as weights. The main reason for this difference between the aggregate elasticity and the disaggregate elasticity evaluated at the mean is due to their nonadditive property since the elasticities estimated from mode-choice models are nonlinear.

Another problem is that some of the more recent work on disaggregated behavioral models have departed from McFadden's (1974) original contribution and as a consequence, as shown by Oum (1979), some of these models (1) impose many rigid a priori conditions on the elasticities and cross-elasticities of demand, (2) result in estimates of elasticities which are not invariant to the choice of the "base" or modal denominators, and (3) possess severely irregular and inconsistent underlying preference or utility structures. Finally, an estimation problem arises whenever the simultaneous mode choices concern more than two modes, and the mode-choice modelers have not been careful about this. Both Theil (1970) and Nerlove and Press (1976) 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 the transportation mode-choice modelers.

A Note of Caution on Elasticities Based on Cross-Sectional Models. In interpreting the demand elasticities in this report, some problems are posed by reliance on elasticity estimates from a cross-sectional data base containing no fare or service changes. One cannot rely on elasticity estimates from cross-sectional studies to provide accurate estimates of annual changes in patronage in response to fare and service changes, because the elasticity estimates from cross-sectional analysis reflect a different type of behavior from that of the annual change behavior 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 which, for lack of better terms, economists have labelled "long-run structural adjustments,"[1] 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 relationships.

The demand elasticities from the cross-sectional models are generally greater than the time-series estimates. Chan and Ou (1978) found that fare elasticities estimated from calibrated cross-sectional models, some of them behavioral-choice models, were almost twice as large as elasticities estimated

---

[1]See Y. Grunfeld, "The Interpretation of Cross-Section Estimates in a Dynamic Model", Econometrica, 1961; E. Kuh, "The Validity of Cross-Sectional Estimated Behavior Equations in Time Series Application", Econometrica, Vol. 27, No. 2, April 1959; E. Kuh and J.R. Meyer, "How Extraneous are Extraneous Estimates?" Review of Economics and Statistics, November 1957.

from actual demonstrations and experiments. Although cross-sectional estimates have some advantages in forecasting structural changes in demand (i.e., introduction of new modes, etc.), dynamic annual-change-type responses cannot be estimated from them with any degree of confidence unless supporting time-series information is available to establish a systematic relationship.

This report shows that the quasi-experimental approaches result in more stable elasticity estimates than the calibrated models relying on cross-sectional data, in spite of the alledged superiority of these models in controlling for the influence of exogenous variables. 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 or service changes have occurred.

3

FARE ELASTICITIES

Few pricing impact formulas in any major industry have achieved the same degree of overall acceptance as the Simpson and Curtin Formula for predicting the impact of fare changes on transit ridership. The Simpson and Curtin Formula[1] predicts shrinkage ratios as a function of the percentage increase in fares in the following fashion:

$$\begin{array}{l}\text{Percent}\\ \text{Ridership}\\ \text{Loss}\end{array} = 0.80 + 0.30 \times \left(\begin{array}{l}\text{Percent}\\ \text{Fare}\\ \text{Increase}\end{array}\right)$$

This formula, estimated from a least-squares regression analysis of 77 fare increases during a period of 20 years, has been extensively used by transit managers and regulatory agencies in the financial planning and analysis of fare policies. In the Curtin (1968) paper, the average shrinkage ratio for the 77 fare increase events was calculated as -0.36. The Simpson and Curtin Formula has reverted over the years into the rule of thumb that transit ridership will increase (decrease) 0.3 percent for every one percent decrease (increase) in fares over their previous level.

---

[1]Although originally developed by John Curtin in 1947 from the results of a survey of fare increases on 91 U.S. transit properties, the most common reference to the Simpson and Curtin Formula is Curtin (1968), p. 13.

Although the Simpson and Curtin Formula is generally correct in highlighting the fact that transit ridership is inelastic (i.e., not very responsive to fare changes), 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)[1] studies (1961, 1968) of losses in passenger traffic due to transit fare increases between 1950 and 1967. Both studies, while finding an average shrinkage ratio of -0.33 (close to the Simpson and Curtin value), showed wide variances in the range of elasticities estimated, ranging from -0.004 to -0.97. Dygert, Holec, and Hill (1976) 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. The conclusions reached in several fare elasticity summaries are consistent with those found in this report, namely:

- Transit demand is inelastic to fare changes; that is, the proportional change in transit patronage is less than the proportional change in fares.
- Fare elasticities vary by city size and are appreciably larger in small cities than in large cities.
- Bus and off-peak fare elasticities are larger than rapid-rail and peak-period elasticities respectively.
- Short-distance trips of less than one mile are more elastic than longer trips of between one and three miles.
- Fare elasticities rise with income and fall with age of the transit rider.

This chapter presents evidence of both aggregate and disaggregate fare elasticity estimates from numerous studies of transit demand. The chapter concludes with a summary of ridership responsiveness to transit fare changes.

---

[1]The American Transit Association (ATA) merged with the Institute for Rapid Transit (IRT) to form the American Public Transit Association (APTA).

AGGREGATE FARE ELASTICITIES

From an analysis of over 60 studies of transit fare demand, the following aggregate fare elasticity means and standard deviations have been estimated:[1]

QUASI-EXPERIMENTAL	-0.28 ± 0.16	(67 cases)
NON-EXPERIMENTAL TIME-SERIES	-0.42 ± 0.24	(28 cases)
NON-EXPERIMENTAL CROSS-SECTIONAL	-0.53 ± 0.35	(28 cases)

The results from demonstrations and other quasi-experiments are not appreciably different from the Simpson and Curtin rule of thumb. However, the fare elasticities developed from non-experimental direct-demand and mode-choice models are noticeably higher especially for those models using cross-sectional data. The previous chapter noted that the fare elasticities from cross-sectional mode-choice models differ from the elasticities estimated using regular time-series analysis. Chan and Ou (1978) have shown that the calibrated elasticities from models are almost twice as large as the empirical elasticities estimated from actual fare changes. The aggregate values presented in this report show the elasticities from studies using cross-sectional data to be 1.89 times the elasticity values from quasi-experiments. Because of their general unreliability, the following discussion will de-emphasize the elasticity results estimated from calibrated models when their basic data does not contain any actual changes in the fares charged.

Fare Elasticities From Fare Increases and Decreases

The conventional wisdom regarding the effects of fare changes (see Bly, 1976) is that the long-run elasticity is larger for fare increases than for fare decreases because patronage losses from fare increases are not easily reversible. Thus, it is argued that faced with increases in fares, passengers either switch to automobiles and become part of the more elastic noncaptive market, or move to other residential locations from which it is more difficult to attract them back to transit.

Partial evidence in support of this hypothesis is provided in Table 3-1 by Kemp's (1974) analysis of Atlanta's fare changes during the period 1970-1973

1See Tables A-1 to A-3 in Appendix A for the background data on which these estimates are based.

and by the Ecosometrics, Inc. analysis of data from a 1979 demonstration in Madison, Wisconsin. Also presented in this table are the results from studies of fare changes in Cincinnati and Chicago. The Cincinnati results suggest that ridership will be more responsive to a fare decrease than to a fare increase. In Chicago, the results suggest the contrary. However, the Cincinnati and Chicago data are less reliable because of differences in the time periods and estimation methodologies used.

Table 3-1

ANALYSIS OF ELASTICITIES OF FARE INCREASES AND DECREASES IN INDIVIDUAL AMERICAN CITIES

City	Fare Increase (year)	Fare Decrease (year)
Atlanta (all hours)	-0.60 (1971) -0.33 (1963)	-0.18 (1972)
Madison (weekend)	-0.50 (1979)	-0.26 (1979)
Cincinnati (all hours)	-0.28 (1957)	-0.38 (1973)
Chicago	-0.26 (1970) -0.33 (1957) (all hours)	-0.09 (1953) (off-peak)

Source: See Table A-4, Appendix A.

On the basis of the elasticities estimated for 23 all-hour fare increases and decreases presented below in Table 3-2, one cannot conclude that the fare elasticities for fare increases are significantly different from those for fare decreases.

Table 3-2

ELASTICITIES OF FARE INCREASES AND DECREASES FROM U.S. CITIES -- ALL HOURS[a]

Type of Fare Change	Mean and Standard Deviation	Number of Cases
Fare Increases	-0.34 ± 0.11	14
Fare Decreases	-0.37 ± 0.11	9

[a]This table includes elasticities from cities of similar size; consequently, the aggregate New York City values (all from fare increases) as well as values from other cities are excluded.

Source: See Table A-1, Appendix A.

Size of Fare Change and Fare Level

Many public transportation analysts have argued that the greater the fare increase and the higher the fare level, the greater the decline in transit riding. Theoretical support for this hypothesis comes from the concept of generalized cost elasticity, in which the fare elasticity increases as the fare proportion of the total travel cost increases. In addition, the findings of several demand analysts of the London Transport, (for example, see Fairhurst and Morris, 1975) suggest that the demand for transit is nonlinear with respect to fares.

To date, however, the empirical work on fare elasticities has not found support for this view. Dygert, Holec, and Hill (1977) reviewed the data reported in the American Transit Association (1968) and concluded that neither the magnitude of the average fare before the fare increase nor the percentage increase in the average fare had any effect on the size of the fare elasticity.

Dygert's review confirmed the earlier empirical validation performed by Bly (1976) using American data. In summary, the theoretical arguments for suggesting that fare elasticity values are dependent on the size of the fare change and fare level have yet to be substantiated.

Fare-Free Elasticities

The fare-free demonstrations and quasi-experiments conducted under the sponsorship of the Urban Mass Transportation Administration provide information on the ridership responsiveness to maximum reductions in fare to fare-free service. Table 3-3 summarizes the fare elasticities calculated from the results of these demonstrations.

Table 3-3

FARE-FREE BUS ELASTICITIES

Service Restrictions	TIME PERIOD		All Unduplicated Cases[a]
	Off-Peak	All Hours	
Central Business District Only	-0.61 ± 0.14 (3 cases)	-0.52 ± 0.13 (3 cases)	-0.52 ± 0.11 (4 cases)
Senior Citizens	-0.33 (1 case)	NA	-0.33 (1 case)
Students Only	NA	-0.38 (1 case)	-0.38 (1 case)
No Restrictions	-0.28 ± 0.05 (4 cases)	-0.36 ± 0.28 (2 cases)	-0.30 ± 0.17 (6 cases)
All Unduplicated Cases[a]	-0.41 ± 0.18 (8 cases)	-0.44 ± 0.20 (6 cases)	-0.38 ± 0.17 (12 cases)

[a]This category was created because some elasticity estimates for all-hour and off-peak periods are derived from the same demonstration. In these instances, the unduplicated case represents only the all-hour fare elasticity.

Source: See Table A-5, Appendix A.

As may be seen from the above Table 3-3, 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 further doubt on the theoretical hypothesis that the greater the relative change in fares the greater the elasticity impact.

Fare Elasticities by City Size

The fare-elasticity evidence collected to date reveals larger fare elasticities in small cities than in larger metropolitan areas. Fare elasticities are smaller in large cities due to their congested central business districts, higher parking costs, and relatively higher level of transit service. Under these congested conditions the automobile experiences a significant relative deterioration of service when contrasted with the usually noncongested central business districts of small cities. The cost of parking and tolls must be added to the problem of congestion which further increases the relative attractiveness of transit, particularly rail transit, in large cities. Finally, the proportion of transit work trips and the level of transit service in large cities are greater than in small cities, thereby strengthening the argument that city size and transit fare elasticities are inversely related.

The data on aggregate fare elasticities collected in this study support this view. The mean all-hours aggregate elasticities from quasi-experimental data for U.S. central cities of different sizes are as follows:[1]

central cities with populations

- greater than 1 million: -0.24 ± 0.10 (19 cases)
- 500,000 to 1 million: -0.30 ± 0.12 (11 cases)
- less than 500,000: -0.35 ± 0.12 (14 cases)

The Carstens and Csanyi (1968) study of 13 small cities in Iowa with populations generally under 100,000 found that the absolute value of the fare elasticities was inversely related to the quality of transit service provided,

[1]See evidence presented in Table A-1, Appendix A.

which is generally related to city size. The very large mean fare elasticity of -0.91 was calculated for an Iowa City population of 55,000.[1] Evidence that fare elasticities are lower in larger metropolitan areas also was compiled by Grey Advertising, Inc. (1976) and is presented in Table 3-4. In this table, however, the differences in elasticities by city size are small. Finally, Dygert, Holec, and Hill (1977) have commented that smaller cities show as much variability in their elasticity estimates as do larger cities, so that analysts must proceed with caution in interpreting individual small city elasticity estimates.

Table 3-4

TRANSIT FARE ELASTICITIES BY CITY SIZE[a]
1947 - 1967

	1947-1952[b]		1960-1961[c]		1961-1967[d]	
Population of Principal City Served	No. of Cities	elasticity	No. of Cities	elasticity	No. of Cities	elasticity
More than 500,000	60[e]	-0.34[e]	51	-0.28	15	-0.22
100,000-500,000	91[f]	-0.36[f]	88	-0.33	35	-0.32
Less than 100,000	44	-0.33	68	-0.36	39	-0.43
TOTAL	195	-0.35	207	-0.32	89	-0.35

[a]Calculated from three months immediately preceding and six months immediatedly following fare change. Expressed as percentage change in ridership per one-percent fare change (i.e., shrinkage ratio).

[b]Source: "Summary of 195 Observations on Estimated Loss in Passenger Traffic Resulting from Fare Increases on U.S. Transit Companies." ATA, April 16, 1953.

[c]Source: "Estimated Loss in Passenger Traffic Incident to Increases in Urban Transit Fares," ATA, November 24, 1961.

[d]Source: "Estimated Loss in Passenger Traffic Due to Increases in Fares (1961-1967)," ATA, February 9, 1968.

[e]Combined figures for cities 500,000-1,000,000 and over 1,000,000.

[f]Combined figures for cities 100,000-250,000 and 250,000-500,000.

Source: Grey Advertising, Inc. (1976).

---

[1]Elasticity calculated at the mean by Ecosometrics, Inc. See calculation [24], Appendix C.

DISAGGREGATE FARE ELASTICITIES

The aggregate fare elasticities presented thus far have been used by transit operators with varying degrees of success to forecast the revenue and ridership effects of system-wide fare changes. Recently, however, 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. The reader will note that currently there is an abundance of fare elasticities, and that not all possible values that could be used in the following discussions have been included. Instead, careful attention has been placed on selecting and presenting comparisons of disaggregate fare elasticities obtained from the same transit system, the same researcher, or for similar fare changes.

Fare Elaticities by Mode

Several studies have confirmed that bus fare elasticities are two times greater than rapid-rail fare elasticities, as shown in Table 3-5. For six independent fare changes in New York City between 1948 and 1977, the mean bus fare elasticity is -0.32 ± 0.11 while the value for subway service is -0.16 ± 0.04. Rendle, Mack, and Fairhurst (1978), in a time-series study of travel demand in London, England, obtained fare elasticities of -0.33 for bus service and -0.16 for rapid-rail service. Slightly smaller values of -0.20 and -0.12 were obtained for bus and rail service in Paris, France as presented in Bly (1976).

Table 3-5

BUS AND RAPID-RAIL FARE ELASTICITIES
FROM SELECTED STUDIES

City	Bus Service	Rapid-Rail Service
New York, NY	-0.32 ± 0.11	-0.16 ± 0.04
London, England	-0.33	-0.16
Paris, France	-0.20	-0.12
Mean and Standard Deviation	-0.30 ± 0.10 (8 cases)	-0.15 ± 0.13 (8 cases)

Source: See Table A-6, Appendix A.

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 mode substitutes and occupies its own right-of-way. Rapid-rail service is also much faster than bus transit operating on surface streets.

Although it can be said for certain that bus fare elasticities are, on the average, twice as large as rapid-rail elasticities, the relationship 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 -- and shown in Table 3-6 -- show inconsistencies that make it impossible to formulate definite conclusions on the subject.

The most reliable of the fare elasticity estimates presented below in Table 3-6 are those from London and from the Boston 1963 demonstration, which show commuter-rail elasticities lower than bus fare elasticities. In particular, the only quasi-experimental elasticities available show smaller fare elasticities for commuter rail. These were calculated by Ecosometrics, Inc. from Maloney (1964) for four Boston commuter-rail lines participating in a 1963 bus/commuter-rail off-peak fare reduction demonstration. The Boston off-peak fare elasticity of -0.31 for commuter-rail service is half the off-peak bus figure.

Table 3-6

BUS AND COMMUTER-RAIL FARE ELASTICITIES
FOR SELECTED CITIES

City	Nature of Estimate	Bus	Commuter Rail
New York, NY (all hours)	non-experimental	-0.25	-0.70
San Francisco, CA (peak)	non-experimental	-0.58	-0.86
Boston, MA (off-peak)	quasi-experimental	-0.65	-0.31
London, England (all hours)[a]	non-experimental	-0.32	-0.13

[a]Because own-price elasticities were not presented in Fairhurst and Smith (1977) 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 (see calculation [13], Appendix C).

Source: See Table A-6, Appendix A.

Two American demand-modeling efforts -- McFadden (San Francisco) and Hartgen and Howe (New York) -- show results that are in conflict with the London Transport estimates and with the results from the Boston 1963 demonstration. However, the results of these modeling efforts are subject to the limitations and uncertainties which surround the estimation of elasticities from models using non-experimental data. McFadden's (1974) higher estimates for commuter-rail work trips might be explained by the newness of BART rail service and by the fact that the automobile is a viable alternative to this service for work trips in the San Francisco Bay Area. Although Long Island commuters are relatively affluent, Hartgen and Howe's (1976) large fare elasticity estimate for commuter railroad operations in the New York City area may only be a result of the specification of the model estimated.[1]

The evidence regarding commuter-rail fare elasticities is inconclusive. While the most reliable estimates show commuter-rail service to be less elastic than bus service, it could well be that commuter-rail service is more elastic, -- as shown by the demand models. Commuter-rail trips are generally much longer and more expensive than bus and subway trips, and long-distance and expensive trips may be more elastic to fare changes. Some evidence to support this conclusion is provided in the next section.

Fare Cross-Elasticities Among Travel Modes

Most of the data on modal cross-elasticities due to transit fare and automobile cost changes come from direct-demand and mode-choice models. Table 3-7 presents the cross-elasticities from twelve models. The cross-elasticities for rail and bus demand with respect to bus and rail fares are essentially the same, with a mean value of $+0.24 \pm 0.06$ for nine cases. The auto-to-transit and transit-to-auto cross-elasticities, however, are quite different. The mean cross-elasticity of auto demand with respect to bus fares is $+0.09 \pm 0.07$ (8 cases), and $+0.08 \pm 0.03$ (3 cases) with respect to rapid-rail fares. These values are substantially larger for travel to CBD destinations where there is a greater propensity to use transit.

[1]Hartgen and Howe's (1976) time-series equation suffers from the absence of time-trend variables. Also, since the vehicle-miles coefficient in their two-variable model is insignificant, the fare variable is left to explain the ridership variation over the nine years for which the model is calibrated, thus diminishing the reliability of the model.

Table 3-7

FARE CROSS-ELASTICITIES AMONG TRAVEL MODES[a]
(Means and Standard Deviations)

	Bus Demand	Rapid-Rail Demand	Auto Demand
Bus Fares			
Peak		+0.21 ± 0.07 (2 cases)	+0.10 ± 0.07 (7 cases)
Off-Peak		+0.28 (1 case)	+0.02 (1 case)
All Hours		+0.25 (1 case)	
Rapid-Rail Fares			
Peak	+0.20 ± 0.06 (2 cases)		+0.08 ± 0.03 (3 cases)
Off-Peak	+0.28 (1 case)		
All Hours	+0.28 ± 0.03 (2 cases)		
Auto Costs			
Peak	+0.74 ± 0.23 (4 cases)	+1.08 ± 0.26 (2 cases)	
Off-Peak	+0.18 (1 case)		

[a]The mean fare cross-elasticities refer to the same time period. For example, the off-peak bus to rapid rail cross-elasticity of +0.28 refers only to the off-peak.

Source: See Table A-6, Appendix A.

The mean cross-elasticity of bus and rail demand with respect to total automobile costs is +0.85 ± 0.29 (6 cases). This large value is principally due to the out-of-the-pocket costs of operating a vehicle, such as parking and toll costs. Table 3-8 presents the cross-elasticities developed by Pratt and DTM (1976) of bus demand with respect to automobile parking and operating costs for CBD and non-CBD trips for the Twin Cities area. Note that bus demand is more responsive to changes in parking costs only in downtown locations.

Table 3-8

CROSS-ELASTICITIES OF BUS DEMAND
WITH RESPECT TO AUTOMOBILE PARKING
AND OPERATING COSTS

Trip Purpose	CBD Destinations	Non-CBD Destination	All Destinations
Work Trips			
Parking Costs	+0.51	+0.03	+0.33
Operating Costs	+0.18	+0.26	+0.21
Non Work Trips			
Parking Cost	+0.38	+0.01	+0.18
Operating Costs	+0.18	+0.12	+0.12

Source: R.H. Pratt Associates, Inc. and DTM, Inc. (1976)

The relatively large cross-elasticities of bus demand with respect to automobile costs, especially for CBD work trips, underscores the opportunities available for the management of transportation demand through pricing. Currently, the UMTA Office of Service and Methods Demonstrations is testing various automobile pricing concepts to reduce automobile usage and stimulate transit ridership.

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. Two factors explain this behavior: (1) cost differentials among modes are less pronounced over the shorter distances which, by offering the possibility of walking or traveling by taxi, increase the number of close substitutes for transit, and (2) short-distance fares form a proportionately larger part of the generalized trip cost[1] than do long-distance fares.

[1]Generalized trip costs include not only the transit trip fare, but the access, wait, and in-vehicle time values as well. See Chapter 5 for a short discussion of the concept of generalized trip costs.

Several studies provide evidence to confirm the hypothesis that short transit trips exhibit larger elasticities than long trips. For example, the London Transport Review Board's 1968 mathematical analysis presented in Oldfield (1974) shows that bus trips of less than one mile exhibit higher fare elasticities (-0.55) than trips of one to three miles (-0.29), as presented in Table 3-9. Rail trips greater than three miles, however, have much higher fare elasticities than those calculated for rail trips with lengths of from one to three miles. Fare elasticities of -0.60 and -0.25 were estimated for rail long- and medium-distance trips respectively.

Table 3-9

FARE ELASTICITIES BY TRIP LENGTH
FOR LONDON'S BUS AND RAPID-RAIL SERVICE

Trip Length	Bus	Rapid Rail
Less than 1 Mile	-0.55	NA
1-3 Miles	-0.29	-0.25
Greater than 3 Miles	NA	-0.60

Source: Ministry of Transport (1968) in Oldfield (1974)

Bly (1976) reports that for the March 1975 fare increase, the London Transport had observed a fare elasticity of -0.50 for trips at the minimum or base level and a system-wide fare elasticity of -0.35. This suggests that long-distance and more expensive trips are less responsive to fare changes than are short-distance and inexpensive trips. Bly (1976) also reports that in Essen, Germany, the fare elasticity for short- and long-distance trips was found to be -0.32 and -0.12 respectively.

With the exception of London Transport's fare elasticity estimates from the 1975 fare increase, very long-distance trips appear to be more elastic to fare changes than short- or medium-distance trips. Since long-distance trips are generally more expensive, the fare proportion of the generalized cost for these trips may equal or even surpass the proportion for shorter trips and thereby reflect the higher fare elasticity. Following a series of reduced fare experiments, the National Bus Company operating in England attributed the higher fare elasticity to the fact that suburban riders pay a higher absolute fare, and, therefore, a higher-percentage fare reduction will have "a significant influence over fairly long journeys where a reasonable actual savings can be made."[1] Other modes may also be substituted for long-distance trips, reflecting the behavior of predominantly choice riders.

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 3-10 presents data from the London Transport experience, which tends to support the view expressed above. The Scenario Model developed by the London Transport (see Fairhurst and Smith, 1977) provides the first comparison between intrasuburban and radial routes. Based on data from the 1971-1972 survey of the London metropolitan area, as well as on actual changes in traffic patterns between 1972 and 1977, the London Transport Scenario Model reproduces disaggregated fare and price elasticities. The passenger-trip fare elasticities presented in Table 3-9 are based on a 10-percent fare increase for all public transit trips. The results show that weekday intrasuburban trips are more elastic than radial trips between central London and the suburbs, with weighted average elasticities of -0.35 for intrasuburban and -0.09 for radial routes. The relatively large intrasuburban fare elasticities suggest that the intrasuburban trips are less "important" and thereby more discretionary than radial trips.

As a general rule, bus fare elaticities are larger for intra-CBD trips because most of these trips are discretionary and also because there are many substitute modes, such as taxi and walking. The sources for the data

[1]National Bus Company (1977) p. 49.

Table 3-10

FARE ELASTICITIES BY ROUTE TYPE
AND TRANSPORT MODE[a]

Mode	Radial Arterial Routes	Intrasuburban Routes	All Routes
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

[a]Because own-price elasticities were not presented in Fairhurst and Smith (1977) 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 (see calculation [13], Appendix C).

Source: Ecosometrics, Inc. from Fairhurst and Smith (1977). See Table A-8, Appendix A.

used to calculate the CBD bus fare elasticities presented in Table 3-11 are the recent case studies and demonstrations of CBD fare-free service sponsored by the Office of Service and Methods Demonstrations of the Urban Mass Transportation Administration. Seattle, Washington and Portland, Oregon initiated CBD fare-free programs in 1973 and 1975 respectively. In 1977 Knoxville, Tennessee began a U.S. Department of Transportation-sponsored demonstration of CBD fare-free service and in 1978 Albany, New York implemented a federally-sponsored CBD fare-free demonstration during off-peak hours only. The midpoint demand elasticities estimated from before and after ridership data for each of the four sites are presented in Table 3-11 along with the time periods over which the elasticities were estimated.

The fare elasticities for intra-CBD trips are all slightly overestimated since other factors influencing demand (especially secular factors) have not been discounted. For example, the fare elasticity of -0.70 obtained in Portland is higher than the values observed in the other fare-free sites primarily because it is a long-term elasticity (i.e., calculated from ridership data spanning 34 months). Nevertheless, the average 15-month CBD fare-free elasticity is -0.50 and, therefore, slightly larger than the aggregate system-wide fare elasticity of -0.28 obtained from other empirical sources. Albany's five-month CBD fare elasticity is equivalent to Hartgen and Howe's (1976) system-wide fare elasticity for the same city estimated from time-series data. Most of the increased riding in the CBD occurred during the midday and represents generated travel and travel previously done on foot.

Table 3-11

BUS FARE ELASTICITIES BY ROUTE TYPE FROM
AMERICAN QUASI-EXPERIMENTAL DATA

City	CBD-Orientation		All Routes
Portland, Oregon (all hours)	Intra-CBD routes: (34 months)	-0.70	-0.33
Albany, New York (off-peak)	Intra-CBD routes: (6 months)	-0.51	-0.52
Seattle, Washington (all hours)	Intra-CBD routes: (10 months)	-0.46	-0.43
Knoxville, Tennessee (all hours)	Intra-CBD routes: (18 months)	-0.41	
San Diego, California (peak)	CBD work trips: Non-CBD trips:	-0.34 -0.73	-0.65
Minneapolis/St. Paul, Minnesota (peak)	CBD work trips: Non-CBD work trips:	-0.45 -0.63	-0.55
	Express/Local Service Orientation		
Washington, D.C. - Virginia (peak)	Shirley Highway: freeway express Lee Highway: conventional arterial	-0.27, -0.53 -0.74	
St. Louis, Missouri/Illinois (all hours)	Arterial express: Local routes, unspecified:	-0.42 -0.23	-0.31
	Intracity/Suburban Orientation		
Seattle, Washington (all hours)	Suburban routes; unspecified:	-0.43	-0.43
York, Pennsylvania (all hours)	Suburban routes, unspecified: Intracity routes, unspecified:	-0.59 -0.46	-0.50
Springfield, Massachusetts (all hours)	Suburban routes, unspecified: Intracity routes, unspecified:	-0.41 -0.33	-0.34

Source: See Table A-8, Appendix A.

Peat, Marwick, Mitchell (1972) and Pratt and DTM (1976) estimated fare elasticities by trip destination from their respective mode-choice logit models for San Diego and Minneapolis/St. Paul. The work-trip fare elasticities for CBD-destined trips in both studies are lower than the values estimated for non-CBD-destined trips as shown in Table 3-11. The non-work trip fare elasticities estimated for Minneapolis/St. Paul are also smaller for CBD-destined trips than for trips with destinations to other parts of the city.

Evidence on differences in elasticities between local and express service is also presented in Table 3-11. In an analysis of the 1975 peak-period fare increase by the Washington Metropolitan Area Transit Authority, Schofer (1978) compared fare elasticities on the Shirley Highway express buses on their exclusive right-of-way with those observed on conventional buses operating on the Lee Highway, a radial arterial route with a mix of express and local service. As shown in Table 3-11, the fare elasticity for the conventional bus service on the Lee Highway was approximately 3 times greater than for elasticity value for the freeway express route, suggesting that commuters using fast bus service that is competitive with the automobile are less responsive to fare increases than commuters using conventional bus service.[1]

These results have been recently contradicted in a study by Mundle, Weidemann, and Roesch (1978) which analyzed the results of a 1973 fare decrease in St. Louis. Fare elasticities from the St. Louis fare decrease were computed by Ecosometrics, Inc. from the shrinkage ratios presented by the authors and are presented in Table 3-11. The results from St. Louis show express service to be more elastic than local route service; however, certain observations are in order. The St. Louis express routes operate on radial arterials similar to the Lee Highway service, and there is nothing in St. Louis equivalent to the Shirley Highway with exclusive bus lanes on a freeway. But more important, the St. Louis study did not attempt to control for the infuence of other variables and the standard errors of the elasticity estimates are large, suggesting greater uncertainty about these estimates.

Also shown in Table 3-11 are the scant American data available on elasticities for suburban routes. In his dissertation, Van Tassel (1956) presented fare elasticity estimates of the York, Pennsylvania and Springfield, Massachusetts fare increases of 1948 and 1949 respectively. Van Tassel's work shows

---

[1]McLynn and Goodman (1973) show a higher fare elasticity for the Shirley Highway than Schofer (1978). See Table A-8, Appendix A.

larger fare elasticities for suburban trips in both cities. However, since these changes took place 30 years ago, when the suburbanization of population and employment had just started in these cities, these estimates may not be applicable to current times.

In summary, while the British data show elasticities corresponding to a priori notions on the elasticity values by route type, the American data are mixed and in some instances contradictory. More demonstrations and measurements of ridership response to fare changes at the route level are needed to resolve these ambiguities.

Peak and Off-Peak Fare Elasticities

Since most peak-period trips are routine work trips, it is generlly understood that peak-period travel is less responsive to fare changes than any other period of the day or week. Off-peak and weekend trips are more discretionary, whereas peak-hour work trips are largely fixed in frequency and time of day. 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 the three cities presented in Table 3-12 are 2.31 times larger than corresponding peak-period values. Moreover, this factor applies equally to bus and rapil-rail travel.

Table 3-12

PEAK AND OFF-PEAK
FARE ELASTICITIES

City	Peak Period	Off-Peak Period	Ratio Off-Peak to Peak
New York, NY -- Rapid Rail	-0.04	-0.11	2.75
London, England -- Rapid Rail	-0.10	-0.25	2.50
-- Bus	-0.27	-0.37	1.37
Stevanage, England -- Bus	-0.32	-0.84	2.63
Mean and Standard Deviation			2.31 ± 0.55

Source: See Table A-9, Appendix A.

Although only limited data are available, a further temporal disaggregation of public transit fare elasticities is presented in Table 3-13. 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. Morning and evening peak-hour fare elasticities of -0.03 and -0.16 respectively were obtained for New York subway riders, and -0.13 and -0.17 for St. Louis bus riders. These values indiate that a greater degree of nonwork or nonessential travel takes place during the evening rush hour.

Table 3-13

DISAGGREGATED FARE ELASTICITIES
BY TIME OF DAY AND WEEK

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

[a]Fare Decrease ($.25 to $.10)
[b]Fare Increase ($.10 to $.25)

Source: See Table A-9, Appendix A.

Evening, late night, and weekend fare elasticities are not much different from the values observed for midday service. The results obtained from Lassow (1968) for New York City show Sunday ridership to be less elastic than Saturday ridership. Table 3-14 presents a comparison of weekday, Saturday, and Sunday fare elasticities for the bus and subway system in New York.

Table 3-14

FARE ELASTICITIES FOR WEEKDAY AND WEEKEND SERVICE IN NEW YORK CITY

Mode	Weekday Service	Saturday Service	Sunday Service	All Hours
Subway	-0.07	-0.15	-0.04	-0.09
Bus-NYCTA	-0.35	-0.43	-0.40	-0.36
Bus-MaBSTOA	-0.36	-0.39	-0.35	-0.37

Source: Ecosometrics, Inc. from Lassow (1968). See Table A-9, Appendix A.

Peak/Off-Peak Fare Cross-Elasticities

As of this writing there are still no accurate estimates of the cross-elasticity between peak and off-peak periods. Nevertheless, the fare cross-elasticities presented in Table 3-15 demonstrate the inability of most transit users to change their time of travel. The adjusted cross-elasticity of +0.14 for peak demand with respect to off-peak fares was estimated by Ecosometrics, Inc. from ridership response data observed by DeLeuw, Cather and Company (1979) during the recently completed off-peak fare-free demonstration Denver sponsored by the Office of Service and Methods Demonstrations of the U.S. Department of Transportation. A value of +0.03 was obtained from the Trenton demonstration. The two larger values are from calculations made by Ecosometrics, Inc. from Hoel and Roszner (1972) and Caruolo and Roess (1974) for travel by the elderly in Pittsburgh and Los Angeles respectively. Clearly, the reason for the extremely low 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 flexitime programs, peak to off-peak fare cross-elasticities may be much larger.

Table 3-15

PEAK/OFF PEAK FARE CROSS-ELASTICITIES

	Peak Demand	Off-Peak Demand
Peak Fares		+0.03[e] +0.02[f]
Off-Peak Fares	+0.14[a] +0.03[b] +0.26[c] +0.38[d] +0.04[e] +0.05[f]	

[a]Denver in 1978-1979
[b]Trenten in 1978-79
[c]Elderly in Los Angeles in 1961
[d]Elderly in Pittsburgh in 1970
[e]Bus travel in London
[f]Rapid rail travel in London

Source: See Table A-9, Appendix A.

Fare Elasticities for Captive and Choice Riders

Passengers with an automobile or alternative mode of transportation available will be more responsive to fare changes than those passengers without an alternative mode available. Using a discriminant model of mode choice, McGillivray (1969) estimates a fare elasticity of -0.19 for all choice trips and -0.11 for trips involving both choice and captive riders in the San Francisco Bay Area. These results indicate that the demand elasticity for the captive market is less than -0.11 or half the value obtained for choice riders. McGillivray and other mode-choice modelers also have shown that the work trip is probably the most elastic trip for choice riders. A choice work-trip fare elasticity of -0.96 was obtained by Warner (1962) for Chicago, -0.87 by McGillivray (1969) for San Francisco, -0.70 by Lave (1968) for Chicago, and -0.40 by Lisco (1967) for rapid-rail service in Chicago.

The only evidence from demonstrations to support McGillivray's conclusion that choice riders are more elastic than captive riders (at least for off-peak travel) is available from DeLeuw, Cather and Company (1979) on the Denver and Trenton off-peak fare-free demonstrations. Calculating a weekday off-peak fare elasticity of -0.28 for all users in Denver, the DeLeuw researchers were able to disaggregate ridership response, showing the fare elasticity for passengers with automobile access to be -0.31 and the elasticity for passengers without automobile access to be -0.25 as indicated in Table 3-15. In Trenton, off-peak ridership response was disaggregated by the degree of automobile ownership. Transit riders with easier access to an automobile exhibited larger fare elasticities, as shown in Table 3-15 along with the Denver values. These fare elasticities are slightly larger than those of McGillivray because these are off-peak values and because these values were calculated over a large fare reduction.

Table 3-15

OFF-PEAK FARE ELASTICITIES FOR CAPTIVE AND CHOICE RIDERS IN DENVER AND TRENTON

DENVER (Weekday Off-Peak Ridership)			TRENTON (Off-Peak Ridership)			
			Automobile Ownership			
Captive Riders	All Riders	Choice Riders	Zero	One	Two	Three
-0.25	-0.28	-0.31	-0.11	-0.22	-0.21	-0.30

Source: DeLeuw, Cather and Company (September 1979 and November 1979).

A study by the London Transport (Collins and Lindsay, 1972, which was reviewed in Bly, 1976), also confirms the results obtained by the American modelers. Bly reports that the fare elasticity for bus passengers with an automobile available is -0.41, while the elasticity for those passengers without an automobile available is only -0.10. Interestingly, Bly also reports that the passenger-miles fare elasticity (as opposed to passenger-trips fare elasticity) is smaller for the automobile-available groups than for those without access to an automobile. These results suggest that whereas captive riders cannot divert to other modes, "they are anxious to save money by riding for a shorter distance and, presumably, walking more at one end or other of the trip."[1] These figures, along with the London Transport's passenger-trip fare elasticities, are presented in Table 3-17.

Table 3-17

PASSENGER-TRIP AND PASENGER-MILE
WORK-TRIP FARE ELASTICITIES FOR CAPTIVE
AND CHOICE RIDERS IN LONDON

	Captive Riders	All Riders	Choice Riders
Passenger-Trip Fare Elasticity	-0.10	-0.27	-0.41
Passenger-Mile Fare Elasticity	-0.38	N.A.	-0.21

Source: Bly (1976) from Collins and Lindsay (1972).

Fare Elasticities by Income Group

Following the discussion of choice and captive markets, 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, conducted by DeLeuw, Cather and Company (1979), provide partial support for this general hypothesis, as shown in Table 3-18.

---

[1] Bly (1976) p. 10.

Table 3-18

FARE ELASTICITIES BY HOUSEHOLD INCOME GROUP
FROM THE DENVER AND TRENTON OFF-PEAK
FARE-FREE DEMONSTRATIONS -- 1979

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

Source: DeLeuw Cather and Co. (September 1979 and November 1979).

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 less-essential or 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.[1]

Another source of evidence of the relative responsiveness of different income groups to transit fare changes comes from Lassow's (1968) article on the 1966 fare increase in New York City. To obtain the ridership impact information he needed, Lassow selected 13 subway stations in low-income areas and monitored the use of these stations before and after the fare change. Fare elasticities for every period of the day were calculated by Ecosometrics, Inc. from Lassow's data on these selected stations and on the entire subway system. The results, given in Table 3-19, show that the smallest effect of the fare increase takes place during the peak periods when people go to and return from work. The significance of the results presented in Table 3-19, contrary to

[1]DeLeuw, Cather and Company (1979), p. 58.

the values obtained in Denver and Trenton, is that transit users from low-income areas were more responsive to the fare increase than transit users from the system as a whole. One explanation is that, unlike Denver's, New York City transit users are captive to the system for most trip purposes. Due to roadway congestion and very high parking costs, the automobile in New York City is not a realistic alternative mode of travel for most households. Unfortunately, the analysis did not assess whether the trips previously taken by subway became walk trips or whether the trips were no longer taken.

Table 3-19

FARE ELASTICITIS BY INCOME AND TIME OF DAY ON THE NEW YORK CITY SUBWAY SYSTEM

Time Period	Low-Income Users	All Users
Morning Peak	-0.16	-0.03
Afternoon Peak	-0.29	-0.06
Midday	-0.34	-0.10
Evening	-0.74	-0.18
Late Night	-0.49	-0.04
All Weekday Hours	-0.31	-0.07

Source: Ecosometrics, Inc. from Lassow (1968). See Table A-11, Appendix A.

Fare Elasticities by Trip Purpose and User Group

The fact that peak-period fare elasticities are smaller than off-peak values has been attributed to the constrained nature of the work trip. Consequently, one would expect the fare elasticity to be lower for work trips than for other trip purposes. The very little evidence available from non-experimental data substantiates this, as shown in Table 3-20.

Table 3-20

FARE ELASTICITIES FOR WORK AND NONWORK TRIPS FROM NON-EXPERIMENTAL DATA

Study	Work Trips	Shopping Trips	All Non-Work Trips
Domencich, et al. (1968) Boston	-0.10	-0.32	
Wabe and Coles (1975) 30 British cities	-0.19[a]		-0.49[a]

[a]Independent variable used was fare per mile; work-trip coefficient not significantly different from zero at 5-percent significance level.

Source: See Table A-12, Appendix A.

