Effects Of Fare Changes On Bus Ridership

American Public Transit Association
1201 New York Avenue, NW
Washington, DC 20005

May 1991

APTA

FOREWORD

This publication is an abridged version of the full report *Fare Elasticity and its Application to Forecasting Transit Demand*.[1] This study represents the first comprehensive effort to estimate the fare elasticities of a large number of transit systems using monthly data, and to test the applicability of the well known Simpson-Curtin formula in today's transit environments.

The study provides a general approximation of system-wide bus ridership loss following a uniform fare increase (without changing the fare structure). It is not intended to replace detailed fare elasticity estimates conducted for specific transit systems.

The authors of the report are Larry H. Pham, Ph.D., Director of Research and Statistics, and Jim Linsalata, Manager of Research, American Public Transit Association.

The analysis has shown that the impact of fare changes on bus ridership, while varying substantially among cities and between peak and off-peak hours, is more pronounced than previously believed.

---

[1]American Public Transit Association, Research and Statistics Division, August 1991.

ABSTRACT

Transit managers are under increasing pressure to obtain sufficient fare revenues to maintain high-quality service while reducing dependence on government assistance. They need an accurate formula to estimate the impacts of fare changes on transit ridership and fare revenues. For years, these managers were given two choices: constructing a fare elasticity model specific to their transit systems or applying the Simpson-Curtin formula which postulates a fare elasticity of -0.33; i.e., a ten percent increase in fare would result in a 3.3 percent decrease in transit patronage.

The models are usually costly and time-consuming to construct, causing delays in the implementation of fare changes. On the other hand, the 30-year-old Simpson-Curtin formula is likely to be inaccurate today. Further, it provides no estimation of the varying fare impacts between peak and off-peak hours, or between large and small cities.

The objectives of this study are to verify the Simpson-Curtin formula using updated data and modern technologies, and to provide a set of fare elasticity estimates for bus service in various cities during peak as well as off-peak hours.

An advanced econometric model, the Autoregressive Integrated Moving Average (ARIMA) model, was used for the estimations. A special survey was conducted to obtain ridership data 24 months before and 24 months after each fare change for 52 transit systems. Monthly information on other factors which may influence ridership, including gasoline price, vehicle miles of service, labor strikes, etc., were also collected. The purpose was to use the model to isolate the impacts of the fare changes from those caused by other factors.

Findings

- On the average, *a ten percent increase in bus fares would result in a four percent decrease in ridership* [elasticity = -0.40; the negative sign (-) indicates that fare and ridership move in opposite directions]. This shows that today's transit users react more severely to fare changes than found by Simpson and Curtin.

FARE ELASTICITY - BUS SERVICES	
Average (all buses, all cities)	-0.40

- Transit riders in small cities are more responsive to fare increases than those in large cities. *The fare elasticity for bus service is found to be -0.36 for systems in urbanized areas of 1 million or more population. In urbanized areas with less than 1 million people, the elasticity is -0.43.*

- Although the data for peak vs. off-peak services are available for only six transit systems, the difference between the fare elasticity levels is very clear: *The average peak-hour elasticity is -0.23 while the off-peak hour elasticity is -0.42*, indicating that peak-hour commuters are much less responsive to fare changes than transit passengers travelling during off-peak hours.

Fare Elasticity Estimates - Bus Services

	CITIES/AREAS WITH	
	More Than 1 Million Population	Less Than 1 Million Population
Average for all hours	**-0.36**	**-0.43**

Peak hour average	**-0.23**	
Off-peak average	**-0.42**	
Peak hours	-0.18	-0.27
Off-peak	-0.39	-0.46

Source: American Public Transit Association, 1991

INTRODUCTION

Fare elasticity measures the response of transit patronage to fare changes. In a simple mathematical sense, it is defined as the ratio of percentage change in ridership to a percentage change in fare. For example, if a one percent increase in fare results in a half percent decrease in ridership, the fare elasticity is -0.5. The negative sign (-) indicates that fare and ridership move in opposite directions. If the absolute value of fare elasticity is greater than 1 (e.g., elasticity = -1.2), any increase in fare would cause a larger decline in ridership, resulting in a decrease of total fare revenue. Alternatively, an absolute fare elasticity of less than 1 implies that a fare increase will result in increased revenues. Knowledge of fare elasticity is extremely important for transit managers, as it provides information on the expected ridership and farebox revenue resulting from a proposed fare change.

