FERRY FARE ELASTICITY STUDY

by

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TABLE OF CONTENTS

Section	<u>Page</u>
Executive Summary	v
Chapter 1: Introduction	., І
Background	1
Related Research	· 2
Elasticity (Definition)	3
Use of Results	
	4
Chapter 2: Data Sources and General Descriptions	5
Patronage	
Summary Data File	- 6
Downloading and Data Reduction	6
Fares	7
Special Events	9
Employment.	20
Gasoline Price	22
Weather Data	22
Time Series Analysis	22
Time Series Analysis	28
Pitfalls in Time Series Analysis	29
Box Jenkins Approach Description of MicroTSP	29
Description of MicroTSP Preliminary Analysis	31
Monthly versus Quarterly Analysis	31
Monthly versus Quarterly Analysis	31
Seasonal Adjustments	32
Significant Variables	32
Analysis of Lags	34
Final Analysis	34
Interpretation of Confidence Intervals	. 35
Fare Elasticity Results	36
Influence of Other Variables	40
Chapter 4: Application of Results	43
General Interpretations	
General Interpretations	43
Route Group Differences	43
Commuter vs. Non-commuter	45
Mode	46
Oversized Vehicles	46
Numerical Forecasting	48
Inflation Adjustment	48
influence of Lags	49
Dealing with Confidence Intervals	49

LIST OF FIGURES

Figure		Page
2-1.	Route Groups	•
2-2.	Average Weekly Ridership	10
2-3.	Average Weekly Commuter Ridership	10
2-4.	Average Weekly Non-commuter Ridership	11
2-5.	Average Weekly Walk-on Ridership	12
2-6.	Average Weekly Vehicle Passenger Ridership	14
2-7.	Average Weekly Vehicle Driver Ridership	15
2-8.	Average Weekly Oversized Vehicles Under 48 Feet Long	16
2-9.	Average Weekly Oversized Vehicles Over 48 Feet Long	10
2-10.	Average Weekly Recreational Vehicles	18
2-11.	Average Weekly Vehicles with Trailers	10
2-12.	Typical Fare Levels	21
2-13.	Total Area Employment	23
2-14.	Average Gasoline Price (1967 \$'s)	23
2-15.	Average Temperature (seasonally adjusted)	24
2-16.	Average Percent Sunshine (seasonally adjusted)	20
3-1.	Fare Elasticity on Vashon Routes	37
3-2.	Fare Elasticity on Cross-Sound Routes	38
3-3.	Fare Elasticity on San Juan Routes	· 39
4-1.	Fare Elasticity for Oversized Vehicles	47
4-2.	Calculation of Ridership for Cross-Sound Commuters	47
	Assuming 11% Fare Increase	50

iv

EXECUTIVE SUMMARY

Historical data on ridership levels, fares, area employment, gasoline prices, inflation and weather formed the basis for this investigation of the fare structure of the Washington State Ferries (WSF). The objective of the study was to determine the ridership response to changes in fares. Past fare changes have consisted only of overall increases in the level of fares, with minor exceptions. Therefore, the results of this study must be used carefully if they are used to predict responses to changes to other than the whole system at once.

The routes and ridership were disaggregated into several categories to permit analysis of responses to fare changes by those categories. First, the routes were segregated into three route groups that were thought to serve different classes of passengers. The Vashon route group included all routes that had one terminus on Vashon Island. The Cross-Sound route group included all routes that connected King or Snohomish counties with Kitsap County. The San Juan route group consisted of all routes traveling to or through the San Juan Islands, plus the Clinton-Port Townsend route.

Ridership categories were disaggregated in two ways. Total riders were separated into commuter and non-commuter riders depending on whether or not frequent user tickets were used. Ridership was also classified by three modes: vehicle drivers, vehicle passengers and walk-ons. In addition, a special study of oversized commercial vehicles and recreational vehicles was conducted.

The major aim of the analysis was to determine the percentage of change in ridership that accompanied a change in fares. Since the only type of fare change that had occurred was an increase, the study focused on ridership loss due to fare increases. Theoretically, a fare decrease will result in the same increase in ridership as a fare

v

increase will lead to a loss in ridership. However, evidence shows that this is not always the case. Under some circumstances, the increase in ridership due to a fare decrease may not be as large as the opposite effect.

The overall effect of fare increases has been a substantial ridership loss. On a system-wide basis, the loss has not been great enough to lead to losses in overall revenue when the fares are increased. For some categories of ridership, however, fare increases have actually resulted in net revenue losses. In other words, the percentage of loss in riders has been greater than the percentage of increase in fares. This result applies to all San Juan ridership and to commuter ridership on the Cross-Sound routes. Evidence also shows strongly that overall fare increases lead to a shift in passengers from driving to walking on. For commercial vehicles and recreational vehicles on the Cross-Sound routes, there was also a substantially greater loss in patronage than the gain due to the increased fares.

The results of this study indicate that the revenue gain from a fare increase could be enhanced by considering different fare increases for different routes and different categories of riders. While other objectives, such as equity and route-by-route operational cost recovery, should be considered in any fare change, revenue enhancement is also an important objective. WSF should consider limiting the fare increases on San Juan routes, giving Cross-Sound commuters a break (perhaps through monthly passes), and offering lower fares for commercial and recreational vehicles (perhaps with an offpeak discount). Changing the ratio of vehicle to passenger fares is a potentially powerful tool to balance the loads of vehicles and people.

vi

CHAPTER 1 INTRODUCTION

The purpose of this report is to describe ferry patron response to changes in fare levels. This information can be used to analyze the impact of proposed fare changes. Historical patronage levels and fare structures provide the basis for the analysis. Other influences on ferry patronage levels, such as employment, gasoline price, weather factors, and special events such as strikes, dock outages and destruction of the Hood Canal bridge are also included in the analysis. The last chapter of the report contains a step-by-step guide to using the results of the analysis to forecast responses to fare changes.