The aggregate direct-demand model by Charles River Associates reported in Domencich, Kraft, and Valette (1968) indicates that work trips are less responsive to changes in transit fares than shopping trips, as expected. Wabe's and Coles' (1975) cross-sectional demand study of 30 British operations in 1966-1967 presents the same conclusion, namely, that nonwork transit fare elasticities are two to three times larger than work-trip fare elasticities.[1]

Fare elasticities were estimated by Habib, et al. (1978) from studies performed as a result of fare changes in several cities. In three of the cities, the fare elaticities were disaggregated by trip purpose and are presented in Table 3-21. Although some of the studies from which the demand elasticities were calculated were incomplete, the relative magnitudes to the shopping-trip fare elasticities vis-a-vis the work-trip elasticities conform to the results obtained by the direct-demand models. The mean work-trip and shopping-trip fare elasticities for the three cities presented in Table 3-21 are -0.07 ± 0.02 and -0.20 ± 0.04, respectively.

[1]The Wabe's and Coles' fare elasticity represents the change in demand for transit due to a change in the average fare per mile.

Table 3-21

WORK-TRIP AND SHOPPING TRIP FARE ELASTICITIES FROM QUASI-EXPERIMENTAL DATA

City	Work Trips	Shopping Trips	All Trips
Baltimore, MD (1976)[a]	-0.09	-0.20	NA
Richmond, VA (1976)[a]	-0.08	-0.25	NA
Birmingham, AL (1975)[a]	-0.05	-0.15	-0.12
Mean Value	-0.07 ± 0.02	-0.20 ± 0.04	

[a]Study year and assumed year of fare change.

Source: See Table A-12, Appendix A.

In its evaluation of the Trenton off-peak fare-free demonstrtion sponsored by the Office of Service and Methods Demonstrations of the U.S. Department of Transportation, DeLeuw, Cather and Company (1979) developed disaggregate fare elasticities by trip purpose which are presented in Table 3-22 below. With the exception of the work-trip fare elasticity, all other trip purposes have fare elasticities equal to or greater than the aggregate off-peak value of -0.19.

Table 3-22

OFF-PEAK FARE ELASTICITIES BY TRIP PURPOSE FOR TRENTON FARE-FREE SERVICE

Trip Purpose	Off-Peak Fare Elasticity
Work	-0.11
School	-0.19
Shop	-0.25
Medical	-0.32
Recreation	-0.37
Social	-0.25
Other	-0.19
Aggregate Value	-0.19

Source: DeLeuw, Cather and Company (1979)

The information on demand elasticities by user group is very limited. In Table 3-23, fare elasticities from two studies for adults, children, and school children are presented. In both studies, children are more elastic than adult riders.

Table 3-23

FARE ELASTICITIES FOR ADULTS, CHILDREN AND SCHOOL CHILDREN

City	Adults	Children	School Children
Warwickshire, England (1975)	-0.32	-0.41	
Montreal, Canada (1956-72)	-0.16		-0.44

Source: See Table A-12, Appendix A.

Bly (1976) reports that the Warwickshire County Council and Midland Red Bus Company in England were able to estimate the fare elasticity for adult and children tickets following a November 1975 fare increase. The adult single ticket estimate of -0.32 ± 0.05, presented in Table 3-23 above, is 78 percent of the children's single ticket fare elasticity, estimated to be -0.41 ± 0.05.

Gaudry's (1978) fare elasticity estimates for adults and school children in Montreal, Canada are based on individual transit-demand equations developed from monthly time-series data on trips between 1956 and 1972. Gaudry's results indicate that school children are three times as elastic as adults.

Although demand elasticities for senior citizen riders have been estimated in numerous cities, they never have been estimated and compared to other user groups. An attempt, howver, has been made in Table 3-24 to compare the fare elasticities of senior citizen riders to other users in New York City and Baltimore.

Table 3-24

SENIOR-CITIZEN AND
AGGREGATE FARE ELASTICITIES
FOR NEW YORK AND BALTIMORE

New York	Senior Citizen Midday	All Modes All Hours	Subway	
			Midday	All Hours
1966		-0.19	-0.10	-0.09
1969	-0.35			
1970		-0.17		

Baltimore	Senior Citizen Off-Peak	Commuter	Shoppers	All Users
1958				-0.09
1972	-0.12			
1976		-0.09	-0.20	

Source: See Table A-12, Appendix A.

In New York City, the fare elasticity of senior-citizen demand for transit is twice as large as the aggregate fare elasticities observed in 1966 and 1970. The only midday value to compare with the senior citizen elasticity is for subway travel. This value of -0.10 is more than one-third of the fare elasticity for senior-citizen travel.

In Baltimore, the senior-citizen fare elasticity is only slightly larger than the aggregate figure and less than the ATE Management estimate (see Habib, et al. 1978) for shopping trips. Since these values were obtained from several sources, there is some question about their validity. Nevertheless, one can conclude that the fare elasticities for senior citizens while low, are slightly higher than for the average transit user. The mean fare elasticity for 14 cities that have monitored senior citizen reduced fare programs is -0.35 ± 0.17.[1]

[1] Estimated by Ecosometrics, Inc. from Caruolo and Roess (1974) and Hoel and Roszner (1972). See Table A-12, Appendix A.

Finally, the Denver and Trenton off-peak free-fare demonstrations have provided some evidence to suggest that there is an inverse relation between age and ridership response. In both demonstrations, young people were most responsive to the off-peak fare elimination, as shown in Table 3-25.

Table 3-25

OFF-PEAK FARE ELASTICITIES BY AGE GROUP

Age Category	Denver Demonstration	Trenton Demonstration	Mean Value
1 to 16 years	-0.32	-0.31	-0.32
17 to 24 years	-0.30	-0.24	-0.27
25 to 44 years	-0.28	-0.08	-0.18
45 to 64 years	-0.18	-0.12	-0.15
65 and more years	-0.16	-0.12	-0.14

<u>Source</u>: DeLeuw, Cather and Company (September 1979 and November 1979).

FARE ELASTICITIES FOR SPECIAL FARE CHANGES

This section discusses some of the factors governing the demand elasticities that result from changes in special fare mechanisms. In particular, the section discusses promotional fares, transit fare prepayment, and changes in fare structures.

Fare Elasticities from Promotional Fare Reductions

Although transit properties across the country are continuously offering "Bargain Fares", "Sunday Specials", and "Fare-Free Day", few of these programs are monitored closely for their short-term and long-term ridership and revenue impacts. Caruolo and Roess (1974), however, have identified two fare-free projects from which fare elasticities could be calculated. The demand elasticities from these short-term fare-free projects are presented in Table 3-26.

Table 3-26

FARE ELASTICITIES FROM TWO FARE-FREE
PROMOTIONAL PROGRAMS

City	Time Period	Promotional Period	Fare Elasticity
Auburn, NY (1973)	All Hours	1 Month	-0.63
Madison, WI (1973)	Off-Peak	1 Week	-0.32

Source: Ecosometrics, Inc. from Caruolo and Roess (1974). See Table A-13, Appendix A.

The Auburn, NY experiment involved the elimination of a 25-cent fare for one month. Although ridership increased over 300 percent during the fare-free month, there is no mention of the level of ridership attrition after the experment.

In Madison, fares were abolished only during off-peak hours and only for one week. The total weekly ridership increased by 93.5 percent, resulting in a fare elasticity of -0.32.[1] This value is lower than that observed in Auburn for two reasons. First, and most importantly, the Madison fare elasticity was calculated using aggregate ridership, not off-peak ridership for which the free fares applied. If half of the predemonstration riding occurred during off-peak hours, then the off-peak fare elasticity for Madison would be -0.59, much closer to the Auburn value. Secondly, the Auburn experiment occurred over a period of one month, allowing individuals more time to adjust their travel behavior to take advantage of the free fares. Following the Madison "fare-free" week, ridership continued increasing for some period. Whether this additional revenue was enough to cover losses during the experiment was not explored.

In 1975, Madison conducted a demonstration project to test the effects of reduced fares and more frequent headways on weekend ridership (see Hicks 1979). 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 in Table 3-27.

---

[1]The fare elasticities for both Auburn and Madison were calculated by Ecosometrics, Inc. from Caruolo and Roess (1974) using the midpoint elasticity formula.

Table 3-27

WEEKEND FARE REDUCTION AND
FARE INCREASE IN MADISON

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

Source: Ecosometrics, Inc. from Hicks (1979). See Table A-13, Appendix A.

Caruolo and Roess (1974) also reviewed the "Save on Sunday" program sponsored by the MTA 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 the modal fare elasticities presented in Table 3-28. As in Auburn and Madison, the price promotion in New York City resulted in a net revenue loss for the operator. For comparative purposes, Table 3-28 also includes the Sunday fare elasticities calculated by Ecosometrics, Inc. from Lassow (1968) resulting from the 1966 system-wide fare increase.

Table 3-28

SUNDAY FARE ELASTICITIES RESULTING FROM THE
NEW YORK CITY "SAVE ON SUNDAY" PROGRAM
AND 1966 FARE INCREASE

Transit System	Fare Elasticities	
	"Save on Sunday"(1974) (Half-Fare)	Sundays (1966) (Fare Increase)
Manhattan and Bronx Bus System	-0.33	-0.35
Statten Island Rapid Transit System	-0.36	NA
New York City Subway System	-0.42	-0.04
New York City Bus System	-0.53	-0.40
Long Island Railroad	-0.59	NA
Harlem, Hudson, and New Haven Railroad	-0.70	NA.
Aggregate Ridership	-0.47	-0.18

Source: Ecosometrics, Inc. from Caruolo and Roess (1974) and Lassow (1968). See Table A-13, Appendix A.

Fare Prepayment Versus Cash Payment

There is scant data available on fare prepayment elasticities. British researchers, particularly Bly (1976), attribute lower elasticities on fare prepayment pass plans to the fact that they are most heavily used for work trips which are inelastic. In support of this view, Bly presents data from Paris, France showing a price elasticity of -0.14 for season tickets (pass) compared to -0.20 for ordinary single tickets. Similarly, he quotes from a Midland Red Bus Company study that estimated a fare elasticity of -0.10 for season tickets, contrasted to -0.32 for adult single tickets.

The American evidence is even scarcer. Using a cross-sectional model of the experience of 62 fare prepayment plans in the United States, Mayworm, Ceglowski, and Lago (1978) of Ecosometrics, Inc. calibrated penetration elasticities of +0.43 to +0.52 for fare prepayment discounts over base fares.[1] Mayworm and Lago (1979) also estimated midpoint elasticities for employees participating in an employer-promoted fare prepayment demonstration in Sacramento, California. The fare elasticities for participating employees were -0.56 for work trips, -0.42 for non-work trips, and -0.55 overall. The higher fare elasticity for work trips compared to that for non-work trips is indicative of the limitations on non-work travel for individuals working every day.

Changes in Fare Structure

Three major options are available for designing fare structures: flat fares, graduated fares, and zone fares. In a flat-fare system, the most common system in American cities, the same fare is paid no matter how far the user travels. In a graduated-fare system, the charge is related to the distance traveled. A variation of this system is the stage-fare concept, where separate fares are charged on a per-stop or stage basis. This fare structure is practical only for transit systems with limited number of stops. In a zone-fare system, the city is divided into several zones and fares at flat rates apply for travel within each zone plus extra charges for crossing zonal boundaries.

Changes in fare structure can lead to changes in both patronage and revenues even if the transition does not result in a change in the average fare

---

[1] The penetration elasticity indicates the proportional change in the market penetration (percentage of total riding using fare prepayment) of a fare-prepayment instrument resulting from a one-percent change in the discount rate of the prepayment plan over cash fare.

paid under the different structures. Two reasons account for the differential impact of changes in fare structure. First, trip rate and trip length are not interdependent. It is possible in a zone-fare system, for example, for the traveler to maintain his trip rate but alight from a bus one zone earlier than usual and, thereby, avoid paying an extra zone charge in response to a fare increase. This behavioral response was examined by Fairhurst and Morris (1975) in their study of the London Transport system. There, they found that the fare elasticity for passenger kilometers of -0.40 was higher than the -0.30 fare elasticity for passenger trips. Second, short-distance trips are more elastic than long-distance trips as this report showed earlier. The fact that people are willing to pay more for long-distance trips than for short-distance trips indicates that graduated- and zone-fare systems are superior to flat-fare systems in their ability to increase patronage and revenues.

Flat-fare systems also pose income redistribution problems since flat fares encourage and provide more subsidy to longer trips, trips which are usually taken by suburbanites and the more affluent transit riders. The revenue implications of changes in fare structures have been investigated in London by Quarmby and Cohen (1973) who found that if London Transport's graduated-fare system were converted to a flat-fare system with no change in the average fares, an 8-percent loss in traffic and a 16-percent loss in revenues would occur. The revenue loss would be uncompensated by the decrease in operating costs resulting from flat fares.

To balance the argument, it should be recognized that flat-fare systems have unique advantages. For example, they are simple to operate and easy for the transit rider to understand, and result in boarding times that are nearly half of the boarding times under most graduated-fare systems. However, as revenue-producing agents, flat fares are inferior to distance-based fares and also regressive in the sense that they benefit the more affluent suburbanites, who take the longest trips.

SUMMARY

The principal focus of this chapter has been on identifying the differences in fare elasticities of transit demand among market groups. Although system-wide elasticity values, such as Simpson and Curtin's rule of thumb, 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 were presented. A summary of the principal findings is presented below. The means and standard deviations of the fare elasticities for various market groups are consolidated and shown in Table 3-29.

- Transit demand is inelastic to fare changes. Transit fare elasticities range in value from -0.04 to -0.87 with a mean of -0.28 ± 0.16 (67 cases). These results, from demonstrations and other quasi-experiments, are not appreciably different from the Simpson and Curtin rule of thumb. However, the fare elasticities developed from non-experimental direct-demand and mode-choice models are noticeably higher especially for those models using cross-sectional data.

- Elasticities for fare increases do not differ from those for fare decreases. Although limited evidence from Atlanta and Madison suggests that larger fare elasticities result from fare increases than from fare decreases, the large sample of fare changes does not confirm this view.

- Fare-free elasticities are slightly smaller than comparable reduced-fare elasticities. With the exception of the fare-free elasticities for intra-CBD service, the fare-free elasticities are smaller than comparable elasticities for reduced-fare programs.

- Small cities have larger fare elasticities than large cities. Fare elasticities vary by city size and are appreciably larger in small and medium-size cities than in large cities.

- Bus travel is more elastic than commuter- and rapid-rail travel. Bus fare elasticities are twice as large as rapid-rail fare elasticities where both modes are available. Fare elasticities for commuter-rail service appear to lie between the values observed for bus and rapid-rail service, but the limited evidence makes this claim uncertain.

- Off-peak fare elasticities are double the size of peak-fare elasticities. Regardless of the mode considered, fare elasticities for off-peak transit service are twice as large as those observed for peak-period service. Weekend fare elasticities are comparable to weekday off-peak elasticities. Cross-elasticities of demand from peak to off-peak hours are relatively small, less than +0.20 in the case of the recent off-peak fare-free demonstrations in Denver and Trenton.

- Short-distance trips are more elastic than long-distance trips. Bus trips less than one mile in length exhibit fare elasticities almost 100 percent larger than trips between one and three miles in length.

- Intrasuburban trips are four times more elastic than radial trips on arterials. The experience in London shows intrasuburban trips to be more elastic than radial trips to and from the central city. No accurate fare elasticity comparisons are possible for express and local service due to scarcity of measurements.

- Fare elasticities rise with income and fall with age. The Trenton and Denver off-peak fare-free demonstrations show that fare elasticities rise with income and fall with the age of the transit rider.

- Of all trip purposes, the work trip is the most inelastic. Shopping and school trips are two to three times more elastic than the work trip.

- Travel by the elderly is slightly more elastic than average. Although travel by the elderly is inelastic, it is more elastic than travel by the average transit rider.

- Promotional fare elasticities are slightly larger than short-term fare elasticities following permanent fare revisions. The fare elasticities estimated from ridership changes following the introduction of promotional fares are larger than those observed for permanent fare changes. Fare elasticities resulting from changes in the prices paid for fare prepayment instruments are not very different from the fare elasticities observed for permanent cash-fare changes.

Finally, the differences in fare elasticities noted above 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 American 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.

Table 3-29

SUMMARY OF FARE ELASTICITIES
PRESENTED IN CHAPTER 3
(Means and Standard Deviations)

AGGREGATE FARE ELASTICITIES		
<u>Estimation Method</u>		
Quasi-experimental:	-0.28 ± 0.16	(67 cases)
Time-series:	-0.42 ± 0.24	(28 cases)
Cross-sectional:	-0.53 ± 0.35	(28 cases)
<u>Type of Fare Change</u>		
Fare increase:	-0.34 ± 0.11	(14 cases)
Fare decrease:	-0.37 ± 0.11	(9 cases)
<u>Fare Change to Fare-Free</u>		
Within CBD only:	-0.52 ± 0.11	(4 cases)
System-wide:	-0.30 ± 0.17	(6 cases)
<u>City Size</u>		
Populations greater than 1 million:	-0.24 ± 0.10	(19 cases)
Populations 500,000 to 1 million:	-0.30 ± 0.12	(11 cases)
Populations less than 500,000:	-0.35 ± 0.12	(14 cases)
DISAGGREGATE FARE ELASTICITIES		
<u>Transit Mode</u>		
Bus:	-0.35 ± 0.14	(12 cases)
Rapid Rail:	-0.17 ± 0.05	(10 cases)
Commuter Rail:	-0.31	(1 case)
<u>Trip Length</u>		
London: Bus		
• trips less than 1 mile:	-0.55	(1 case)
• trips between 1 and 3 miles	-0.29	(1 case)
London: Rapid Rail		
• trips between 1 and 3 miles:	-0.25	(1 case)
• trips greater than 3 miles:	-0.60	(1 case)
<u>Route Type</u>		
Radial arterial:	-0.09 ± 0.02	(3 cases)
Intrasuburban:	-0.31 ± 0.05	(3 cases)
System-wide:	-0.24 ± 0.08	(3 cases)
CBD oriented:	-0.40 ± 0.04	(3 cases)
Non-CBD oriented:	-0.62 ± 0.09	(3 cases)
System-wide:	-0.55 ± 0.08	(3 cases)
Intra-CBD:	-0.52 ± 0.11	(4 cases)
System-wide:	-0.43 ± 0.08	(3 cases)

Table 3-29 (continued)

Time Period:		
Peak:	-0.17 ± 0.09	(5 cases)
Off-peak:	-0.40 ± 0.26	(5 cases)
All hours:	-0.29 ± 0.19	(5 cases)
Trip Purpose		
Work:	-0.10 ± 0.04	(6 cases)
School:	-0.19 to -0.44	(3 cases)
Shop:	-0.23 ± 0.06	(5 cases)
Income Group		
Less than $5,000:	-0.19 ± 0.10	(2 cases)
$5,000 to $14,999:	-0.25 ± 0.11	(4 cases)
More than $15,000:	-0.28 ± 0.13	(4 cases)
Age Group		
1-16 years:	-0.32 ± 0.01	(2 cases)
17-24 years:	-0.27 ± 0.03	(2 cases)
25-44 years:	-0.18 ± 0.10	(2 cases)
45-64 years:	-0.15 ± 0.03	(2 cases)
More than 65 years:	-0.14 ± 0.02	(2 cases)

4

SERVICE ELASTICITIES

In contrast to the relative abundance of data on fare elasticities, the data on service elasticities are scarce. For example, no quasi-experimental data are available on wait- and transfer-time elasticities, and only a few cases are available on in-vehicle time elasticities. Although the number of case studies is not large enough to support conclusions based on rigorous statistical testing, some generalizations are possible. It can be said with some certainty that:

- Transit demand is inelastic to service changes; that is, the proportional change in transit patronage is less than the proportional change in service.
- Service elasticities are inversely proportional to the original level of service, being greater in areas of poor service than in high-service areas.
- Off-peak and weekend elasticities are invariably higher than peak-period elasticities.
- Although service elasticities are invariably greater than fare elasticities in low-service areas, the issue is not clear in conditions of high service during peak periods.

In this review of transit services, demand elasticity values were obtained from both quasi-experimental and non-experimental data sources. This chapter reviews service elasticities based on passenger responses to changes in headways, aggregate vehicle miles, and travel time components. Other service attributes, such as reliability and comfort, which appear to be important in the travel decision-making process but for which no demand elasticities are available, are reviewed in terms of their impact on ridership. The chapter concludes with a summary of ridership responsiveness to transit service adjustments.

HEADWAY ELASTICITIES

Public transportation headway elasticities vary considerably, in part due to the characteristics of the route in question, but the aggregate values show a remarkable similarity. Table 4-1 below summarizes the mean values obtained from both quasi-experimental and non-experimental data sources.

The evidence shows that average bus and commuter-rail headway elasticities are equivalent with a mean value for all service hours of -0.47 ± 0.17. In addition, off-peak elasticities are larger than those observed for the peak period. For both bus and commuter-rail services, ridership appears to be proportionally less responsive to increases in service when the level of service is satisfactory than when it is poor.

Table 4-1

SUMMARY OF MEAN BUS AND COMMUTER-RAIL HEADWAY ELASTICITIES

Time Period	QUASI-EXPERIMENTAL DATA		NON-EXPERIMENTAL DATA
	Bus	Commuter Rail	Commuter Rail
All Hours	-0.47	-0.47	-0.47
Peak	-0.37	-0.38	NA
Off-Peak	-0.46	-0.65	NA

Source: See Tables B-1 through B-3, Appendix B.

Although the mean bus headway elasticity from quasi-experimental data is -0.47 ± 0.21 for all service hours, each elasticity value appears to depend on the level of service before headway adjustments are made. During both peak and off-peak periods, headway elasticities -- as shown in Table 4-2 -- are correlated with the level of service.

Table 4-2

SIMPLE CORRELATIONS BETWEEN BUS HEADWAY ELASTICITIES AND ORIGINAL HEADWAYS FROM QUASI-EXPERIMENTAL DATA

Peak (3 values)	Off-Peak (9 values)	Weekends (4 values)	All Hours (7 values)	Aggregate Values (23 values)
+0.82	+0.71	+0.48	+0.47	+0.62

Source: See Table B-1, Appendix B.

As confirmed in Table 4-3, headway elasticities depend on the previous level of service for both peak and off-peak periods. During the peak period, the headway elasticity on a low-service route is -0.58. This value exceeds by more than 110 percent the mean elasticity value of -0.27 ± 0.14 for high-service routes. The same is true during off-peak periods where the highest elasticities, with a mean value of -0.71 ± 0.11, predominate among low-service routes.

With regard to differences in headway elasticities by time of day, off-peak elasticities are appreciably higher than peak-period elasticities, the Stevenage bus demonstration[1] in England analyzed by Mullen (1975) notwithstanding. In the Chesapeake/Norfolk demonstrations of 1965-67, the off-peak elasticities were more than 50 percent above the morning peak elasticity of -0.58. The same is true of the 1962 Grand River Avenue demonstration where

[1]The results of the Stevenage "Super Bus" Demonstration indicate that off-peak ridership is less responsive than peak ridership to headway improvements when service frequency is already very high. Therefore, the use of the Stevenage elasticities in the data base leads to the hypothesis that off-peak ridership is more responsive to service improvements than peak ridership up to a point where the level of service is judged to be adequate. Off-peak ridership becomes less responsive to further service improvements but at a slower rate. However, there is need for more experimentation before this hypothesis can be generalized to other sites.

off-peak elasticities were almost 100 percent above the peak-hour elasticity of -0.13. The limited evidence on weekend headway elasticities indicates that these values are similar to the off-peak weekday elasticities. However, the data from the 1975 Madison and the Detroit Grand River Avenue demonstrations presented in Appendix B show the bus headway elasticities during Sunday to be larger than the Saturday values.

Table 4-3

BUS HEADWAY ELASTICITIES BY
SERVICE LEVEL AND TIME PERIOD
(Means and Standard Deviations)

Original Service Level[a]	Peak Hours	Off-Peak Hours	Weekends	All Hours	Aggregate Values
High	-0.27 ± 0.14 (2 cases)	-0.19 ± 0.09 (3 cases)	-0.22 (1 case)	-0.25 (1 case)	-0.22 ± 0.10 (7 cases)
Medium	NA	-0.49 ± 0.20 (3 cases)	-0.43 ± 0.16 (3 cases)	NA	-0.46 ± 0.18 (6 cases)
Low	-0.58 (1 case)	-0.71 ± 0.11 (3 cases)	NA	-0.51 ± 0.20 (6 cases)	-0.58 ± 0.19 (10 cases)
Aggregate Value	-0.37 ± 0.19 (3 cases)	-0.46 ± 0.26 (9 cases)	-0.38 ± 0.17 (4 cases)	-0.47 ± 0.21 (7 cases)	-0.44 ± 0.22 (23 cases)

[a]The level of service was classified as follows:

High: less than 10-minute headways
Medium: 10- to 50-minute headways
Low: more than 50-minute headways

Source: See Table B-1, Appendix B.

In conclusion, bus headway elasticities are inelastic, although their mean value at -0.47 is higher than the mean bus fare elasticity. Operators should expect bus headway elasticities to be 50 to 100 percent higher during the off-peak (the Stevenage, England demonstration being an exception) with the value dependent on the original level of service. Bus headway elasticities should decline numerically with the quality of service and be lowest when high service levels of less than 10-minute headways prevail on the routes.

Commuter-Rail Headway Elasticities: Evidence from Quasi-Experimental Data

Analysis of the commuter-rail headway elasticity values shows the mean elasticity for all hours to be -0.47 ± 0.14, which is congruent with the mean headway elasticity value obtained for bus service. Furthermore, most of the generalizations made for bus headway elasticities are confirmed by similar experiences with commuter-rail elasticities. For example, as shown in Table 4-4, commuter-rail elasticities are positively correlated with both the original headway level (r = +0.85) and with route length (r = +0.77). Furthermore, this high level of correlation extends across all the time periods analyzed.

Table 4-4

SIMPLE CORRELATIONS BETWEEN
COMMUTER-RAIL HEADWAY ELASTICITIES AND ROUTE
LENGTHS AND ORIGIONAL HEADWAYS FROM
QUASI-EXPERIMENTAL DATA

	Peak (5 values)	Off-Peak (5 values)	All Hours (5 values)	Aggregate Values (15 values)
Original Headway	+0.52	+0.93	+0.99	+0.85
Route Length	+0.90	+0.98	+0.94	+0.77

Source: See Table B-2, Appendix B.

As presented in Table 4-5, the commuter-rail elasticities, which were estimated from the five corridor demonstration in the Boston area in 1962-1964, show the mean off-peak elasticity of -0.65 ± 0.19 approximately 82 percent above the mean peak elasticitiy value of -0.38 ± 0.16. The comparison of peak with off-peak elasticities for the Lowell and Reading corridors, which had approximately identical headways for both periods, reinforces the conclusion that off-peak ridership is more responsive to service improvements, as the off-peak period elasticities were 75 percent higher than the peak-period elasticities in these corridors.

Table 4-5

COMMUTER-RAIL HEADWAY ELASTICITIES
BY SERVICE LEVEL AND TIME PERIOD
(Means and Standard Deviations)

Service Level[a]	Peak Hours	Off-Peak Hours	All Hours	Aggregate Values
Medium	-0.38 ± 0.16 (5 cases)	-0.46 ± 0.09 (2 cases)	-0.41 ± 0.09 (4 cases)	-0.41 ± 0.13 (11 cases)
Low	NA	-0.78 ± 0.10 (3 cases)	-0.69 (1 case)	-0.76 ± 0.10 (4 cases)
Aggregate Levels	-0.38 ± 0.16 (5 cases)	-0.65 ± 0.19 (5 cases)	-0.47 ± 0.14 (5 cases)	-0.50 ± 0.20 (15 cases)

[a]The level of service was classified as follows:
low: more than 50-minute headways
medium: 10- to 50-minute headways

Source: See Table B-2, Appendix B.

Analysis of the 1962-1964 Boston area demonstrations, summarized in Appendix B, Table B-2, reveals the similarity in ranking of corridors according to both headway level and elasticity value. Taking the off-peak period elasticities as an example, the elasticity values descend from -0.37 and -0.54 at high-service levels in Lowell and Reading to -0.89 for the low service in the Fitchburg corridor. The same is true of the relationship between route length and elasticity, with the longest route (Fitchburg) showing the largest elasticities during both peak and off-peak periods.

In summary, the analysis of commuter-rail headway elasticities supports the earlier conclusions advanced for bus headway elasticities. The mean headway elasticity is -0.47 for both modes. Furthermore, they are appreciably higher (more than 38 percent) for the off-peak period and depend on the headway level before the service change.

Commuter-Rail Headway Elasticities: Evidence from Non-Experimental Data

Although several studies have attempted to estimate ridership response to public transportation headway variations from a non-experimental data base, only two studies, involving the London region, have had any success. These studies by Safavi and Stanard (1970) and Sturt (1974) result in a mean all-hours elasticity value of:

$$-0.47 \pm 0.11$$
(4 cases)

reinforcing the results obtained from the quasi-experimental demonstration in Boston. These two British studies, which were reviewed by Hepburn (1977), provide the only reliable information on this subject.

VEHICLE-MILES ELASTICITIES

Until this point, public transportation level of service has been loosely aligned with the frequency of bus or rail service. Indeed, other measures of transit service quality may be more important indicators. Accessibility, for example, may be measured by route density, area of coverage, and hours of service. Taken together, accessibility and frequency changes can be estimated using vehicle-miles of service as the aggregate indicator. Reliability, while perhaps a more important indicator of the quality of service, is unrelated to the quantity of vehicle-miles run. In this section, aggregate vehicle-miles service elasticities are discussed irrespective of whether they relate to frequency, route length, route density, or service-hour changes.

Evidence from Quasi-Experimental Data

Although most work in estimating vehicle-miles service elasticities has been developed from cross-sectional and time-series studies, two important studies using quasi-experimental data were performed for the cities of San Diego and Atlanta. In San Diego, Kemp (1974) and Goodman, Green, and Beesley (1977), developed vehicle-miles elasticities using least-squares regressions of time-series data over the 40-month period during which service expanded by approximately 80 percent. The aggregate vehicle-miles elasticity varied from +0.75 to +0.85. In Atlanta, where more service was available and where service expansion occurred over a much shorter period of time, Kemp estimated a vehicle-miles elasticity of +0.30.

These results suggest that ridership response to increases in vehicle miles of service depends, in part, on the initial quantity of service provided, the amount of service added, and the period of time over which the expansion takes place. Although these factors may be important in explaining the difference between San Diego's and Atlanta's service elasticities, other factors, such as fare level, auto availability, and size of the urbanized area may be equally important.

In San Diego, the vehicle-miles elasticity was higher for suburban routes than for central-city and radial routes to the central business district (CBD) as shown in Table 4-6 below. Thus, ridership appears to be more responsive to service improvements in low-service areas than in high-service areas. No empirical data are available on ridership response rates to service reductions.

Table 4-6

SAN DIEGO VEHICLE-MILES ELASTICITIES

Radial Routes to CBD	+0.65
Central-City Routes	+0.72
Suburban Routes	+1.01

Source: Goodman, Green, and Beesley (1977)

Evidence from Non-Experimental Data

The results from transportation demand modeling efforts using non-experimental data confirm the evidence presented earlier that transit demand response is inelastic to variations in vehicle miles. Some studies, particularly the cross-sectional studies of Iowa cities by Carstens and Csanyi (1968) and of 39 Canadian cities by Litt (1975) present elasticities with elastic responses. These elasticities must be viewed as suspect, owing to the nature of their modeling work using cross-sectional data. The mean service elasticity for all 28 cases presented in Table B-5 of Appendix B is +0.61 ± 0.31, a value slightly larger than the mean elasticity obtained from studies of headway variations. As shown in Table 4-7, vehicle-miles elasticities during the peak period are found to be only half the value observed during off-peak hours. Again, this indicates the varying ridership responsiveness at different levels of service. The mean bus-miles elasticitiy of +0.64 is twice the elasticity of +0.30 observed for rapid-rail service. This observation must be tempered by the lack of cases for rapid-rail service.

The previously observed relationship between headway levels and headway elasticities has only a weak correspondence in the case of vehicle-miles elasticities. Except for the high elasticity of +1.26 estimated by Hartgen and Howe (1976) for the NYCTA bus system, the vehicle-miles elasticities show a low simple correlation ($r = -0.27$) with transit-system size. Although it is not possible to make generalizations in presence of such a weak correlation, the fact still remains that medium-sized urban areas such as Utica/Rome, Albany, and Rochester exhibit much higher elasticities than larger urban areas such as Buffalo, New York, London, and Atlanta.

Table 4-7

VEHICLE-MILES ELASTICITIES FROM NON-EXPERIMENTAL DATA BY MODE AND TIME OF DAY
(Means and Standard Deviations)

Mode	Peak Hours	Off-Peak Hours	All Hours	Aggregate Values
Bus	+0.33 ± 0.18 (3 cases)	+0.63 ± 0.11 (3 cases)	+0.69 ± 0.31 (17 cases)	+0.64 ± 0.30 (23 cases)
Rapid Rail	+0.10 (1 case)	+0.25 (1 case)	+0.55 (1 case)	+0.31 ± 0.19 (3 cases)
Bus and Rapid Rail	NA	NA	+0.77 ± 0.27 (2 cases)	+0.77 ± 0.27 (2 cases)
Aggregate Values	+0.27 ± 0.19 (4 cases)	+0.54 ± 0.20 (4 cases)	+0.69 ± 0.30 (20 cases)	+0.61 ± 0.31 (28 cases)

Source: See Table B-5, Appendix B.

TRAVEL-TIME ELASTICITIES

Perhaps the most important factor affecting public transportation ridership is travel time. Unfortunately, measuring ridership response to total travel-time changes, as well as to changes in trip-time components, is a difficult task. In contrast to the previous sections on service elasticities, there has been almost no experimentation with travel-time variations. Because most of the travel-time elasticities -- except for the in-vehicle time elasticities from quasi-experimental demonstrations -- come from transit-demand and mode-choice models, these service elasticities are surrounded by great uncertainty. Consequently, travel-time elasticity comparisons should be restricted to specific individual models, and their values should be used primarily as ordinal numbers to help explain the relative degree of ridership responsiveness to travel-time changes.

Total Travel-Time Elasticities

The scant evidence on total travel-time elasticities comes from mode-choice models estimated from household cross-sectional data. Table 4-8 presents total trends from mode-choice elasticities for several user and trip-purpose categories. Choice rider and work-trip total travel-time elasticities are considerably higher than the average elasticities for all trips and for shopping trips. Thus, improvements in total travel time result in a proportionally greater response by individuals with an automobile or alternate mode available, especially for the work trip. This observation reinforces the conclusion reached in other studies, such as Kraft and Domencich (1968), that transit riding, especially during peak hours and for choice riders, is more responsive to travel-time improvements than to fare reductions.

Table 4-8

TOTAL TRAVEL-TIME MODE-CHOICE ELASTICITIES
FOR BUS AND RAPID-RAIL TRANSIT

All Choice Trips	Choice Work Trips	All Work Trips	All Shopping Trips	All Trips
San Francisco	San Francisco	Chicago	Boston	San Francisco
-1.29	-1.16	-0.90	-0.59	-0.55

Source: See Table B-6, Appendix B

The travel-time mode-choice elasticity for all trips of -0.55 estimated by McGillivray (1969) provides the standard for comparison with estimates from the quasi-experimental demonstrations presented next.

In-Vehicle Travel-Time Elasticities: Evidence from Quasi-Experimental Data

The only travel-time elasticities available from quasi-experimental data are estimates of ridership response to in-vehicle travel-time improvements obtained from bus priority demonstrations in three cities: Seattle, Miami, and Boston. As shown in Table 4-9, the aggregate elasticity from the quasi-experimental data is -0.35 ± 0.21, lower than the total travel-time elasticities presented earlier. However, as shown in Table 4-9, the aggregate elasticity is dominated by peak-period elasticities which comprise 90 percent of the observations.

Table 4-9

IN-VEHICLE TIME ELASTICITIES
BY TIME PERIOD

Time Period	Elasticities	Bus Priority Projects
Peak	-0.29 ± 0.13 (9 cases)	Miami I-95 Seattle Blue Streak Boston Southeast Expressway
Off-Peak	-0.83 (1 case)	Seattle Blue Streak
Aggregate Value	-0.35 ± 0.21 (10 cases)	All the Above

Source: See Table B-7, Appendix B.

The results of the 1970 Seattle Blue Streak demonstration are used in Table 4-10 to present the differential effects of time periods on the invehicle time elasticities. Seattle's peak-period reverse-commute service elasticity, while smaller than the off-peak value, is 25 percent larger than the travel-time elasticity obtained in the peak direction.

Table 4-10

SEATTLE'S BLUE STREAK
IN-VEHICLE TRAVEL-TIME ELASTICITIES

Peak Direction	Reverse Commute	Off-Peak Hour
-0.44	-0.55	-0.83

Source: Ecosometrics, Inc. from A.M. Voorhees and Associates (1974). See Table B-7, Appendix B

In the peak period category, Seattle's Blue Streak mean in-vehicle travel-time elasticity (-0.50) is twice the mean value calculated from Miami's I-95 express service (-0.25). There are two explanations for this difference. First, the Seattle bus priority demonstration included an increase in the frequency of bus service in addition to the improvement in trip time. Overall, the number of daily bus runs increased 12 percent. This service improvement was not discounted when the elasticities were calculated, because of lack of relevant data.

A second possible explanation for the discrepancy can be found in the higher travel times in the Seattle demonstration, which exceed Miami's travel times by 50 percent. The absolute value of the elasticities estimated in the Appendix correlates directly with travel time ($r = +0.70$), suggesting that the elasticity is higher for longer trips than for shorter trips. Thus, a proportional reduction in travel time is likely to be more noticable and more important to a long-distance rider than to a short-distance rider.

In-Vehicle Travel-Time Elasticities: Evidence from Non-Experimental Data

With the exception of a few very high values from mode-choice models, in-vehicle travel-time elasticities for combined bus and rail services from demand and mode-choice models appear to agree with the values obtained from quasi-experimntal data. As shown in Table 4-11, the aggregate in-vehicle travel-time mode-choice elasticities estimated separately for bus and rapid rail are nearly identical, but are greater than the value observed for commuter-rail service estimated from direct-demand models. Although slightly smaller than the mean, McFadden's (1974) bus and rapid-rail in-vehicle travel-time elasticities also are relatively similar and relatively close to the quasi-experimental elasticities. Talvitie (1973) shows a larger mode-choice elasticity for bus service; however, his elasticities greatly exceed the quasi-experimental elasticity values and, consequently, are suspect.

Table 4-11

COMPARISON OF IN-VEHICLE TRAVEL-TIME ELASTICITIES
BY MODE AND MODEL FROM NON-EXPERIMENTAL DATA

Mode	Mean Elasticity and Standard Deviation	Talvitie's Mode-Choice Work-Trip Elasticities for Chicago	McFadden's Mode-Choice Work-Trip Elasticities for San Francisco
Bus	-0.68 ± 0.32 (7 cases)	-1.10	-0.46 to -0.60[a]
Rapid Rail	-0.70 ± 0.10 (2 cases)	-0.80	-0.60
Combined Bus & Rail	-0.29 ± 0.08 (3 cases)	-0.20	NA
Commuter Rail	-0.59 ± 0.28 (9 cases)	NA	NA

[a]The smaller value of -0.46 refers to McFadden's 2-mode-choice model, while the larger value is from his 3-mode-choice model.

Source: See Tables B-8 through B-11, Appendix B.

Several British direct-demand-model studies of ridership response to in-vehicle travel-time changes on London's commuter-rail system provide a wide range of elasticity estimates. The mean value for nine cases is -0.59 ± 0.28. This value compares with McFadden's in-vehicle travel-time elasticity (-0.60) for the BART system in the San Francisco Bay Area, a system essentially serving the commuter market.

In 1977, Hepburn (1977) analyzed the commuter-rail routes serving the London metropolitan area during the period 1966-1971. The in-vehicle travel-time elasticities he obtained are provided in Table 4-12. Hepburn's findings, namely that in-vehicle travel-time elasticities increase with trip length, support the results discussed earlier for priority-treatment bus service.

Table 4-12

LONDON'S COMMUTER-RAIL IN-VEHICLE
TRAVEL-TIME ELASTICITIES
BY ROUTE LENGTH
1966-1971

Routes Shorter Than 25 Miles	All Routes	Routes Longer Than 25 Miles
-0.49	-0.56	-0.86

Source: Hepburn (1977)

Out-of-Vehicle Time Elasticities

All the evidence regarding out-of-vehicle time elasticities come from non-experimental data estimates, mainly from mode-choice models. The lack of quasi-experimental elasticity estimates to support the validity of elasticity estimates developed from the mode-choice models makes the latter estimates uncertain. The mean elasticity of total out-of-vehicle time is -0.59 ± 0.15, a value in general agreement (in spite of its value being derived from only three studies) with the headway elasticity values estimated earlier. It is reasonable to expect headway and out-of-vehicle time elasticities to be similar, since wait and transfer times, the major components of out-of-vehicle time, are equal to half the headway where very frequent transit service is provided or where the schedule is unknown and passengers arrive at transit stops at random.