The impact of fare on transit ridership has been an unsettled issue for many decades. While it generally is recognized that a fare increase would result in some ridership decrease, the magnitude of such decrease is difficult to measure and can vary greatly among transit systems. The problem stems from the fact that ridership does not respond to fare changes immediately. However, over a longer time period, the observed ridership changes may be caused by factors other than the fare change, resulting in an erroneous elasticity estimation.

Dozens of fare elasticity studies have been completed in the past decades. Many suffer from serious analytical shortcomings rendering the results questionable. Others are either overly complicated or overly specific to individual transit properties. For example, fare elasticities are commonly estimated on specific routes for specific transit systems. The results cannot be generalized, and the usefulness of the studies are limited to the particular situations for which the studies are designed. As a result, most smaller and medium-size transit operators with limited research resources have often made important fare decisions based on a simple rule of thumb which assumes a fare elasticity value of -0.33 for all transit routes during all times of day. This method, commonly referred to as the Simpson-Curtin formula[2], is inadequate to meet the information needs for determining fare policies.

This study attempts to establish a fare elasticity estimation procedure that preserves the Simpson-Curtin simplicity while using the econometric methods and computer technology of the 1990s. The purpose of this study is two-fold. First, it develops an advanced econometric model, **the transfer function model**, to be applied by transit systems in estimating fare elasticities. Secondly, the results are used to search for a pattern of fare elasticity behavior which enables those transit systems without a modeling capability to arrive at an approximate elasticity estimate by using those of similar systems. To accomplish these purposes, the fare elasticities of a

[2]John F. Curtin, "Effect of Fares on Transit Riding", *Highway Research Record*, No. 213, 1968.

sample of fifty-two transit systems are estimated, with six systems having the elasticities broken down to peak and off-peak hours. The sample is selected such that transit systems of different sizes, serving large cities as well as small rural areas are represented. Clearly, this method is not as desirable as applying the model directly for elasticity estimation. However, it is superior to indiscriminate use of the Simpson-Curtin rule of thumb.

METHODOLOGY

Overview

Popular methods used for estimating transit fare elasticity may be divided into three broad categories:

- Preference Survey
- Shrinkage Analysis
- Econometric Studies

Preference Survey. Surveys are conducted to obtain information on the intended modes of travel under various conditions. For example, survey respondents are asked if they intend to commute to work by car or transit if the bus fare is raised by 25 cents, waiting time averages 10 minutes, and the parking cost is $60 per month. With a large number of responses on similar questions, it is possible to statistically estimate the relative importance of the fare, service attributes and other transportation factors to determine the fare elasticities for various market segments.

A major shortcoming of this approach is that the respondents' intentions may and usually do differ from the actual events. A Chicago study[3] found that this method resulted in high elasticity estimates because individuals responding to the questionnaire had assumed that a car would be available for their journey, whereas in practice this was not always the case.

Shrinkage Analysis. This approach measures fare elasticities by monitoring the ridership levels prior to and after a fare change. Fare elasticity is estimated by computing the ratio of the percentage change in ridership to percentage change in fare.

This method is simple, but may not provide accurate results because of unavoidable outside interferences. For example, if a transit authority raises fare on June 1, the observed decrease in ridership may also be caused by fewer student riders as the summer vacation begins. Taking the ratio of ridership change to fare change between May and June would capture the effects of both the fare change and the school year seasonality, resulting in an erroneous fare elasticity estimate. The June ridership may be compared to the previous year's June ridership to avoid seasonal bias. The results of this comparison could be misleading since other fac-

[3]C. Phillips Cummings, et al., "Market Segmentation of Transit Fare Elasticities", *Transportation Quarterly*, July 1989, pp.418-19.

tors, such as changes in gas prices and transit service, may have influenced ridership during this twelve month span.

Econometric Studies. Most popular among this group is regression analysis, which uses historical data to estimate the demand function for transit patronage. Econometrics allows the relationship between ridership and its influential factors such as fare, time of day, trip purposes, cost of alternative modes, and socioeconomic characteristics of the population to be expressed in mathematical forms. The effects of fare changes on transit patronage can then be isolated to arrive at unbiased fare elasticity estimates. The model may be a *cross sectional analysis* which uses data over many geographic areas for a given point in time, or *a time series analysis* which models the variation of fare and demand over time.