The evidence on component out-of-vehicle time elasticities (i.e., walk-, wait-, and transfer-time elasticities) is mixed, especially in relation to in-vehicle travel-time elasticities. The value of out-of-vehicle time has been estimated by several investigators, such as Quarmby (1967), to be two to three times greater than the value of in-vehicle time. A mode-choice model estimated for Stockholm and other Swedish cities by Algers, Hansen, and Tegner (1975), resulted in relative values of waiting times which were 3 to 12 times the in-vehicle travel-time values. This study also indicated that the relative waiting-time value will increase rapidly as headways are increased, a finding which corresponds to the earlier conclusion that the absolute value of headway elasticities is directly proportional to the level of service.

The walk-time elasticities estimated by Pratt and DTM (1976) for Minneapolis/St. Paul are very small as shown in Table 4-13. The value for all-work trips is -0.26, or half the in-vehicle time elasticity; for non-work trips, the walk-time demand elasticity is -0.14. Passenger demand on bus routes leading to the central business district (CBD) was estimated by Pratt to be less elastic to changes in walk time than the demand on non-CBD-oriented routes.

The study also shows that wait-time elasticities are only slightly larger than walk-time elasticities. As a rule of thumb for planning headways and route density, transit planners equalize the average wait time at a bus stop to the average walk time to the stop (see Webster, 1977). This allocation of buses to routes suggests that wait- and walk-time elasticities are equivalent as confirmed by the Pratt model.

Table 4-13

COMPARISON OF IN-VEHICLE TIME AND
COMPONENT OUT-OF-VEHICLE TIME ELASTICITIES

	Gaudry for Montreal	McFadden for San Francisco			Pratt for Minneapolis/ St. Paul	
	Bus and Rapid Rail	Bus (2-mode)	Bus (3-mode)	Rapid Rail	Bus Work	Bus Non-Work
In-Vehicle Time	-0.27	-0.46	-0.60	-0.60	-0.52	-0.12
Out-of-Vehicle Time						
Walk Time	NA	NA	NA	NA	-0.26	-0.14
Wait Time	-0.54	-0.17	-0.19	-0.12	-0.32	-0.21
Transfer Time	NA	-0.26	-0.29	-0.66	NA	NA

Source: Tables B-8,9,10,13,14,15, Appendix B.

As shown in Table 4-13, Gaudry (1974) presents a wait-time elasticity twice the size of the in-vehicle time elasticity; however, McFadden (1974) shows just the opposite, and the Pratt and DTM (1976) results suggest the difference is dependent on the trip purpose. McFadden's transfer-time elasticities for peak hour service are higher than the comparable first-wait-time elasticities. Notice also that although the rail transfer-time elasticity is greater than the values observed for bus service, the opposite is true for first-wait time. The inconsistencies in the above table point out the need for quasi-experimental demonstrations of transit service.

Travel-Time Cross-Elasticities

The only data available on travel-time cross-elasticities come from transportation demand models estimated from non-experimental data sources as shown in Table 4-14. These demand-modeling efforts show relatively low cross-elasticities except for those referring to the effects of auto in-vehicle travel times on both bus and rail ridership. In particular, McFadden (1974) shows +0.36 to +0.39 for the cross-elasticity of auto in-vehicle time on bus ridership in San Francisco. These relatively high-impact elasticities of auto travel time on public transit demand highlight the potential of auto restraint and other traffic-management strategies on increasing transit ridership.

OTHER SERVICE ATTRIBUTES

Although headways, vehicle miles, and travel times have been the principal service characteristics used in studies of transit demand, other very important service attributes have been neglected in most models and demonstrations. In addition to travel time and cost, research studies have identified reliability, comfort, and convenience as the most important factors in the choice of transportation modes. Gustafson, Curd, and Golob (1971), for example, found that the following three characteristics were more important than lower fares:

- arriving when planned,
- having a seat, and
- not having to transfer.

The problem with using reliability, seat availaility, number of transfers, and other comfort and convenience variables has been in obtaining reliable data and in defining the qualitative variables in quantitive terms. Nevertheless, a few selected studies have attempted to quantify the importance of reliability, comfort, and convenience, and explicitly incorporate them into mode-choice models. A summary of the state of knowledge on ridership responsiveness to reliability, seat availability, and number of transfers is presented below.

Tale 4-14

TRAVEL-TIME CROSS-ELASTICITIES
FROM NON-EXPERIMENTAL DATA

	Demand For		
	Bus	Rail	Auto
BUS			
• In-Vehicle Time (Peak)		+0.23 (2 cases)	+0.10 ± 0.05 (4 cases)
(Off-Peak)			+0.09 ± 0.01 (2 cases)
• Out-of-Vehicle Time (Peak)			+0.37 (1 case)
• Walk Time (Peak)			+0.01 (1 case)
• Wait Time (Peak)		+0.06 (1 case)	+0.05 ± 0.01 (3 cases)
(Off-Peak)			+0.01 (1 case)
• Transfer Time (Peak)		+0.09 (1 case)	+0.08 ± 0.01 (2 cases)
RAIL			
• In-Vehicle Time (Peak)	+0.13 (1 case)		+0.10 (1 case)
• Out-of-Vehicle Time (Peak)	+1.00 (1 case)		
• Wait Time (Peak)	+0.03 (1 case)		+0.02 (1 case)
• Transfer Time (Peak)	+0.16 (1 case)		+0.11 (1 case)
AUTO			
• In-Vehicle Time (Peak)	+0.32 ± 0.06 (4 cases)	+0.84 (1 case)	
(Off-Peak)	+0.06 (1 case)		
• Parking Time (Peak)	+0.82 (1 case)		
(Off-Peak)	+1.40 (1 case)		

Source: See Table B-16, Appendix B.

Reliability

The importance of reliability as a service attribute affecting bus transit ridership has been pointed out by numerous attitudinal surveys. For example, Paine's (1967) attitudinal survey[1] provides evidence that transit users place a greater importance on transit reliability than on travel time and trip cost. However, in spite of its importance, demand elasticities with respect to service reliability are not presented here because no empirical measurements have been made of ridership responses to changes in transit reliability. This is another area needing demonstrations and experimentation.

Most available knowledge on the effects of service reliability comes from the United Kingdom. There, Bly (1976) developed a theoretical model for estimating the effect of random service interruptions on reductions in passenger waiting times. He discovered that at high-service frequencies, the percentage increase in mean passenger waiting time is roughly twice the percentage of bus miles reduced; for longer headways, the effect is greater by a factor of three or more. Webster (1977) reviewed these facts and concluded that if excess waiting time due to irregularities in transit service is twice the value of normal waiting time, then the demand elasticity "would be expected to be four or more times that of the normal bus-kilometers elasticity, and this seems in keeping with the importance attached to regularity and reliability by both operators and the public, as indicated in attitude surveys."[2]

Seat Availiability

The importance of seat availability for transit users has been documented in several studies. Schneider (1965), for example, partly attributes the success of several express-bus demonstrations to seat availability. In a study of mode choice, Lansing (1964) states that the most important factor in determining comfort appears to be seat availability. In that study, approximately 57 percent of the positive comments about comfort related to getting a seat.

In an attempt to quantify the value of getting a seat, Algers, Hansen, and Tegner (1975) introduced a dummy variable into their logit mode-choice models to

---

[1]Reviewed in Transit Service Reliability, Multisystems, Inc. and Transportation Systems Center, 1978.

[2]Webster (1977), p. 22.

test the hypothesis that people who do not get a seat value their travel time higher than people who get a seat. They found that the trip value for individuals who do not have a seat was 40 to 75 percent higher than the travel time value for people who have a seat. In view of the importance of seat availability, the current introduction of articulated buses on congested routes offers a unique opportunity for testing the effect of seat availability on transit ridership.[1]

Number of Transfers

The need to change buses or trains in the course of a trip is generally disliked, not only because it disrupts and prolongs the trip but also because it exposes the traveler to some discomfort. In a review of several British studies, Webster (1977) states that passengers regard transfers as equivalent to three to four minutes of extra waiting time (i.e., in addition to the actual time in transfer). In a survey conducted by the University of Maryland (see Paine, et al., 1967), commuters in Philadelphia and Baltimore were asked to rank a list of transportation attributes in order of their importance. For work trips in the combined Philadelphia, Baltimore sample, "avoid changing vehicle" was ranked seventh in importance among 33 attributes. For non-work trips, avoiding a transfer was ranked fifth.

Using mode-choice estimation models, Algers, Hansen, and Tegner (1975) discovered that the overall cash value of a transfer was 30 percent higher than the cash fare per trip and corresponded to approximately 24 minutes of door-to-door travel time. Thus, passengers appear to be willing to pay more than twice the base fare to avoid having to transfer. As shown in Table 4-15, their model showed that the value of avoiding a transfer was greater for bus than for rail, primarily because of the higher potential discomfort involved with bus transfers.

[1]Unfortunately, an earlier survey following the introduction of double-decker buses in two cities, which could have evaluated the impact of expanded seat availability on ridership, focused only on the quality of service and maintenance (see CACI, 1978).

Table 4-15

DERIVED VALUES OF TRANSFERS
FROM STOCKHOLM (1968)

	Value Per Transfer Relative to Fares per Trip[a]
Subway to Subway	0.22
Rail to Rail	0.72
Bus to Rail	1.12
Bus to Bus	2.41
Other Combinations	1.50
Weighted Average	1.30

[a]In a generalized cost sense, with 1.00 denoting a value per transfer equal to the average fare.

Source: Algers, Hansen, and Tegner (1975).

In one of the few studies to focus on transit demand and the number of transfers, Pratt and DTM (1976) estimated a transfer elasticity of -0.59 in their nonwork mode-split model for Minneapolis/St. Paul. This value is much larger than the wait-time and transfer-time elasticities estimated from the same 3-mode choice model (-0.24 and -0.17 respectively), thus confirming the previously mentioned studies that avoiding having to transfer is more important to the user than the time spent waiting for a bus.

SUMMARY

This chapter has reviewed the most important service-variation experiments and demand and mode-choice models in an attempt to quantify ridership responsiveness to different service changes. Demand elasticities for such service variables as headways, vehicle miles, and travel time were presented. In addition, the chapter reviewed evidence concerning the relative importance of other major service attributes, for which demand elasticities were not available. A summary of the means and standard deviations of the service elasticities is presented in Table 4-16. From this table and from the the analysis presented in the text, several generalizations can be advanced.

- Ridership response to service changes is inelastic. All services exhibit elasticities of demand with absolute values lower than 1.00. Thus, the proportional increases (decreases) in services are greater than the proportional increases (decreases) in passengers and revenues.

- Off-peak ridership is more responsive than peak ridership. Service elasticities are invariably 50 to 100 percent higher for the off-peak periods than for the peak periods (the Stevenage, England experience being the sole exception).

- Ridership is more responsive in lower-service areas. Service elasticities are higher in low-service areas than in high-service areas during all time periods. Thus, the proportional change in patronage is much less than the proportional change in service when frequent or fast service exists.

- Ridership response is similar across modes. Bus and commuter-rail headway elasticities are similar, as are bus and rapid-rail in-vehicle time elasticities. The limited number of cases available, however, prevents making final conclusions concering modal difference in service elasticities.

- Headway and vehicle-miles elasticities are similar. There are no apparent numerical differences between the quasi-experimental bus headway elasticities (-0.47) and bus-miles elasticities (+0.30 to +0.85), a conclusion that is supported by comparison with the non-experimental elasticities in Table 4-16.

- Ridership is more responsive to improvements in headways than in in-vehicle time. The quasi-experimental service elasticity for in-vehicle bus travel time during peak periods (-0.29) is much lower than the equivalent quasi-experimental headway elasticity (-0.42).

- Most non-experimental travel-time elasticities are questionable. There are discrepancies in the relative values of in-vehicle and out-of-vehicle travel-time elasticities from the non-experimental or mode-choice models. As a general rule, the elasticities estimated from direct-demand and mode-choice models based on non-experimental data sources are less reliable and contain more discrepancies than the elasticities obtained from quasi-experimental data.

- Service elasticities are not available for changes in many important service variables. Although transportation analysts have confirmed the importance of other service attributes on transit ridership, demand elasticities have not been estimated for such service attributes as seat availability and service reliability. Few demand elasticities exist for number of transfers.

Table 4-16

SUMMARY OF SERVICE ELASTICITIES
PRESENTED IN CHAPTER 4
(Means and Standard Deviations)

HEADWAY ELASTICITIES		
Bus (Quasi-Experimental)		
Peak:	−0.37 ± 0.19	(3 cases)
Off-Peak:	−0.46 ± 0.26	(9 cases)
All Hours:	−0.47 ± 0.21	(7 cases)
Commuter Rail (Quasi-Experimental)		
Peak:	−0.38 ± 0.16	(5 cases)
Off-Peak:	−0.65 ± 0.19	(5 cases)
All Hours:	−0.47 ± 0.14	(5 cases)
Commuter Rail (Non-Experimental)		
All Hours:	−0.47 ± 0.11	(4 cases)
VEHICLE-MILES ELASTICITIES		
Bus (Quasi-Experimental)		
All Hours:	+0.63 ± 0.24	(3 cases)
Bus (Non-Experimental)		
Peak:	+0.33 ± 0.18	(3 cases)
Off-Peak:	+0.63 ± 0.11	(3 cases)
All Hours:	+0.69 ± 0.31	(17 cases)
Rapid Rail (Non-Experimental)		
Peak:	+0.10	(1 case)
Off-Peak:	+0.25	(1 case)
All Hours:	+0.55	(1 case)
TOTAL TRAVEL-TIME ELASTICITIES		
Bus (Non-Experimental)		
Peak:	−1.03 ± 0.13	(2 cases)
All Hours:	−0.92 ± 0.37	(2 cases)
Bus and Rapid Rail (Non-Experimental)		
Off-Peak	−0.59	(1 case)

IN-VEHICLE TIME ELASTICITIES		
Bus(Quasi-Experimental)		
Peak:	-0.29 ± 0.13	(9 cases)
Off-Peak:	-0.83	(1 case)
Bus (Non-Experimental)		
Peak:	-0.68 ± 0.32	(7 cases)
Off-Peak:	-0.12	(1 case)
Rapid Rail (Non-Experimental)		
Peak:	-0.70 ± 0.10	(2 cases)
Bus and Rapid Rail (Non-Experimental)		
Peak:	-0.30 ± 0.10	(2 cases)
All Hours:	-0.27	(1 case)
Commuter Rail (Non-Experimental)		
All Hours:	-0.59 ± 0.28	(9 cases)
TOTAL OUT-OF-VEHICLE TIME ELASTICITIES		
Bus and Rapid Rail (Non-Experimental)		
All Hours:	-0.59 ± 0.15	(3 cases)
WALK-TIME ELASTICITIES		
Bus(Non-Experimental)		
Peak:	-0.26	(1 case)
Off-Peak:	-0.14	(1 case)
WAIT-TIME ELASTICITIES		
Bus and Rapid Rail (Non-Experimental)		
Peak:	-0.20 ± 0.07	(4 cases)
Off-Peak:	-0.21	(1 case)
All Hours:	-0.54	(1 case)
TRANSFER-TIME ELASTICITIES		
Bus and Rapid Rail (Non-Experimental)		
Peak:	-0.40 ± 0.18	(3 cases)
NUMBER OF TRANSFERS ELASTICITIES		
Bus (Non-Experimental)		
Off-Peak:	-0.59	(1 case)

5

SELECTED USES OF DEMAND ELASTICITIES

A comprehensive review of transit fare and service elasticities was presented in the previous two chapters. This review confirms the fact that transit demand is inelastic with respect to fares and services; that is, the proportional change in transit patronage in response to fare and service variations is less than the proportional change in fares and services. More importantly, however, the collection of data indicates that there is a large degree of consistency in the aggregate system-wide demand elasticities. Although there is variation in the disaggregate elasticity values, this variation is reduced and remarkable stability emerges when the analysis focuses on individual disaggregate categories (i.e., time period, transit mode, route length). This underlying consistency, which exists across many types of cities and even countries, provides us with a reliable body of knowledge on transit ridership behavior. Guidelines on the use of this information are presented in this chapter under three major headings: fare variations, service variations, and the interaction of transit fares and services.

The demand elasticity concept, which indicates the percentage change in transit patronage resulting from a one percent change in fares or services, is particularly useful for policy analysis purposes. Although the elasticity conveys a limited amount of demand information pertaining to only a segment of the overall demand surface, it is useful as a summary of the type of behavior -- especially possible traffic diversions -- that characterizes demand for a particular service. In addition to providing the numerical values needed to assist transit operators in estimating passenger response to future fare and service variations, disaggregate demand elasticities can provide operators with an indication of how ridership and revenues can be increased by manipulating both fare and service levels. They can thus be used for transit operational and financial planning, and for the generation of general transportation policy options. Moreover, demand elasticities are dimensionless so that their measurement is not tied to particular currency units or absolute values.

Regarding the application of demand elasticities to the design of appropriate pricing and service level policies, it must be recognized at the outset that these policies cannot properly be formulated without incorporating into the analysis considerations of costs. However, since the analysis of transit costs was beyond the scope of this study, the following examples and discussions on the uses of demand elasticities rely on convenient analytical assumptions regarding the influence of costs on setting appropriate fare and service levels. Obviously, the real-world situation is much more complex and cost considerations do and should play an important role in pricing transit services efficiently.

TRANSIT FARE ELASTICITIES

Fare Variations

The quasi-experimental fare elasticities presented in Chapter 3 result in a mean all-hours fare elasticity of -0.29 ± 0.13 (49 cases), with the fare elasticities generally varying between -0.15 and -0.60. Although the mean fare elasticity does not deviate much from the Simpson and Curtin rule of -0.30, there are several reasons to argue against the indiscriminate use of this aggregate value. First, there is a high variability in fare elasticities among cities of different sizes suggesting that each city has a unique elasticity associated with its characteristics and peculiarities of population, extent of ridership peaks, proportion of work trips, and decentralization of area employment. Second, there are predictable differences in the fare elasticities that exist among various transit modes, time periods, trip lengths, types of service, and even trip locations. Variations in fare elasticities are also noted by trip purpose and by the age and income of transit riders. These significant differences in transit fare elasticities, which are submerged in the use of an aggregate mean elasticity, offer substantial opportunities for pricing transit services differently depending on the city and transit market in question.

The elasticities compiled in Chapter 3 reveal that the demand for transit is fare inelastic; thus, any attempt at demand stimulation through fare reductions will result in deterioration of the operating deficit picture of the transit authority. Fare increases will, at least in the short-run, reduce the system's operating deficit. In fact, the data presented in this report have shown no instance where increments in fares resulted in short-run reductions in transit revenues. Nevertheless, there are uncertainties over the long-run effects of increments in fares, uncertainties that argue against haste in becoming committed to a policy of rapid and large fare increases to resolve a transit system's financial problems.

The dilemma of fare increases is that the resulting reductions in patronage may increase the operating cost per passenger carried and, in the end, stimulate further fare increases as well as reductions in transit service. A partial way out of this dilemma is to make use of the significant differences in fare elasticities that exist for different periods of the day or week, types of service, service locations, trip lengths, trip purposes, and ages of the transit riding population. Fare policies, which take into account these differences in elasticity values, can be designed to increase transit revenues with minimum possible patronage disruptions.

For example, fare elasticities vary by the time of day and the day of week. Ridership losses resulting from attempts to increase revenues can be minimized by incresing fares more during the times of low fare elasticity and less at other times. In fact, fares can be increased during peak hours and reduced during the midday, evenings, or weekends, and result in a net revenue increase at no loss of total ridership. This occurs because the higher fares during peak periods lose fewer passengers than would be gained by proportionally lower fares offered during the off-peak hours.

Fare elasticities also vary by type of route in the region. Although these values are highly correlated with time period and trip purpose, the variations provide transit managers with the opportunities to increase ridership in subareas of the region, such as on intra-CBD or intrasuburban routes, while financing the fare reductions with fare increases on radial, CBD-oriented routes. Once again, the net effect could be a total ridership improvement at no loss in revenues.

Similarly, fare elasticities vary with trip length. The data presented in Chapter 3 show that short-distance transit trips are nearly twice as responsive to fare changes as long-distance trips. Thus, if fares were to be reduced for short-distance trips and increased for the longer trips, overall ridership could be increased with no change in total revenue.

Other findings concerning the relative values of disaggregte fare elasticities presented in this report include the following:

- bus ridership is approximately twice as elastic as rapid-rail ridership to fare changes.
- commuter-rail fare elasticity estimates are too few to permit a comparison, although a demonstration in Boston and a study in London claim that commuter-rail elasticities are lower than bus fare elasticities.
- work-trip fare elasticities are the lowest of all trip purposes, with school and shopping trips being two to three times more elastic.
- higher income groups are only slightly more fare elastic than low income groups, while the fare elasticity of the population decreases with age as shown by the fare-free demonstrations in Denver and Trenton.

The above list suggests that there are many possible differential fare combinations that take advantage of the disaggregate fare elasticity information presented in this report. Unfortunately, most of the opportunities for innovative pricing of transit services are stymied by continued transit operator reliance on a system of flat fares. Although there are many advantages to flat fares, such systems do not allow transit managers to implement effective price discrimination policies and thereby charge more for the less elastic trips and transit services.

<u>Use of Disaggregate Fare Elasticities</u>

This report has emphasized that aggregate fare elasticity values, such as the -0.30 rule of thumb, are adequate only to describe the elasticity for all trip purposes, all periods of the day, and all types of passengers. Within a particular transit system operation, however, the actual elasticities of demand may be larger or smaller depending on the characteristics of the city in question and the travel habits of the local population. To be able to estimate the impact of fare changes on individual market subgroups, the transit analyst should use the following guidelines:

Step One: Analyze Past Ridership Response

Many transit properties in the United States do not have information on their fare elasticities. The transit analyst, therefore, must attempt to study ridership changes across several fare increases and decreases controlling as much as possible for seasonal and secular trends. The time periods chosen for this estimation should include those periods where services (i.e., vehicle miles) and energy prices remained stable. The period of the late sixties and early seventies and to a lesser extent, the more recent 1976-1978 period should be considered. The years 1972-1975 and the more recent gasoline deregulation period should be avoided to control somewhat for the extraneous forces on demand that are not directly related to fare changes. Obviously, if previous studies by the transit staff or an outside consultant are available on the approximate level of the fare elasticity, this task may not be required. The transit analyst, however, should validate this estimate against the elasticity ranges presented in this report.

Step Two: Compute Average Fare Elasticity

Following the analysis of fare changes, the transit analyst should compute a fare elasticity for each fare change using the midpoint formula presented in Chapter 2. An average fare elasticity for the transit system can then be computed from the individual fare elasticity estimates. This average value should be used to predict aggregate ridership changes resulting from future fare adjustments.

Step Three: Compute Disaggregate Fare Elasticities

The aggregate fare elasticity obtained in the previous step can now be modified so that it can be applied to individual market subgroups. To do this, the analyst should multiply the aggregate fare elasticity by the adjustment factors presented in Table 5-1 for the market in question. The resulting values will be estimated disaggregate fare elasticities. For example, if the city's aggregate fare elasticity is -0.41, then the estimated peak and off-peak fare elasticities are:

Peak: $-0.41 \times 0.59 = \underline{-0.24}$

Off-Peak: $-0.41 \times 1.38 = \underline{-0.57}$

Table 5-1

ADJUSTMENT FACTORS FOR ESTIMATING DISAGGREGATE FARE ELASTICITIES FROM AGGREGATE VALUES[1]

Disaggregate Group	Adjustment Factor
	Multiply Aggregate Elasticity by:
Transit Mode	
Bus:	1.57
Rapid Rail:	0.72
Trip Length	
Short-Distance:	1.43
Long-Distance:	0.66
Route Type	
Intra-CBD:	1.39
Intrasuburban:	1.32
Non-CBD Oriented:	1.16
CBD Oriented:	0.56
Time Period:	
Off-Peak:	1.38
Peak:	0.59
Trip Purpose:	
Shop:	1.29
Work:	0.50
Ridership Type:	
Choice:	1.31
Captive:	0.63
Rider's Income	
High:	1.67
Medium:	1.13
Low:	0.72
Rider's Age:	
1-16 years:	1.37
17-24 years:	1.15
25-44 years:	0.70
45-65 years:	0.63
65+ years:	0.59

[1]The adjustment factors are based on the data presented in Appendix A.

Step Four: Estimating Ridership Impact

The disaggregate fare elasticities can now be used for estimating the ridership impacts of alternative pricing policies. The following formula should be used for this purpose:

$$\text{Ridership Generated or Lost} = \left(\frac{\text{Change in Fare}}{\text{Existing Fare}}\right) \times \left(\begin{array}{c}\text{Disaggregate}\\\text{Market}\\\text{Elasticity}\end{array}\right) \times \left(\begin{array}{c}\text{Existing}\\\text{Market}\\\text{Ridership}\end{array}\right)$$

As an example, assume off-peak ridership is currently at 53,000 passenger trips per day. The transit authority is interested in predicting the potential ridership change that would result by reducing the off-peak fare from 35 to 30 cents. Thus:

$$\text{Ridership Generated} = \frac{(0.30-0.35)}{0.35} \times (-0.57) \times (53{,}000)$$

$$\text{Ridership Generated} = 4{,}316 \text{ passenger trips per day.}$$

Step Five: Estimate Revenue Impact

The final step in the analysis of a single fare change is to estimate the revenue impact resulting from the proposed fare change. The revenue generated or lost can be estimated from the following formula:

$$\text{Revenue Generated or Lost} = \left(\text{Change in Fare}\right) \times \left(\begin{array}{c}\text{Disaggregate}\\\text{Market}\\\text{Elasticity}\end{array} + 1\right) \times \left(\begin{array}{c}\text{Existing}\\\text{Market}\\\text{Ridership}\end{array}\right)$$

Using the example presented above, the revenue loss resulting from reduction in the off-peak fare from 35 to 30 cents is:

$$\text{Revenue Loss} = (0.30 - 0.35) \times (-0.57 + 1) \times (53{,}000)$$

$$\text{Revenue Loss} = \$1{,}139.50 \text{ per day.}$$

The reader should remember that the fare elasticities presented in this report are short-run changes of within one year or less. Therefore, the use of demand elasticities for predicting the patronage effects of fare changes should be restricted to relatively short time periods such as one year.

The reader should also be aware of the limitations on the transferability of demand elasticities from one setting to another. A purist would argue that demand elasticities should only be used in conjunction with the demand model from which they were estimated and in the context of the city to which they apply. Although this approach is essentially correct, it unfortunately has only limited real-world value and application. In reality, transit planners and executives are asked to provide best-guess estimates of the impacts of fare and service changes where, because of the promptness of the response period, there is no time for estimating demand models appropriate to the task. In these situations, transit planners can benefit from the data on passenger response to fare and service changes experienced in comparable environments. It is with this thought in mind that the adjustment factors presented in this chapter have been developed. Needless to say, they are not an alternative to actual estimation of demand models if the situation allows for such an endeavor.

TRANSIT SERVICE ELASTICITIES

Service Variations

In contrast to the situation just described on transit fare elasticities, demand elasticities by service attribute are rare. The service elasticities reviewed in Chapter 4 covered elasticities for bus and commuter-rail headways, aggregate vehicle miles, in-vehicle time, and walk, wait, and transfer time. Elasticities for other very important attributes of service quality, such as reliability and seat availability, are not available in the literature. Nevertheless, there are enough consistencies within the service categories presented in Chapter 4 to justify the following guidelines.

The first general observation on the demand impacts of changes in transit service is that service elasticities are less than unitary. Therefore, the proportional change in passenger demand will be less than the proportional change in transit service. The net effect is that changes in service alone will not appreciably change the revenue position of a transit agency, particularly since some service changes are quite expensive.

Transit service elasticities, however, are very often numerically larger than fare elasticities. Studies have repeatedly shown that frequency of service is a more important factor than lower fares in both retaining present passengers and in attracting additional riders. There are situations, however, where further headway improvements are not productive. Data on bus and commuter-rail headway elasticities presented in Chapter 4 reveal that passengers are more responsive to headway variations in low-service areas than in high-service areas. The correlations between the elasticities and the headway levels prior to the service changes are consistently high across all time periods. Headway elasticities disaggregated by time of day and service level can be used effectively with productivity indicators to evaluate alternative service adjustment policies.

Vehicle- and bus-miles variables are consistently used as aggregate indicators of the level of service provided by a transit property because they can be related to average service frequency (and thus average wait time) and average route density (and thus average walk time). It is important, however, to distinguish between the effects of providing vehicle-miles for the purpose of extending or increasing service and for the purpose of maintaining or improving the reliability of transit service.[1] When transit service is extended or increased, passenger walk and wait times are generally reduced in proportion to the increased vehicle-miles of service provided. Changes in transit service reliability, however, affect the "extra" time in waiting. This extra time is much more annoying to passengers and, consequently, the vehicle-miles service elasticity will be affected accordingly.

Like headway elasticities, vehicle-miles elasticities vary by time of day with ridership responding more to changes during the off-peak than to changes during the peak period. Bus ridership is slightly more elastic to changes in vehicle-miles than rapid-rail ridership and, like fare elasticities, vehicle-miles service elasticities are numerically larger for suburban services than for central city and CBD-oriented services.

Although the non-experimental elasticities show otherwise, several studies suggest that out-of-vehicle time elasticities are larger than in-vehicle time elasticities. Indeed, in-vehicle time elasticities are quite small (-0.29) and thus, reductions in access time through headway improvements should have more of an impact on transit demand than comparable in-vehicle travel-time reductions.

---

[1] See Webster, (1977).

Other important findings concerning the relative values of disaggregate service elasticities include the following:

- bus and commuter-rail headway elasticities are similar, as are bus and rapid-rail in-vehicle time elasticities.
- long-distance commuter-rail trips are more responsive to in-vehicle travel time changes than short-distance trips.
- elasticities derived from mode-choice and other cross-sectional models show transfer-time elasticities to be twice as large as first wait-time elasticities.
- although work trips appear to be proportionally more responsive to changes in walk- and wait-time than non-work trips, non-CBD-oriented trips exhibit higher wait- and walk-time elasticities than CBD-oriented trips.

Finally, the literature review uncovered studies which claimed that the demand elasticities associated with service reliability and number of transfers were larger than conventional service elasticities. These claims remain to be proven under controlled experimental conditions.

Use of Disaggregate Service Elasticities

Unlike the situation with respect to fare policies, most transit agencies do not have estimates of service elasticities. In this case, a transit analyst can estimate a headway or vehicle-miles service elasticity by analyzing ridership variations over periods when fares were constant and fuel prices stable. The analyst should follow the same procedures outlined in the previous section on the estimation of aggregate fare elasticities. If such an analysis is not possible, the transit agency should rely on the most appropriate service elasticities presented in Chapter 4 and Appendix B.

To estimate the ridership impacts of service adjustments for specific periods of the day, route type, or trip purpose, the planner should use the adjustment factors presented in Table 5-2. The methodology used for calculating disaggregate ridership response to fare changes should also be followed for the analysis of disaggregate service variations.[1]

INTERACTIONS OF TRANSIT FARES AND SERVICE LEVELS

The aggregate fare and service elasticities presented earlier in Chapter 3 and 4 indicate that transit demand is inelastic to both fares and services. Consequently, independent variations of fares and services will not by themselves increase both revenues and patronage at the same time. For example, an increase in service -- without a corresponding fare change -- will probably not result in revenue increases large enough to cover the extra costs of the service improvement because the proportional change in patronage is less than the proportional change in service.

Aggregate service elasticities (measured in vehicle miles), however, are twice as large as aggregate fare elasticities suggesting that passengers are more responsive to service changes than to fare changes. On the aggregate level this is true. However, because both fare or service elasticities vary considerably from one area to another and by the time of day, type of route, and other classifications, this generalization is not always true. For example, using the data presented in Chapters 3 and 4, the mean bus headway elasticity on routes with less than ten-minute headways is -0.19 during off-peak hours. The average off-peak fare elasticity for bus service, however, is -0.37. Since the service elasticity is so low, a transit agency cannot hope to increase ridership and revenues substantially by further headway improvements. If anything, headways should be reduced with the operating cost savings applied either to other corridors with relatively poor service or to the same route in the form of a fare reduction.

---

[1]To estimate the revenue impacts of service adjustments, use the following formula:

$$\begin{matrix}\text{Ridership}\\\text{Generated}\\\text{or Lost}\end{matrix} = \left(\frac{\text{Change in Service Level}}{\text{Existing Service Level}}\right) \times \left(\text{Existing Fare}\right) \times \left(\begin{matrix}\text{Disaggregate}\\\text{Market}\\\text{Elasticity}\end{matrix}\right) \times \left(\begin{matrix}\text{Existing}\\\text{Market}\\\text{Ridership}\end{matrix}\right)$$

Table 5-2

ADJUSTMENT FACTORS FOR ESTIMATING DISAGGREGATE SERVICE ELASTICITIES FROM AGGREGATE VALUES

Service Variable and Disaggregate Group (Aggregate Elasticity)	Adjustment Factor: Multiply Aggregate Service Elasticity By:
BUS HEADWAYS (-0.47 ± 0.21)	
Time Period	
Off-Peak:	1.10
Peak:	0.63
Service Level:	
Low (more than 50 minutes):	1.32
Medium (10-50 minutes):	1.05
High (less than 10 minutes):	0.50
COMMUTER-RAIL HEADWAYS (-0.47 ± 0.14)	
Time Period	
Off-Peak:	1.41
Peak:	0.79
Service Level	
Low (more than 50 minutes):	1.52
Medium (10-50 minutes):	0.82
VEHICLE-MILES (+0.61 ± 0.31)	
Time Period	
Off-Peak:	1.19
Peak:	0.62
Transit Mode	
Bus:	1.21
Rapid Rail:	0.57
Route Type	
Intrasuburban:	1.19
Central City:	0.85
CBD Oriented:	0.76

[1]The adjustment factors are based on the data presented in Appendix B.

Service Variable and Disaggregate Group (Aggregate Elasticity)	Adjustment Factor: Multiply Aggregate Service Elasticity By:
BUS IN-VEHICLE TIME (-0.35 ± 0.21)	
Time Period	
Off-Peak:	1.38
Peak (Reverse Commute):	0.92
Peak Direction:	0.73
Route Type	
Non-CBD Oriented:	1.13
CBD Oriented:	0.90
Trip Purpose	
Work:	1.52
Non-Work:	0.33
COMMUTER-RAIL IN-VEHICLE TIME (-0.59 ± 0.28)	
Route Length	
More than 25 miles:	1.54
Less than 25 miles:	0.88
WALK TIME TO BUS (-0.20 ± 0.06)	
Route Type	
Non-CBD Oriented:	1.23
CBD Oriented:	0.84
Trip Purpose	
Work:	1.26
Non-Work:	0.66
WAIT TIME FOR BUS (-0.26 ± 0.14)	
Route Type	
Non-CBD Oriented:	1.41
CBD Oriented:	0.66
Trip Purpose	
Work:	1.21
Non-Work:	0.72

Patronage losses associated with attempts to increase revenue can be minimized by increasing fares only for users exhibiting small demand elasticities, such as commuters. The service saved as a result of reduced demand, albeit little during the peak period, could be applied to routes with relatively poor service and result in further revenue increases if the patronage gained by the service adjustment is greater than the patronage lost due to the fare increase. Since the marginal cost per vehicle-hour of operation during off-peak periods is at least 30-50 percent lower than during the peak period,[1] the cost savings due to the reduction in peak service should be applied to off-peak routes with infrequent service, thus enabling a further gain in total ridership and revenues to take place.

If the disaggregate fare and service elasticities are known for a particular transit market, the ridership or revenues generated by a particular action or set of actions could be improved by manipulating both the fare and service levels. If the revenues generated by an improvement in service are assumed equal to the additional costs of providing that service for analytical convenience purposes (i.e., a break-even operating cost situation) and if the fare and service elasticities are not numerically equivalent, then transit ridership can be increased with no net effect on revenues by proper fare and service adjustments. These adjustments will in turn cause the demand elasticities to change if the elasticities are assumed variable and dependent on the respective fare and service levels. Opportunities for further ridership increases will cease when the fare and service elasticities are equal.[2] Thus, when the service elasticity for a particular market is larger than the fare elasticity, a transit agency should raise fares and use the revenues produced to finance service improvements. Conversely, if the fare elasticity is larger than the service elasticity, then fares should be decreased with the revenue loss covered by the cost savings of a simultaneous service reduction.

As an example, consider the situation presented in Table 5-3. Assuming an aggregate fare and service elasticity of -0.35 and -0.47 respectively, and using the adjustment factors presented earlier in this chapter, disaggregate fare and service elasticities were calculated and are presented in the cells of Table 5-3. With the objective of increasing total ridership with no change in net revenue, two fare and service adjustment strategies are possible when the disaggregate elasticities are not equal:

---

[1]See Thompson (1971) and Mohring (1972).

[2]The model used to arrive at this conclusion includes simple revenue and cost equations. For more information on the functional form of the equations and the assumptions used, see Black (1976).

Table 5-3

AN EXAMPLE OF BUS FARE AND SERVICE INTERACTION STRATEGIES[a]

BUS HEADWAY LEVEL	TIME PERIOD	
	PEAK -0.21[b]	OFF-PEAK -0.48[b]
FREQUENT SERVICE (less than 10 minute headways)	-0.15[c] finance a fare reduction with the cost savings from a service reduction	-0.26 finance a fare reduction with the cost savings from a service reduction
MEDIUM SERVICE (10-50 minute headways)	-0.31 finance a service improvement with the revenue from a fare increase	-0.54 finance a service improvement with the revenue from a fare increase
INFREQUENT SERVICE (more than 50 minute headways)	-0.39 finance a service improvement with the revenue from a fare increase	-0.68 finance a service improvement with the revenue from a fare increase

[a]This table presents an example of two fare and service adjustment strategies to increase total bus ridership with no change in net revenue based on disaggregate fare and service elasticities. The model assumes a break-even operating cost situation for analytical convenience purposes so that revenue -- cost considerations can be de-emphasized.

[b]Disaggregate fare elasticities for peak and off-peak periods assuming an aggregate bus fare elasticity of -0.35 and applying the adjustment factors presented earlier in Table 5-1.

[c]Disaggregate service elasticities for time period and service levels assuming an aggregate headway elasticity of -0.47 and applying the adjustment factors presented earlier in Table 5-2.

1) finance a service improvement with the revenues obtained from a fare increase, or

2) finance a fare reduction with the cost savings resulting from a service reduction.

The two strategies presented in the cells of Table 5-3, however, are not the only fare and service adjustment options available for increasing patronage. The peak to off-peak cross-subsidy scenario described earlier is an example of such an alternative. Whatever service adjustment decision is taken, the premise on the extent to which transit riders are willing to pay more for improved service or trade one service attribute for another must be based on the disaggregate fare and service elasticities.

In spite of the obvious need for more analysis of the interactions of fares and services, most of the demand approaches, whether from the quasi-experimental demonstrations or the more sophisticated mode-choice models, 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 de-emphasized in favor of variable-elasticity models with interaction effects, such as the translog models.[1] However, in spite of the general lack of recognition of the interaction between fares and services, several approaches stand out which recognize the importance of their joint consideration.

Total Generalized-Cost Approach

The generalized-cost approach consists of assigning monetary values to the time spent getting to, and riding on a transit vehicle and any other inconvenience encountered on the way, and adding this monetary value of time with the fare to produce what is defined as the total "generalized cost" of the transit trip. A statistical demand analysis is then performed to estimate the passenger demand elasticity with respect to generalized cost rather than estimating separate elasticities for fares and in-vehicle, walk, wait, and transfer times. The total generalized-cost elasticities estimated in the United Kingdom (see Oldfield, 1974) have a mean elasticity of -1.50. Of this value, fares account for 21 to 30 percent resulting in fare elasticities of -0.30 to -0.45 which correspond to the quasi-experimental values reported in British studies of fare elasticities (see Bly, 1976). Although the generalized-cost elasticity studies do not rigorously

[1]See Christensen, Jorgensen, and Lau (1975).

address the issue of fare and service interactions, they do provide for partial analysis of their joint effects on bus ridership.

The London Transport Passenger-Maximization Analytical Programs

A series of analytical studies undertaken by the London Transport[1] provide some examples of the possible use of fare and service elasticities for policy planning purposes. Essentially, the London Transport planners use estimates of fare and vehicle-miles elasticities derived from experimental and measurement studies, and theoretically postulate a maximization of passenger miles subject to constraints on the level of subsidy available. From this theoretical maximization, they derive the concept of the passmark (equivalent to lagrangian multipliers in constrainted maximization formulations) which, defined in terms of passenger-miles per pound sterling, measures the marginal value per unit of deficit of the optimal combination of fares and services.

The passmark level is then used to assess the effectiveness of policies, such as service improvements and expansions, station renovations, and equipment selection. For each policy option, the planners estimate demand and cost impacts in terms of the ratio of passenger-miles generated to net costs. The policies that cannot generate ratios higher than the passmark level are rejected as inefficient. Obviously, the British planners are still some distance away from joint fare and service planning decisions. However, the theoretical and analytical apparatus that would enable them to expand into joint comprehensive planning of fares and services is indeed in place.

Here in the United Stated, performance indicators provide transit managers with quantitative information from which many service-level decisions are made. Joint fare and service planning decisions, however, are seldom taken since techniques for assessing alternative fare and service levels are not immediately available. In addition, most transit systems have flat-fare structures or rigid zone systems which do not provide transit managers with the opportunities to explore discriminant pricing polices. Nevertheless, in the near future national demonstrations of joint fare and service level variations will be performed to provide the transit industry with more information on fare and service demand elasticities, on their interactions, and on their use for policy planning purposes.

---

[1]See London Transport Executive Business Policy Office (1975, 1976 and 1979), Fairhurst and Smith (1977), Nash (1978), and Glaister and Collings (1978).

REFERENCES

REFERENCES

Algers, Staffan, Stein Hansen, and Goran Tegner. "Role of Waiting Time, Comfort, and Convenience in Modal Choice for Work Trip." Transportation Research Record 534. Transportation Research Board, Washington, D.C., 1975.

Algers, Staffan, Stein Hansen, and Goran Tegner. "On the Evaluation of Comfort and Convenience in Urban Transportation -- A Choice Analytic Approach." Proceedings of the 15th Annual Meeting of the Transportation Research Forum, Vol. 15, No. 1, 1974.

American Transit Association. Estimated Loss in Passenger Traffic Due to Increases in Fares (1961 - 1967). American Transit Association, Washington, D.C., 1968.

American Transit Association. Estimated Loss in Passenger Traffic Incident to Increases in Urban Transit Fares. American Transit Association, Washington, D.C., 1961.

American Transit Association. Summary of 195 Observations on Estimated Loss in Passenger Traffic Resulting from Fare Increases on U.S. Transit Companies. American American Transit Association, Washington, D.C., April 1953.

ATE Management and Service Company, Inc. Southwest Ohio Regional Transit Authority Fare Study -- Summary Report. Prepared for the Southwest Ohio Regional Transit Authority. ATE Management, Cincinnati, August 1976.

Ballou, Donald P., David T. Hartgen, and Lakshmi Mohan. Distance-Based Transit Fares: Robin Hood or Sheriff of Nottingham? Preliminary Research Report 145. Planning Research Unit, New York State Department of Transportation, Albany, New York, August 1978.

Bates, J.W. "The Effect of Fare Reduction on Transit Ridership in the Atlanta Region: Summary of Transit Patronage Data." Transportation Research Record No. 499. Transportation Research Board, Washington, D.C., 1974.

Baum, Herbert J. "Free Public Transport." Journal of Transport Economics and Policy, Vol. 7, No. 1, January 1973.

Bell, G.J. Bus Service Elasticity, Headway and Distance Travelled. Economic Research Memorandum M311. London Transport Executive, London, 1975.

Billheimer, J.W., R.J. Bullemer, and C. Fratessa. The Santa Monica Freeway Diamond Lanes. Volume II: Technical Report. Prepared for the Transportation Systems Center, U.S. Department of Transportation. Systan, Inc., Los Altos, California, September 1977.

Black, Ian G. Reduced Fares or Increased Frequency? Working Paper 34. Urban Transport Research Group, University of Warwick, West Midlands, United Kingdom, October 1976.

Bly, P.H. Depleted Bus Services: The Effect of Rescheduling. TRRL Laboratory Report 699. Department of the Environment, Transport and Road Research Laboratory, Crowthorne, United Kindom, 1976.

Bly, P.H. The Effect of Fares on Bus Patronage. TRRL Laboratory Report 733. Department of the Environment, Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1976.

Bos, Dieter. "Distributional Effects of Maximization of Passenger Miles." Journal of Transport Economics and Policy, Vol. 12, No. 3, September 1978.

Boyd, J. Hayden, and Gary R. Nelson. Demand for Urban Bus Transit: Two Studies of Fare and Service Elasticities. Prepared for the Assistant Secretary for Policy and International Affairs, U.S. Department of Transportation. Institute for Defense Analyses, Arlington, Virginia, October 1973.

Buckles, P.A. The Stevenage Bus Experiment. Research Group in Traffic Studies, University College, London, September 1972.

CACI, Inc. The Double Deck Bus Demonstration Project -- Executive Summary. Prepared for the Transportation Systems Center, U.S. Department of Transportation. CACI, Inc., Los Angeles, May 1978.

Carstens, R.L., and L.H. Csanyi. "A Model for Estimating Transit Usage in Cities in Iowa." Highway Research Record 213. Highway Research Board, Washington, D.C., 1968.

Caruolo, John R., and Roger P. Roess. The Effect of Fare Reductions on Public Transit Ridership. Prepared for the Urban Mass Transportation Administration, U.S. Department of Transportation. Polytechnic Institute of New York, Brooklyn, 1974.

Chan, Y., and F.L. Ou. "A Tabulation of Demand Elasticities for Urban Travel Forecasting." Presented at the 57th Annual Meeting of the Transportation Research Board, Washington, D.C., February 1978.

Charles River Associates, Inc. An Evaluation of Free Transit Service. Prepared for the Office of Economics, Assistant Secretary for Policy Development, U.S. Department of Transportation. Charles River Associates, Cambridge, August 1968.

Christensen, Laurits R., Dale W. Jorgenson, and Lawrence J. Lau. "Transandental Logarithmic Utility Functions." The American Economic Review, Vol. 65, No. 3, June 1976.

Collins, P.H., and J.F. Lindsay. Analysis of Effect of September 1969 Fares Revision on Work Journeys. Operational Research Report R181. London Transport Executive, London, June 1972.

Collings, J.J., D. Rigby, and J.K. Welsby. Passenger Response to Bus Fares: Some Evidence. Economic Statistical Note 22. Department of the Environment, London, 1976.

Colman, Steven B. Case Studies in Reduced-Fare Transit: Portland's Fareless Square. Prepared for the Urban Mass Transportation Administration, U.S. Department of Transportation. DeLeuw, Cather and Company, San Francisco, April 1979.

Colman, Steven B. Case Studies in Reduced-Fare Transit: Seattle's Magic Carpet. Prepared for the Urban Mass Transportation Administration, U.S. Department of Transportation. DeLeuw, Cather and Company, San Francisco, April 1979.

Connor, David L. Findings of Preliminary Analyses of the Trenton Off-Peak Fare-Free Transit Demonstration. Prepared for the Transportation Systems Center, U.S. Department of Transportation. DeLeuw, Cather and Company, New York, January 1979.

Connor, David L., and A.H. Studenmund. "Summary Final Report: Evaluation of the Mercer County Fare-Free Transit Demonstration." Paper presented at the 59th Annual Meeting of the Transportation Research Board, Washington, D.C., January 1980.

Crain and Associates. San Bernardino Freeway Express Busway: Evaluation of Mixed Mode Operations. Final Report. Prepared for the Southern California Association of Governments. Crain and Associates, Menlo Park, California, July 1978.

Crain, John L., Peter G. Fitzgerald, and Sydwell Flynn. The Golden Gate Corridor Bus Priority System. Final Report. Prepared for the Transportation Systems Center, U.S. Department of Transportation. Bigelow-Crain Associates, Menlo Park, California, May 1975.

Curtin, John F. "Effect of Fares on Transit Riding." Highway Research Record 213. Highway Research Board, Washington, D.C., 1968.

Daly, A.J., and H.S. Gale. Elasticity of Demand for Public Transport. TRRL Report Supplementary Report 68 UC. Department of the Environment, Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1974.

Daly, A.J., and S. Zachary. The Effect of Free Public Transport on the Journey to Work. TRRL Supplementary Report 338. Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1977.

Damm, David. "Knoxville Service and Fare Demonstration Project: Progress Report for April, 1979." Multisystems, Inc., Cambridge, April 1979.

DeLeuw, Cather and Company. Evaluation of the Denver RTD Off-Peak Fare-Free Transit Demonstration. Draft Final Report. Prepared for the Transportation Systems Center, U.S Department of Transportation. DeLeuw, Cather and Company, San Francisco, November 1979.

DeLeuw, Cather and Company. Evaluation of the Trenton Off-Peak Fare-Free Transit Demonstration. Draft Final Report. Prepared for the Transportation Systems Center, U.S. Department of Transportation. DeLeuw, Cather and Company, New York, September 1979.

Detroit, City of. Grand River Avenue Transit Survey. Final Report. Prepared for the Housing and Home Finance Agency Demonstration Grant Program. Department of Street Railways, City of Detroit, January 1963.

Difiglio, Carmen. "Transit Fare and Ridership: A Review." Technical Notes. Highway Users Federation, Washington, D.C., December 1974.

Dobson, Ricardo, Thomas F. Golob, and Richard L. Gustafson. "Multidimensional Scaling of Consumer Preferences for a Public Transportation System: An Application of Two Approaches." Socio-Economic Planning Sciences, Vol. 8, No. 1, February 1974.

Domencich, Thomas A., Gerald Kraft, and Jean-Paul Valette. "Estimation of Urban Passenger Travel Behavior: An Economic Demand Model." Highway Research Record 238. Highway Research Board, Washington, D.C., 1968.

Domencich, Thomas A., and Daniel McFadden. Urban Travel Demand: A Behavioral Analysis. North Holland Publishing Company, Amsterdam, 1975.

Donnelly, Elene P. "Preference Elasticities for Transit Fare Increases and Decreases by Demographic Groups." Transportation Research Record 589. Transportation Research Board, Washington, D.C., 1976.

Doxsey, Lawrence B. "Elasticity Measures of Behavioral Response to Off-Peak Fare-Free Transit." Paper presented at the 59th Annual Meeting of the Transportation Research Board, Washington, D.C., January 1980.

Dupree, John H., and Richard H. Pratt. A Study of Low Cost Alternatives to Increase the Effectiveness of Existing Transportation Facilities -- Results of Case Studies and Analysis of Busway Applications. Prepared for the Office of the Secretary, U.S. Department of Transportation. R.H. Pratt Associates, Inc., Kensington, Maryland, January 1973.

Dygert, Paul, James Holec, and Donald Hill. Public Transportation Fare Policy. Prepared for the Assistant Secretary for Policy Plans and International Affairs, U.S. Department of Transportation. Peat, Marwick, Mitchell and Co., Washington, D.C., 1977.

European Conference of Ministers of Transport (ECMT). "Determination of Elasticities of Demand for the Various Means of Urban Passenger Transport." Report of the Thirteenth Round Table of Transport Economics. Organization of Economic Coordination and Development (OECD), Paris, April 1971.

Fairhurst, M.H. Bus Service Levels, Passenger Waiting Times and Patronage. Economic Research Report R238. London Transport Executive, London, January 1979.

Fairhurst, M.H. "Passenger Demand Research in London Transport." Paper N24. Presented at the Annual Meeting of Planning and Transport Research and Computation Ltd., London, July 1975.

Fairhurst, M.H. An Analysis of Factors Affecting Bus and Rail Receipts (1970-1972). Research Report R201. London Transport Executive, November 1973.

Fairhurst, M.H., J. F. Lindsay, and P.J. Morris. An Analysis of the Fares Revision Introduced on 23 March 1975. Economic Research Report R218. London Transport Executive, London, October 1975.

Fairhurst, M.H., and P.J. Morris. Variations in the Demand for Bus and Rail Travel Up to 1974. Economic Research Report R210. London Transport Executive, April 1975.

Fairhurst, M.H., and R.S. Smith. Development and Calibration of London Transport's Scenario Model. Economic Research Report R229. London Transport Executive, September 1977.

Frankena, Mark W. "The Demand for Urban Bus Transit in Canada." Journal of Transport Economics and Policy, Vol. 12, No. 3, September 1978.

Fulkerson, Heidi. "A Direct Demand Model of Work Trips in Louisville, Kentucky." Transportation Systems Division, Massachusetts Institute of Technology. Cambridge, Massachusetts, 1975.

Furniss, Robert E. Evolution and Operations of the Reston Virginia Commuter Bus Service. Prepared for the Transportation Systems Center, U.S. Department of Transportation. CACI, Inc., Los Angeles, August 1977.

Garbade, K.D., and N.M. Soss. "Fare Policies for Mass Transit Deficit Control: Analysis by Optimization." Transportation Research 10, 1976.

Gaudry, Marc. "Seemingly Unrelated Urban Travel Demands." Transportation Research 12, 1978.

Gaudry, Marc. "An Aggregate Time-Series Model of Urban Transit Demand: The Montreal Case." Transportation Research, Vol. 9, August 1975.

Glaister, Stephan. "Variations in the Demand for Bus and Rail Travel in London, 1970 to 1975." Manuscript. London School of Economics, London, 1976.

Glaister, Stephan, and J.J. Collings. "Maximization of Passenger Miles in Theory and Practice." Journal of Transport Economics and Policy, Vol. 12, No. 3, September 1978.

Glaister, Stephen, and David Lewis. "An Integrated Fares Policy for Transport in London." Journal of Public Economics 9, 1978.

Goodman, Keith M., and Melinda A. Green. Low-Fare and Fare-Free Transit: Some Recent Applications by U.S. Transit Systems. Prepared for the Urban Mass Transportation Administration, U.S. Department of Transportation. Urban Institute, Washington, D.C., February 1977.

Goodman, Keith M., Melinda A. Green, and Michael E. Beesley. The San Diego Transit Corporation: The Impacts of Fare and Service Changes on Ridership and Deficits, 1972-1975. Prepared for the Urban Mass Transportation Administration, U.S. Department of Transportation. The Urban Institute, Washington, D.C., May 1977.

Goodman, Leon. Urban Corridor Demonstration Program, Exclusive Bus Lane. Interstate 495 - New Jersey Approach to Lincoln Tunnel. Prepared for the Urban Mass Transportation Administration, U.S. Department of Transportation. Tri-State Regional Planning Commission, New York, July 1972.

Goodwin, P.B. "Some Data on the Effects of Free Public Transport." Transportation Planning and Technology 1, 1973.

Grey Advertising, Inc. Transit Marketing Management Handbook: Pricing. Prepared for the Office of Transit Management, Urban Mass Transportation Administration, U.S. Department of Transportation, Washington, D.C., April 1976.

Grey, Alexander. Urban Fares Policy. D.C. Heath and Co., Lexington, Massachusetts, 1975.

Grunfeld, Y. "The Interpretation of Cross-Section Estimates in a Dynamic Model." Econometrica, 1961.

Gustafson, Richard L., H.N. Curd, and Thomas F. Golob." User Preferences for a Demand-Responsive Transportation System: A Case Study Report." Highway Research Record 367. Highway Research Board, Washington, D.C. 1971.

Habib, Philip, Eliot Linzer, C. Jones, R. Nason, and R. Ablamsky. Fare Policy and Structure. Prepared for the Urban Mass Transportation Administration, U.S. Department of Transportation. Polytechnic Institute of New York, Brooklyn, September 1978.

Hajek, J.J. Revenue and Ridership Changes in Ontario Cities Due to Transit Fare Increases. Ministry of Transportation and Communications, Downsview, Ontario, May 1978.

Hartgen, David T., and Stephen M. Howe. "Transit Deficits: A Projection for New York State." Transportation Research Record 589. Transportation Research Board, Washington, D.C., 1976.

Hepburn, D.R.C. Analysis of Changes in Rail Commuting to Central London, 1966-1971. TRRL Supplementary Report 268. Department of the Environment, Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1977.

Hicks, Kathy. A Study to Determine Consumer Reaction to Weekend Service Changes and to Evaluate the Downtown Transit Information Center Demonstration Program. Department of Transportation, City of Madison, March 1979.

Hoel, Lester A., and Ervin S. Roszner. "Impact of Reduced Transit Fares for the Elderly." Traffic Quarterly, July 1972.

Holland, Dempster K. A Review of Reports Relating to the Effect of Fare and Service Changes in Metropolitan Public Transit Systems. Prepared for the Federal Highway Administration, U.S. Department of Transportation. St. Louis University, St. Louis, June 1974.

Huang, T.J. An Econometric Analysis of the Determanents of Demand for Local Transit in Edmonton, 1961-1970. Department of Finance, Edmonton, Alberta, 1973.

Illinois, University of. Mass Transportation Demonstration Projects, Illinois, MTD 3,4. Prepared for the U.S. Department of Housing and Urban Development. Bureau of Economic and Business Research, University of Illinois, Champaign-Urbana, Illinois, 1968.

Jackson, R.L., G.A. Coe, and A.J. Finnamore. A Study of Some Factors Affecting Bus Service Performance. TRRL Laboratory Report 767. Department of Environment, Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1977.

Kemp, Michael A. Reduced Fare and Fare-Free Urban Transit Services -- Some Case Studies. Report UI 1212-3. The Urban Institute, Washington, D.C., July 1974.

Kemp, Michael A. Transit Improvements in Atlanta -- The Effects of Fare and Service Changes. Report UI 1212-2-1. The Urban Institute, Washington, D.C., March 1974.

Kemp, Michael A. "Some Evidence of Transit Demand Elasticities." Transportation, Vol. 2, 1973.

Koppelman, Frank. "Prediction with Disaggregate Models: The Aggregation Issue." Transportation Research Record 527. Transportation Research Board, Washington, D.C., 1975.

Kraft, Gerald. "Free Transit Revisited." Public Policy 21, 1973.

Kraft, Gerald, and Thomas A. Domencich. "Free Transit." in M. Edel and J. Rothenberg (eds.), Readings in Urban Economics. MacMillan, New York, 1972.

Kraft, Gerald, and Thomas A. Domencich. Free Transit. D.C. Heath and Co., Lexington, Massachusetts, 1970.

Kuh, E. "The Validity of Cross-Sectional Estimated Behavior Equations in Time Series Application." Econometrica, Vol. 27, No. 2, April 1959.

Kuh, E., and J.R. Meyer. "How Extraneous are Extraneous Estimates?" Review of Economics and Statistics, November 1957.

Lansing, J.B., and G. Hendricks. "How People Perceive the Cost of the Journey to Work." Highway Research Record 197. Highway Research Board, Washington, D.C., 1967.

Lassow, William. "Effect of the Fare Increase of July 1966 on the Number of Passengers Carried on the New York City Transit System." Highway Research Record 213. Highway Research Board, Washington, D.C., 1968.

Lave, Charles A. "The Demand for Urban Mass Transportation." The Review of Economics and Statistics, 1973.

Lave, Charles A. "A Behavioral Approach to Modal Split Forecasting." Transportation Research, Vol. 3, No. 4, 1969.

Lave, Charles A. "Modal Choice in Urban Transportation: A Behavior Approach." Ph.D. Dissertation. Stanford University, Palo Alto, California, 1968.

Lee, Yuk, and Vasant H. Surti. Effect of Fare Reduction on Transit Patronage. Prepared for the Urban Mass Transportation Administration, U.S. Department of Transportation. Center for Urban Transportation Studies, University of Colorado, Denver, 1972.

Lewis, David L. "Public Policy and Road Traffic Levels: A Rejoinder." Journal of Transport Economics and Policy, Vol. 12, No. 1, January 1978.

Lewis, David L. "Estimating the Influence of Public Policy on Road Traffic Levels in Greater London." Journal of Transport Economics and Policy, Vol. 11, No. 2, May 1977.

Lion, P.M., and Richard M. Oberman. "Analysis of Transit Operations: Fare/Frequency Tradeoffs." Presented at the International Federation of Automatic Control International Symposium: Control in Transportation Systems, Columbus, Ohio, August 1976.

Lisco, T.E. "The Value of Commuters' Travel Time: A Study of Urban Transportation." Ph.D. Dissertation. University of Chicago, Chicago, 1967.

Litt, R.M. A Cross-Sectional Study of the Demand for Urban Transit in Canada. Department of Economics, University of Western Ontario, London, Ontario, 1975.

London Transport Executive. 5 Year Plan. Business Policy Office, London Transport Executive, London, April 1979.

London Transport Executive. London Transport's Corporate Aim. Business Policy Note BN2. Business Policy Office, London Transport Executive, London, November 1976.

London Transport Executive. London Transport's Corporate Aim Explained. Business Policy Office, London Transport Executive, London, 1975.

Maloney, J.F., and Associates. Mass Transportation in Massachusetts. Commonwealth of Massachusetts Mass Transportation Commission, Boston, 1964.

Mayworm, Patrick, Kenneth P. Ceglowski, and Armando M. Lago. Recommendations for Transit Fare Prepayment Demonstrations. Research Report No. RR-125-2. Prepared for the Office of Service and Methods Demonstrations, Urban Mass Transportation Administration, U.S. Department of Transportation. Ecosometrics, Inc., Bethesda, Maryland, February 20, 1978.

Mayworm, Patrick and Armando M. Lago. Demonstration Plan for the Variable Work Hours/Employee Pass Demonstration: Duluth, Minnesota. Research Report No. RR-125-4. Prepared for the Office of Service and Methods Demonstrations, Urban Mass Transportation Administration, U.S. Department of Transportation. Ecosometrics, Inc., Bethesda, Maryland, December 7, 1979.

McDonough, Carol C. "The Demand for Commuter Rail Transport." Journal of Transport Economics and Policy, Vol. 7, No. 2, May 1973.

McFadden, Daniel. "The Measurement of Urban Travel Demand." Journal of Public Economics 3, 1974.

McFadden, Daniel, and Fred Reid. "Aggregate Travel Demand Forecasting from Disaggregated Behavioral Models." Transportation Research Record 534. Transportation Research Board, Washington, D.C., 1975.

McGillivray, Robert G. "Binary Choice of Transport Mode in the San Francisco Bay Area." Ph.D. Dissertation. University of California, Berkeley, 1969.

McGillivray, Robert G. "Demand and Choice Model of Modal Split." Journal of Transport Economics and Policy, Vol. 1, No. 3, September 1967.

McLynn, J. M., and Keith M. Goodman. Mode Choice and the Shirley Highway Experiment. Prepared for the Urban Mass Transportation Administration, U.S. Department of Transportation. National Bureau of Standards, Washington, D.C., November 1973.

McQueen, James T., R.F. Yates, and G.K. Miller. The Shirley Highway Express-Bus-on-Freeway Demonstration Project -- Second Year Results. Prepared for the Urban Mass Transportation Administration, U.S. Department of Transportation. National Bureau of Standards, Washington, D.C., November 1973.

Metropolitan Dade County. U.S. 1/South Dixie Highway Transportation Demonstration Project. Prepared for the Florida Department of Transportation, November 24, 1975.

Metropolitan Transit Commission (MTC). Convenience Fares. Appendices. Citations of ATE Management and Service Company, Inc. data. MTC, Minneapolis, April 1976.

Meyer, J. "Theory and Practice of Urban Traffic Planning." Proceedings of the 37th Congress of the International Public Transport Union (UITP), Vol. 8, UITP, Brussels, 1967.

Ministry of Transport. Transport in London. Cmnd 3686. London Transport Review Board, London, July 1968.

Mohring, Herbert. "Optimization and Scale Economies in Urban Bus Transportation." The American Economic Review 62, No. 4, September 1972.

Mullen, Paul. "Estimating the Demand for Urban Bus Travel." Transportation, Vol. 4, No. 3, September 1975.

Multisystems, Inc. and Transportation Systems Center. Transit Service Reliability. Transportation Systems Center, Cambridge, December 1978.

Mundle, Subhash R., Wayne E. Weidemann, and Susan R. Roesch. "Transit Price Elasticities in St. Louis." Paper included in the Compendium of Technical Papers for the Institute for Transportation Engineers 48th Annual Meeting, 1978.

Nagin, Daniel, and Ellyn Eder. "Albany Free-Fare Zone Demonstration." Memorandum. Cambridge Systematics, Inc., Cambridge, June 29, 1979.

Nash, C.A. "Management Objectives, Fares and Service Levels in Bus Transport." Journal of Transport Economics and Policy, Vol. 12, No. 1, January 1978.

National Bus Company. Reduced Fares Experiments. NBC Research Report No. 13. National Bus Company, Peterborough, United Kingdom, March 1977.

Nelson, Gary R. An Econometric Model of Urban Bus Transit Operations. Paper P-863. Institute for Defense Analyses, Arlington, Virginia, 1972.

Nerlove, M., and S.J. Press. "Multivariate Log-Linear Probability Models for the Analysis of Qualitative Data." Discussion Paper No. 1. Center for Statistics and Probability, Northwestern University, Evanston, Illinois, June 1976.

Oi, Walter Y., and P.W. Shuldiner. An Analysis of Urban Travel Demands. Northwestern University Press, Evanston, Illinois, 1962.

Oldfield, R.H. Effect of Car Ownership on Bus Patronage. TRRL Laboratory Report 872. Department of the Environment, Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1979.

Oldfield, R.H. Elasticities of Demand for Travel. TRRL Supplementary Report 116 UC. Department of the Environment, Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1974.

Oum, Tae Hoon. "A Warning on the Use of Linear Logit Models in Transport Mode Choice Studies." The Bell Journal of Economics, Vol. 19, No. 1, Spring 1979.

Paine, F.T., A.N. Nash, S.J. Hille, and G.A. Brunner. Consumer Conceived Attributes of Transportation: An Attitude Study. University of Maryland, College Park, Maryland, 1967.

Parody, Thomas E., and Daniel Brand. "Forecasting Demand and Revenue for Transit Prepaid Pass and Fare Alternatives." Paper presented at the 58th Annual Meeting of the Transportation Research Board, Washington, D.C., January 1979.

Passenger Transport. "Free Day Scores with Tulsa Riders." Passenger Transport, Vol. 34, No. 47. American Public Transit Association, Washington, D.C., November 23, 1979.

Peat, Marwick, Mitchell and Company. Implementation of the N-Dimensional Logit Model. Final Report. Prepared for the Comprehensive Planning Organization, San Diego County, California. Peat, Marwick, Mitchell and Company, Washington, D.C., May 1972.

Pignataro, Louis J. "Summary of Results from HHFA/HUD Mass Transit Demonstration Studies." Urban Mass Transit Planning. Edited by Wolfgang S. Homburger. Institute of Transportation and Traffic Engineers, University of California, Berkeley, 1967.

Pisarkiewicz, John Jr. "Demand and Demonstration Projects." Unpublished paper. Office of Economics, U.S. Department of Transportation, Washington, D.C., Summer 1968.

Pitts, Robert Loy. "The Demand for Bus Transportation in Houston -- An Analysis of Price and Service Sensitivity." American Economist, Spring 1977.

Pratt, R.H., and Associates, Inc. and DTM, Inc. Development and Calibration of Mode Choice Models for the Twin Cities Area. Prepared for the Metropolitan Coun-Council, Minneapolis/St. Paul, Minnesota, November 1976.

Pratt, R.H., Neil J. Pedersen, and Joseph J. Mather. Traveler Response to Transportation System Changes -- A Handbook for Transportation Planners. Prepared for the Federal Highway Administration, U.S. Department of Transportation. R.H. Pratt Associates, Inc., Kensington, Maryland, February 1977.

Pucher, John, and Jerome Rothenberg. Pricing in Urban Transportation: A Survey of Empirical Evidence on the Elasticity of Traved Demand. Prepared for the Office of University Research, U.S. Department of Transportration. Center for Transportation Studies, Massachusetts Institute of Technology, Cambridge, April 1976.

Quandt, R.E. "Estimation of Modal Splits." Transportation Research, Vol. 2, 1968.

Quandt, R.E., and W.J. Baumol. "The Demand for Abstract Transport Modes: Theory and Measurement." Journal of Regional Science, Vol. 6, 1966.

Quarmby, David A. "Effect of Alternative Fares Systems on Operational Efficiency: British Experience." Symposium on Public Transport Fare Structure: Papers and Discussion. TRRL Supplementary Report 37UC. Department of Environment, Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1974.

Quarmby, David A. "Travel Mode for Journey to Work." Journal of Transport Economics and Policy, Vol. 1, No. 3, September 1967.

Quarmby, David A., and N.V. Cohen. "The Decision to Retain Crew Operation in Central London." Paper presented at the 5th Seminar on Operational Research in the Bus Industry, University of Leeds, July 1973.

Rainville, W.S. Transit Riding, Revenues and Fare Structures: Basic Approach and Computations. Statistical Laboratory, Division of Industrial Cooperation of the Massachusetts Institute of Technology. American Transit Association, Washington, D.C., 1948.

Rechel, Ralph E., and Lee H. Rogers. Review and Analysis of Reports of Mass Transportation Demonstration Projects Supported by the Urban Transportation Administration, Department of Housing and Urban Development. Institute of Public Administration, Washington, D.C., October 15, 1967.

Rendle, G., and C.P. Cummings. "Bus Passengers' Walking and Waiting Times." Technical Note TN117. Economic Research, London Transport Executive, London, December 1976.

Rendle, G., T. Mack, and M. Fairhurst. Bus and Underground Travel in London: An Analysis of the Years 1966-1976. Economic Research Report R235. London Transport Executive, London, March 1978.

Richards, M.G., and Moshe Ben-Akiva. "A Simultaneous Destination and Modal Choice Model for Shopping Trips." Transportation 3, 1974.

Safavi, H.A., and R.B. Stannard. Rail Commuting to Central London. Research Memorandum 225. Department of Planning and Transportation, Greater London Council, London, February 1970.

Wabe, J.S. "Commuter Travel into Central London." Journal of Transport Economics and Policy, Vol. 3, No. 1, January 1969.

Wabe, J. Stuart, and Oliver B. Coles. "The Peak and Off-Peak Demand for Bus Transport: A Cross-Sectional Analysis of British Municipal Operators." Applied Economics 7, 1975.

Warner, S. L. Stochastic Choice of Mode in Urban Travel: A Study in Binary Choice Northwestern University Press, Evanston, Illinois, 1962.

Wattleworth, Joseph A., Kenneth G. Courage, and Charles E. Wallace. Report II-2, Evaluation of the Effects of the I-95 Exclusive Bus/Carpool Lane Priority System on Vehicular and Passenger Movement. Prepared for the Florida Department of Transportation. Transportation Research Center, University of Florida, Gainesville, Florida, September 1978.

Webster, F.V. "Some Implications of the Results of Elasticity Determinations." Factors Affecting Public Transport Patronage. TRRL Supplementary Report 413. Department of the Environment, Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1977.

Webster, F.V. Urban Passenger Transport: Some Trends and Prospects. TRRL Laboratory Report 771. Department of the Environment, Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1977.

Webster, F.V. Fare Structure for Bus Stage Services. TRRL Report LR 704. Department of the Environment, Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1976.

Webster, F.V., and P.H. Bly. "Passenger Response to Changes in Fares and Service Levels." Proceedings of the Conference on Public Transport and People. Institut de Recherche des Transports, Paris, April 1975.

Weiss, David L., and David T. Hartgen. Revenue, Ridership, and Equity of Differential Time-of-Day Fares. Preliminary Research Report 99. Planning Research Unit, New York State Department of Transportation, Albany, April 1976.

Wheeler, Porter K. "Price and Service Sensitivity in Urban Passenger Transportation." Ph.D. Dissertation. Department of Economics, Harvard University, Cambridge, 1968.

White, P.R. "Relationships Between Patronage and Main Determinants of Travel." Factors Affecting Public Transport Patronage. TRRL Supplementary Report 413. Department of the Environment, Transport and Road Research Laboratory, Crowthorne, United Kingdom, 1977.

Wilbur Smith and Associates. Chesapeake Mass Transportation Demonstration Project. Final Report. Prepared for City of Chesapeake, Virginia. Wilbur Smith and Associates, New Haven, Connecticut, January 1969.

Zupan, J.M., and B. Pushkarev. "Future Ridership on New York City's Rapid Transit System (Abridgment)." Transportation Research Record 662. Transportation Research Board, Washington, D.C., 1978.

APPENDICES

There are three appendices to this report. The first two contain all the fare and service elasticities used in the text. Specifically, Appendix A contains the fare elasticity information referred to in Chapter 3; the service elasticities from Chapter 4 are presented in Appendix B. Appendix C contains the demand elasticity calculations and conversions made by Ecosometrics, Inc.

The individual tables in Appendices A and B follow directly from the text — each table referring to a disaggregate fare category or service attribute. The six columns have been arranged to provide as much information as possible concerning each demand elasticity value. The first column provides the principal division for each table. Transit mode, time period, and service level are the principal classifications used. In the second column, the city, route description, year of fare change or data collection period, and other site information are presented. Columns three and four indicate the fare or service levels before and after the actual change. For non-experimental data, only one column is provided to present the mean fare or service levels used in the calibration of the models; unfortunately, very often this information is not readily available. The fifth column includes the demand elasticities. In the last column, the information source and a brief description of the elasticity measure or type of model used in its calibration are presented. The bracketed numbers refer to the calculations or conversions made by Ecosometrics, Inc. and are presented in numerical order in Appendix C. A full citation for each source can be found in the References. Following each table, a set of observations and summary statistics are presented.

APPENDIX A

FARE ELASTICITIES

Table A-1

AGGREGATE FARE ELASTICITIES FROM QUASI-EXPERIMENTAL DATA

Mode and Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
BUS					
Peak	Stevenage, England (1971-72) system-wide bus	6 p.	4 p.	-0.27	Smith, et al., (1973) midpoint
	London, England (1969) system-wide bus	N.A.	N.A.	-0.27	Collins, et al., (1972) in Bly (1976)
	St. Louis, MO (1973) system-wide bus	45	25	-0.15	Ecosometrics, Inc. [1] from Holland (1974) midpoint
	Baltimore, MD (1976) system-wide bus	30[a]	40[a]	-0.09	ATE (1976) in Habib, et al., (1978)
	Richmond, VA (1976) system-wide bus	35[a]	40[a]	-0.08	ATE (1976) in Habib, et al., (1978)
	Birmingham, AL (1975) system-wide bus	N.A.	N.A.	-0.05	ATE (1976) in Habib, et al., (1978)
Off-Peak	Stevenage, England (1971-72) system-wide bus	6 p.	4 p.	-0.87	Smith, et al., (1973) midpoint
	Boston, MA (1963-1964) northern suburbs	96	63	-0.65	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
	St. Louis, MO (1973) system-wide bus	45	25	-0.39	Ecosometrics, Inc. [1] from Holland (1974) midpoint
	Madison, WI (1973) one week fare free, system-wide bus	25	0	-0.32	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Denver, CO (1978-1979) system-wide bus	25	0	-0.29	Ecosometrics, Inc. [4] from DeLeuw (1974) midpoint
	Richmond, VA (1976) shopping trips, system-wide bus	35[a]	40[a]	-0.25	ATE (1976) in Habib, et al., (1978)
	Baltimore, MD (1976) shopping trips, system-wide bus	30[a]	35[a]	-0.20	ATE (1976) in Habib, et al., (1978)
	Trenton, NJ (1978) system-wide bus	15	0	-0.19	Ecosometrics, Inc. [5] from Connor (1979) midpoint

[a] Assumed fare change occuring during year of study.

Table A-1

AGGREGATE FARE ELASTICITIES FROM QUASI-EXPERIMENTAL DATA
(continued)

Mode and Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
BUS Off-Peak (continued)	Birmingham, AL (1975) shopping trips, system-wide bus	N.A.	N.A.	-0.15	ATE (1976) in Habib, et al., (1978)
All Hours	Stevenage, England (1971-72) system-wide bus	6 p	4 p.	-0.64	Smith, et al., (1973) midpoint
	Atlanta, GA (1970-1973) system-wide bus (+)[a]	35	40	-0.60	Kemp (1974) least-squares regression of time-series data
	San Diego, CA (1972-1975) system-wide bus (-)[a]	40	25	-0.51	Goodman, et al., (1977) least-squares regression of time-series data
	Richmond, VA (1973) system-wide bus (-)[a]	35	30	-0.50	Ecosometrics, Inc. [6] from MTC (1976) midpoint
	York, PA (1948) system-wide bus (+)[a]	8	10	-0.50	Ecosometrics, Inc. [7] from Van Tassel (1956) midpoint
	New York, NY (1953) system-wide bus	10	15	-0.44	Ecosometrics, Inc. [8] from Kemp (1973) arc
	San Diego, CA (1972-1973) system-wide bus (-)[a]	40	25	-0.43	Kemp (1974) least-squares regression of time-series data
	Seattle, WA (1973) system-wide bus (-)[a]	25	20	-0.43	Ecosometrics, Inc. [6] from MTC (1976) midpoint
	Cleveland, OH (1973) system-wide bus (+)[a]	45	50	-0.39	Ecosometrics, Inc. [6] from MTC (1976) midpoint
	Jacksonville, FL (1970) system-wide bus (+)[a]	25	33	-0.39	Ecosometrics, Inc. [9] from Parody, et al., (1979) midpoint
	Cincinnati, OH (1973) system-wide bus (-)[a]	55	25	-0.38	Kemp (1974) least-squares regression of time-series data

Table A-1

AGGREGATE FARE ELASTICITIES FROM QUASI-EXPERIMENTAL DATA
(continued)

Mode and Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
BUS					
All Hours (continued)	Kent, OH (1967) campus bus system (-)[a]	5	0	-0.38	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	New York, NY (1974) system-wide bus	35	50	-0.38	Pucher, et al., (1976) midpoint
	New York, NY (1966) system-wide bus	15	20	-0.37	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	New York, NY (1977) system-wide bus	50	65	-0.36	Pucher, et al., (1976) midpoint
	New York, NY (1954) omnibus	10	13	-0.36	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	Springfield, MA (1949) system-wide bus (+)[a]	9	11	-0.34	Ecosometrics, Inc. [7] from Van Vassel (1956) midpoint
	Portland, OR (1958) system-wide bus (+)[a]	20	25	-0.33	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	Hartford, CN (1958) system-wide bus (+)[a]	15	20	-0.33	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	Atlanta, GA (1963) system-wide bus (+)[a]	20	25	-0.33	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	St. Louis, MO (1973) system-wide bus (-)[a]	45	25	-0.31	Ecosometrics, Inc. [12] from Mundle, et al., (1978) midpoint
	New Orleans, LA (1975) system-wide bus	N.A.	N.A.	-0.30	Habib, et al., (1978)
	Cincinnati, OH (1957) system-wide bus (+)[a]	20	25	-0.28	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	Peoria, IL (1976) system-wide bus	N.A.	N.A.	-0.25	Habib, et al., (1978)

Table A-1

AGGREGATE FARE ELASTICITIES FROM QUASI-EXPERIMENTAL DATA (continued)

Mode and Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
BUS					
All Hours (continued)	San Francisco, CA (1952) system-wide bus (+)[a]	10	15	-0.24	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	St. Louis, MO (1973) system-wide bus (-)[a]	45	25	-0.24	Ecosometrics, Inc. [1] from Holland (1974) midpoint
	Boston, MA (1955) system-wide bus (+)[a]	13	15	-0.21	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	Paris, France	N.A.	N.A.	-0.20	ECMT (1971) in Bly (1976)
	Atlanta, GA (1970-1973) system-wide bus (-)[a]	40	15	-0.18	Kemp (1974) least-squares regression of time-series data
	New York, NY (1970) system-wide bus	20	30	-0.18	Pucher, *et al.*, (1976) midpoint
	New York, NY (1948) system-wide bus	5	7	-0.16	Pucher, *et al.*, (1976) midpoint
	Salt Lake City, UT (1963) system-wide bus	20	25	-0.14	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	Birmingham, AL (1975) system-wide bus	N.A.	N.A.	-0.12	ATE (1976) in Habib, *et al.*, (1978)
	Baltimore, MD (1958) system-wide bus	20	25	-0.09	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
RAPID RAIL					
Peak	New York, NY (1966) system-wide rapid rail	15	20	-0.04	Ecosometrics, Inc. [10] from Lassow (1968) midpoint

Table A-1

AGGREGATE FARE ELASTICITIES FROM QUASI-EXPERIMENTAL DATA (continued)

Mode and Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
RAPID RAIL Off-Peak	New York, NY (1966) system-wide rapid rail	15	20	-0.11	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
All Hours	New York, NY (1953) system-wide rapid rail	10	15	-0.21	Ecosometrics, Inc. [8] from Kemp (1973) arc
	Boston, MA (1955) system-wide rapid rail (+)[a]	19	20	-0.20	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	New York, NY (1977) system-wide rapid rail	50	65	-0.18	Pucher, *et al.*, (1976) midpoint
	New York, NY (1970) system-wide rapid rail	20	30	-0.17	Pucher, *et al.*, (1976) midpoint
	New York, NY (1974) system-wide rapid rail	35	50	-0.15	Pucher, *et al.*, (1976) midpoint
	New York, NY (1948) system-wide rapid rail	5	7	-0.15	Ecosometrics, Inc. [8] from Kemp (1973) arc
	Paris, France	N.A.	N.A.	-0.12	ECMT (1971) in Bly (1976)
	New York, NY (1966) system-wide rapid rail	15	20	-0.09	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
COMMUTER RAIL Off-Peak	Boston, MA (1963-1964) northern suburbs	96	63	-0.31	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
COMBINED MODES All Hours	London, England (1975) system-wide bus and rapid rail, fare increase	N.A.	N.A.	-0.35	London Transport (unpublished) in Bly (1976)

Table A-1

AGGREGATE FARE ELASTICITIES FROM QUASI-EXPERIMENTAL DATA
(continued)

Mode and Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
COMBINED MODES					
All Hours (continued)	Chicago, IL (1957) system-wide bus and rapid rail (+)[a]	20	25	-0.33	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	New York, NY (1953) system-wide bus and rapid rail	10	15	-0.26	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	Chicago, IL (1970) system-wide bus and rapid rail (+)[a]	40	45	-0.26	Ecosometrics, Inc. [6] from MTC (1976) midpoint
	New York, NY (1966) system-wide bus and rapid rail	15	20	-0.19	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	Philadelphia, PA (1954) system-wide bus and rapid rail	15	18	-0.17	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	New York, NY (1972) system-wide bus and rapid rail	30	35	-0.07	Ecosometrics, Inc. [6] from MTC (1976) midpoint

[a] The analysis of fare increases and decreases presented in the text is based on these 23 fare changes. The cases used for fare increases are identified by the symbol +; for fare decreases by the symbol -.