From a theoretical standpoint, the time series analysis is a preferred method. The *cross sectional analysis*, which does not consider the effects of time, may not adequately capture the responses of individuals or cities in response to fare changes over time. Rather, it reflects how different population segments behave at different fare levels. For lack of better terms, cross-sectional models are often considered as an indication of "long run adjustments." Thus, although cross-sectional estimates have some advantage in forecasting structural changes in demand, it cannot be used to measure the short run responses of ridership to fare changes with a reasonable degree of confidence unless supporting time series information is available. Nevertheless, data limitations frequently necessitate independent use of cross-sectional analysis in fare elasticity research and ridership forecasting.

On the other hand, traditional *time series analysis* also suffers drawbacks. This approach commonly involves regression analysis in which the ordinary least square (OLS) method is used to fit transit demand functions. Several crucial assumptions, including one requiring no serial correlation present in the error term, are usually violated, rendering the estimated transit demand function biased and the fare elasticities unreliable. This well-known autocorrelation problem has been an unresolved issue facing researchers for decades.

The Transfer Function Model

The present study is a time series analysis. However, it eliminates the autocorrelation and other methodological deficiencies by applying the transfer function model to estimate the transit demand function and fare elasticities. This model is an extended version of the Autoregressive Integrated Moving Average (ARIMA) or Box-Jenkins model, made popular among researchers because of the revolutionary advancement of computer technology.

The *transfer function model* represents a substantial improvement over the standard OLS-time series method in two major aspects. First, it eliminates not only the autocorrelation, but also the multicollinearity and inefficient estimates problems which are common in OLS models. Secondly, it allows for a richer dynamic structure in the relationship between the dependent variable (transit demand) and the explanatory variables (fare, services, gas price, etc.). The model is able to isolate the seasonal fluctuation of transit ridership and capture the delayed effects of ridership responses to fare changes.

When the function is expressed in natural logarithm, the coefficient of the fare variable measures the change in ridership in response to fare change which is, by definition, the fare elasticity. Monthly time series data for fifty-two individual transit systems are used to estimate their transit demand functions.

Data Collection

A special survey was conducted to obtain monthly data for four year periods, 24 months before to 24 months after the latest identified fare change date for each transit system. The data requested included monthly ridership, vehicle miles, vehicle hours, basic adult cash fare, and total farebox revenues during peak and off-peak periods. Other information such as work stoppages and variation in peak-hour definitions were also collected. In addition, monthly data were gathered from nationally published sources on local consumer price indexes, gasoline prices, and local employment for use in the model.

In total, 189 survey questionnaires were mailed to transit operators, and 79 were returned before the internal deadline.

Transfer Function Model Functional Form

The transfer function model takes the following general form:

$$R_t = f\,(SL_{t-k}\,,\ FC_{t-k}\,,\ AC_{t-k}\,,\ MC_{t-k}\,,\ I_{t-k}) + e_t$$

where:

R_t = Transit ridership, measured by unlinked transit passenger trips.

SL_{t-k} = The service level, measured by revenue vehicle miles and/or revenue vehicle hours.

FC_{t-k} = Transit cost, measured by average fare, deflated by the local consumer price indexes.

AC_{t-k} = Cost of major alternative modes, measured by gasoline price.

MC_{t-k} = Market characteristics or the size of the transportation market, approximated by the number of people employed locally.

I_{t-k} = Intervention factors. These include, where appropriate, work stoppages, gasoline shortages and other abrupt changes. The I variables are given the value of 1 during the event and 0 otherwise.

e_t = Disturbance term

t = Time period

k = Time lag

The response rate of 42 percent is considered very high for this type of survey as many transit systems do not keep monthly operating data. Twenty-eight returned questionnaires were unusable, resulting in 52 useable questionnaires and a useable response rate of 28 percent.

Model Application

The Time Transfer Function model was applied to fifty-two transit systems in cities of various sizes, ranging from 51,000 to nearly 10 million in population. In six cases, for which data are available, the transit demand functions were estimated for peak hours as well as off-peak hours.