Fare Increases: -0.34 ± 0.11 (14 cases)
Fare Decreases: -0.37 ± 0.11 (9 cases)

OBSERVATIONS

- Mean fare elasticity from quasi-experimental data is -0.28 ± 0.16 (67 cases).
- Mean peak fare elasticity value is less than half the mean off-peak value.
- Bus ridership is twice as elastic as rapid-rail ridership.
- Aggregate fare elasticities are only slightly correlated with the original fare level ($r = +0.31$ for 55 cases).
- Aggregate fare elasticities are not correlated with the change in the fare level ($r = +0.18$ for 55 cases).
- Aggregate all-hour fare elasticities are larger for small cities than for large metropolitan areas. The mean all-hour fare elasticities for U.S. cities were:

Cities With Central City Populations[a]	
greater than 1 million:	-0.24 ± 0.10 (19 cases)
500,000 to 1 million:	-0.30 ± 0.12 (11 cases)
less than 500,000:	-0.35 ± 0.12 (14 cases)
All Cities:	-0.29 ± 0.12 (44 cases)

[a]Large central cities included New York, Chicago, and Philadelphia. Medium central cities included San Diego, Seattle, Cleveland, New Orleans, St. Louis, San Francisco, Boston, and Baltimore. Small central cities included Atlanta, Richmond, York, Jacksonville, Cincinnati, Kent, Springfield, Portland, Hartford, Peoria, and Salt Lake City.

Table A-1

AGGREGATE FARE ELASTICITY
SUMMARY STATISTICS
FROM QUASI-EXPERIMENTAL DATA

	PUBLIC TRANSIT MODE				
TIME PERIOD	Bus	Rapid Rail	Commuter Rail	Combined Rail	Aggregate Values
PEAK	-0.15 ± 0.09 (6 cases)	-0.04 (1 case)	N.A.	N.A.	-0.14 ± 0.09 (7 cases)
OFF-PEAK	-0.37 ± 0.23 (9 cases)	-0.11 (1 case)	-0.31 (1 case)	N.A.	-0.34 ± 0.22 (11 cases)
ALL HOURS	-0.33 ± 0.13 (34 cases)	-0.16 ± 0.04 (8 cases)	N.A.	-0.23 ± 0.09 (7 cases)	-0.29 ± 0.13 (49 cases)
AGGREGATE VALUES	-0.32 ± 0.16 (49 cases)	-0.14 ± 0.05 (10 cases)	-0.31 (1 case)	-0.23 ± 0.09 (7 cases)	-0.28 ± 0.16 (67 cases)

Table A-2

AGGREGATE FARE ELASTICITIES FROM
NON-EXPERIMENTAL TIME-SERIES DATA

Mode and Time Period	City and Route Description	Mean Fare Level (cents)	Elasticity	Source and Elasticity Measure
BUS Peak	London, England (1966-1976) system-wide bus	N.A.	-0.27	Rendle, et al., (1978) least-squares regression of time-series data
Off-Peak	London, England (1966-1976) system-wide bus	N.A.	-0.37	Rendle, et al., (1978) least-squares regression of time-series data
All Hours	Binghamton, NY (1964-1973) system-wide bus	30	-1.15	Hartgen, et al., (1976) least-squares regression of time-series data
	London, England (1970-1973) system-wide bus	N.A.	-0.60	Fairhurst, et al., (1975) in Glaister et al.,(1978) least-squares regression of time-series data
	Westchester Co.,NY (1964-1973) system-wide bus	40	-0.57	Hartgen, et al., (1976) least-squares regression of time-series data
	Nassau Co.,NY (1964-1973) system-wide bus	36	-0.56	Hartgen, et al., (1976) least-squares regression of time-series data
	Syracuse, NY (1964-1973) system-wide bus	25	-0.56	Hartgen, et al., (1976) least-squares regression of time-series data
	London, England (1970-1975) system-wide bus	N.A.	-0.56	Glaister (1976) in Glaister, et al., (1978) generalized least-squares regression of time-series data
	Rochester, NY (1964-1973) system-wide bus	30	-0.54	Hartgen, et al., (1976) least-squares regression of time-series data
	Albany, Schenectedy & Troy, NY (1964-1973) system-wide bus	30	-0.52	Hartgen, et al., (1976) least-sqaures regression of time-series data

Table A-2

AGGREGATE FARE ELASTICITIES FROM NON-EXPERIMENTAL TIME-SERIES DATA (continued)

Mode and Time Period	City and Route Description	Mean Fare Level (cents)	Elasticity	Source and Elasticity Measure
BUS All Hours (continued)	48 British transit operations (1970-1975) system-wide bus, mean elasticity value	N.A.	-0.41	Collings, et al., (1977) in Glaister, et al., (1978) least-squares regression of time-series data
	New York, NY (1954-1973) system-wide bus	N.A.	-0.37	Garbade, et al., (1976) in Frankena (1978) two-stage least-squares regression of time-series data
	London, England (1966-1976) system-wide bus	N.A.	-0.33	Rendle, et al, (1978) least-squares regression of time-series data
	12 British transit operations (1960-1973) system-wide bus, mean elasticity value	N.A.	-0.31	Mullen (1975) least-squares regression of times-series data
	New York, NY (1964-1973) NYCTA bus system	23	-0.26	Hartgen, et al., (1976) least-squares regression of time-series data
	New York, NY (1964-1973) NYC private bus system	27	-0.25	Hartgen, et al., (1976) least-squares regression of time-series data
	Buffalo, NY (1964-1973) system-wide bus	31	-0.25	Hartgen, et al., (1976) least-squares regression of time-series data
	New York, NY (1964-1973) MABSTOA bus system	23	-0.24	Hartgen, et al., (1976) least-squares regression of time-series data
	Edmonton, Canada (1961-1970) system-wide bus	N.A.	-0.22	Huang (1973) in Frankena (1978) least-squares regression of time-series data
RAPID RAIL Peak	London, England (1966-1976) system-wide rapid rail	N.A.	-0.10	Rendle, et al., (1978) least-squares regression of time-series data

Table A-2

AGGREGATE FARE ELASTICITIES FROM NON-EXPERIMENTAL TIME-SERIES DATA (continued)

Mode and Time Period	City and Route Description	Mean Fare Level (cents)	Elasticity	Source and Elasticity Measure
RAPID RAIL Off-Peak (continued)	London, England (1966-1976) system-wide rapid rail	N.A.	-0.25	Rendle, et al., (1978) least-squares regression of time-series data
All Hours	London, England (1970-1975) system-wide rapid rail	N.A.	-1.00	Glaister (1976) in Glaister, et al., (1978) generalized least-squares regression of time-series data
	London, England (1970-1973) system-wide rapid rail	N.A.	-0.40	Fairhurst, et al., (1975) in Glaister, et al., (1978) least-squares regression of time-series data
	New York, NY (1964-1973) system-wide rapid rail	23	-0.23	Hartgen, et al., (1976) least-squares regression of time-series data
	London, England (1966-1976) system-wide rapid rail	N.A.	-0.16	Rendle, et al., (1978) least-squares regression of time-series data
COMMUTER RAIL All Hours	New York, NY (1964-1973) system-wide commuter rail service	116	-0.70	Hartgen, et al., (1976) least-squares regression of time-series data
COMBINED MODES All Hours	New York, NY (1947-1971) system-wide bus and rapid rail	N.A.	-0.30	Sohn (1975) in Frankena (1978) least-squares regression of time-series data
	Montreal, Canada (1956-1971) adult riders, system-wide bus and rapid rail	N.A.	-0.15	Gaudry (1975) least-squares regression of time-series data with adjustment for serial correlation

Table A-2

OBSERVATIONS

- Mean fare elasticity from non-experimental time-series data is -0.42 ± 0.24 (28 cases) or 1.50 times the mean value estimated from quasi-experimental data.
- Mean peak-period fare elasticity is -0.19 ± 0.09 (2 cases) while the off-peak mean value is -0.31 ± 0.06 (2 cases).
- Contrary to the evidence from quasi-experimental data, the mean bus fare elasticity from time-series data is more than 20 percent larger than the mean rapid-rail fare elasticity.

Table A-2

AGGREGATE FARE ELASTICITY
SUMMARY STATISTICS
FROM NON-EXPERIMENTAL TIME-SERIES DATA

	PUBLIC TRANSIT MODE				
TIME PERIOD	Bus	Rapid Rail	Commuter Rail	Combined Rail	Aggregate Values
PEAK	-0.27 (1 case)	-0.10 (1 case)	N.A.	N.A.	-0.19 ± 0.09 (2 cases)
OFF-PEAK	-0.37 (1 case)	-0.25 (1 case)	N.A.	N.A.	-0.31 ± 0.06 (2 cases)
ALL HOURS	-0.45 ± 0.22 (17 cases)	-0.45 ± 0.33 (4 cases)	-0.70 (1 case)	-0.23 ± 0.08 (2 cases)	-0.44 ± 0.25 (24 cases)
AGGREGATE VALUES	-0.44 ± 0.21 (19 cases)	-0.36 ± 0.30 (6 cases)	-0.70 (1 case)	-0.23 ± 0.08 (2 cases)	-0.42 ± 0.24 (28 cases)

Table A-3

AGGREGATE FARE ELASTICITIES FROM
NON-EXPERIMENTAL CROSS-SECTIONAL DATA

Mode and Time Period	City and Route Description	Mean Fare Level (cents)	Elasticity	Source and Elasticity Measure
BUS				
Peak	San Francisco, CA (1965) choice trips only	N.A.	-0.87	McGillivray (1969) binary-choice model estimated from household cross-sectional data
	Chicago, IL (1956) choice bus work trips	N.A.	-0.70	Lave (1968) probit model estimated from household cross-sectional data
	San Diego, CA (1966) system-wide bus, work trips	46	-0.65	Peat (1972) n-dimensional logit model estimated from household cross-sectional data
	San Francisco, CA (1973) work trips with BART as a mode choice	N.A.	-0.58	McFadden (1974) 3-mode-choice logit model estimated from household cross-sectional data
	Minneapolis/St.Paul, MN (1970) system-wide bus, work trips	48	-0.55	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data
	Chicago, IL (1969) system-wide bus, work trips	N.A.	-0.51	Talvitie (1973) constrained least-squares regression of household cross-sectional data
	Louisville, KY (1974) system-wide bus, work trips	N.A.	-0.40	Fulkerson (1975) least-squares regression of household cross-sectional data
	London, England (1970-1975) system-wide bus	N.A.	-0.35	Glaister, et al., (1978) 3-mode-choice logit/utile model estimated from cross-sectional time-series data
	30 British cities (1966-1967) system-wide bus, work trips	N.A.	-0.19	Wabe, et al., (1975) least-squares regression of bus-trips cross-sectional data

AGGREGATE FARE ELASTICITIES FROM NON-EXPERIMENTAL CROSS-SECTIONAL DATA (continued)

Mode and Time Period	City and Route Description	Mean Fare Level (cents)	Elasticity	Source and Elasticity Measure
BUS Off-Peak (continued)	London, England (1970-1975) system-wide bus	N.A.	-0.87	Glaister, et al., (1978) 3-mode-choice logit/utile model estimated from cross-sectional time-series data
	30 British cities (1966-1967) system-wide bus, non-work trips	N.A.	-0.49	Wabe, et al., (1975) least-squares regression of bus-trips cross-sectional data
	Minneapolis/St.Paul, MN (1970) system-wide bus, non-work trips	46	-0.46	Pratt, et al., (1976) multinominal mode-choice logit model estimated from household cross-sectional data
All Hours	13 Iowa cities (1955-1966) system-wide bus	19	-0.91	Ecosometrics, Inc. [24] from Carstens, et al., (1978) least-squares regression of cross-sectional time-series data
	44 U.S. cities (1960) system-wide bus	N.A.	-0.81	Nelson (1972) two-stage least-squares regression of cross-sectional data
	51 U.S. cities (1968) system-wide bus	N.A.	-0.67	Nelson (1972) two-stage least-squares regression of cross-sectional data
	17 U.S. cities (1960-1970) system-wide bus	N.A.	-0.53	Boyd, et al., (1973) least-squares regression of transit operator cross-sectional time-series data
	28 Canadian cities (1962-74) system-wide bus	N.A.	-0.38	Frankena (1978) two-stage least-squares regression of cross-sectional time-series data
	London, England (1972-1977) system-wide bus	6 p.	-0.32	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data

Table A-3

AGGREGATE FARE ELASTICITIES FROM NON-EXPERIMENTAL CROSS-SECTIONAL DATA (continued)

Mode and Time Period	City and Route Description	Mean Fare Level (cents)	Elasticity	Source and Elasticity Measure
BUS				
All Hours (continued)	San Francisco, CA (1965) system-wide bus	N.A.	-0.11	McGillivray (1969) binary-choice model estimated from household cross-sectional data
RAPID RAIL				
Peak	Chicago, IL (1969) system-wide rapid rail, work trips	N.A.	-1.80	Talvitie (1973) constrained least-squares regression of household cross-sectional data
	Chicago, IL (1964) system-wide rapid rail, choice work trips	50	-0.40	Lisco (1967) 2-mode-choice probit model estimated from household cross-sectional data
	London, England (1970-1975) system-wide rapid rail	N.A.	-0.30	Glaister, et al., (1978) 3-mode-choice logit/utile model estimated from cross-sectional time-series data
Off-Peak	London, England (1970-1975) system-wide rapid rail	N.A.	-0.75	Glaister, et al., (1978) 3-mode-choice logit/utile model estimated from cross-sectional time-series data
All Hours	London, England (1972-1977) system-wide rapid rail	11 p.	-0.26	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data
COMMUTER RAIL				
Peak	San Francisco, CA (1973) BART system, work trips	N.A.	-0.86	McFadden (1974) 3-mode-choice logit model estimated from household cross-sectional data

Table A-3

AGGREGATE FARE ELASTICITIES FROM NON-EXPERIMENTAL CROSS-SECTIONAL DATA (continued)

Mode and Time Period	City and Route Description	Mean Fare Level (cents)	Elasticity	Source and Elasticity Measure
COMMUTER RAIL (continued) All Hours	London, England (1972-1977) system-wide rapid rail	15 p.	-0.13	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data
COMBINED MODES Peak	Chicago, IL (1956) system-wide bus and rapid rail, work trips	N.A.	-0.80	Warner (1962) in Kemp (1973) binary-choice discriminant-analysis model estimated from household cross-sectional data
	Chicago, IL (1969) system-wide bus and rapid rail, work trips	N.A.	-0.38	Talvitie (1973) constrained least-squares regression of household cross-sectional data
	Boston, MA (1963-1964) system-wide bus and rapid rail, work trips	45	-0.10	Domencich, et al., (1968) constrained least-squares regression of household cross-sectional data
Off-Peak	Boston, MA (1963-1964) system-wide bus and rapid rail, shopping trips	45	-0.32	Domencich, et al., (1968) constrained least-squares regression of household cross-sectional data
All Hours	39 Canadian cities (1971) system-wide bus and rapid rail	N.A.	-0.15	Litt (1975) in Frankena (1978) least-squares regression of transit operator cross-sectional data.

Table A-3

OBSERVATIONS

- Mean fare elasticity from non-experimental cross-sectional data is -0.53 ± 0.35 (28 cases) or 1.89 times the mean value estimated from quasi-experimental data.
- The mean peak and off-peak fare elasticities from cross-sectional data are essentially equivalent for 16 and 5 cases respectively.
- Mean fare elasticity for rapid-rail service is larger than the mean value for bus service which is contrary to empirical evidence.

Table A-3

AGGREGATE FARE ELASTICITIES
SUMMARY STATISTICS
FROM NON-EXPERIMENTAL CROSS-SECTIONAL DATA

	PUBLIC TRANSIT MODE				
TIME PERIOD	Bus	Rapid Rail	Commuter Rail	Combined Modes	Aggregate Values
PEAK	-0.53 ± 0.19 (9 cases)	-0.83 ± 0.68 (3 cases)	-0.86 (1 case)	-0.43 ± 0.29 (3 cases)	-0.59 ± 0.38 (16 cases)
OFF-PEAK	-0.61 ± 0.19 (3 cases)	-0.75 (1 case)	N.A.	-0.32 (1 case)	-0.58 ± 0.20 (5 cases)
ALL HOURS	-0.53 ± 0.26 (7 cases)	-0.26 (1 case)	-0.13 (1 case)	-0.15 (1 case)	-0.43 ± 0.28 (10 cases)
AGGREGATE VALUES	-0.54 ± 0.22 (19 cases)	-0.70 ± 0.58 (5 cases)	-0.50 ± 0.37 (2 cases)	-0.35 ± 0.25 (5 cases)	-0.53 ± 0.35 (28 cases)

Table A-4

FARE ELASTICITIES FROM FARE INCREASES AND DECREASES

Mode and Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
FARE INCREASE	Atlanta, GA (1970-1973) system-wide bus	35	40	-0.60	Kemp (1974) least-squares regression of time-series data
	Atlanta, GA (1963) system-wide bus	20	25	-0.33	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
FARE DECREASE	Atlanta, GA (1970-1973) system-wide bus	40	15	-0.18	Kemp (1974) least-squares regression of time-series data
FARE INCREASE	Madison, WI (1975) system-wide bus, weekends	10	25	-0.50	Ecosometrics, Inc. [14] from Hicks (1979) midpoint
FARE DECREASE	Madison, WI (1975) system-wide bus, weekends	25	10	-0.26	Ecosometrics, Inc. [14] from Hicks (1979) midpoint
FARE INCREASE	Cincinnati, OH (1957) system-wide bus	20	25	-0.28	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
FARE DECREASE	Cincinnati, OH (1973) system-wide bus	55	25	-0.38	Kemp (1974) least-squares regression of time-series data
FARE INCREASE	Chicago, IL (1957) system wide bus and rapid rail	20	25	-0.33	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
	Chicago, IL (1970) system-wide bus and rapid rail	40	45	-0.26	Ecosometrics, Inc. [6] from MTC (1976) midpoint
FARE DECREASE	Chicago, IL (1953) system-wide bus and rapid rail, four Tuesdays between 9:30 a.m. and 1:30 p.m.	20	10	-0.09	Ecosometrics, Inc. [15] from Schroeder (1954) in Kemp (1973) midpoint

Table A-4

FARE ELASTICITIES FROM FARE INCREASES AND DECREASES

OBSERVATIONS

- Demand elasticities from fare increases are larger than those observed for fare decreases in three of the four cities presented.
- The aggregate all-hour fare elasticities presented in Table A-1 show a mean value of -0.27 ± 0.12 (34 cases) for fare increases, while the mean for fare decreases is -0.40 ± 0.13 (10 cases). The fare increases, however, are heavily weighted by the very low New York City values. Thus, the mean fare elasticities for fare increases and decreases among cities of comparable size are -0.34 ± 0.11 (14 cases) and -0.37 ± 0.11 (9 cases) respectively (see Table A-1, page A-6).

Table A-5

FARE-FREE ELASTICITIES

Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
OFF-PEAK	Portland, OR (1975) midday, CBD only	10	0	-0.81	Ecosometrics, Inc. [16] from Colman (1979) midpoint
	Seattle, WA (1973) midday, CBD only	10	0	-0.52	Ecosometrics, Inc. [16] from Colman (1979) midpoint
	Albany, NY (1978) midday and Saturday, CBD only	40	0	-0.51	Ecosometrics, Inc. [17] from Nagin, et al., (1979) midpoint
	Minneapolis, MN (1972) midday and weekends, senior citizens only	30	0	-0.33	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Madison, WI (1973) all off-peak hours, one week only	25	0	-0.32	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Tulsa, OK (1979) one Saturday	35	0	-0.30	Ecosometrics, Inc. [18] from Passenger Transport (1979) midpoint
	Denver, CO (1978-1979) system-wide bus	25	0	-0.29	Ecosometrics, Inc. [4] from DeLeuw (1979) midpoint
	Trenton, NJ (1978) system-wide bus	15	0	-0.19	Ecosometrics, Inc. [5] from Connor (1979) midpoint
ALL HOURS	Portland, OR (1975) CBD only	10	0	-0.70	Ecosometrics, Inc. [16] from Colman (1979) midpoint
	Auburn, NY (1973) one month only	25	0	-0.63	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Seattle, WA (1973) CBD only	10	0	-0.46	Ecosometrics, Inc. [16] from Colman (1979) midpoint
	Knoxville, TN (1977) CBD only	40	0	-0.41	Ecosometrics, Inc. [19] from Damm (1979) midpoint

Table A-5

FARE-FREE ELASTICITIES
(continued)

Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
ALL-HOURS (continued)	Kent, OH (1967) students only	5	0	-0.38	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Rome, Italy (1972) nine days only	9	0	-0.08	Kemp (1974) arc

OBSERVATIONS

- Mean fare-free elasticity for all unduplicated cases is -0.38 ± 0.17 (12 cases).
- CBD ridership, especially during midday hours, is the most elastic group represented in Table A-5.

SUMMARY STATISTICS OF FARE-FREE BUS ELASTICITIES

	Time Period		
Service Restrictions	Off-Peak	All Hours	All Unduplicated Cases[a]
CBD Only	-0.61 ± 0.14 (3 cases)	-0.52 ± 0.13 (3 cases)	-0.52 ± 0.11 (4 cases)
Senior Citizen Only	-0.33 (1 case)	N.A.	-0.33 (1 case)
Student Only	N.A.	-0.38 (1 case)	-0.38 (1 case)
No Restriction	-0.28 ± 0.05 (4 cases)	-0.36 ± 0.28 (2 cases)	-0.30 ± 0.17 (6 cases)
All Unduplicated Cases[a]	-0.41 ± 0.18 (8 cases)	-0.44 ± 0.20 (6 cases)	-0.38 ± 0.17 (12 cases)

[a]This category was created because some elasticity estimates for all hours and off-peak periods correspond to the same demonstration. In these instances, the unduplicated cases represent the all hour fare elasticity estimate.

Table A-6

BUS, RAPID-RAIL, AND COMMUTER-RAIL FARE ELASTICITIES

Mode	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Bus	New York, NY (1977) all hours, system-wide	50	65	-0.36	Pucher, et al.,(1976) midpoint
Rapid Rail	New York, NY (1977) all hours, system-wide	50	65	-0.18	Pucher, et al.,(1976) midpoint
Bus	New York, NY (1974) all hours, system-wide	35	50	-0.38	Pucher, et al.,(1976) midpoint
Rapid Rail	New York, NY (1974) all hours, system-wide	35	50	-0.15	Pucher, et al.,(1976) midpoint
Bus	New York, NY (1970) all hours, system-wide	20	30	-0.18	Pucher, et al.,(1976) midpoint
Rapid Rail	New York, NY (1970) all hours, system-wide	20	30	-0.17	Pucher, et al.,(1976) midpoint
Bus	New York, NY (1966) all hours, system-wide	15	20	-0.37	Ecosometrics,Inc. [10] from Lassow (1968) midpoint
Rapid Rail	New York, NY (1966) all hours, system-wide	15	20	-0.09	Ecosometrics,Inc. [10] from Lassow (1968) midpoint
Bus	New York, NY (1953) all hours, system-wide	10	15	-0.44	Ecosometrics,Inc. [8] from Kemp (1973) arc
Rapid Rail	New York, NY (1953) all hours, system-wide	10	15	-0.21	Ecosometrics,Inc. [8] from Kemp (1973) arc
Bus	New York, NY (1948) all hours, system-wide	5	7	-0.16	Pucher, et al.,(1976) midpoint
Rapid Rail	New York, NY (1948) all hours, system-wide	5	7	-0.15	Ecosometrics,Inc. [8] from Kemp (1973) arc
Bus	London, England (1966-1976) all hours, system-wide	N.A.	N.A.	-0.33	Rendle, et al.,(1978) least-squares regression of time-series data
Rapid Rail	London, England (1966-1976) all hours, system-wide	N.A.	N.A.	-0.16	Rendle, et al.,(1978) least-squares regression of time-series data

Table A-6
BUS, RAPID-RAIL, AND COMMUTER-RAIL FARE ELASTICITIES
(continued)

Mode	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Bus	Paris, France (N.A.)	N.A.	N.A.	-0.20	ECMT (1971) in Bly (1976)
Rapid Rail	Paris, France (N.A.)	N.A.	N.A.	-0.12	ECMT (1971 in Bly (1976)
Bus	New York, NY (1964-1973) all hours, system-wide	N.A.	N.A.	-0.25	Hartgen, et al., (1976) least-squares regression of time-series data
Rapid Rail	New York, NY (1964-1973) all hours, system-wide	N.A.	N.A.	-0.23	Hartgen, et al., (1976) least-squares regression of time-series data
Commuter Rail	New York, NY (1964-1973) all hours, system-wide	N.A.	N.A.	-0.70	Hartgen, et al., (1976) least-squares regression of time-series data
Bus	San Francisco, CA (1973) a.m. & p.m. work trips with BART as a mode choice	N.A.	N.A.	-0.58	McFadden (1974) 3-mode-choice logit model estimated from household cross-sectional data
Commuter Rail	San Francisco, CA (1973) a.m. & p.m. work trips, BART system	N.A.	N.A.	-0.86	McFadden (1974) 3-mode-choice logit model estimated from household cross-sectional data
Bus	Boston, MA (1963-1964) off-peak hours, northern suburbs	96	63	-0.65	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
Commuter Rail	Boston, MA (1963-1964) off-peak hours, northern suburbs	96	63	-0.31	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
Bus	London, England (1972-1977) all hours, system-wide	N.A.	N.A.	-0.32	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model from household cross-sectional time-series data

Table A-6

BUS, RAPID-RAIL, AND COMMUTER-RAIL FARE ELASTICITIES
(continued)

Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Rapid Rail	London, England (1972-1977) all hours, system-wide	N.A.	N.A.	-0.26	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model from household cross-sectional time-series model
Commuter Rail	London, England (1972-1977) all hours, system-wide	N.A.	N.A.	-0.13	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model from household cross-sectional time-series model

OBSERVATIONS

- Mean bus fare elasticity of -0.35 ±0.14 (12 cases) is twice the mean value for rapid-rail service -0.17 ±0.05 (10 cases).
- In nine cases where bus and rapid-rail fare changes occurred simultaneously, the bus to rapid-rail fare elasticity ratio ranges from 1.07 to 4.11 with a mean value of 1.97 ±0.91.
- For six fare changes in New York City, the mean bus fare elasticity (-0.32 ±0.11) is twice the value obtained for rapid-rail service (-0.16 ±0.04).
- The only empirical evidence to compare bus and commuter-rail fare elasticities (Boston 1963-1964) is from an off-peak fare reduction and shows the bus fare elasticity to be twice as large as the commuter-rail elasticity.
- McFadden (1974) and Hartgen, et al., (1976) present fare elasticities for BART and New York City's commuter railroads respectively at much larger values than those obtained for bus service. With the exception of Rendle, et al., (1978), and Fairhurst, et al., (1977) these are the only non-experimental data sources presented in this table.

Table A-6

FARE ELASTICITY COMPARISON STATISTICS

New York, N.Y.	FARE ELASTICITIES		Bus/ Rapid Rail
	Bus	Rapid Rail	
1977	-0.36	-0.18	2.00
1974	-0.38	-0.15	2.53
1970	-0.18	-0.17	1.06
1966	-0.37	-0.09	4.11
1953	-0.44	-0.21	2.10
1948	-0.16	-0.15	1.07
Mean and Standard Deviation	-0.32 ±0.11 (6 cases)	-0.16 ±0.04 (6 cases)	2.15 ±1.03 (6 cases)

OTHER CITIES

City	FARE ELASTICITIES			Bus/ Rapid Rail	Bus/ Commuter Rail
	Bus	Rapid Rail	Commuter Rail		
London (1966-1976)	-0.33	-0.16	N.A.	2.06	N.A.
Paris (N.A.)	-0.20	-0.12	N.A.	1.67	N.A.
Boston (1963-1964)	-0.65	N.A.	-0.31	N.A.	2.10
New York (1964-1973)	-0.25	-0.23	-0.70	1.09	0.36
San Francisco (1973)	-0.58	N.A.	-0.86	N.A.	0.67
Mean and Standard Deviation	-0.40 ± 0.18 (5 cases)	-0.17 ± 0.05 (3 cases)	-0.62 ± 0.23 (3 cases)	1.61 ± 0.40 (3 cases)	1.04 ± 0.76 (3 cases)

Table A-6

FARE CROSS-ELASTICITIES AMONG TRAVEL MODES*

	Bus Demand	Rapid-Rail Demand	Auto Demand
BUS FARES			
Peak		+0.28[1], +0.14[5]	+0.12[1], +0.15[2], +0.03[5] +0.21[9], +0.15[10], +0.02[11] +0.05[12]
Off-Peak		+0.28[5]	+0.02[12]
All Hours		+0.25[6]	
RAPID-RAIL FARES			
Peak	+0.25[1], +0.14[5]		+0.13[1], +0.06[5], +0.06[8]
Off-Peak	+0.28[5]		
All Hours	+0.25[6], +0.30[7]		
AUTO COSTS			
Peak	+0.81[1], +0.97[2], +0.80[3], +0.36[3]	+0.82[1], +1.34[3]	

*The fare cross-elasticities refer to the same time period. For example, the off-peak bus to rapid-rail cross-elasticity of +0.28 refers only to the off-peak period.

Source: [1]McFadden (1974) 3-mode-choice-logit model estimated from household cross-sectional data.

[2]McFadden (1974) 2-mode-choice logit model estimated from household cross-sectional data.

[3]Talvitie (1973) constrained least-squares regression estimated from household cross-sectional data.

[4]Domencich, Kraft, and Valette (1968) constrained least-squares regression estimated from household cross-sectional data.

[5]Glaister and Lewis (1978) 3-mode-choice logit/utile model estimated from cross-sectional time-series data (1970-1975).

[6]Fairhurst and Morris (1975) in Glaister and Lewis (1978) least-squares regression estimated from weekly time-series data (1970-1973).

[7]Glaister (1976) in Glaister and Lewis (1978) least-squares regression estimated from weekly time-series data (1970-1075).

[8]Lewis (1978) in Glaister and Lewis (1978) least-squares regression from time-series data (1970-1975).

[9]Warner (1962) discriminant analysis of mode choice estimated from household cross-sectional data.

[10]Fulkerson (1975) least-squares regression estimated from household cross-sectional data.

[11]Peat, Marwick, Mitchell (1972) n-dimensional logit model estimated from household cross-sectional data.

[12]Pratt and DTM (1976) multinomial mode-choice logit model estimated from household cross-sectional data.

Table A-6

BUS AND AUTOMOBILE FARE CROSS-ELASTICITIES BY ROUTE ORIENTATION AND TRIP PURPOSE

	DEMAND FOR AUTOMOBILE		
Bus Fares	CBD Destinations	Non-CBD Destinations	All Destinations
Work Trips			
San Diego (1966)[a]	+0.03	+0.02	+0.02
Minneapolis/St.Paul (1970)[b]	+0.18	+0.03	+0.05
Non-Work Trips			
Minneapolis/St.Paul (1970)[b]	+0.10	+0.01	+0.02

	DEMAND FOR BUS		
Automobile Costs	CBD Destinations	Non-CBD Destinations	All Destinations
Work Trips			
Parking Costs			
San Diego (1966)[a]	+0.29	N.A.	+0.06
Minneapolis/St.Paul (1970)[b]	+0.51	+0.03	+0.33
Operating Costs			
Minneapolis/St.Paul (1970)[b]	+0.18	+0.26	+0.21
Non-Work Trips			
Parking Costs			
Minneapolis/St.Paul (1970)[b]	+0.38	+0.01	+0.18
Operating Costs			
Minneapolis/St.Paul (1970)[b]	+0.18	+0.12	+0.12

[a] Peat, Marwick, Mitchell (1972) n-dimensional logit model estimated from household cross-sectional data.

[b] Pratt and DTM (1976) multinomial mode-choice logit model estimated from household cross-sectional data.

Table A-7

LONG- AND SHORT-DISTANCE FARE ELASTICITIES

Trip Distance	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Short	London, England (N.A.) bus trips less than 1 mile in length	N.A.	N.A.	-0.55	Ministry of Transport (1968) in Oldfield (1974) "mathematical approach"
Medium	London, England (N.A.) bus trips 1-3 miles in length	N.A.	N.A.	-0.29	Ministry of Transport (1968) in Oldfield (1974) "mathematical approach"
Medium	London, England (N.A.) rapid-rail trips 1-3 miles in length	N.A.	N.A.	-0.25	Ministry of Transport (1968) in Oldfield (1974) "mathematical approach"
Long	London, England (N.A.) rapid-rail trips greater than 3 miles in length	N.A.	N.A.	-0.60	Ministry of Transport (1968) in Oldfield (1974) "mathematical approach"
Short	London, England (1975) all trips at minimum or base fare level	N.A.	N.A.	-0.50	London Transport (unpublished) in Bly (1976)
Medium	London, England (1975) system-wide trips at all fare levels	N.A.	N.A.	-0.35	London Transport (unpublished) in Bly (1976)
Short	Essen, Germany short-distrance trips	N.A.	N.A.	-0.32	Meyer (1967) in Bly (1976)
Long	Essen, Germany long-distance trips	N.A.	N.A.	-0.12	Meyer (1967) in Bly (1976)

OBSERVATIONS

- Fare elasticities for very short-distance bus trips are generally larger than the values observed for medium- and long-distance trips. There is no evidence to suggest the same relationship holds true for rapid-rail service.
- Fare elasticities for long-distance rapid-rail trips, however, are larger than the fare elasticities observed for short- and medium-distance trips in one case.

Table A-8

FARE ELASTICITIES BY ROUTE TYPE

Route Type	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Radial Arterial	London, England (1972-1977) bus trips	N.A.	N.A.	-0.09	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data
Intra-Suburban	London, England (1972-1977) bus trips	N.A.	N.A.	-0.38	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data
System-Wide	London, England (1972-1977) bus trips	N.A.	N.A.	-0.32	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data
Radial Arterial	London, England (1972-1977) rapid-rail trips	N.A.	N.A.	-0.11	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data
Intra-Suburban	London, England (1972-1977) rapid-rail trips	N.A.	N.A.	-0.28	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data
System-Wide	London, England (1972-1977) rapid-rail trips	N.A.	N.A.	-0.26	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data

Table A-8

FARE ELASTICITIES BY ROUTE TYPE
(continued)

Route Type	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Radial Arterial	London, England (1972-1977) commuter-rail trips	N.A.	N.A.	-0.06	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data
Intra-Suburban	London, England (1972-1977) commuter-rail trips	N.A.	N.A.	-0.26	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data
System-Wide	London, England (1972-1977) commuter-rail trips	N.A.	N.A.	-0.13	Ecosometrics, Inc. [13] from Fairhurst, et al., (1977) Scenario Model estimated from household cross-sectional time-series data
CBD-Oriented	Minneapolis/St. Paul, MN (1970) system-wide bus, work trips	48	N.A.	-0.45	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data
Non-CBD-Oriented	Minneapolis/St. Paul, MN (1970) system-wide bus, work trips	48	N.A.	-0.63	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data
System-Wide	Minneapolis/St. Paul, MN (1970) system-wide bus, work trips	48	N.A.	-0.55	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data

Table A-8

FARE ELASTICITIES BY ROUTE TYPE
(continued)

Route Type	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
CBD-Oriented	Minneapolis/St. Paul, MN (1970) system-wide bus, non-work trips	46	N.A.	-0.40	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data
Non-CBD-Oriented	Minneapolis/St. Paul, MN (1970) system-wide bus, non-work trips	46	N.A.	-0.51	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data
System-Wide	Minneapolis/St. Paul, MN (1970) system-wide bus, non-work trips	46	N.A.	-0.46	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data
CBD-Oriented	San Diego, CA (1966) system-wide bus, work trips	44	N.A.	-0.34	Peat (1972) n-dimensional logit model estimated from household cross-sectional data
Non-CBD-Oriented	San Diego, CA (1966) system-wide bus, work trips	47	N.A.	-0.73	Peat (1972) n-dimensional logit model estimated from household cross-sectional data
System-Wide	San Diego, CA (1966) system-wide bus, work trips	46	N.A.	-0.65	Peat (1972) n-dimensional logit model estimated from household cross-sectional data

Table A-8

FARE ELASTICITIES BY ROUTE TYPE
(continued)

Route Type	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
CBD-Oriented	San Diego, CA (1972-1975) all hours, bus routes ending in CBD	40	25	-0.74	Goodman, et al., (1977) least-squares regression of time-series data
Non-CBD-Oriented	San Diego, CA (1972-1975) all hours, bus routes without ends in CBD	40	25	-0.64	Goodman, et al., (1977) least-squares regression of time-series data
System-wide	San Diego, CA (1972-1975) all hours, bus trips	40	25	-0.51	Goodman, et al., (1977) least-squares regression of time-series data
Freeway Express	Arlington, VA (1973) peak hours, Shirley Highway	73	63	-0.53	Ecosometrics, Inc. [28] from McLynn, et al., (1973) 2-mode-choice logit model estimated from household cross-sectional data
Freeway Express	Arlington, VA (1975) peak hours, Shirley Highway	67	86	-0.27	Schofer (1978) arc
Radial Arterial	Arlington, VA (1975) peak hours, Lee Highway	67	88	-0.74	Schofer (1978) arc
Express	St. Louis, MO (1973) all hours average of 25 bus routes	45	25	-0.42	Ecosometrics, Inc. [12] from Mundle, et al., (1978) midpoint
Local	St. Louis, MO (1973) all hours average of 39 bus routes	45	25	-0.23	Ecosometrics, Inc. [12] from Mundle, et al., (1978) midpoint
Suburban	York, PA (1948) all hours, bus trips	14	18	-0.59	Ecosometrics, Inc. [7] from Van Tassel (1956) midpoint
Intra-City	York, PA (1948) all hours, bus trips	6	8	-0.46	Ecosometrics, Inc. [7] from Van Tassel (1956) midpoint
System-Wide	York, PA (1948) all hours, bus trips	8	10	-0.50	Ecosometrics, Inc. [7] from Van Tassel (1956) midpoint

Table A-8

FARE ELASTICITIES BY ROUTE TYPE
(continued)

Route Type	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Soure and Elasticity Measure
Suburban	Springfield, MA (1949) all hours, bus trips	12	16	-0.41	Ecosometrics, Inc. [7] from Van Tassel (1956) midpoint
Intercity	Springfield, MA (1949) all hours, bus trips	9	10	-0.33	Ecosometrics, Inc. [7] from Van Tassel (1956) midpoint
System-Wide	Springfield, MA (1949) all hours, bus trips	9	11	-0.34	Ecosometrics, Inc. [7] from Van Tassel (1956) midpoint
Intra-CBD	Knoxville, TN (1977) all hours, bus trips	40	0	-0.41	Ecosometrics, Inc. [19] from Damm (1979) midpoint
Intra-CBD	Seattle, WA (1973) all hours, bus trips	10	0	-0.46	Ecosometrics, Inc. [16] from Colman (1979) midpoint
Intra-Suburban	Seattle, WA (1973) all hours, bus trips	25	20	-0.43	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
System-Wide	Seattle, WA (1973) all hours, bus trips	25	20	-0.43	Ecosometrics, Inc. [6] from MTC (1976) midpoint
Intra-CBD	Portland, OR (1975-1979) all hours, bus trips	10	0	-0.70	Ecosometrics, Inc. [16] from Colman (1979) midpoint
System-Wide	Portland, OR (1958) all hours, bus trips	20	25	-0.33	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
Intra-CBD	Albany, NY (1978-1979) midday & Saturday, bus trips	5	0	-0.51	Ecosometrics, Inc. [17] from Nagin, et al., (1979) midpoint
System-Wide	Albany, NY (1964-1973) all hours, bus trips	30	N.A.	-0.52	Hartgen, et al., (1976) least-squares regression of time series data

Table A-8

FARE ELASTICITIES BY ROUTE TYPE
(continued)

OBSERVATIONS

- Intra-suburban travel is 3 to 4 times more elastic than travel on radial, arterial routes in London and 30 percent more elastic than aggregate ridership. These observations are similiar for bus, rapid rail, and commuter rail service.
- CBD-destined trips are less elastic than trips with destinations to other parts of the city.
- The elasticities for peak period freeway express services are smaller than those observed for peak-period radial arterial services. The St. Louis experience, however, shows contrary evidence.
- Suburban routes exhibit fare elasticities approximately 25 percent larger than intra-city routes in two cities in the late 1940's.
- Intra-CBD routes exhibit larger fare elasticities than those observed system-wide. The average 15 month CBD fare-free elasticity is -0.50.

Table A-9

PEAK AND OFF-PEAK FARE ELASTICITIES

Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
PEAK					
a.m.	New York, NY (1966) rapid-rail trips	15	20	-0.03	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
p.m.	New York, NY (1966) rapid-rail trips	15	20	-0.06	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
OFF-PEAK					
Midday	New York, NY (1966) rapid-rail trips	15	20	-0.10	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
Evening	New York, NY (1966) rapid-rail trips	15	20	-0.18	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
Late Night	New York, NY (1966) rapid-rail trips	15	20	-0.04	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
Saturday	New York, NY (1966) rapid-rail trips	15	20	-0.15	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
Sunday	New York, NY (1966) rapid-rail trips	15	20	-0.04	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
All Off-Peak	New York, NY (1966) rapid-rail trips	15	20	-0.11	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
All Hours	New York, NY (1966) rapid-rail trips	15	20	-0.09	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
Weekday	New York, NY (1966) NYCTA bus system	15	20	-0.35	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
Saturday	New York, NY (1966) NYCTA bus system	15	20	-0.43	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
Sunday	New York, NY (1966) NYCTA bus system	15	20	-0.40	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
All Hours	New York, NY (1966) NYCTA bus system	15	20	-0.36	Ecosometrics, Inc. [10] from Lassow (1968) midpoint

Table A-9

PEAK AND OFF-PEAK ELASTICITIES
(continued)

Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Weekday	New York, NY (1966) MaBSTOA bus system	15	20	-0.36	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
Saturday	New York, NY (1966) MaBSTOA bus system	15	20	-0.39	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
Sunday	New York, NY (1966) MaBSTOA bus system	15	20	-0.35	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
ALL HOURS	New York, NY (1966) MaBSTOA bus system	15	20	-0.37	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
PEAK					
a.m.	St. Louis, MO (1973) system-wide bus	45	25	-0.13	Ecosometrics, Inc. [1] from Holland (1974) midpoint
p.m.	St. Louis, MO (1973) system-wide bus	45	25	-0.17	Ecosometrics, Inc. [1] from Holland (1974) midpoint
OFF-PEAK					
Midday	St. Louis, MO (1973) system-wide bus	45	25	-0.40	Ecosometrics, Inc. [1] from Holland (1974) midpoint
Evening	St. Louis, MO (1973) system-wide bus	45	25	-0.38	Ecosometrics, Inc. [1] from Holland (1974) midpoint
ALL HOURS	St. Louis, MO (1973) system-wide bus	45	25	-0.24	Ecosometrics, Inc. [1] from Holland (1974) midpoint
OFF-PEAK					
All Off-Peak	Madison, WI (1973) one week fare free, bus trips	25	0	-0.32	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
Saturday	Madison, WI (1973) temporary fare reduction, bus trips	25	10	-0.28	Ecosometrics, Inc. [14] from Hicks (1979) midpoint
Sunday	Madison, WI (1975) temporary fare reduction, bus trips	25	10	-0.20	Ecosometrics, Inc. [14] from Hicks (1979) midpoint

Table A-9

PEAK AND OFF-PEAK FARE ELASTICITIES
(continued)

Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
OFF-PEAK Saturday	Madison, WI (1975) fare increase, bus trips	10	25	-0.51	Ecosometrics, Inc. [14] from Hicks (1979) midpoint
Sunday	Madison, WI (1975) fare increase, bus trips	10	25	-0.64	Ecosometrics, Inc. [14] from Hicks (1979) midpoint
OFF-PEAK					
Midday	Denver, CO (1978-1979) system-wide bus	25	0	-0.28	Ecosometrics, Inc. [4] from DeLeuw (1979) midpoint
Saturday	Denver, CO (1978-1979) system-wide bus	25	0	-0.28	Ecosometrics, Inc. [4] from DeLeuw (1979) midpoint
Sunday	Denver, CO (1978-1979) system-wide bus	25	0	-0.45	Ecosometrics, Inc. [4] from DeLeuw (1979) midpoint
All Off-Peak	Denver, CO (1978-1979) system-wide bus	25	0	-0.29	Ecosometrics, Inc. [4] from DeLeuw (1979) midpoint
OFF-PEAK					
Midday	Trenton, NJ (1978) system-wide bus	15	0	-0.18	Ecosometrics, Inc. [5] from Connor (1979) midpoint
Evening	Trenton, NJ (1978) system-wide bus	15	0	-0.22	Ecosometrics, Inc. [5] from Connor (1979) midpoint
Saturday	Trenton, NJ (1978) system-wide bus	15	0	-0.13	Ecosometrics, Inc. [5] from Connor (1979) midpoint
Sunday	Trenton, NJ (1978) system-wide bus	15	0	-0.26	Ecosometrics, Inc. [5] from Connor (1979) midpoint
All Off-Peak	Trenton, NJ (1978) system-wide bus	15	0	-0.19	Ecosometrics, Inc. [5] from Connor (1979) midpoint

Table A-9

PEAK AND OFF-PEAK FARE ELASTICITIES
(continued)

Time Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
PEAK	London, England (1966-1976) system-wide bus	N.A.	N.A.	-0.27	Rendle, et al., (1978) least-squares regression of time-series data
OFF-PEAK	London, England (1966-1976) system-wide bus	N.A.	N.A.	-0.37	Rendle, et al., (1978) least-squares regression of time-series data
ALL HOURS	London, England (1966-1976) system-wide bus	N.A.	N.A.	-0.33	Rendle, et al., (1978) least-squares regression of time-series data
PEAK	London, England (1966-1976) system-wide rapid rail	N.A.	N.A.	-0.10	Rendle, et al., (1978) least-squares regression of time-series data
OFF-PEAK	London, England (1966-1976) system-wide rapid rail	N.A.	N.A.	-0.25	Rendle, et al., (1978) least-squares regression of time-series data
ALL HOURS	London, England (1966-1976) system-wide rapid rail	N.A.	N.A.	-0.16	Rendle, et al., (1978) least-squares regression of time-series data
PEAK	Stevenage, England (1971) system-wide bus	6 pence	4 pence	-0.27	Smith, et al., (1973) midpoint
OFF-PEAK	Stevenage, England (1971) system-wide bus	6 pence	4 pence	-0.87	Smith, et al., (1973) midpoint
ALL HOURS	Stevenage, England (1971) system-wide bus	6 pence	4 pence	-0.64	Smith, et al., (1973) midpoint

Table A-9

OBSERVATIONS

- Off-peak fare elasticities are two-to-three times larger than the values observed for peak travel. The off-peak fare elasticities for three cities presented above are 2.49 ± 0.61 times larger than the corresponding peak-period values.
- Afternoon peak-period fare elasticities are larger than morning peak-period fare elasticities. In New York and St. Louis, the afternoon peak-period values are 1.66 ± 0.35 times larger than the corresponding morning peak-period elasticities.
- Midday off-peak fare elasticities are only slightly smaller than aggregate off-peak values. Evening period elasticities, however, are larger than aggregate off-peak elasticities by a factor of 1.4. The one case from New York on late-night service found such service 0.36 times the overall off-peak value.
- Weekend service elasticities are not distinctively different than the aggregate elasticities from all time periods. The New York City data show Sunday travel to be less elastic than Saturday travel; however, Trenton and Denver show elasticities for Sunday service to be approximately twice the value observed for Saturday service.
- Peak/off-peak fare cross-elasticities are very small except for riders who have the ability to change their time of travel such as the elderly.

Table A-9

PEAK/OFF-PEAK FARE ELASTICITY COMPARISON STATISTICS

Time Periods	Mean and Standard Deviation of Ratio	Number of Cases
Off-Peak/Peak	2.49 ±0.61	(5 cases)
Peak/All Hours	0.59 ±0.14	(5 cases)
Off-Peak/All Hours	1.38 ±0.19	(5 cases)
Midday/Off-Peak	0.94 ±0.02	(3 cases)
Evening/Off-Peak	1.40 ±0.24	(2 cases)
Late Night/Off-Peak	0.36	(1 case)
Saturday/All Hours	1.30 ±0.26	(3 cases)
Sunday/All Hours	0.83 ±0.29	(3 cases)
Sunday/Saturday	1.10 ±0.54	(7 cases)

PEAK/OFF-PEAK FARE CROSS-ELASTICITIES

As a Result of a Change in:	Change in:	
	Peak Demand	Off-Peak Demand
Peak Fares		+0.03[5] +0.02[6]
Off-Peak Fares	+0.14[1] +0.03[2] +0.26[3] +0.38[4] +0.04[5] +0.05[6]	

[1] Ecosometrics, Inc. [4] from DeLeuw, Cather and Company (1979) for Denver, Colorado off-peak fare-free demonstration (1978-1979) using midpoint formula.

[2] Ecosometrics, Inc. [5] from Connor (1979) for Trenton, New Jersey off-peak fare-free demonstration (1978-1979) using midpoint formula.

[3] Ecosometrics, Inc. [3] from Caruolo and Roess (1974) for elderly travel in Los Angeles, California (1961) using midpoint formula.

[4] Ecosometrics, Inc. [20] from Hoel and Roszner (1972) for elderly travel in Pittsburg, Pennsylvania (1970) using midpoint formula.

[5] Glaister and Lewis (1978) for bus travel in London, England using 3-mode-choice logit/utile model estimated from cross-sectional time-series data (1970-1975).

[6] Glaister and Lewis (1978) for rapid-rail travel in London, England using 3-mode-choice logit/utile model estimated from cross-sectional time-series data (1970-1975).

Table A-10

CAPTIVE- AND CHOICE-RIDER FARE ELASTICITIES

Type Of Rider/Trip	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Choice Work Trips	San Francisco, CA (1965) system-wide bus	N.A.	N.A.	-0.87	McGillivray (1969) binary-choice model estimated from household cross-sectional data
All Choice Trips	San Francisco, CA (1965) system-wide bus	N.A.	N.A.	-0.19	McGillivray (1969) binary-choice model estimated from household cross - sectional data
All Trips	San Francisco, CA (1965) system-wide bus	N.A.	N.A.	-0.11	McGillivray (1969) binary-choice model estimated from household cross-sectional data
Choice Work Trips	Chicago, IL (1956) system-wide bus and rapid rapid rail	N.A.	N.A.	-0.96	Warner (1962) binary-choice model estimated from household cross-sectional data
Choice Work Trips	Chicago, IL (1964) system-wide rapid rail	45	55	-0.40	Lisco (1967) probit model estimated from household-cross-sectional data
Choice Work Trips	Chicago, IL (1964) system-wide bus	N.A.	N.A.	-0.70	Lave (1968) probit model estimated from household cross-sectional data
Choice Trips	Denver, CO (1978-1979) weekday, off-peak hours	25	0	-0.31	DeLeuw (1979) midpoint
Captive Trips	Denver, CO (1978-1979) weekday, off-peak hours	25	0	-0.25	DeLeuw (1979) midpoint
All Trips	Denver, CO (1978-1979) weekday, off-peak hours	25	0	-0.28	DeLeuw (1979) midpoint

Table A-10

CAPTIVE- AND CHOICE-RIDER FARE ELASTICITIES
(continued)

Type Of Rider/Trip	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Automobiles Owned					
Zero	Trenton, NJ (1978-1979) all off-peak hours	15	0	-0.11	DeLeuw (1979) midpoint
One	Trenton, NJ (1978-1979) all off-peak hours	15	0	-0.22	DeLeuw (1979) midpoint
Two	Trenton, NJ (1978-1979) all off-peak hours	15	0	-0.21	DeLeuw (1979) midpoint
Three(+)	Trenton, NJ (1978-1979) all off-peak hours	15	0	-0.30	DeLeuw (1979) midpoint
Choice Work Trips	London, England (1969) bus trips with auto available, passenger-trips fare elasticity	N.A.	N.A.	-0.41	Collins, et al., (1972) in Bly (1976)
Captive Work Trips	London, England (1969) bus trips without auto available, passenger-trips fare elasticity	N.A.	N.A.	-0.10	Collins, et al., (1972) in Bly (1976)
All Work Trips	London, England (1969) all bus trips, passenger-trips fare elasticity	N.A.	N.A.	-0.27	Collins, et al., (1972) in Bly (1976)
Choice Work Trips	London, England (1969) all bus trips with auto available, passenger-miles fare elasticity	N.A.	N.A.	-0.21	Collins, et al., (1972) in Bly (1976)
Captive Work Trips	London, England (1969) all bus trips without auto available, passenger-miles elasticity	N.A.	N.A.	-0.38	Collins, et al., (1972) in Bly (1976)

Table A-10

CAPTIVE- AND CHOICE-RIDER FARE ELASTICITIES
(continued)

Type Of Rider/Trip	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Automobiles Owned					
Zero	Trenton, NJ (1978-1979) all off-peak hours	15	0	-0.11	DeLeuw (1979) midpoint
One	Trenton, NJ (1978-1979) all off-peak hours	15	0	-0.22	DeLeuw (1979) midpoint
Two	Trenton, NJ (1978-1979) all off-peak hours	15	0	-0.21	DeLeuw (1979) midpoint
Three(+)	Trenton, NJ (1978-1979) all off-peak hours	15	0	-0.30	DeLeuw (1979) midpoint
Choice Work Trips	London, England (1969) bus trips with auto available, passenger-trips fare elasticity	N.A.	N.A.	-0.41	Collins, et al., (1972) in Bly (1976)
Captive Work Trips	London, England (1969) bus trips without auto available, passenger-trips fare elasticity	N.A.	N.A.	-0.10	Collins, et al., (1972) in Bly (1976)
All Work Trips	London, England (1969) all bus trips, passenger-trips fare elasticity	N.A.	N.A.	-0.27	Collins, et al., (1972) in Bly (1976)
Choice Work Trips	London, England (1969) all bus trips with auto available, passenger-miles fare elasticity	N.A.	N.A.	-0.21	Collins, et al., (1972) in Bly (1976)
Captive Work Trips	London, England (1969) all bus trips without auto available, passenger-miles elasticity	N.A.	N.A.	-0.38	Collins, et al., (1972) in Bly (1976)

Table A-10

OBSERVATIONS

- Choice transit trips are considerably more elastic than captive transit trips. In Denver, off-peak choice riders exhibited fare elasticities 25 percent larger than captive riders. In London, the difference was much greater.
- Mode-choice models have shown that the work trip is probably the most elastic trip for choice riders. The mean choice work trip fare elasticity is -0.73 ±0.21 for four mode-choice models.
- Although choice riders exhibit larger passenger-trip fare elasticities than captive riders, captive riders will save money by riding shorter distances when zone fares are increased.

Table A-11

FARE ELASTICITIES BY INCOME GROUP

Income Group	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Low Income	Denver, CO (1978-1979) off-peak, system-wide bus under $5,000	25	0	-0.28	DeLeuw (1979) midpoint
	Denver, CO (1978-1979) off-peak, system-wide bus $5,000 to $9,999	25	0	-0.24	DeLeuw (1979) midpoint
Medium Income	Denver, CO (1978-1979) off-peak, system-wide bus $10,000 to $14,999	25	0	-0.25	DeLeuw (1979) midpoint
	Denver, CO (1978-1979) off-peak, system-wide bus $15,000 to $24,999	25	0	-0.28	DeLeuw (1979) midpoint
High Income	Denver, CO (1978-1979) off-peak, system-wide bus $25,000 or more	25	0	-0.31	DeLeuw (1979) midpoint
Low Income	Trenton, NJ (1978-1979) off-peak, system-wide bus under $5,000	15	0	-0.09	DeLeuw (1979) midpoint
	Trenton, NJ (1978-1979) off-peak, system-wide bus $5,000 to $9,999	15	0	-0.10	DeLeuw (1979) midpoint
Medium Income	Trenton, NJ (1978-1979) off-peak, system-wide bus $10,000 to $14,999	15	0	-0.41	DeLeuw (1979) midpoint
	Trenton, NJ (1978-1979) off-peak, system-wide bus $15,000 to $24,999	15	0	-0.08	DeLeuw (1979) midpoint
High Income	Trenton, NJ (1978-1979) off-peak, system-wide bus $25,000 or more	15	0	-0.43	DeLeuw (1979) midpoint
Low Income	New York, NY (1966) 13 subway stations in low income areas				
	Morning Peak	15	20	-0.16	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	Afternoon Peak	15	20	-0.29	Ecosometrics, Inc. [10] from Lassow (1968) midpoint

FARE ELASTICITIES BY INCOME GROUP
(continued)

Income Group	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Low Income (continued)	New York, NY (1966) (cont.)				
	Midday	15	20	-0.34	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	Evening	15	20	-0.74	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	Late Night	15	20	-0.49	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	All Hours	15	20	-0.31	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
All Users	Morning Peak	15	20	-0.03	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	Afternoon Peak	15	20	-0.06	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	Midday	15	20	-0.10	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	Evening	15	20	-0.18	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	Late Night	15	20	-0.04	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	All Weekday Hours	15	20	-0.07	Ecosometrics, Inc. [10] from Lassow (1968) midpoint

OBSERVATIONS

- Fare elasticities rise as household income rises as partially shown in Denver and Trenton.
- In New York City, however, low-income subway users are more responsive to a fare increase than subway riders as a whole. With the exception of the late night values, low income riders were 4.22 ±0.65 (5 cases) times more elastic than all subway users.

Table A-12

FARE ELASTICITIES BY TRIP PURPOSE
AND USER GROUP

Trip Purpose or User Group	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Work	Boston, MA (1963-1964) system-wide bus and rapid rail	45	N.A.	-0.10	Domencich, et al., (1968) constrained least-squares regression of household cross-sectional data
Shopping	Boston, MA (1963-1964) system-wide bus and rapid rail	45	N.A.	-0.32	Domencich, et al., (1968) constrained least-squares regression of household cross-sectional data
Work	30 British cities (1966-67) system-wide bus	N.A.	N.A.	-0.19	Wabe, et al., (1975) least-squares regression of bus-trips cross-sectional data
All Non-Work	30 British cities (1966-67) system wide bus	N.A.	N.A.	-0.49	Wabe, et al., (1975) least-squares regression of bus-trips cross-sectional data
Work	Baltimore, MD (1976) system-wide bus	30 [a]	40 [a]	-0.09	ATE (1976) in Habib, et al., (1978)
Shopping	Baltimore, MD (1976) system-wide bus	30 [a]	35 [a]	-0.20	ATE (1976) in Habib, et al., (1978)
Work	Richmond, VA (1976) system-wide bus	35 [a]	40 [a]	-0.08	ATE (1976) in Habib, et al., (1978)
Shopping	Richmond, VA (1976) system-wide bus	35 [a]	40 [a]	-0.25	ATE (1976) in Habib, et al., (1978)
Work	Birmingham, AL (1975) system-wide bus	N.A.	N.A.	-0.05	ATE (1976) in Habib, et al., (1978)
Shopping	Birmingham, AL (1975) system-wide bus	N.A.	N.A.	-0.15	ATE (1976) in Habib, et al., (1978)
All	Birmingham, AL (1975) system-wide bus	N.A.	N.A.	-0.12	ATE (1976) in Habib, et al., (1978)

[a] Assumed fare change occuring during year of study.

Table A-12

FARE ELASTICITIES BY TRIP PURPOSE
AND USER GROUP
(continued)

Trip Purpose or User Group	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Work	Trenton, NJ (1978-1979) off-peak hours, system-wide bus	15	0	-0.11	DeLeuw (1979) midpoint
School	Trenton, NJ (1978-1979) off-peak hours, system-wide bus	15	0	-0.19	DeLeuw (1979) midpoint
Shopping	Trenton, NJ (1978-1979) off-peak hours, system-wide bus	15	0	-0.25	DeLeuw (1979) midpoint
Medical	Trenton, NJ (1978-1979) off-peak hours, system-wide bus	15	0	-0.32	DeLeuw (1979) midpoint
Recreation	Trenton, NJ (1978-1979) off-peak hours, system-wide bus	15	0	-0.37	DeLeuw (1979) midpoint
Social	Trenton, NJ (1978-1979) off-peak hours, system-wide bus	15	0	-0.25	DeLeuw (1979) midpoint
Other	Trenton, NJ (1978-1979) off-peak hours, system-wide bus	15	0	-0.19	DeLeuw (1979) midpoint
All	Trenton, NJ (1978-1979) off-peak hours, system-wide bus	15	0	-0.19	DeLeuw (1979) midpoint
Adults	Warwickshire, England (1975) system-wide bus	N.A.	N.A.	-0.32	Unpublished report in Bly (1976)
Children	Warwickshire, England (1975) system-wide bus	N.A.	N.A.	-0.41	Unpublished report in Bly (1976)
Adults	Montreal. Canada (1956-1972) all hours, system-wide bus and rapid rail	N.A.	N.A.	-0.16	Gaudry (1975) least-squares regression of time-series data with adjustments for serial correlation
School Children	Montreal, Canada (1956-1972) all hours, system-wide bus and rapid rail	N.A.	N.A.	-0.44	Gaudry (1975) least-squares regression of time-series data with adjustments for serial correlation

Table A-12
FARE ELASTICITIES BY TRIP PURPOSE
AND USER GROUP
(continued)

Trip Purpose or User Group	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Senior Citizens	New York, NY (1969) midday, system-wide bus and rapid rail	20	10	-0.35	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
All Users	New York, NY (1966) all hours, system-wide bus and rapid rail	15	20	-0.19	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	New York, NY (1966) midday, system-wide rapid rail	15	20	-0.10	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	New York, NY (1966) all hours, system-wide rapid rail	15	20	-0.09	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
	New York, NY (1970) all hours, system-wide bus and rapid rail	20	30	-0.18	Pucher, et al., (1966) midpoint
Senior Citizens	Baltimore, MD (1972) off-peak, system-wide bus	30	15	-0.12	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
Commuters	Baltimore, MD (1976) system-wide bus	30[a]	40[a]	-0.09	ATE (1976) in Habib, et al., (1978)
Shoppers	Baltimore, MD (1976) system-wide bus	30[a]	35[a]	-0.20	ATE (1976) in Habib, et al., (1978)
All Users	Baltimore, MD (1958) system-wide bus	20	25	-0.09	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
Age Category					
1-16 years	Denver, CO (1978-1979) off-peak, system-wide bus	25	0	-0.32	Deleuw (1979) midpoint
17-24 years	Denver, CO (1978-1979) off-peak, system-wide bus	25	0	-0.30	DeLeuw (1979) midpoint
25-44 years	Denver, CO (1978-1979) off-peak, system-wide bus	25	0	-0.28	DeLeuw (1979) midpoint
45-64 years	Denver, CO (1978-1979) off-peak, system-wide bus	25	0	-0.18	DeLeuw (1979) midpoint
65 and more years	Denver, Co (1978-1979) off-peak, system-wide bus	25	0	-0.16	DeLeuw (1979) midpoint

[a] Assumed fare change occuring during year of study.

Table A-12

FARE ELASTICITIES BY TRIP PURPOSE
AND USER GROUP
(continued)

Trip Purpose or User Group	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Age Category					
1-16 years	Trenton, NJ (1978-1979) off-peak, system-wide bus	15	0	-0.31	DeLeuw (1979) midpoint
17-24 years	Trenton, NJ (1978-1979) off-peak, system-wide bus	15	0	-0.24	DeLeuw (1979) midpoint
25-44 years	Trenton, NJ (1978-1979) off-peak, system-wide bus	15	0	-0.08	DeLeuw (1979) midpoint
45-64 years	Trenton, NJ (1978-1979) off-peak, system-wide bus	15	0	-0.12	DeLeuw (1979) midpoint
65 and more years	Trenton, NJ (1978-1979) off-peak, system-wide bus	15	0	-0.12	DeLeuw (1979) midpoint
Senior Citizens	Pittsburgh, PA (1970) off-peak, system-wide bus	34	19	-0.72	Ecosometrics, Inc. [20] from Hoel, et al., (1972) midpoint
	Los Angeles, CA (1961) off-peak, system-wide bus	22.5	15	-0.53	Caruolo, et al., (1974) midpoint
	Albuquerque, NM (1968) all hours, system-wide bus	30	20	-0.52	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Washington, DC (1971) off-peak, system-wide bus	40	25	-0.49	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Miami, FL (1972) off-peak, system-wide bus	30	15	-0.44	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Madison, WI (1973) off-peak, system-wide bus	25	15	-0.36	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	New York, NY (1969) off-peak, system-wide bus and rapid rail	20	10	-0.35	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Minneapolis, MN (1972) off-peak, system-wide bus	30	0	-0.33	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	San Antonio, TX (1972) all hours, system-wide bus	25	10	-0.30	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	South Bend, IN (1965) off-peak, system-wide bus	30	15	-0.27	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint

Table A-12

FARE ELASTICITIES BY TRIP PURPOSE
AND USER GROUP
(continued)

Trip Purpose or User Group	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Senior Citizens (continued)	Torrance, CA (1970) all hours, system-wide bus	35	10	-0.23	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Euclid, OH (1967) all hours, system-wide bus	25	15	-0.14	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Milwaukee, WI (1973) off-peak, system-wide bus	50	25	-0.13	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	Baltimore, MD (1972) off-peak, system-wide bus	30	15	-0.12	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint

OBSERVATIONS

- Travelers on work trips are two to three times less responsive to changes in transit fares than shoppers. The mean work-trip and shopping-trip fare elasticities for three cities are -0.07 ± 0.02 and -0.20 ± 0.04, respectively.
- With the exception of the work trip, all other trip purposes in Trenton have fare elasticities equal to or greater than the aggregate off-peak value of -0.19, recreation travel being most responsive to the fare reduction.
- Children are more elastic than adult riders in Warwickshire, England and Montreal, Canada.
- In New York City, the fare elasticity of senior citizen demand for transit is twice as large as the aggregate fare elasticities observed in 1966 and 1970. However, in Baltimore the senior citizen fare elasticity is only 30 percent larger than the aggregate figure and less than the estimate for shopping trips.
- The mean fare elasticity for 14 cities that have monitored senior citizen reduced fare programs is -0.35 ± 0.17.
- The numerical value of the fare elasticity decreases as transit rider's age increases. Thus, young people are more responsive to fare changes than the elderly.

Table A-13

FARE ELASTICITIES FROM PROMOTIONAL FARE REDUCTIONS

Fare Reduction Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
1 Month	Auburn, NY (1973) all hours, system-wide bus	25	0	-0.63	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
1 Week	Madison, WI (1973) off-peak, system-wide bus	25	0	-0.32	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
5 Months	Madison, WI (1975) Saturday fare reduction, system-wide bus	25	10	-0.28	Ecosometrics, Inc. [14] from Hicks (1979) midpoint
Permanent	Madison, WI (1975) Saturday fare increase system-wide bus	10	25	-0.51	Ecosometrics, Inc. [14] from Hicks (1979) midpoint
5 Months	Madison, WI (1975) Sunday fare reduction system-wide bus	25	10	-0.20	Ecosometrics, Inc. [14] from Hicks (1979) midpoint
Permanent	Madison, WI (1975) Sunday fare increase system-wide bus	10	25	-0.64	Ecosometrics, Inc. [14] from Hicks (1979) midpoint
1 Month	Chicago, IL (1953) Tuesdays, 9:30 a.m. to 1:30 p.m.	20	10	-0.09	Ecosometrics, Inc. [15] from Schroeder (1954) in Kemp (1973) midpoint
Permanent	Chicago, IL (1957) all hours	20	25	-0.33	Ecosometrics, Inc. [11] from Curtin (1968) midpoint
6 Months	New York, NY (1974) Sundays, Manhattan & Bronx Bus System	N.A.	-50%	-0.33	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
Permanent	New York, NY (1966) Sundays, Manhattan & Bronx Bus System	15	20	-0.35	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
6 Months	New York, NY (1974) Sundays, New York City Subway System	N.A.	-50%	-0.42	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
Permanent	New York, NY (1966) Sundays, New York City Subway System	15	20	-0.04	Ecosometrics, Inc. [10] from Lassow (1968) midpoint

Table A-13

FARE ELASTICITIES FROM PROMOTIONAL FARE REDUCTIONS (continued)

Fare Reduction Period	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
6 Months	New York, NY (1974) Sundays, New York City Bus System	N.A.	-50%	-0.53	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
Permanent	New York, NY (1966) Sundays, New York City Bus System	15	20	-0.40	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
6 Months	New York, NY (1974) Sundays, system-wide all modes	N.A.	-50%	-0.47	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
Permanent	New York, NY (1966) Sundays, system-wide all modes	15	20	-0.18	Ecosometrics, Inc. [10] from Lassow (1968) midpoint
6 Months	New York, NY (1974) Sundays, Staten Island Rapid Transit System	N.A.	-50%	-0.36	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	New York, NY (1974) Long Island Railroad	N.A.	-50%	-0.59	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint
	New York, NY (1974) Harlem, Hudson & New Haven Railroad	N.A.	-50%	-0.70	Ecosometrics, Inc. [3] from Caruolo, et al., (1974) midpoint

OBSERVATIONS

- Passenger demand in Madison, Wisconsin was less elastic to the 5-month weekend fare reduction than to the permanent fare increase.
- Sunday 6-month fare reduction program in New York City resulted in significantly larger fare elasticities than those estimated from the 1966 fare increase. The promotion, nevertheless, resulted in a net revenue loss.

Table A-14

FARE ELASTICITIES BY PAYMENT METHOD

Payment Method	City and Route Description	Fare Level Before (cents)	Fare Level After (cents)	Elasticity	Source and Elasticity Measure
Season Ticket (Pass)	Paris, France all hours, system-wide bus and rapid rail	N.A.	N.A.	-0.14	ECMT (1971) in Bly (1976)
Single Ticket	Paris, France all hours, system-wide bus and rapid rail	N.A.	N.A.	-0.20	ECMT (1971) in Bly (1976)
Season Ticket (Pass)	Warwickshire, England (1975), system-wide bus	N.A.	N.A.	-0.10	Unpublished report in Bly (1976)
Single Ticket	Warwickshire, England (1975), system-wide bus	N.A.	N.A.	-0.32	Unpublished report in Bly (1976)
Employee Monthly Pass	Sacramento, CA (1978) all trips, participating employees	32	24	-0.56	Ecosometrics, Inc. [21] from Systan (1979) midpoint
Employee Monthly Pass	Sacramento, CA (1978) non-work trips, participating employees	33	28	-0.42	Ecosometrics, Inc. [21] from Systan (1979) midpoint
Employee Monthly Pass	Sacramento, CA (1978) all trips, participating employees	32	25	-0.55	Ecosometrics, Inc. [21] from Systan (1979) midpoint
Fare Prepayment Penetration	62 U.S. fare prepayment plans (1975) penetration elasticity	N.A.	N.A.	-0.47	Ecosometrics, Inc. (1978) point

OBSERVATIONS

- Long-term pass plans in both Paris, France and Warwickshire, England exhibit smaller fare elasticities than single tickets.
- Employees in Sacramento increased transit riding for the work trip at a greater rate than for non-work trips as a result of a monthly pass discount period. No comparison can be made with cash fare passengers.

APPENDIX B

SERVICE ELASTICITIES

Table B-1

BUS HEADWAY ELASTICITIES FROM QUASI-EXPERIMENTAL DATA

Time Period and Service Level	City and Route Description	Headway Before (Minutes)	Headway After (Minutes)	Elasticity	Source and Elasticity Measure
PEAK					
Low	Chesapeake/Norfolk, VA (1965-67) a.m. commuter route, 13.9 miles	70	35	-0.58	Ecosometrics, Inc.[22] from Wilbur Smith (1969) midpoint
High	Stevenage, England (1971-72) all routes, 2.7 miles	8	5	-0.41	Mullen (1975) arc
	Detroit, MI (1962) Grand River Avenue route	4	2	-0.13	Ecosometrics, Inc.[23] from City of Detroit (1963) midpoint
OFF-PEAK					
Low	Chesapeake/Norfolk, VA (1965-67) midday route, 13.9 miles	360	36	-0.85	Ecosometrics, Inc.[22] from Wilbur Smith (1969) midpoint
	Chesapeake/Norfolk, VA (1965-67) evening route, 13.9 miles	210	42	-0.70	Ecosometrics, Inc. [22] from Wilbur Smith (1969) midpoint
	Adams/Williamstown, MA (1963-64) rural route, midday and evening, 13 miles	51	30	-0.58	Pratt, et al., (1977) midpoint
Medium	Boston, MA (1963-64) downtown distributor, 1 mile	25	5	-0.75	Pratt, et al., (1977) midpoint
	Leominster/Fitchburg, MA (1963-64) rural route, midday and evening, 7.9 miles	20	10	-0.25	Pratt, et al., (1977) midpoint
	Detroit, MI (1962) Grand River Avenue route, evenings	13	9	-0.47	Ecosometrics, Inc. [23] from City of Detroit (1963) midpoint
High	Medford, MA (1963-64) suburban feeder to rapid transit	10	5	-0.06	Pratt, et al., (1977) midpoint

Table B-1

BUS HEADWAY ELASTICITIES FROM QUASI-EXPERIMENTAL DATA

(continued)

Time Period and Service Level	City and Route Description	Headway Before (Minutes)	Headway After (Minutes)	Elasticity	Source and Elasticity Measure
OFF-PEAK (continued) High	Stevenage, England (1971-72) all routes, 2.7 miles	8	5	-0.27	Mullen (1975) arc
	Detroit, MI (1962) Grand River Avenue route, midday	6	4	-0.23	Ecosometrics, Inc.[23] from City of Detroit (1963) midpoint
WEEKEND					
Medium	Madison, WI (1975) circulator routes, Sunday	50	30	-0.55	Ecosometrics, Inc.[14] from Hicks (1979) midpoint
	Madison, WI (1975) circulator routes, Saturday	30	20	-0.21	Ecosometrics, Inc.[14] from Hicks (1979) midpoint
	Detroit, MI (1962) Grand River Avenue route, Sunday	18	12	-0.54	Ecosometrics, Inc.[23] from City of Detroit (1963) midpoint
High	Detroit, MI (1962) Grand River Avenue route, Saturday	9	6	-0.22	Ecosometrics, Inc.[23] from City of Detroit (1963) midpoint
ALL HOURS					
Low	Pittsfield, MA (1963-64) circulator route, 3.3 miles	240	90	-0.66	Pratt, *et al.*, (1977) midpoint
	Chesapeake/Norfolk, VA (1965-67) single route, 13.9 miles	120	37	-0.79	Ecosometrics, Inc.[22] from Wilbur Smith (1969) midpoint
	Worcester/Uxbridge, MA (1963-64) rural route, 17 miles	120	60	-0.20	Pratt, *et al.*, (1977) midpoint
	Milford/Boston, MA (1963-64) commuter route, 33 miles	120	60	-0.42	Pratt, *et al.*, (1977) midpoint
	Newburyport/Amesbury, MA (1963-64) rural route, 10 miles	90	45	-0.35	Pratt, *et al.*, (1977) midpoint

Table B-1

BUS HEADWAY ELASTICITIES FROM QUASI-EXPERIMENTAL DATA
(continued)

Time Period and Service Level	City and Route Description	Headway Before (Minutes)	Headway After (Minutes)	Elasticity	Source and Elasticity Measure
ALL HOURS					
Low (continued)	Pittsfield, MA (1963-64) circulator route, 3 miles	78	48	-0.64	Pratt, *et al.*, (1977) midpoint
High	Detroit, MI (1962) Grand River Avenue route	7	5	-0.25	Ecosometrics, Inc.[23] from City of Detroit (1963) midpoint

OBSERVATIONS

- Mean all-hours headway elasticity is -0.47± 0.21 (7 cases), while the aggregate bus headway elasticity is -0.44 ± 0.22 (23 cases).
- Headway elasticities appear to be dependent on the level of service before headway adjustments are made. Headway elasticities are higher for low-service routes, even after adjustment for peak/off-peak time periods.
- Mean off-peak headway elasticities are 1.5 to 2 times greater than peak headway elasticities (excluding the Stevenage, England demonstration).
- Weekend headway elasticities are similar to off-peak elasticities. Sundays exhibit larger headway elasticities than Saturdays.

SIMPLE CORRELATIONS BETWEEN BUS HEADWAY ELASTICITIES AND ORIGINAL HEADWAYS FROM QUASI-EXPERIMENTAL DATA[a]

Peak (3 values)	Off-Peak (9 values)	Weekends (4 values)	All Hours (7 values)	Aggregate Values (23 values)
+0.82	+0.71	+0.48	+0.47	+0.62

a. Absolute value of headway elasticity used.

Table B-1

BUS HEADWAY ELASTICITIES BY
SERVICE LEVEL AND TIME PERIOD

(Means and ± Standard Deviations)

Original Service Level[a]	Peak Hours	Off-Peak Hours	Weekends	All Hours	Aggregate Values
High	-0.27 ± 0.14 (2 cases)	-0.19 ± 0.09 (3 cases)	-0.22 (1 case)	-0.25 (1 case)	-0.22 ± 0.10 (7 cases)
Medium	N.A.	-0.49 ± 0.20 (3 cases)	-0.43 ± 0.16 (3 cases)	N.A.	-0.46 ± 0.18 (6 cases)
Low	-0.58 (1 case)	-0.71 ± 0.11 (3 cases)	N.A.	-0.51 ± 0.20 (6 cases)	-0.58 ± 0.19 (10 cases)
Aggregate Values	-0.37 ± 0.19 (3 cases)	-0.46 ± 0.26 (9 cases)	-0.38 ± 0.17 (4 cases)	-0.47 ± 0.21 (7 cases)	-0.44 ± 0.22 (23 cases)

a. The level of service was classified as follows:
High: less than 10 minute headways
Medium: 10 to 50 minute headways
Low: more than 50 minute headways

Table B-2

COMMUTER-RAIL HEADWAY ELASTICITIES FROM QUASI-EXPERIMENTAL DATA

Time Period and Service Level	City and Route Description	Headway Before (Minutes)	Headway After (Minutes)	Elasticity	Source and Elasticity Measure
PEAK					
Medium	Haverhill/Boston, MA (1962-64) 8 stations, 33 miles	41	26	-0.34	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
	Fitchburg/Boston, MA (1962-64) 17 stations, 50 miles	38	22	-0.69	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
	Lowell/Boston, MA (1962-64) 11 stations, 25 miles	33	16	-0.31	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
	Reading/Boston, MA (1962-64) 7 stations 12 miles	21	9	-0.21	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
	Newburyport/Boston, MA (1962-64) 17 stations 37 miles	20	11	-0.35	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
OFF-PEAK					
Low	Fitchburg/Boston, MA (1962-64) 17 stations, 50 miles	88	41	-0.89	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
	Newburyport/Boston, MA (1962-64) 17 stations, 37 miles	54	22	-0.81	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
	Haverhill/Boston, MA (1962-64) 8 stations, 33 miles	50	35	-0.64	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
Medium	Lowell/Boston, MA (1962-64) 11 stations, 25 miles	34	18	-0.54	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
	Reading/Boston, MA (1962-64) 7 stations, 12 miles	22	10	-0.37	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
ALL HOURS					
Low	Fitchburg/Boston, MA (1962-64) 17 stations, 50 miles	68	35	-0.69	Ecosometrics, Inc. [2] from Maloney (1964) midpoint

Table B-2

COMMUTER-RAIL HEADWAY ELASTICITIES FROM QUASI-EXPERIMENTAL DATA
(continued)

Time Period and Service Level	City and Route Description	Headway Before (Minutes)	Headway After (Minutes)	Elasticity	Source and Elasticity Measure
ALL HOURS (continued)					
Medium	Haverhill/Boston, MA (1962-64) 8 stations 33 miles	48	33	-0.53	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
	Newburyport/Boston, MA (1962-64) 17 stations 37 miles	39	18	-0.44	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
	Lowell/Boston, MA (1962-64) 11 stations, 25 miles	34	18	-0.41	Ecosometrics, Inc. [2] from Maloney (1964) midpoint
	Reading/Boston, MA (1962-64) 7 stations, 12 miles	21	10	-0.27	Ecosometrics, Inc. [2] from Maloney (1964) midpoint

OBSERVATIONS

- Mean commuter-rail headway elasticity is -0.50 ± 0.20 (15 cases).
- Mean off-peak headway elasticity is approximately twice the mean value observed during the peak.
- There appears to be a direct correlation between the original level of service and the absolute value of the headway elasticity [r =+0.85].
- There also appears to be a direct correlation between route length and the absolute value of the headway elasticity [r =+0.77]. Route length may be a proxy for trip length.