Generally, the economic behavior of the transit riders is well predicted by the model. The corrected coefficient of determination ($\bar{R}^2$) ranges from 0.51 to 0.97, denoting that more than 50 percent and up to 97 percent of the fluctuation in transit ridership is explained by the model. Twenty-five cases have a $\bar{R}^2$ of 0.80 or higher, and for seven cases, the model is able to explain more than 90 percent of the ridership variations. Figures 1, 2 and 3 depict examples of how the model performs at different $\bar{R}^2$ levels.

The t-statistics indicate that the fare elasticity coefficients are statistically significant at the 90 to 99 percent confidence level.

Figure 1. Actual vs. Estimated Unlinked Passenger Trips: $\bar{R}^2$=0.92 (Denver, Colo.)

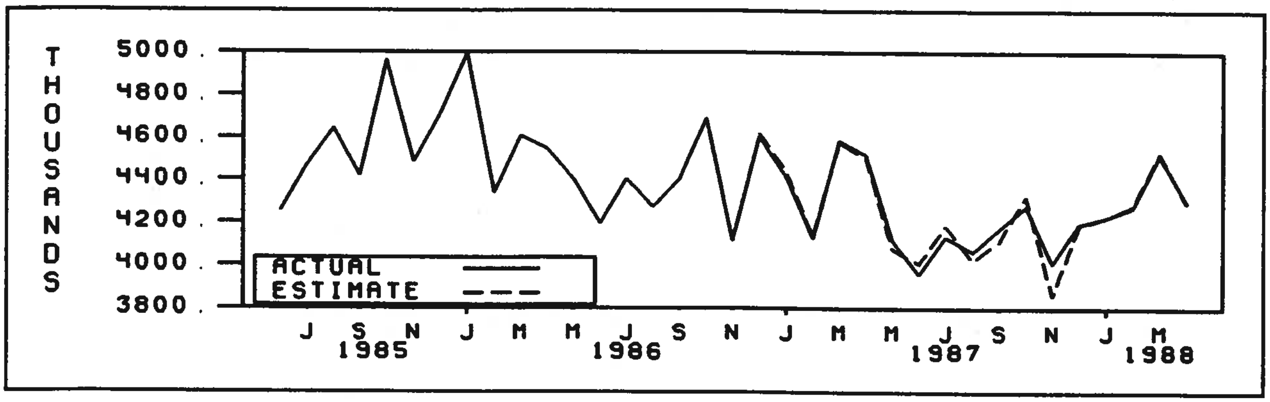


Figure 2. Actual vs. Estimated Unlinked Passenger Trips: $\bar{R}^2$=0.77 (Gretna, La.)

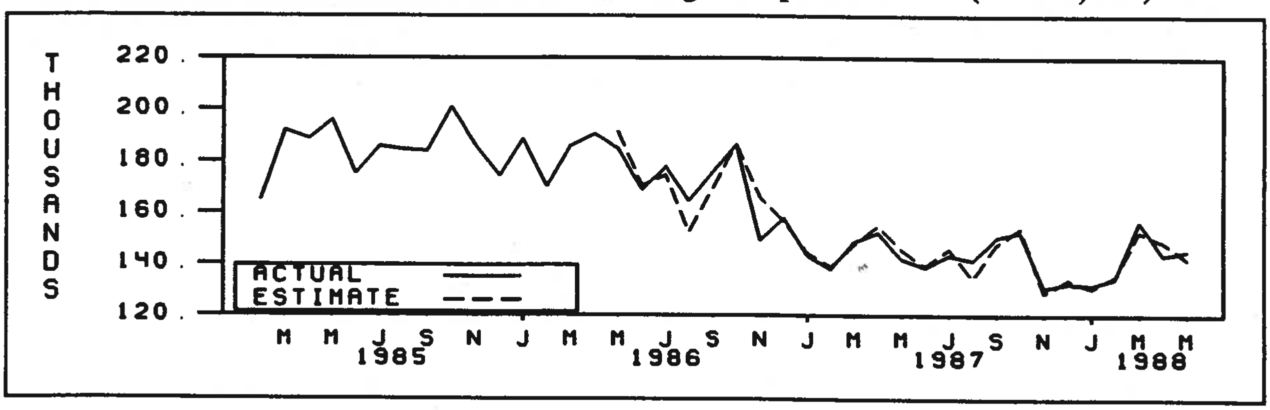
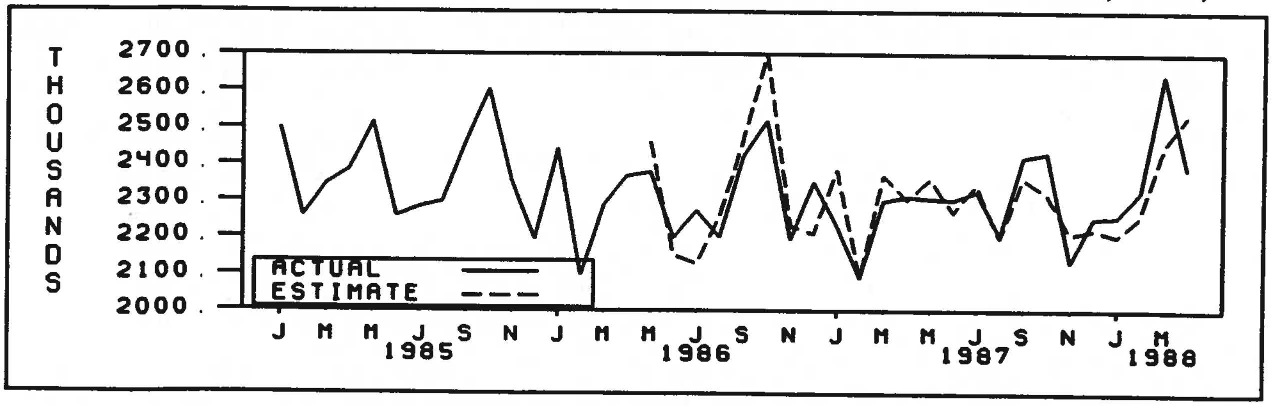


Figure 3. Actual vs. Estimated Unlinked Passenger Trips: $\bar{R}^2=0.52$ (San Jose, Calif.)



RESEARCH RESULTS

The fare elasticities of bus service for fifty-two transit systems under study are presented in Table 1 (all day average) and Table 2 (peak/off-peak differential). Briefly, the results are as follows:

- The all-hour fare elasticity for all systems averages at -0.40, notably higher than the Simpson-Curtin formula.

- The elasticity levels of individual transit systems, however, vary widely, from -0.12 for Riverside, Calif. to -0.85 for Toledo, Ohio. The local population work places, income, driving conditions, transit services, etc. cause different levels of sensitivity of travellers to fare changes. In any event, the large variation clearly illustrates the danger of applying the Simpson-Curtin rule to all areas.

- The average elasticity for large cities (more than 1 million population) is much smaller (in absolute value) than the smaller cities, indicating that transit users in large cities are less sensitive to fare increases.

- The relatively inelastic transit demand with respect to fare of large cities holds true for both peak and off-peak travelling. However, the differences in off-peak hours are less pronounced.

- The elasticity during off-peak hours is about twice as high as that during peak hours for both population groups. This finding is consistent with existing studies.

Table 1. Transit Fare Elasticity Estimates of 52 Transit Systems

	CITIES	URBAN AREA POPULATION	FARE ELASTICITY	T-STAT	$\bar{R}$ SQUARED	FARE ELAST GROUP MEANS
	BUS SERVICES IN URBANIZED AREAS WITH MORE THAN 1 MILLION POPULATION					
1	Los Angeles, CA	9,479,436	-0.231	5.83	0.87	
2	Des Plaines, IL	6,779,799	-0.117	1.75	0.73	
3	Detroit, MI	3,809,327	-0.247	3.18	0.92	
4	San Francisco, CA	3,190,698	-0.151	2.28	0.88	
5	Alexandria, VA	2,763,105	-0.412	2.29	0.91	
6	Dallas, TX	2,451,390	-0.134	1.77	0.91	
7	Baltimore, MD	1,755,477	-0.495	3.40	0.78	
8	San Diego, CA	1,704,352	-0.270	1.85	0.66	
9	Oceanside, CA	1,704,352	-0.350	2.64	0.68	
10	Atlanta, GA	1,613,357	-0.277	2.72	0.51	
11	Phoenix, AZ	1,409,279	-0.321	1.86	0.66	-0.361
12	Seattle, WA	1,391,535	-0.266	2.35	0.86	(0.154)*
13	Everett, WA	1,391,535	-0.429	1.82	0.51	
14	Denver, CO	1,352,070	-0.562	20.60	0.92	
15	San Jose, CA	1,243,952	-0.460	2.17	0.52	
16	Cincinnati, OH	1,123,412	-0.738	1.98	0.80	
17	Kansas City, MO	1,097,793	-0.511	4.32	0.92	
18	Gretna, LA	1,078,299	-0.354	3.10	0.77	
19	Portland, OR	1,026,144	-0.387	4.30	0.64	