Table B-2

SIMPLE CORRELATIONS BETWEEN COMMUTER-RAIL HEADWAY ELASTICITIES AND ROUTE LENGTHS AND ORIGINAL HEADWAYS FROM QUASI-EXPERIMENTAL DATA[a]

	Peak (5 values)	Off-Peak (5 values)	All Hours (5 values)	Aggregate Values (15 values)
Original Headway	+0.52	+0.93	+0.99	+0.85
Route Length	+0.90	+0.98	+0.94	+0.77

a. Absolute value of headway elasticity used.

COMMUTER-RAIL HEADWAY ELASTICITIES BY SERVICE LEVEL AND TIME PERIOD

(Means ± Standard Deviation)

Service Level[a]	Peak Hours	Off-Peak Hours	All Hours	Aggregate Values
Medium	-0.38 ± 0.16 (5 cases)	-0.46 ± 0.09 (2 cases)	-0.41 ± 0.09 (4 cases)	-0.41 ± 0.13 (11 cases)
Low	N.A.	-0.78 ± 0.10 (3 cases)	-0.69 (1 case)	-0.76 ± 0.10 (4 cases)
Aggregate Values	-0.38 ± 0.16 (5 cases)	-0.65 ± 0.19 (5 cases)	-0.47 ± 0.14 (5 cases)	-0.50 ± 0.20 (15 cases)

a. The level of service was classified as follows:

Medium: 10 to 50 minute headways
Low: more than 50 minute headways

Table B-3

COMMUTER-RAIL HEADWAY ELASTICITIES FROM NON-EXPERIMENTAL DATA

Time Period and Level of Service	City and Route Description	Mean Headway (Minutes)	Elasticity	Source and Elasticity Measure
ALL HOURS	London, England (1966) system-wide	N.A.	-0.61	Safavi, *et al.*, (1970) in Hepburn (1977) least-squares regression of household cross-sectional data
	London, England (1961) system-wide	N.A.	-0.56	Sturt (1974) in Hepburn (1977) least-squares regression of household cross-sectional data
	London, England (1951) system-wide	N.A.	-0.36	Sturt (1974) in Hepburn (1977) least-squares regression of household cross-sectional data
	London, England (1966) system-wide	N.A.	-0.36	Sturt (1974) in Hepburn (1977) least-squares regression of household cross-sectional data

OBSERVATIONS

- Mean commuter-rail headway elasticity in London is -0.47 ±0.11 (4 cases).

Table B-4

VEHICLE-MILES ELASTICITIES FROM QUASI-EXPERIMENTAL DATA

Time Period	City and Route Description	Vehicle Miles Before (Millions)	Vehicle Miles After (Millions)	Elasticity	Source and Elasticity Measure
ALL HOURS	San Diego, CA (1972-1975) new suburban bus routes	N.A.	N.A.	+1.01	Goodman, <u>et al</u>., (1977) least-squares regression of time-series data
	San Diego, CA (1972-1975) system-wide bus	7.5	13.5	+0.85	Goodman, <u>et al</u>., (1977) least-squares regression of time-series data
	San Diego, CA (1970-1973) system-wide bus	7.5	13.4	+0.75	Kemp (1974) least-squares regression of time-series data
	San Diego, CA (1972-1975) four non-CBD bus routes	N.A.	N.A.	+0.72	Goodman, <u>et al</u>., (1977) least-squares regression of time-series data
	San Diego, CA (1972-1975) four non-CBD bus routes and sixteen radial bus routes to CBD	N.A.	N.A.	+0.65	Goodman, <u>et al</u>., (1977) least-squares regression of time-series data
	Atlanta, GA (1970-1973) system-wide bus	19.43	21.43	+0.30	Kemp (1974) least-squares regression of time-series data

OBSERVATIONS

- Mean vehicle-miles elasticity for bus service is +0.71 ± 0.22 (6 cases).
- System-wide vehicle-miles elasticity in two cities is +0.63 ± 0.24 (3 cases).
- Vehicle-miles elasticities vary from +0.75 to +0.85 in San Diego to lower values in Atlanta (+0.30) where more service is provided.
- In San Diego the elasticities were higher in suburban routes (+1.01) than in central-city routes (+0.72) and radial routes to CBD (+0.65).

Table B-5

VEHICLE-MILES ELASTICITIES FROM NON-EXPERIMENTAL DATA

Time Period	City and Route Description	Mean Service Level (Millions)	Elasticity	Source and Elasticity Measure
PEAK	30 British cities (1966-1967) system-wide bus, work trips	N.A.	+0.58	Wabe, et al., (1975) least-squares regression of bus trips cross-sectional data
	London, England (1970-1972) system-wide bus	N.A.	+0.25	Fairhurst (1973) in White (1978) least-squares regression of time-series data
	London, England (1966-1976) system-wide bus	N.A.	+0.15	Rendle, et al., (1978) least-squares regression of time-series data
	London, England (1970-1972) system-wide rapid rail	N.A.	+0.10	Fairhurst (1973) in White (1978) least-squares regression of time-series data
OFF-PEAK	30 British cities (1966-1967) system-wide bus, non-work trips	N.A.	+0.76	Wabe, et al., (1975) least-squares regression of bus trips cross-sectional data
	London, England (1966-1976) system-wide bus	N.A.	+0.62	Rendle, et al., (1978) least-squares regression of time-series data
	London, England (1970-1972) system-wide bus	N.A.	+0.50	Fairhurst (1973) in White (1978) least-squares regression of time-series data
	London, England (1970-1972) system-wide rapid rail	N.A.	+0.25	Fairhurst (1973) in White (1978) least-squares regression of time-series data
ALL HOURS	13 Iowa cities (1955-1966) system-wide bus	.480	+1.30	Ecosometrics, Inc. [24] from Carstens, et al., (1978) least-squares regression of cross-sectional time-series data

Table B-5

VEHICLE-MILES ELASTICITIES FROM NON-EXPERIMENTAL DATA (continued)

Time Period	City and Route Description	Mean Service Level (Millions)	Elasticity	Source and Elasticity Measure
ALL HOURS (continued)	New York, NY (1964-1973) NYCTA bus system	66.499	+1.26	Hartgen, et al., (1976) least-squares regression of time-series data
	Utica/Rome, NY (1964-1973) system-wide bus	1.194	+1.14	Hartgen, et al., (1976) least-squares regression of time-series data
	39 Canadian cities (1971) system-wide bus and rapid rail	N.A.	+1.03	Litt (1975) in Frankena (1978) least-squares regression of transit operator cross-sectional data
	Nassau County, NY (1964-1973) system-wide bus	7.746	+0.87	Hartgen, et al., (1976) least-squares regression of time-series data
	Rochester, NY (1964-1973) system-wide bus	6.485	+0.86	Hartgen, et al., (1976) least-squares regression of time-series data
	17 U.S. cities (1960-1970) system-wide bus	3.600	+0.77	Boyd, et al., (1973) least-squares regression of transit operator cross-sectional time-series data
	10 British cities (1963-1970) system-wide bus (mean values)	N.A.	+0.71	Smith, et al., (1974) least-squares regression of time-series data
	Albany/Schenectady/Troy, NY (1964-1973) system-wide bus	5.906	+0.70	Hartgen, et al., (1976) least-squares regression of time-series data
	12 British cities (1960-1973) system-wide bus	N.A.	+0.63	Mullen (1975) least-squares regression of transit operator cross-sectional time-series data
	Syracuse, NY (1964-1973) system-wide bus	4.395	+0.61	Hartgen, et al., (1976) least-squares regression of time-series data
	New York, NY (1964-1973) MABSTDA bus system	44.700	+0.57	Hartgen, et al., (1976) least-squares regression of time-series data

Table B-5

VEHICLE-MILES ELASTICITIES FROM NON-EXPERIMENTAL DATA (continued)

Time Period	City and Route Description	Mean Service Level (Millions)	Elasticity	Source and Elasticity Measure
ALL HOURS (continued)	New York, NY (1964-1973) NYCTA rapid-rail system	330.598	+0.55	Hartgen, et al., (1976) least-squares regression of time-series data
	New York, NY (1964-1973) private bus system	16.406	+0.52	Hartgen, et al., (1976) least-squares regression of time-series data
	Buffalo, NY (1964-1973) system-wide bus	14.100	+0.50	Hartgen, et al., (1976) least-squares regression of time-series data
	London, England (1953-1973) system-wide bus and rapid rail	N.A.	+0.50	Fairhurst, et al., (1975) least-squares regression of time-series data
	All British cities (1964-1976) aggregate system-wide bus	N.A.	+0.44	Oldfield (1979) least-squares regression of bus ridership time-series data
	London, England (1966-1976) system-wide bus	N.A.	+0.35	Rendle, et al., (1978) least-squares regression of time-series data
	Binghamton, NY (1964-1973) system-wide bus	.887	+0.24	Hartgen, et al., (1978) least-squares regression of time-series data
ALL HOURS WEEKDAYS ONLY	London, England (1966-1976) system-wide bus	N.A.	+0.29	Rendle, et al., (1978) least-squares regression of time-series data

OBSERVATIONS

- Mean vehicle-miles service elasticity is +0.61 ±0.31 (28 cases).
- Mean off-peak vehicle-miles elasticity (+0.54) is twice the mean value observed during the peak (+0.27).
- Mean vehicle-miles elasticity for bus service (+0.64) is twice the mean elasticity observed for rapid rail service (+0.30).
- The correlation between the vehicle-miles elasticity and the size of the transit agency is relatively weak (r = -0.27 after excluding the Hartgen and Howe NYCTA bus system value).

Table B-5

SUMMARY ELASTICITY DATA

Mode	Peak	Off-Peak	All Hours	Aggregate
Bus	+0.33 ± 0.18 (3 cases)	+0.63 ± 0.11 (3 cases)	+0.69 ± 0.31 (17 cases)	+0.64 ± 0.30 (23 cases)
Rapid Rail	+0.10 (1 case)	+0.25 (1 case)	+0.55 (1 case)	+0.30 ± 0.19 (3 cases)
Bus & Rail	N.A.	N.A.	+0.77 ± 0.27 (2 cases)	+0.77 ± 0.27 (2 cases)
Aggregate	+0.27 ± 0.19 (4 cases)	+0.54 ± 0.20 (4 cases)	+0.69 ± 0.30 (20 cases)	+0.61 ± 0.31 (28 cases)

Table B-6

TOTAL TRAVEL-TIME ELASTICITIES FROM NON-EXPERIMENTAL DATA

Time Period and Level of Service	City and Route Description	Mean Time (Minutes)	Elasticity	Source and Elasticity Measure
PEAK	San Francisco, CA (1965) choice bus work trips	N.A.	-1.16	McGillivray (1969) binary-choice model estimated from household cross-sectional data
	Chicago, IL (1956) choice bus work trips	N.A.	-0.90	Lave (1968) probit model estimated from household cross-sectional data
OFF-PEAK	Boston, MA (1963-1964) bus and rapid-rail shopping trips	N.A.	-0.59	Domencich, <u>et al</u>.,(1968) constrained least-squares regression of household cross-sectional data
ALL HOURS	San Francisco, CA (1965) all choice bus trips	N.A.	-1.29	McGillivray (1969) binary-choice model estimated from household cross-sectional data
	San Francisco, CA (1965) all bus trips	N.A.	-0.55	McGillivray (1969) binary-choice model estimated from household cross-sectional data

OBSERVATIONS

- Mean total travel-time elasticity is -0.90 ±0.30 (5 cases).
- Total travel-time elasticities are -0.55 and -0.59 for all trips and shopping trips respectively.
- Mean choice-rider and work-trip total travel-time elasticity of -1.12 ±0.16 (3 cases) is considerably higher than all-trip and shopping-trip travel-time elasticities.

Table B-7

BUS IN-VEHICLE TIME ELASTICITIES FROM
QUASI-EXPERIMENTAL DATA

Time Period Service Level	City and Route Description	Time Before (minutes)	Time After (minutes)	Elasticity	Source and Elasticity Measure
PEAK	Seattle, WA (1970) Blue Streak on I-5, a.m. & p.m. peak direction	46	38	-0.44	Ecosometrics, Inc. [25] from A.M. Voorhees (1974) midpoint
	Seattle, WA (1970) Blue Streak on I-5, a.m. & p.m. reverse commute	40	38	-0.55	Ecosometrics, Inc. [25] from A.M. Voorhees (1974) midpoint
	Miami, FL (1975) I-95 Express to 36th St., p.m.	31	26	-0.31	Ecosometrics, Inc. [26] from Wattleworth (1978) midpoint
	Miami, FL (1975) I-95 Express to downtown, p.m.	30	23	-0.19	Ecosometrics, Inc. [26] from Wattleworth (1978) midpoint
	Miami, FL (1975) I-95 Express to Civic Center, p.m.	28	21	-0.15	Ecosometrics, Inc. [26] from Wattleworth (1978) midpoint
	Miami, FL (1975) I-95 Express to Civic Center, a.m.	26	19	-0.24	Ecosometrics, Inc. [26] from Wattleworth (1978) midpoint
	Miami, FL (1975) I-95 Express to 36th St., a.m.	26	18	-0.19	Ecosometrics, Inc. [26] from Wattleworth (1978) midpoint
	Boston, MA (1971) Southeast Expressway, a.m. & p.m.	24	10	-0.16	Ecosometrics, Inc. [27] from Dupree, et al., (1973) midpoint
	Miami, FL (1975) I-95 Express to downtown, a.m.	22	18	-0.39	Ecosometrics, Inc. [26] from Wattleworth (1978) midpoint
OFF-PEAK	Seattle, WA (1970) Blue Streak on I-5	41	38	-0.83	Ecosometrics, Inc. [25] from A.M. Voorhees (1974) midpoint

Table B-7

OBSERVATIONS

- Mean in-vehicle time elasticity for express bus service is -0.35 ± 0.21 (10 cases).
- Mean peak period in-vehicle time elasticity is -0.29 ± 0.13 while the sole off-peak value is -0.83. The averages are affected by the very high values observed during the Seattle Blue Streak Demonstration, which failed to properly control for influence of other variables such as park-and-ride lots.
- Seattle's Blue Streak express bus service exhibited a higher travel-time elasticity for base period operation than for peak-period service. The reverse commute elasticity was slightly higher than the value observed for the peak direction.
- The absolute value of the elasticities appears to be directly correlated with in-vehicle time before the service improvement (r = 0.70).

AGGREGATE VALUES

PEAK:	-0.29 ± 0.13	(9 cases)
OFF-PEAK:	-0.83	(1 case)
ALL HOURS:	-0.35 ± 0.21	(10 cases)

Table B-8

BUS IN-VEHICLE TIME ELASTICITIES FROM NON-EXPERIMENTAL DATA

Time Period	City and Route Description	Mean Time (Minutes)	Elasticity	Source and Elasticity Measure
PEAK	Washington, DC (1971) Shirley Highway, exclusive bus lane	47	-1.14	Ecosometrics, Inc. [28] from McLynn & Goodman (1973) 2-mode-choice logit model estimated from household cross-sectional data
	Chicago, IL (1969) a.m. & p.m. work trips	N.A.	-1.10	Talvite (1973) constrained least-squares regression of household cross-sectional data
	San Diego, CA (1966) work trips	30	-0.73	Peat (1972) n-dimensional logit model estimated from household cross-sectional data
	San Francisco, CA (1973) a.m. & p.m. work trips with BART as a mode choice	N.A.	-0.60	McFadden (1974) 3-mode-choice logit model estimated from household cross-sectional data
	Minneapolis/St. Paul, MN (1970) work trips	30	-0.52	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data
	San Francisco, CA (1973) a.m. & p.m. work trips without BART as a mode choice	N.A.	-0.46	McFadden (1974) 2-mode-choice logit model estimated from household cross-sectional data
	Louisville, KY (1974) a.m. & p.m. work trips	N.A.	-0.19	Fulkerson (1975) least-squares regression of household cross-sectional data
OFF-PEAK	Minneapolis/St. Paul, MN (1970) non-work trips	23	-0.12	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data

OBSERVATIONS

- Mean in-vehicle time elasticity for peak bus service is -0.68 ± 0.32 (7 cases).
- Bus in-vehicle time elasticities are significantly lower for non-work trips than work trips in Minneapolis/St.Paul.
- In Minneapolis/St. Paul the bus in-vehicle time elasticities are larger on non-CBD oriented routes than on CBD oriented routes. The contrary is true in San Diego.
- Bus in-vehicle time elasticity in San Francisco is 30 percent greater when BART is included as mode option.

Table B-8

BUS IN-VEHICLE TIME ELASTICITIES BY TRIP PURPOSE AND ROUTE ORIENTATION

	ROUTE ORIENTATION		
City and Trip Purpose	CBD Direction	Non-CBD Direction	All Directions
Minneapolis/St. Paul, MN (1970)[a]			
Work-Trip	-0.45	-0.65	-0.52
Non-Work Trip	-0.11	-0.12	-0.12
San Diego, CA (1966)[b]			
Work-Trip	-1.22	-0.61	-0.73

[a]Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data.

[b]Peat (1972) n-dimensional logit model estimated from household cross-sectional data.

Table B-9

RAPID-RAIL IN-VEHICLE TIME ELASTICITIES FROM NON-EXPERIMENTAL DATA

Time Period	City and Route Description	Mean Time (Minutes)	Elasticity	Source and Elasticity Measure
PEAK	Chicago, IL (1969) a.m. & p.m. work trips	N.A.	-0.80	Talvitie (1973) constrained least-squares regression of household cross-sectional data
	San Francisco, CA (1973) a.m. & p.m. work trips	N.A.	-0.60	McFadden (1974) 3-mode-choice logit model estimated from household cross-sectional data

OBSERVATIONS

- Mean in-vehicle time elasticity for rapid rail-service is -0.70 ± 0.10 (2 cases).

Table B-10

COMBINED BUS AND RAPID-RAIL IN-VEHICLE TIME ELASTICITIES FROM NON-EXPERIMENTAL DATA

Time Period	City and Route Description	Mean Time (Minutes)	Elasticity	Source and Elasticity Measure
PEAK	Boston, MA (1963-1964) a.m. & p.m. work trips	N.A.	-0.39	Domencich (1968) constrained least-squares regression of household cross-sectional data
	Chicago, IL (1969) a.m. & p.m. work trips	N.A.	-0.20	Talvitie (1973) constrained least-squares regression of household cross-sectional data
ALL HOURS	Montreal, Canada (1956-1971) adult riders	N.A.	-0.27	Gaudry (1975) least-squares regression of times-series data with adjustments for serial correlation

OBSERVATIONS

- Mean in-vehicle time elasticity for bus and-rapid rail service is -0.29 ± 0.08 (3 cases).

Table B-11
COMMUTER-RAIL IN-VEHICLE TIME ELASTICITIES FROM
NON-EXPERIMENTAL DATA

Time Period	City and Route Description	Mean Time (Minutes)	Elasticity	Source and Elasticity Measure
ALL HOURS	London, England (1961) system-wide	N.A.	-1.15	Sturt (1968) in Hepburn (1977) least-squares regression of household cross-sectional data
	London, England (1966-1971) 33 routes longer than 40 km. (25 miles)	(reduced 6%)	-0.86	Hepburn (1977) least-squares regression of time-series data
	London, England (1966) system-wide	N.A.	-0.84	Safavi, et al., (1970) in Hepburn (1977) least-squares regression of household cross-sectional data
	London, England (1966-1971) 65 routes	(reduced 7%)	-0.56	Hepburn (1977) least-squares regression of time-series data
	London, England (1966-1971) 32 routes shorter than 40 km. (25 miles)	(reduced 8%)	-0.49	Hepburn (1977) least-squares regression of time-series data
	London, England (1961) system-wide, males only	N.A.	-0.41	Wabe (1969) least-squares regression of household cross-sectional data
	London, England (1961) system-wide, females only	N.A.	-0.38	Wabe (1969) least-squares regression of household cross-sectional data
	London, England (1951) system-wide, females only	N.A.	-0.33	Wabe (1969) least-squares regression of household cross-sectional data
	London, England (1951) system-wide, males only	N.A.	-0.30	Wabe (1969) least-squares regression of household cross-sectional data

OBSERVATIONS

- Mean in-vehicle time elasticity for commuter-rail service is -0.59 ± 0.28 (9 cases).
- Hepburn shows a higher elasticity of -0.86 for routes longer than 25 miles and -0.49 for route lengths shorter than 25 miles.

Table B-12

TOTAL OUT-OF-VEHICLE TIME ELASTICITIES FROM NON-EXPERIMENTAL DATA

Time Period	City and Route Description	Mean Time (Minutes)	Elasticity	Source and Elasticity Measure
PEAK	Boston, MA (1963-1964) bus and rapid rail a.m. & p.m. work trips	N.A.	-0.71	Domencich (1968) constrained least-squares regression of household cross-sectional data
	Chicago, IL (1969) bus and rapid rail a.m. & p.m. work trips	N.A.	-0.69	Talvitie (1973) constrained least-squares regression of household cross-sectional data
	Louisville, KY (1974) a.m. & p.m. bus work trips	N.A.	-0.38	Fulkerson (1975) least-squares regression of household cross-sectional data

OBSERVATIONS

- Mean total out-of-vehicle time elasticity is -0.59 ± -0.15 (3 cases) during the peak period.

Table B-13

WALK-TIME ELASTICITIES FROM NON-EXPERIMENTAL DATA

Time Period	City and Route Description	Mean Time (Minutes)	Elasticity	Source and Elasticity Measure
PEAK	Minneapolis/St. Paul, MN (1970) bus work trips	7.0	-0.26	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data
OFF-PEAK	Minneapolis/St. Paul, MN (1970) bus non-work trips	6.9	-0.14	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data

OBSERVATIONS

- Mean walk-time elasticity is -0.20 ± 0.06 (2 cases) for Minneapolis/St. Paul.
- Walk-time elasticities for work trips are 75 to 100 percent larger than the comparable walk-time elasticities for non-work trips.
- Non-CBD oriented routes are slightly more elastic than CBD routes with respect to changes in walk time.

WALK-TIME ELASTICITIES BY TRIP PURPOSE AND ROUTE ORIENTATION FOR MINNEAPOLIS/ST. PAUL (1970)[a]

	ROUTE ORIENTATION		
Trip Purpose	CBD Direction	Non-CBD Direction	All Direction
Work Trip	-0.21	-0.34	-0.26
Non-Work Trip	-0.12	-0.16	-0.14

[a]Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data.

Table B-14

WAIT-TIME ELASTICITIES FROM NON-EXPERIMENTAL DATA

Time Period	City and Route Description	Mean Time (Minutes)	Elasticity	Source and Elasticity Measure
PEAK	Minneapolis/St.Paul, MN (1970) bus work trips	21	-0.32	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data
	San Francisco, CA (1973) a.m. & p.m. bus work trips with BART as a mode choice	N.A.	-0.19	McFadden (1974) 3-mode-choice logit model estimated from household cross-sectional data
	San Francisco, CA (1973) a.m. & p.m. bus work trips without BART as a mode choice	N.A.	-0.17	McFadden (1974) 2-mode-choice logit model estimated from household cross-sectional data
	San Francisco, CA (1973) a.m. & p.m. rapid-rail work trips	N.A.	-0.12	McFadden (1974) 3-mode-choice logit model estimated from household cross-sectional data
OFF-PEAK	Minneapolis/St.Paul, MN (1970) bus non-work trips	20	-0.21	Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data
ALL HOURS	Montreal, Canada (1956-1971) bus and rapid-rail adult trips	N.A.	-0.54	Gaudry (1975) least-squares regression of time-series data

OBSERVATIONS

- Mean wait-time elasticity is -0.26 ± 0.14 (6 cases).
- Rail first-wait-time elasticity is 30 percent smaller than the first-wait-time elasticity for bus service.
- Gaudry's all-hours wait-time elasticity is twice the size of his in-vehicle elasticity, while the opposite occurs in McFadden's models.
- Wait-time elasticities are 75 percent larger for work trips than for non-work trips.
- Wait-time elasticities on non-CBD-oriented routes are twice as large as those on CBD-oriented routes.

Table B-14

WAIT-TIME ELASTICITIES BY TRIP PURPOSE AND ROUTE ORIENTATION FOR MINNEAPOLIS/ST. PAUL (1970)[a]

	ROUTE ORIENTATION		
Trip Purpose	CBD Direction	Non-CBD Direction	All Direction
Work Trip	-0.22	-0.49	-0.32
Non-Work Trip	-0.13	-0.27	-0.21

[a]Pratt, et al., (1976) multinomial mode-choice logit model estimated from household cross-sectional data.

Table B-15

TRANSFER-TIME ELASTICITIES FROM
NON-EXPERIMENTAL DATA

Time Period	City and Route Description	Mean Time (Minutes)	Elasticity	Source and Elasticity Measure
PEAK	San Francisco, CA (1973) a.m. & p.m. rapid-rail work trips	N.A.	-0.66	McFadden (1974) 3-mode-choice logit model estimated from household cross-sectional data
	San Francisco, CA (1973) a.m. & p.m. bus work trips with BART as a mode choice	N.A.	-0.29	McFadden (1974) 3-mode-choice logit model estimated from household cross-sectional data
	San Francisco, CA (1973) a.m. & p.m. bus work trips without BART as a mode choice	N.A.	-0.26	McFadden (1974) 2-mode-choice logit model estimated from household cross-sectional data

OBSERVATIONS

- Mean transfer-time elasticity is -0.40 ± 0.18 (3 cases).
- Mean bus and rail transfer-time elasticities for peak-hour service are higher than the comparable first-wait-time elasticities.
- Although the first-wait-time elasticity is smaller for rail service than for bus service, the rail transfer-time elasticity of -0.66 is more than twice the mean bus transfer-time elasticity.

Table B-16

TRAVEL-TIME CROSS-ELASTICITIES
FROM NON-EXPERIMENTAL DATA

Changes in	DEMAND FOR		
	Bus	Rail	Auto
BUS			
• In-Vehicle Time (Peak)		+0.23[2], +0.23[3]	+0.15[1], +0.14[2] +0.05[5], +0.04[6]
(Off-Peak)			+0.10[4], +0.08[6]
• Out-of-Vehicle Time (Peak)			+0.37[4]
• Walk Time (Peak)			+0.01[5]
• Wait Time (Peak)		+0.06[2]	+0.06[1], +0.05[2] +0.03[5]
(Off-Peak)			+0.01[5]
• Transfer Time (Peak)		+0.09[2]	+0.09[1], +0.07[2]
RAIL			
• In-Vehicle Time (Peak)	+0.13[2]		+0.10[2]
• Out-of-Vehicle Time (Peak)	+1.00[3]		
• Wait Time (Peak)	+0.03[2]		+0.02[2]
• Transfer Time (Peak)	+0.16[2]		+0.11[2]
AUTO			
• In-Vehicle Time (Peak)	+0.39[1], +0.36[2] +0.27[6], +0.25[5]	+0.84[3]	
(Off-Peak)	+0.06[5]		
• Parking Time (Peak)	+0.82[5]		
(Off-Peak)	+1.40[5]		

Sources:

[1] McFadden (1974) 2-mode-choice logit model using household cross-sectional data.
[2] McFadden (1974) 3-mode-choice logit model using household cross-sectional data.
[3] Talvitie (1973) constrained least-squares regression using household cross-sectional data.
[4] Domencich, Kraft and Vallette (1968) constrained least-squares regression using household cross-sectional data.
[5] Pratt and DTM (1976) multinomial mode-choice logit model estimated from household cross-sectional data.
[6] Peat, Marwick, Mitchell (1972) n-dimensional logit model estimated from household cross-sectional data.

APPENDIX C

DEMAND ELASTICITY CALCULATIONS AND CONVERSIONS MADE BY ECOSOMETRICS, INC.

This appendix presents the data, methodologies, and assumptions used in the elasticity calculations made by Ecosometrics, Inc. which appear in Appendices A and B. Two types of calculations were performed. Midpoint elasticities were calculated in instances where pertinant before and after data were given but where elasticities were not calculated. In other cases, Ecosometrics, Inc. converted shrinkage ratios into midpoint and arc elasticities to ensure that more reliable comparisons could be made.

The calculations are presented sequentially as they are numbered in Appendices A and B. The author(s), report title, and year of publication are presented.[1] The important data from the publication are then provided followed by the individual midpoint elasticities calculated by Ecosometrics, Inc.

[1] A full citation can be found in the References.

[1] Holland, Dempster K. A Review of Reports Relating to the Effect of Fare and Service Changes in Metropolitan Public Transportation Systems, June 1974.

For the 1973 St. Louis fare reduction, Holland reports the following:

- fares were reduced from $.45 to $.25 (p. 7)
- system-wide ridership increased 15% (p. 7)
- day-time ridership increased 26% (p. 9)
- evening ridership increased 24% (p. 9)
- morning peak ridership increased 8% (p. 9)
- evening peak ridership increased 10% (p. 9)

Using these percentage changes, Ecosometrics calculated the following mid-point elasticities:

weekday morning peak:	e = -0.13
weekday evening peak:	e = -0.17
average morning and evening peak:	e = -0.15
midday:	e = -0.40
evening:	e = -0.38
average off-peak:	e = -0.39
all hours:	e = -0.24

[2] Maloney, J.F. and Associates. Mass Transportation in Massachusetts, 1964.

Description of Demonstration

This demonstration was a three-phase experiment involving five commuter-rail lines between Boston and its suburbs. Phase I consisted of weekday service expansion (i.e., reduced headways) and fare concessions for both one-way and 20-ride commutation tickets. This experiment was in effect between January and July, 1963. During Phase II (August through December, 1963) the prices of the 20-ride commutations and one-way tickets were returned to pre-experimental levels, but off-peak fares were reduced.[1] In Phase III the expanded service was again retained but a variety of pricing changes were implemented to test for the efficient mixes of fare and service levels.

Description of Service Areas

The areas covered in this demonstration were five commuter-rail corridors. These corridors are:

1. Newburyport Corridor[2] - consisting of 17 stations and which included the communities of Lynn, Newburyport, Swampscott, Salem, Beverly, Gloucester, and Rockport.

2. Reading Corridor - consisting of 7 stations and which included the communities of Malden, Wyoming, Melrose, Wakefield and Reading.

3. Lowell Corridor[3] - consisting of 11 stations and which included the communities of West Medford, Winchester, Woburn, Wilmington and Lowell.

4. Haverhill Corridor[4] - consisting of 8 stations and which included the communities of Andover, Shawsheen, Lawrence, Bradford and Haverhill.

5. Fitchburg Corridor - consisting of 17 stations and which included the communities of Walthan, Riverview, Hastings, Lincoln, Concord, Ayer, North Leominster and Fitchburg.

Procedures Used to Calculate Service Elasticities

The peak period headway elasticities were computed by comparing Phase II ridership figures with the pre-experimental patronage figures for the same months in 1962. An implicit assumption made in these calculations is that people react in exactly the same manner to fare increases as fare decreases, given that fares were lowered during Phase I and returned to their previous level in Phase II. As shown in Chapter 3 "Fare Elasticities", fare elasticities from fare increases are not significantly different from the elasticities calculated from fare reductions. Therefore, this assumption seems reasonable.

The off-peak and all-hours service elasticities were subject to more complex manipulations. During Phase II, the Maloney report states that drastic off-peak fare reductions were implemented. However, during Phase I, off-peak fares appear to have remained at about their previous level with an increase in service level.[5]

[1]This was taken into account when the off-peak headway elasticities were calculated.

[2]This corridor is termed the "Eastern Route" in Maloney.

[3]This corridor is termed the "New Hampshire Route" in Maloney.

[4]This corridor is termed the "Western Route" in Maloney.

[5]Although the Maloney report makes no mention of off-peak fare reductions for Phase I, there is a listing of some selected off-peak fare reductions. For the purpose of computing these elasticities, Ecosometrics assumed that the increased patronage was due to service increases only and not fare changes. Therefore, the off-peak service elasticities may tend to overstate actual ridership response.

Therefore, the off-peak headway elasticities are based on the first five months of Phase I ridership data compared with the same months in 1962.

The all-hours service elasticities were calculated from ridership data that were subjected to several procedures aimed at discounting the off-peak fare reductions of Phase II. Initially, a time-trend index based on a monthly moving average was developed for the months of 1962. Since the service expansion stayed the same for all months in 1963, this time-trend index was applied to the first seven months of 1963 (i.e., Phase I) from which projections were made for the five months of Phase II. The difference between the projected ridership and the actual ridership was assumed to be directly attributable to the fare reduction and fare elasticities were calculated as shown latter. Finally, after discounting the all-hour ridership figures using the percent fare reduction and fare elasticities, the Phase II all-hour ridership data was compared to the same period in 1962 to develop all-hours service elasticities.

The original headway levels are not reported in Maloney; only the percentage increase in service is presented in his Table 8, page 27. Train frequency data, however, is presented in Porter K. Wheeler's Ph.D. Dissertation "Price and Service Sensitivity in Urban Passenger Transportation," Harvard University, 1968. Passenger and train frequency data are presented below for each of the five commuter rail lines participating in the demonstration. Train frequency weighted averages were computed and, then, divided into the time period in question to obtain average headways. The peak-period headways are for the 2-hour afternoon rush hour only. The off-peak was assumed to last seven hours. The percentage service increases reported in Maloney were applied to the weighted average train frequency levels before the service improvement to obtain the new frequencies. New average headway levels were then computed. The following tables document the data results.

BOSTON COMMUTER RAIL DEMONSTRATION

TRAIN FREQUENCY AND HEADWAY LEVELS
BY COMMUTER RAIL LINE

Route and Time Period	Initial Train Frequency (trains per period)	Service Increase	New Train Frequency (trains per period)	Time Period (minutes)	Average Initial Headway (minutes)	Average New Headway (minutes)
Haverhill Route						
Peak	2.91	58%	4.60	120	41.24	26.09
Off-Peak	8.33	44%	12.00	420	50.42	35.00
All Hours	11.24	46%	16.41	540	48.04	32.91
Fitchburg Route						
Peak	3.20	68%	5.38	120	37.50	22.30
Off-Peak	4.80	112%	10.18	420	87.50	41.26
All Hours	8.00	95%	15.60	540	67.50	34.62
Lowell Route[1]						
Peak	3.66	100%	7.32	120	32.79	16.39
Off-Peak	12.45	89%	23.53	420	33.73	17.85
All Hours	16.11	90%	30.61	540	33.52	17.64
Newburyport Route						
Peak	5.91	81%	10.70	120	20.30	11.21
Off-Peak	7.85	143%	19.08	420	53.50	22.01
All Hours	13.76	120%	30.27	540	39.24	17.84
Reading Route						
Peak	5.84	117%	12.67	120	20.55	9.47
Off-Peak	19.32	109%	40.38	420	21.74	10.40
All Hours	25.16	111%	53.09	540	21.46	10.17

[1]The Lowell Route service charge is an average of the service charges reported for both the Lowell and Woburn Routes from Maloney's report, Table 8, page 27.

BOSTON COMMUTER RAIL DEMONSTRATION

BEFORE AND AFTER RIDERSHIP FIGURES BY
ROUTE AND TIME PERIOD
AND HEADWAY ELASTICITIES

Route and Time Period	5-Month Ridership Before	Ridership After	5-Month Headway Elasticity
Haverhill Route			
Peak	169,835	198,251	-0.34
Off-Peak	82,716	104,297	-0.64
All Hours	263,909	321,908	-0.53
Fitchburg Route			
Peak	136,274	194,329	-0.69
Off-Peak	34,920	67,695	-0.89
All Hours	173,580	273,086	-0.69
Lowell Route			
Peak	373,206	460,286	-0.31
Off-Peak	155,752	217,271	-0.54
All Hours	538,769	696,762	-0.41
Newburyport Route			
Peak	390,046	478,840	-0.35
Off-Peak	103,600	210,020	-0.81
All Hours	495,337	691,136	-0.44
Reading Route			
Peak	504,699	589,882	-0.21
Off-Peak	154,671	201,353	-0.37
All Hours	656,581	798,549	-0.27

Procedures Used to Calculate Fare Elasticities

The before ridership on the B&M Commuter Rail Lines presented below was computed using a monthly moving average index developed from 1962 data. This index was applied to the Phase I monthly data and projections were made for the five month period in Phase II. The after ridership is from Table 15, page 36. The difference between the projected ridership and the actual ridership is assumed to be attributable to the off-peak fare reduction. The average fares are from Table 10 on page 30.

The off-peak bus fare elasticity was calculated from the information presented on page 64 of Maloney's report. The off-peak period included the time periods, 9:30 a.m. - 4:30 p.m., after 6:30 p.m., and all day Saturday and Sunday. Off-peak fares were reduced 30 percent resulting in a 12 percent revenue reduction. The fare elasticities were computed as follows:

Base Revenue (R_1) (Aug. 1962-March 1963)	=	\$2,070,000
Revenue During Demo (R_2) (Aug. 1963-March 1964)	=	\$1,821,490

$R_2 = 0.88\ R_1$ $\qquad\qquad$ $F_2 = 0.70\ F_1$

Ridership Before $= Q_1$

Ridership During $= Q_2$

$$Q_2F_2 = 0.88\ Q_1F_1$$

$$Q_2(0.70\ F_1) = 0.88\ Q_1F_1$$

$$Q_2 = 1.26\ Q_1$$

Off-Peak Bus Fare Elasticity $= -0.65$

BOSTON COMMUTER RAIL DEMONSTRATION

PHASE II OFF-PEAK FARE ELASTICITIES

	5-Month Ridership Before	5-Month Ridership After	Average Fare Before	Average Fare After	Elasticity
Haverhill	276,237	320,908	$1.02	$0.68	-0.37
Fitchburg	233,567	273,086	$1.25	$0.73	-0.30
Lowell	645,349	696,762	$0.73	$0.54	-0.26
Newburyport	641,242	715,661	$0.82	$0.58	-0.32
All Routes Average					-0.31

Source: Calculations performed from Maloney (1964) p. 36, Table 15.

[3] Caruolo, John R., and Roger P. Roess. The Effect of Fare Reductions on Public Transit Ridership, 1974.

Caruolo and Roess presented ridership response data on many different fare changes. The data used to calculate the midpoint elasticities presented in this report are shown below:

Madison:

- off-peak fare-free week in September 1973
- fares reduced from $.25 to zero (p. 41)
- ridership increased 93.5% (p. 41)

e = -0.32

Kent:

- 1967 campus system-wide fare free
- fares reduced from $.05 to zero (p. 41)
- ridership increased by a factor of 2.2 (p. 41)

e = -0.38

Auburn:

- 1973 one-month fare free
- fare reduced from $.25 to zero (p. 41)
- ridership increased from 18,000 to 80,000 (p. 41)

e = -0.63

Seattle:

- 1973 base fare reduction
- base fare reduced from $.25 to $.20 (p. 3)
- ridership on suburban lines increased 10% (p. 3)

e = -0.43

Los Angeles:

- 1961 off-peak fare reduction for senior citizens
- average token fare reduced from $.225 to $.15 (p. 19)
- over 10% of previously peak period trips were diverted to off-peak periods (from Hoel and Roszner, 1972, p. 345).

fare cross-elasticity: e = +0.26

New York:
- 1969 off-peak fare reduction for senior citizens
- base fare reduced from $.20 to $.10 (p. 20)
- midday ridership increased 26.7% (p. 21)

$$e = -0.35$$

Baltimore:
- 1972 off-peak fare reduction for senior citizens
- base fare reduced from $.30 to $.15 (p. 24)
- ridership increased 8% (p. 24)

$$e = -0.12$$

Albuquerque:
- 1968 system-wide fare reduction for senior citizens
- base fare reduced from $.30 to $.20 (p. 27)
- ridership increased 23% (p. 27)

$$e = -0.52$$

Washington, D.C.:
- 1971 off-peak fare reduction for senior citizens
- base fare reduced from $.40 to $.25 (p. 26)
- ridership increased from 47,000 to 59,000 (p. 26)

$$e = -0.49$$

Miami:
- 1972 off-peak fare reduction for senior citizens
- base fare reduced from $.30 to $.15 (p. 22)
- ridership increased 34.5% (p. 22)

$$e = -0.44$$

Madison:
- 1973 off-peak fare reduction for senior citizens
- base fare reduced from $.25 to $.15 (p. 23)
- ridership increased 20% (p. 23)

$$e = -0.36$$

Minneapolis:
- 1972 off-peak fare-free for senior citizens
- base fare reduced from $.30 to zero (p. 25)
- annual senior citizen ridership increased from 3,528,026 to 7,021,225 (p. 25)

$$e = -0.33$$

San Antonio:
- 1972 system-wide fare reduction for senior citizens
- base fare reduced from $.25 to $.10 (p. 61)
- ridership increased 30% (p. 61)

$$e = -0.30$$

South Bend:

- 1965 off-peak fare reduction for senior citizens
- base fare reduced from \$.30 to \$.15 (p. 28)
- ridership increased 20% (p. 28)

$$e = -0.27$$

Torrance:

- 1970 system-wide fare reduction for senior citizens
- base fare reduced from \$.35 to \$.10 (p. 28)
- ridership increased 30% (p. 28)

$$e = -0.23$$

Euclid:

- 1967 system-wide fare reduction for senior citizens
- base fare reduced from \$.25 to \$.15 (p. 27)
- ridership increased 7% (p. 27)

$$e = -0.14$$

Milwaukee:

- 1973 off-peak fare reduction for senior citizens
- base fare reduced from \$.50 to \$.25 (p.23)
- ridership increased 8% to 10% (p. 23)
- assumed a 9% ridership increase

$$e = -0.13$$

New York:

- 1974 "Save on Sunday" system-wide Sunday reduced fare program
- Sunday fares were reduced 50% (p. 45)
- the following percentage increases in ridership were reported (p. 46)

Transit System	Percent Increase in Ridership	Midpoint Elasticity
MaBSTOA	25	-0.33
SIRTOA	27	-0.36
Subways	33	-0.42
NYC Buses	43	-0.53
L.I.R.R.	49	-0.59
Harlem, Hudson, & New Haven	61	-0.70
Overall Ridership	37	-0.47

[4] DeLeuw, Cather and Company. Evaluation of the Denver RTD Off-Peak Free-Fare Transit Demonstration, November 1979

Table B.7 of the DeLeuw report presents estimates of the ridership impacts resulting from the off-peak fare free service. Fares were reduced from $.25 to zero. Ecosometrics calculated midpoint elasticities from the projected base and estimated actual ridership data for 1978:

Time-Period	Projected Base	Estimated Actual	Midpoint Elasticity
Weekday Off-Peak	51,800	77,500	-0.20
Saturday	34,700	52,000	-0.20
Sunday	14,000	27,000	-0.32
All Off-Peak Hours	308,000	467,000	-0.21

The midpoint elasticities shown above are unadjusted values; that is, the ridership figures do not take into consideration the deterioration in service during off-peak hours and the resulting ridership loss. On page 75, DeLeuw reports that the adjusted base off-peak fare elasticity is between -0.25 and -0.30. Ecosometrics assumed the value -0.28. Applying the same proportional change to the other time periods shown above, the following adjusted midpoint elasticities result:

Time Period	Unadjusted Midpoint Elasticity	Adjusted Midpoint Elasticity
Weekday Off-Peak (assumed midday)	-0.20	-0.28
Saturday	-0.20	-0.28
Sunday	-0.32	-0.45
All Off-Peak Hours	-0.21	-0.29

The fare cross-elasticity of peak demand with respect to off-peak fares was obtained from the data presented in Table B.8.