20	Buffalo, NY	1,002,285	-0.503	3.27	0.84	
	BUS SERVICES IN URBANIZED AREAS WITH LESS THAN 1 MILLION POPULATION					
21	Sacramento, CA	796,266	-0.162	7.58	0.84	
22	Riverside, CA	705,175	-0.119	3.96	0.76	
23	Honolulu, HI	582,463	-0.652	5.99	0.80	
24	St. Petersburg, FL	520,912	-0.478	3.19	0.74	
25	Nashville, TN	518,325	-0.527	3.25	0.82	
26	Richmond, VA	491,627	-0.624	2.43	0.70	
27	Albany, NY	490,015	-0.456	3.42	0.57	
28	West Palm Beach, FL	487,044	-0.605	2.92	0.86	
29	Toledo, OH	485,440	-0.855	29.54	0.97	
30	El Paso, TX	454,159	-0.294	2.54	0.50	
31	Tacoma, WA	402,077	-0.432	4.70	0.63	
32	Allentown, PA	381,734	-0.747	2.60	0.70	
33	Grand Rapids, MI	374,744	-0.430	6.89	0.84	
34	Flint, MI	331,931	-0.585	2.98	0.87	
35	Fresno, CA	331,551	-0.311	4.99	0.74	
36	Sarasota, FL	305,431	-0.214	2.67	0.68	
37	Chattanooga, TN	301,515	-0.341	4.75	0.88	-0.430
38	Spokane, WA	266,709	-0.527	3.15	0.69	(0.189)*
39	Fort Wayne, IN	236,479	-0.116	1.77	0.90	
40	South Bend, IN	226,331	-0.261	4.58	0.66	
41	Madison, WI	213,675	-0.401	2.34	0.83	
42	Eugene, OR	182,495	-0.184	1.89	0.84	
43	Lincoln, NE	173,550	-0.500	3.26	0.55	
44	South Daytona, FL	170,749	-0.423	2.88	0.61	
45	Binghamton, NY	161,132	-0.704	10.95	0.93	
46	Lancaster, PA	157,385	-0.428	2.94	0.79	
47	Appleton, WI	142,151	-0.255	2.86	0.61	
48	Springfield, MO	139,030	-0.481	8.57	0.65	
49	Williamsport, PA	58,650	-0.299	2.52	0.75	
50	Oshkosh, WI	52,958	-0.167	3.09	0.86	
51	State College, PA	51,298	-0.642	4.57	0.89	
52	Boone, NC	Non-UZA	-0.528	5.66	0.81	
	ALL SYSTEMS:					-0.403 (0.179)*

* - Standard Deviation
Source: American Public Transit Association

Table 2. Fare Elasticity: Peak and Off-Peak Travel

Urbanized Area	Peak	Off Peak	Population
Binghamton, NY[1]	-0.26		161,312
Spokane, WA	-0.32	-0.73	266,709
Grand Rapids, MI	-0.29	-0.49	374,744
Sacramento, CA[2]	-0.22	-0.14	796,266
GROUP I AVERAGE[3]	-0.27 [0.04]	-0.45 [0.30]	1 million and less
Portland, OR/WA	-0.20	-0.58	1,026,144
San Francisco, CA[4]	-0.14	-0.31	3,190,698
Los Angeles, CA	-0.21	-0.29	9,479,436
GROUP II AVERAGE[3]	-0.18 [0.04]	-0.39 [0.16]	1 million and more
ALL SYSTEMS AVERAGE[3]	-0.23 [0.06]	-0.42 [0.22]	

Notes:
1. This system enacted a peak period fare increase in January 1988 and an off-peak period fare decrease in February 1987.
2. Light rail initiated March 1987, which was during the observation period.
3. The standard deviations of the group and total means are contained in square brackets.
4. Transit system serves Marin and Sonoma counties.