- peak ridership before = 41,200
- peak ridership during = 31,200

$$e = +0.14$$

[5] Connor, David L. Findings of Preliminary Analyses of the Trenton, New Jersey Off-Peak Fare-Free Transit Demonstration, January 1979.

In Table A.1, page C.7, Connor presents typical ridership figures projected with fares and estimated without fares. These data were used in the elasticity calculations. The following data were used:

Time Period	Ridership with Fares ($.15)	Ridership Without Fares	Midpoint Elasticity
Midday (10 a.m.-2 p.m.)	6,000	8,600	-0.18
Evening (after 6 p.m.)	1,200	1,900	-0.22
Saturday	11,500	14,900	-0.13
Sunday	3,900	6,600	-0.26
Weekday Off-Peak	45,100	65,900	-0.19
All Off-Peak	2,333,000	3,414,000	-0.19
Peak Period (cross-elasticity)	4,459,000	4,221,000	+0.03

[6] Metropolitan Transit Commission (MTC). Convenience Fares: Appendices, April 1976.

Data on ridership response to transit fare changes were reported in the appendices to the MTC document. This material was obtained from ATE Management and Service Company, Inc. The relevant data and midpoint elasticities are presented below.

City	Date	Fare Change	Percent Ridership Change	Midpoint Elasticity
Chicago	July 1970	$.40 to $.45	-3	-0.26
Cleveland	March 1973	$.45 to $.50	-4	-0.39
New York	Jan. 1972	$.30 to $.35	-1	-0.07
Richmond	Sept. 1973	$.35 to $.30	+8	-0.50
Seattle	Jan. 1973	$.25 to $.20	+10	-0.43

[7] Van Tassel, Roger C. "Economics of the Pricing of Urban Bus Transportation", Unpublished Ph.D. Dissertation. Brown University, 1956.

Passenger response data from two independent fare changes were reported in Van Tassel. The fare change in York, Pennsylvania occurred on December 18, 1948. Prior to the fare change ridership had been declining at the annual rates provided in Table 8, p. 173 and presented below:

city routes	-2.83%
suburban routes	-4.79%
system-wide routes	-3.18%

Assuming a constant ridership decline, Ecosometrics projected the ridership levels during the fare increase period had the fare increase not occurred.

Route	Actual Ridership Before Fare Change	Attrition Rate	Projected Ridership Without Fare Change
City Routes	2,227,874	-2.83%	2,164,825
Suburban Routes	476,001	-4.79%	453,201
System-Wide Routes	2,703,875	-3.18%	2,617,892

Using the projected ridership without the fare change, the average fare before and after the fare increase, and the new ridership data presented in Table 9, p. 174, the following 3-month midpoint elasticities were obtained

Route	Ridership Before	Ridership After	Average Fare Before	Average Fare After	Midpoint Elasticity
City Routes	2,164,825	1,963,066	$.0636	$.0787	-0.46
Suburban Routes	453,201	394,915	$.1419	$.1796	-0.59
System-wide Routes	2,617,893	2,357,981	$.0774	$.0956	-0.50

On August 14, 1949 Springfield, Massachusetts had a transit fare increase. From Table 10, p. 175 of Van Tassel's dissertation, the following data are provided. Three-month midpoint elasticities computed by Ecosometrics are also provided.

Route	Average Fare Before	Average Fare After	Net Change in Traffic	Midpoint Elasticity
City Routes	$.0867	$.1037	-5.65%	-0.33
Suburban Routes	$.1241	$.1576	-9.28%	-0.41
System-Wide Routes	$.0924	$.1114	-6.21%	-0.34

[8] Kemp, Michael A. "Some Evidence of Transit Demand Elasticities," June 1973.

Shrinkage ratios from New York City fare changes are presented in Table II, p. 32 of Kemp's paper. Three shrinkage ratios corrected to discount the secular trend in ridership occurring during the period of the fare adjustment are used in this report. The important data from Table II include the following:

Mode	Year	Fare Before	Fare After	Shrinkage Ratio
Rapid Rail	July, 1948	\$.05	\$.10	-0.10
Rapid Rail	July, 1953	\$.10	\$.15	-0.16
Bus	July, 1953	\$.10	\$.15	-0.325

The following formula was used to convert these shrinkage ratios (e_{SR}) into arc elasticities (e_{arc}):

$$e_{arc} = \log\left[1 + (e_{SR} \times \Delta F/F_1)\right] \div \log\left(1 + \Delta F/F_1\right)$$

Shrinkage Ratio	Arc Elasticity
-0.10	-0.15
-0.16	-0.21
-0.325	-0.44

---

[9] Parody, Thomas E., and Daniel Brand. "Forecasting Demand and Revenues for Transit Prepaid Pass and Fare Alternatives," January 1979.

For comparative purposes, the shrinkage ratio presented on page 14 of Parody's paper was converted to a midpoint elasticity. The following data were used to calculate a midpoint elasticity:

- average system-wide fares increased from \$.25 to \$.33 (p. 11)
- net ridership loss was 10.7% of existing ridership (p. 12)
- simultaneous ridership loss due to a decline in bus-miles provided was (0.56) x (-0.86) = -0.48% (p. 13)

Therefore, the midpoint elasticity is: -0.39

[10] Lassow, William. "Effect of the Fare Increase of July 1966 on the Number of Passengers carried on the New York City Transit System," 1968.

In July 1966, New York City transit fares increased from $.15 to $.20. In this paper, Lassow reported ridership response information by mode, day of week, time of day, and income. Many disaggregate fare elasticities were calculated from this data base. Aggregate ridership data after the fare change is reported in Table 2, page 2. Weekday, Saturday, and Sunday after ridership figures are shown in Table 4. Table 3 presents the percentage ridership changes by mode and day of the week. This information and the midpoint elasticities are presented below. The combined bus and system-wide figures are weighted averages and not reported in Lassow's paper. The before ridership figures were obtained from the percent change and after ridership data.

All Hours	Annual Passengers Before (millions)	Annual Ridership Change (percent)	Annual Ridership After (millions)	Midpoint Elasticity
NYC Subway	1,274	-2.4	1,243	-0.09
NYC Bus	401	-9.8	362	-0.36
MaBSTOA Bus	406	-10.0	365	-0.37
Combined Bus	807	-9.9	727	-0.37
System-Wide	2,081	-5.3	1,970	-0.19

All Hours	Average Daily Ridership Before (millions)	Ridership Change (percent)	Average Daily Ridership After (millions)	Midpoint Elasticity
Regular Weekdays				
NYC Subway	4.28	-1.9	4.20	-0.07
NYC Bus	1.26	-9.4	1.14	-0.35
MaBSTOA Bus	1.27	-9.7	1.15	-0.36
Combined Bus	2.53	-9.5	2.29	-0.35
System-Wide	6.81	-4.7	6.49	-0.17
Saturdays				
NYC Subway	2.05	-4.1	1.97	-0.15
NYC Bus	0.92	-11.6	0.81	-0.43
MaBSTOA Bus	0.95	-10.5	0.85	-0.39
Combined Bus	1.87	-11.2	1.66	-0.42
System-Wide	3.92	-7.4	3.63	-0.27
Sundays				
NYC Subway	1.26	-1.0	1.25	-0.04
NYC Bus	0.55	-10.8	0.49	-0.40
MaBSTOA Bus	0.55	-9.5	0.50	-0.35
Combined Bus	1.10	-10.0	0.99	-0.37
System-Wide	2.36	-5.1	2.24	-0.18

The subway response rates shown in Table 6 on page 5 of Lassow's report was used to obtain time-of-day rapid-rail fare elasticities. However, the 24 hour subway ridership decrease reported in Table 6 (5.8%) is not in agreement with the average weekday figure just used (1.9%). Therefore, a new set of percentage decrease figures was obtained using the proportional values presented in Table 6 such that the 24-hour weighted average remains 1.9%. The complete time-of-day figures, as well as the subway midpoint elasticities are presented below.

Time Period	Distribution Before (percent)	Ridership Before (millions)	Ridership Decrease (percent)	Ridership After (millions)	Midpoint Elasticity
7 a.m. - 10 a.m.	31	1.33	0.80	1.32	-0.03
10 a.m. - 4 p.m.	21	0.90	2.68	0.88	-0.10
4 p.m. - 7 p.m.	30	1.28	1.67	1.26	-0.06
7 p.m. - 11 p.m.	10	0.43	4.88	0.41	-0.18
11 p.m. - 7 a.m.	8	0.34	1.24	0.34	-0.04
All Hours	100	4.28	1.90	4.20	-0.07

Lassow obtained information on low-income user ridership response from observations at 13 subway stations in low-income areas. In October 1965, 149,000 passengers entered stations in low income areas (p. 5). Using this figure and the data presented in Table 8, page 6, Ecosometrics calculated the low income subway fare elasticities presented below. Notice that the data on "commuter" stations were not used since during three time periods ridership increases were observed.

	Distribution Before (percent)	Ridership Before (thousands)	Ridership Decrease (percent)	Ridership After (thousands)	Midpoint Elasticity
7 a.m. - 10 a.m.	42	62.58	4.5	59.76	-0.16
10 a.m. - 4 p.m.	21	31.29	9.3	28.38	-0.34
4 p.m. - 7 p.m.	14	20.86	8.0	19.19	-0.29
7 p.m. - 11 p.m.	10	14.90	19.1	12.05	-0.74
11 p.m. - 7 a.m.	13	19.37	13.1	16.83	-0.49
All Hours	100	149.00	8.6	136.19	-0.31

Finally, aggregate off-peak and peak midpoint elasticities were calculated for subway trips. The weighted averages as well as the disaggregate before ridership and demand elasticities are presented on the next page.

OFF-PEAK — RAPID RAIL

Time Period	Ridership Before (millions)	Midpoint Elasticity
Midday	0.90	-0.10
Evening	0.43	-0.18
Late Night	0.34	-0.04
Saturday	2.05	-0.15
Sunday	1.26	-0.04
Weighted Average	4.98	-0.11

PEAK — RAPID RAIL

Time Period	Ridership Before (millions)	Midpoint Elasticity
Morning Peak	1.33	-0.03
Evening Peak	1.28	-0.06
Weighted Average	2.61	-0.04

[11] Curtin, John F. "Effect of Fares on Transit Riding", 1968.

In Table 2, page 14 of this paper, Curtin presents 13 shrinkage ratios from fare increases in eleven cities. For comparative purposes these values were converted to midpoint elasticities. The twelve values used in this report are shown below.

City	Fare Before (cents)	Fare After (cents)	Shrinkage Ratio	Midpoint Elasticity
New York-Omnibus (1954)	10	13	-0.30	-0.36
Chicago (1957)	20	25	-0.30	-0.33
Portland (1958)	20	25	-0.28	-0.33
Hartford (1958)	15	20	-0.28	-0.33
Atlanta (1963)	20	25	-0.28	-0.33
Cincinnati (1957)	20	25	-0.24	-0.28
San Francisco (1952)	10	15	-0.18	-0.24
Boston-Bus (1955)	13	15	-0.19	-0.21
Boston-Rapid Rail (1955)	19	20	-0.19	-0.20
Philadelphia (1954)	15	18	-0.14	-0.17
Salt Lake City (1963)	20	25	-0.12	-0.14
Baltimore (1958)	20	25	-0.08	-0.09

[12] Mundle, Subhash R., Wayne E. Weidemann, and Susan R. Roesch. "Transit Price Elasticities in St. Louis," 1978.

Table 1 on page 45 of Mundle's paper presents shrinkage ratios for 65 individual routes. Both local and express routes in Illinois and Missouri are provided. One route (Rt. 4032) had no observed ridership change. Midpoint elasticities were calculated by Ecosometrics for each of the remaining 64 cases. The results are shown below.

	Midpoint Elasticity (mean and standard deviation)
29 local routes in Missouri:	-0.19 ± 0.12
10 local routes in Illinois:	-0.35 ± 0.10
39 local routes:	-0.23 ± 0.13
21 express routes in Missouri:	-0.35 ± 0.15
4 express routes in Illinois:	-0.78 ± 0.36
25 express routes:	-0.42 ± 0.25
All 64 routes:	-0.31 ± 0.21

[13] Fairhurst, M.H. and R.S. Smith. Development and Calibration of London Transport's Scenario Model, September 1977.

Fairhurst's and Smith's research report presents ridership response data from several texts. Table 10 on page 28 presents data on the effects of increasing all public transit fares by 10 percent. Weekday passenger-trip data are available for three modes and for suburban, radial, and all trips. Ecosometrics computed midpoint elasticities from data on this table, as follows:

	Trips Before (thousands)	Trips After (thousands)	Midpoint Elasticity
Bus			
Suburban Trips:	1,823	1,759	-0.38
Radial Trips:	365	362	-0.09
All Bus Trips (millions):	1,376	1,335	-0.32
Rapid Rail (Tube)			
Suburban Trips:	344	335	-0.28
Radial Trips:	668	661	-0.11
All Rapid-Rail Trips: (millions)	655	639	-0.26
Commuter Rail			
Suburban Trips:	249	243	-0.26
Radial Trips:	567	564	-0.06
All Commuter-Rail Trips (millions):	252	249	-0.13

[14] Hicks, Kathy. A Study to Determine Consumer Reaction to Weekend Service Changes and to Evaluate the Downtown Transit Information Center Demonstration Program, March 29, 1979.

The weekend service and fare changes are outlined on page 3 of Hick's report. The following fare and service adjustments were made as part of the 3-phase demonstration in Madison, Wisconson:

Date	Change
Jan 18, 1975	Weekend fares reduced from $.25 to $.10.
March 15, 1975	Saturday headways reduced from 30 minutes to 20 minutes and on Sundays from 50 minutes to 30 minutes. The reduced $.10 fares were retained.
May 10, 1975	Service level held constant but $.25 fares restored.

The ridership response data comparing the demonstration period with ridership levels during the same period during the previous year is provided in Table 10, page 16. These percentage ridership increases are presented below along with the corresponding fare and headway elasticity.

	PERCENT RIDERSHIP CHANGE			MIDPOINT ELASTICITY		
	Saturday	Sunday	Total	Saturday	Sunday	Total
Reduced Fares	+27.1	+18.6	+24.6	-0.28	-0.20	-0.26
Increase Service (Adjusted for Reduced Fares)	+ 8.7	+31.9	-12.7	-0.21	-0.55	-0.26
Increase Fares (Adjusted for Increased Service)	-35.7	-43.1	-35.3	-0.51	-0.64	-0.50

[15] Schroeder, W.W. (1954) in Kemp, Michael A. "Some Evidence of Transit Demand Elasticities", June 1973.

On page 37, Kemp reports that on four successive Tuesdays in 1953, the Chicago Transit Authority reduced the base fare from $.20 to $.10 for trips taken between 9:30 a.m. and 1:30 p.m. Ridership increased approximately 6% during this period. The midpoint elasticity from this information is -0.09.

[16] Colman, Steven B. Case Studies in Reduced-Fare Transit: Portland's Fareless Square, April 1979.

Fare-free transit service began in Portland's CBD in January 1975. Prior to this date, Tri-Met operated a 10 cent "Shop Hop" shuttle bus service in the downtown area. In 34 months, ridership on the CBD fare-free system increased nine-fold, from an estimated 900-1,000 to 8,200 trips per day (p. 15). Tri-Met system-wide ridership increased 43 percent over this period from approximately 86,000 average weekday riders to approximately 123,000 average weekday riders (Figure 7, page 10). Assuming CBD ridership was at 1,000 passengers per day before fare-free service, only 1,430 daily passengers would have been using CBD service in November 1977 had the 10 cent fare been retained. This figure, assumes a CBD-ridership growth rate equal to that of the system as a whole.

A midpoint elasticity for all-hour CBD service can then be computed from the following:

Ridership With 10-Cent Fare	Ridership Without 10-Cent Fare	Midpoint Elasticity
1,430	8,200	-0.70

CBD ridership during the midday period (i.e., 11 a.m. to 2 p.m.) increased from 11 to 19 percent of all CBD ridership between January — when the service began - and May of that same year (p. 16). Assuming midday ridership remained at 19 percent of all CBD trips in November 1977, then the midday midpoint elasticity would be -0.81.

Note that there were several actions taken simultaneously by Tri-Met that would affect CBD ridership:

- 35¢ to 75¢ zone fare changed to 35¢ flat fare (p. 13).
- introduction of monthly passes (p. 13).
- a 0.6% increase in bus-hours of service especially during the afternoon peak (p. 13).

Case Studies in Reduced-Fare Transit: Seattle's Magic Carpet, April 1979. This case study of Seattle's magic carpet was also analyzed by Steven B. Colman.

Free-fare Magic Carpet service began in September 1973. Fare before fare-free service was \$.20 and \$.10 for the off-peak "Dime Shuttle" service. During a 10-month period between July 1973 and May 1974, ridership increased from 4,100 to 12,250 trips per weekday (p. 15). Annual ridership on the entire Seattle Metro system increased in 1973 from 32,391,000 passenger trips to 35,466,000 passenger trips in 1974.[1] This represents a 9.49 percent ridership increase.

[1]Data obtained from Seattle Metro by Ecosometrics, Inc. and contained in: Mayworm, Patrick. "Intermodal/Interagency Fare Prepayment Demonstration: Candidate Site Visit — Seattle, Washington." Memorandum to Bert Arrillaga, Urban Mass Transportation Administration, U.S. Dept. of Transportation, Ecosometrics, Inc., Bethesda, Maryland, August 25, 1978.

Applying this secular trend to CBD ridership before fare-free service, ridership would have been 1.0949 x 4100 = 4489 had fares not been reduced. Therefore, the midpoint elasticity is -0.46.

Data on midday ridership response was obtained from Figure 11, page 17. The approximate ridership values are presented below:

	Before	After
11 a.m. - 12 noon	500	800
12 noon - 1 p.m.	1,100	5,600
1 p.m. - 2 p.m.	825	1,200
TOTAL MIDDAY	2,425	7,600

Applying the same annual ridership rate of growth:

$$(2425) \times (1.0949) = 2655$$

$$e = -0.52$$

---

[17] Nagin, Daniel and Ellyn Eder. "Albany Fare-Free Zone Demonstration." Memorandum, June 29, 1979.

The Albany off-peak CBD fare-free demonstration was implemented in November of 1978. Since that time, the Capital District Transit Authority (CDTA) has been making regular counts of passengers in the "Free-Fare Zone." The mean before and after ridership figures are presented in Figure 2-1 of the memorandum and shown below.

	Ridership Before	Ridership After	Midpoint Elasticity
Weekday	1,006	2,870	-0.48
Saturday	276	1,080	-0.60
All Off-Peak	1,276	3,950	-0.51

Midday fare before the demonstration was $.40.

Although sufficient data have not been presented in the memorandum to enable Ecosometrics to calculate the peak/off-peak cross-elasticities, it appears that morning peak-period ridership has not shifted to late morning; however, there has been a large increase in mid-afternoon ridership, assumed attracted from the afternoon peak. Evidently, many afternoon peak riders are not commuters (i.e., they may be shoppers returning home) thus making afternoon peak riders appear more elastic to off-peak fare reductions than morning peak riders.

Other observations made in the memorandum include:

- trip lengths have shortened (i.e., diversion from walk trips)
- large percentage of infrequent transit users and auto users are riding.

---

[18] Passenger Transport. "Free Day Scores with Tulsa Riders," November 23, 1979.

From this article Ecosometrics obtained the following data:

Average Saturday Ridership	"Free-Day" Saturday Ridership	Midpoint Elasticity
3,900	7,194	-0.30

Normal Saturday fare is \$.35.

---

[19] Damm, David. "Knoxville Service and Fare Demonstration Project: Progress Report for April, 1979".

This two-page progress report contains an approximation of the intra-CBD ridership growth from pre-implementation levels. The basic data is provided below.

- fare reduced from \$.35 to zero
- ridership increased approximately 238% over an 18-month period.

$$e = -0.41$$

---

[20] Hoel, Lester A., and Ervin S. Roszner. "Impact of Reduced Transit Fares for the Elderly," July 1972.

The following important data was provided in their paper on the evaluations of the Pittsburgh program of reduced fares for the elderly.

- average one-way trip costs decreased from \$.34 to \$.19 (p. 345)
- change in annual number of round trips because of the fare reduction (p. 355):

	Expected	Actual
Off-Peak	3,117,000	4,719,000
Peak	2,312,000	1,867,000
Total	5,429,000	6,586,000

Off-Peak: $e = -0.72$

Peak/Off-Peak: $e = +0.38$

---

[21] Systan, Inc. Sacramento Transit Fare Prepayment Demonstration: Results of the Second Employee Survey, February 1979.

During the three-month period from October to December 1978, monthly transit passes sold to participating employees were discounted 25% from $12 to $9 per month. The ridership statistics resulting from the price reduction are presented in Appendix A of Systan's report. The relevant data are reproduced below:

Daily Ridership Before

• pass users commuting:	1,485 persons	2,810 trips
• cash users commuting:	3,170 persons	2,866 trips
• all non-work trips:	4,655 persons	1,122 trips
	TOTAL	6,798 trips

Daily Ridership in December

• pass users commuting:	2,802 persons	5,194 trips
• cash users commuting	2,273 persons	1,373 trips
• all non-work trips:	5,075 persons	1,204 trips
	TOTAL	7,771 trips

Assuming all non-work trips are distributed between pass and cash users proportionally to the number of individuals in each group, then:

Daily Ridership Before

Pass users:	work trips	2,810 trips
	non-work trips	358 trips
	TOTAL PASS:	3,168 trips
Cash users:	work trips	2,866 trips
	non-work trips	764 trips
	TOTAL CASH:	3,630 trips

Daily Ridership in December

Pass users:	work trips	5,194 trips
	non-work trips	656 trips
	TOTAL PASS:	5,850 trips
Cash users:	work trips	1,373 trips
	non-work trips	548 trips
	TOTAL CASH:	1,931 trips

Average trip cost was estimated from the number of individual pass purchasers and the average trip rate. Thus:

Average Cost Per Trip Before

Pass: 1,485 passes x \$12 = \$17,820/month

3,168 daily trips x 20 days/month = 63,360 trips per month

\$17,820 ÷ 63,360 = \$.28125 per trip

Cash: \$0.35 per trip

Average Cost Per Trip in December

Pass: 2,802 passes x \$9 = \$25,218/month

5,850 daily trips x 20 days/month = 117,000 trips/month

\$25,218 ÷ 117,000 = \$.21554 per trip

Cash: \$0.35 per trip

From the above data, the following midpoint elasticities were computed:

Work Trip

Demand before = 5,676 trips

$$\text{Average fare} = \frac{(2810 \times .28125) + (2866 \times .35)}{5{,}676} = \$.31596$$

Demand after = 6,567 trips

$$\text{Average fare} = \frac{(5{,}194 \times .21554) + (1{,}373 \times .35)}{6{,}567} = \$.24365$$

$$e = -0.56$$

Non-Work Trip

Demand before = 1,122 trips

$$\text{After fare} = \frac{(358 \times .28125) + (764 \times .35)}{1{,}122} = \$.32806$$

Demand after = 1,204 trips

$$\text{Average fare} = \frac{(656 \times .21554) + (548 \times .35)}{1{,}204} = \$.27674$$

$$e = -0.42$$

All Trips

Demand before = 6,798 trips

$$\text{Average fare} = \frac{(3{,}168 \times .28125) + (3{,}630 \times .35)}{6{,}798} = \$.31796$$

Demand after = 7,771 trips

$$\text{Average fare} = \frac{(5{,}850 \times .21554) + (1{,}931 \times .35)}{7{,}771} = \$.24923$$

$e = -0.55$

---

[22] Wilbur Smith and Associates. Chesapeake Mass Transportation Demonstration Project, January 1969.

Data on inbound transit service from Chesapeake to Norfolk are presented in Table 4, page 14 and Table 7, page 20. A summary of the relevant data is presented below.

A.M. Peak: 5:30 a.m. - 9:00 a.m. (3.5 hours)

	Before	After
No. of buses:	3	6
Average headway:	70 min.	35 min.
Ridership:	80	119

$e = -0.58$

Midday: 9:00 a.m. - 3:00 p.m. (6 hours)

	Before	After
No. of buses:	1	10
Average headway:	360 min.	36 min.
Ridership:	18	101

$e = -0.85$

Evening: 7:00 p.m. - 10:30 p.m. (3.5 hours)

	Before	After
No. of buses:	1	5
Average headway:	210 min.	42 min.
Ridership:	4	11

$e = -0.70$

All Hours:	5:00 a.m. - 10:30 p.m. less the one-hour period from 5:00 p.m. to 6:00 p.m.[1] (16 hours)	
	Before	After
No. of buses:	8	26
Average headway:	120 min.	37 min.
Ridership:	119	289

$$e = -0.79$$

The afternoon peak period was not included in this report as a disaggregate category because of the data problem during the 5-6:00 p.m. period and also because this is a reverse-commute direction during the afternoon.

[1]There are two problems with the data from this one-hour period. A line in Table 4 during this period is missing. Thus, buses during the entire day during the demonstration total 26 buses and not 27. Also, in Table 7 ridership increased from 4 trips to 41 trips during the 5-6 p.m. period — a 925% increase. This period was excluded from the all-hours calculation.

[23] City of Detroit. Grand River Avenue Transit Survey, January 1963.

The relevant headway and ridership data appear in Tables I, VI, VII, VIII, and IX. Ecosometrics' headway elasticities were calculated from the figures presented below.

		Local Service	
PEAK PERIOD	Fridays	Mondays	Total
Headway before:	3.5 min.	4 min.	3.68 min.
Ridership before:	22,257	12,145	34,402
Headway after:	2 min.	2 min.	2.0 min.
Ridership after:	19,852	17,884	37,736
		Express Service	
Headway before:	6 min.	8 min.	6.71 min.
Ridership before	3,825	2,117	5,942
Headway after:	3 min.	4 min.	3.43 min.
Ridership after:	3,401	2,589	5,990
Peak-period elasticity (including local and express service)			-0.13

MIDDAY	INBOUND Friday	INBOUND Monday	OUTBOUND Friday	OUTBOUND Monday	Total
Ridership before	5,160	6,810	4,260	6,190	22,420
Ridership after	5,915	6,916	5,580	6,510	24,921
Headway before	6	5	6	5.5	5.56
Headway after	3.5	3.5	3.5	3.5	3.50
EVENING					
Ridership before	1,400	1,200	2,120	2,137	6,857
Ridership after	1,934	1,484	2,290	2,480	8,188
Headway before	15	12	15	10	12.92
Headway after	10	10	8	8	8.84

Midday elasticity = -0.23
Evening elasticity = -0.47

SATURDAY	12:00 mid-6:00 a.m.	6:00 a.m.-12:00 noon	12:00 noon-6:00 p.m.	6:00 p.m.-12:00 mid.	Total
Ridership before	1,178	7,300	9,966	2,960	21,404
Ridership after	1,285	7,700	10,805	3,643	23,433
Headway before	24	8	6	14	8.78
Headway after	20	5	3.5	9	5.75
SUNDAY					
Ridership before	889	2,013	3,073	1,491	7,466
Ridership after	798	2,657	3,855	2,231	9,541
Headway before	24	18	16	20	18.29
Headway after	19	9.5	9.5	15	11.58

Saturday elasticity = -0.22
Sunday elasticity = -0.54

ALL HOURS

Ridership before	98,491
Ridership after	109,810
Headway before	7.15
Headway after	4.56

All-hours elasticity = -0.25

[24] Carstens, R. L. and L.H. Csanyi. "A Model for Estimating Transit Usage in Cities in Iowa," 1968.

Carstens' and Csanyi's model is as follows:

$$R_c = -33.97 + 1.46W + 0.033C + 3.00S$$

where

R_c = passengers per capita (for service area)

W = work force factor = $N (\log P)$

C = city size and cost factor = $(\log P)^3/F$

S = service factor = M/P_s

N = non-worker/worker ratio for central city

P = population of central city of service area

F = average fare

M = annual revenue - miles of service

P_s = population of transit service area

Service Elasticity (evaluated at the mean)

$$e = \left(\frac{dR_c}{dS}\right) \left(\frac{\bar{S}}{\bar{R}_c}\right) = +3.00 \frac{\bar{S}}{\bar{R}_c}$$

$\bar{S}$ = 8.62 annual revenue miles per capita (Table 3, p. 47).

$\bar{R}_c$ = 19.95 annual ridership per capita (Table 3, p. 47)

$$e = 3 \left(\frac{8.62}{19.95}\right) = +1.30$$

Fare Elasticity (evaluated at the mean)

$$e = \left(\frac{dR_c}{dF}\right) \left(\frac{\bar{F}}{\bar{R}_c}\right) = -0.033 \frac{(\log \bar{P}_s)^3}{\bar{F}\ \bar{R}_c}$$

Assume P (population of city proper) = P_s

	1960 City Population[1]
Des Moines	208,000
Cedar Rapids	88,292
Sioux City	89,018
Dubuque	56,019
Council Bluffs	55,438
Iowa City	28,063
Ames	21,318
Ottumwa	33,437
Clinton	33,539
Burlington	32,509
Fort Dodge	28,105
Marshalltown	22,042
Muscatine[2]	22,194
$\bar{P}$ =	55,229

$\bar{F}$ = \$.193

$\bar{P}$ = 55,229

$\bar{R}_c$ = 19.95 annual ridership per capita

$$e = \frac{-0.033\ (\log 55{,}229)^3}{(.193)\ \ (19.95)} = -0.91$$

[1]U.S. Department of Commerce, County and City Data Book 1972: A Statistical Abstract Supplement, 1973.

[2]Not in census book. Used 1966 population from Table 1, p. 44 in Carstens and Csanyi

---

[25] Voorhees, Alan M., and Associates, Inc. Blue Streak Bus Rapid Transit Demonstration Project, June 1973.

This report analyzes the results of the Blue Streak demonstration in Seattle, Wash. The routes considered in this analysis were only those directly affected by the Blue Streak operation. The figures presented below were taken from Figure C-5 on pages C-5 and C-6, and allocated to three time periods based on the proportions presented in Figure C-3. The time periods are:

6 a.m. - 9 a.m.	(AM Peak)
9 a.m. - 4 p.m.	(Off-Peak)
4 p.m. - 8 p.m.	(PM Peak)

In addition, transit demand for northbound (NB) and southbound (SB) travel was provided. Allcoated to the three time periods, the following ridership figures were calculated by route. All Route 7 runs were combined.

BEFORE DEMONSTRATION – DAILY RIDERSHIP FIGURES

		Rt. 5	Rt. 7		Rt. 8		Rt. 16		Rt. 22	
		Local	Local	Express	Local	Express	Local	Express	Local	Total
AM Peak	SB	749	1,026	590	291	148	310	170	295	3,579
	NB	235	322	NS	91	NS	97	NS	92	837
Off-Peak	SB	940	1,289	NS	365	NS	390	NS	370	3,354
	NB	706	968	NS	274	NS	292	NS	278	2,518
PM Peak	NB	834	1,144	658	324	165	346	190	329	3,990
	SB	301	412	NS	116	NS	125	NS	119	1,073
14 Hr. Total		3,765	5,161	1,248	1,461	313	1,560	360	1,483	15,351

NS = No Service

WITH DEMONSTRATION — DAILY RIDERSHIP FIGURES

		Rt. 5		Rt. 7		Rt. 8		Rt. 16		Rt. 22		
		Local	BS	Local	Express BS	Local	Express BS	Local	Express BS	Local	BS	TOTAL
AM Peak	SB	716	263	645	1,108	142	223	360	141	90	186	3,874
	NB	136	50	123	210	27	42	68	NS	17	35	708
Off-Peak	SB	649	238	585	1,004	129	202	326	101	82	169	3,485
	NB	532	195	479	823	106	165	267	83	67	138	2,855
PM Peak	NB	806	296	725	1,246	160	250	405	155	101	209	4,353
	SB	233	86	209	361	46	72	116	NS	29	61	1,213
14 Hr. Total		3,072	1,128	2,766	4,752	610	954	1,542	480	386	798	16,488

NS = No Service
BS = Blue Streak Service

Express bus service on I-5 was combined with Blue Streak service on Routes 7, 8, and 16. In addition, after ridership data on two express routes were combined in the report. The numbers shown above for Rt. 8 and Rt. 22 were disaggregated from their combined values in proportion to their respective ridership levels before Blue Streak service. For example:

Total Rt. 22 ridership before = 1,483

Total Rt. 22 & Rt. 8 ridership before = 1,483 + 1,461 + 313 = 3,257

Therefore, the RT.22 proportion is: $\frac{1,483}{3,257} = 0.4553$

Aggregate express and Blue Streak ridership on Rt. 22 and Rt. 8 after Blue Streak service was initiated was 1,752 passengers. Thus, Blue Streak ridership on Rt. 22 alone was:

$$(1,752) \times (0.4553) = 798$$

$$\text{Rt. 8 ridership} = 1,752 - 798 = 954.$$

IN-VEHICLE TRAVEL TIME

		Rt. 5		Rt. 7[a]			Rt. 8			Rt. 16[b]			Rt. 22	
		Local	BS	Local	Express	BS	Local	Express	BS	Local	Express	BS	Local	BS
AM Peak	SB	41	34	48	45	36	50	43	40	53	40	38	40	36
	NB	35	33	39	NS	35	47	NS	39	43	NS	NS	50	41
Off-Peak	SB	34	31	43	NS	40	45	NS	40	52	NS	38	37	37
	NB	36	35	41	NS	39	48	NS	40	47	NS	38	42	37
PM Peak	NB	45	43	49	42	37	56	47	49	51	37	39	42	33
	SB	32	30	44	NS	44	45	NS	45	51	NS	NS	41	34

[a]Averages of all three "7" routes

[b]Off-peak period in-vehicle times for Rt. 16 are a.m. and p.m. peak period averages.

On the basis of the data just presented, Ecosometrics calculated in-vehicle travel-time elasticities as follows:

	Peak Period (Peak Direction)	Peak Period (Reverse Commute)	Off-Peak Midday
Ridership before BS:	7,569	1,688	5,872
Ridership with BS:	8,227	1,737	6,340
Weighted average travel time before BS (minutes):	45.89	39.81	41.12
Weighted average travel time with BS (minutes):	37.98	37.78	37.50
In-vehicle travel-time elasticity:	-0.44	-0.55	-0.83

In addition to the reduced travel time, other service improvements were made. Bus frequency, for example, increased 12.42% over the period considered in this analysis.

[26] Wattleworth, Joseph H., Kenneth G. Courage, and Charles E. Wallace. Report II-2 Evaluation of the Effects of the I-95 Exclusive Bus/Carpool Lane Priority System on Vehicular and Passenger Movement, September 1978.

This report covers a priority lane demonstration in Miami, Florida. Before ridership data presented in Appendix A, pages A-3 through A-24, were projected to the period during which the demonstration took place. This was done in order to estimate transit passenger levels had the service improvement not been made. The time-trend analysis was performed using the following formula:

$$\frac{Q_i}{Q_{i-12}} = e^{\alpha_0} (1 + 1/Q_{i-12})^{\alpha_1}$$

where:

Q_i = actual ridership during month i

Q_{i-12} = actual ridership during the same month i of the previous year.

α_0, α_1 = regression coefficients and are different for each route and time period

The regression equation was calibrated for each route and time period. The simple correlation for each regression is presented below.

Route	Time Period	Correlation
Downtown	a.m.	+0.94
	p.m.	+0.89
Civic Center	a.m.	+0.94
	p.m.	+0.90
36th Street	a.m.	+0.91
	p.m.	+0.91

The ridership figures during the demonstration period were obtained from Appendix A, pages A-1 through A-3 of Wattleworth's report. The travel time information was taken from Figure 3.1, page 3-2. The midpoint elasticity estimates for peak period demand with respect to in-vehicle travel time are presented on the next page. Three, six, and twelve month estimates were made; however, only the 12-month figures were used in this report.

	Ridership with I-95 Express	Ridership Without I-95 Express	Travel Time with I-95 Express	Travel Time Without I-95 Express	Midpoint Elasticity
Downtown--A.M.					
3-month	1,617	1,530	18.4	22.1	-0.30
6- month	3,261	3,068	18.4	22.1	-0.33
12-month	6,599	6,140	18.4	22.1	-0.39
Downtown--P.M.					
3-month	1,618	1,565	22.9	29.6	-0.13
6-month	3,271	3,136	22.9	29.6	-0.17
12-month	6,574	6,268	22.9	29.6	-0.19
Civic Center--A.M.					
3-month	479	453	18.8	26.0	-0.17
6-month	967	908	18.8	26.0	-0.20
12-month	1,957	1,811	18.8	26.0	-0.24
Civic Center--P.M.					
3-month	360	349	20.9	28.1	-0.11
6-month	728	699	20.9	28.1	-0.14
12-month	1,463	1,399	20.9	28.1	-0.15
36th Street--A.M.					
3-month	268	255	18.1	26.1	-0.14
6-month	541	509	18.1	26.1	-0.17
12-month	1,096	1,022	18.1	26.1	-0.19
36th Street--P.M.					
3-month	237	230	26.1	30.5	-0.19
6-month	481	461	26.1	30.5	-0.27
12-month	966	921	26.1	30.5	-0.31

---

[27] Dupree, John H. and Richard H. Pratt. A Study of Low Cost Alternatives to Increase the Effectiveness of Existing Transportation Facilities — Results of Case Studies and Analysis of Busway Applications, January 1973.

Very limited demand response information is available on the Boston Southeast Expressway and exclusive bus lane. In Table 3-6, page 51 of Dupree's and Pratt's report, the following information is provided:

	Before	After
Bus Passengers	2,152	2,454
Bus Travel Time	24 minutes	10 minutes

From this data, the in-vehicle travel-time elasticity is -0.16.

---

[28] McLynn, James M., and Keith M. Goodman. Mode Choice and the Shirley Highway Experiment, November 1973.

This report covers the results of the Shirley Highway Demonstration in the Nation's Capital. The McLynn and Goodman report presents the data used in the calibration of the competitive, logit, and utile mode-choice models. Table 9.3, page 9-18 presents information on the ridership response to policy options for each of the three models. The results of the logit model to two policy options are presented below.

Reduce bus cost 10 cents: 8.1% increase in patronage

The weighted average bus cost is \$.73 from page 4-22 of the report.

$$e = -0.53$$

Reduce bus travel-time 10%: 12.8% increase in patronage

The weighted average bus travel-time is 46.5 minutes from page 4-20 of the report.

$$e = -1.14$$