BACKGROUND

Since the Washington State Ferries (WSF) was formed with the purchase of the privately-owned Black Ball lines in 1951, the fare structure has not changed significantly, except for periodic, across-the-board increases to cover rising operating costs. Relatively minor changes in the structure have included various kinds of discounts for frequent users and surcharges applied during the summer months.

The WSF is currently considering a revision of its tariffs to provide a more equitable distribution of ferry system costs and to simplify the fare structure. In order to assess the revenue implications of alternative fare structures, it is important to have information on the elasticity of fares for various segments of the system. The investigation described in this report provides this information.

RELATED RESEARCH

In 1982, a study of fare elasticity was published by the TRANSPO group for the WSF.¹ Data from 1970 to 1981 were used in the analysis. The report contained analysis of fare elasticity for four routes and for the total system. The analysis has two important shortcomings for current purposes. The first is that the analysis was confined primarily to the time period before 1979 when gasoline price and area employment were rising constantly. The results represented relationships in an economic environment that was quite different from that existing today.

The second fault is the lack of consideration of lags in the effects of variables. The study considered only concurrent effects of variables on ridership. However, it is important to realize that changes such as fare levels may have effects that are not realized for several months or even years. For instance, decisions to reside or work in places that require travel by ferry are influenced by ferry fare levels. However, such decisions cannot be made in a very short time. As a result, the impact of fare changes on ridership may lag. By not considering these lagged effects, the long-term impact of fare changes were probably underestimated in the TRANSPO study.

Another recent study of ferry patronage was an analysis of service elasticity conducted by Ritchie in 1985.² While fare levels were not explicitly considered in the analysis, the methodology employed was similar to the current study.

Numerous studies of fare elasticity for public transportation agencies have been conducted in the past several years. Among them were studies by Mayworm, Lago and

Bullock, Kari and Leonard, Elena. "Fare Elasticity Study," The TRANSPO Group, February 1982.

² Ritchie, Stephen G. "Washington State Ferries Service Elasticity Study," October 1985.

McEnroe,³ and Cervero.⁴ A recent study conducted by Kyte, Stoner and Cryer⁵ reported an analysis of ridership at Tri-Met in Portland, Oregon, which closely followed the Box-Jenkins methodology. This study employs a similar approach.

ELASTICITY (DEFINITION)

Elasticity is a concept used in economics to describe the relationship between two variables. It is the ratio of the change in one variable to the change in another variable. For instance, the elasticity of ridership with respect to fare is -0.3 if an increase in fare of 10 percent is accompanied by a decrease in ridership of 3 percent.

Elasticity can be positive or negative depending on the relationship between two variables. If the elasticity is less than -1 or greater than +1, it is said to be "elastic." It is "inelastic" if it is between -1 and +1. In the analysis of fare elasticity, this distinction is important. If fare elasticity is elastic (that is, less than -1), this fact implies that a fare increase will lead to a loss in revenue, since the percentage loss of riders will be greater than the percentage gain in average fare. If the relationship is inelastic and negative, a fare increase will lead to a loss of riders, but an increase in total revenue.

There is no theoretical reason to believe that the elasticity of one variable will be constant over the range of values of another variable. However, generally, ridership will become more elastic if the fare increases substantially. Elasticities are usually estimated over a narrow range of values and can be used to predict changes within that range.

³ Mayworm, Patrick; Lago, Armando M.; and McEnroe, J. Matthew. <u>Patronage Impacts</u> of <u>Changes in Transit Fares and Services</u>, U. S. Department of Transportation, Urban Mass Transportation Administration, Washington, D. C., 1980.

⁴ Cervero, Robert. "Examining Likely Consequences of a New Transit Fare Policy, <u>Transportation Research Record 877</u>, 1982, pp. 79-84.

⁵ Kyte, Michael; Stoner, james; and Cryer, Jonathon. "A Time-Series Analysis of Public Transit Ridership in Portland, Oregon, 1971-1982," submitted for publication in the <u>Transportation Research Record</u>, October 1986.

Care should be exercised in predicting the impacts of major changes in fare levels. Historical elasticities may be underestimated for current fare increases.

USE OF RESULTS

The fare elasticities from this study can be used to investigate the ridership and revenue impacts of various fare structures. By holding all other variables constant that might influence ridership, the marginal differences in ridership resulting from different fare structure scenarios may be computed. From these marginal differences, the impact on revenues may be estimated.

The elasticity data for other variables, such as employment and gasoline price may be used to predict actual ridership in the future. Of course, the use of these data requires that forecasts of employment and gasoline price also be made. While it is difficult to predict exactly what will happen to economic factors such as these, ridership can be projected under various economic scenarios and ranges of ridership forecasts can be established.

CHAPTER 2 DATA SOURCES AND GENERAL DESCRIPTIONS

The data for this study come from a variety of sources. All methods for forecasting transportation demand generally draw on a similar set of variables for two reasons: (1) all kinds of transportation demand decisions are based on the same set of criteria and (2) a limited number of reliable and complete time series data sets are available for the researcher's use.

In order to develop a model for fare elasticity, time series for ridership (in various disaggregations) and fare levels were required. In addition, an effort was made to find other factors that could explain variance in ridership that could not be explained by fare level alone. The use of these factors did not have a strong effect on the relationships between fare and ridership, but it did account for additional variance and provided more precise measurements of the fare elasticities.

Factors that were considered included those that (1) indicate the level of demand, such as population, employment, weather and measures of economic activity such as retail sales, and (2) measure the cost of ferry transportation and of competing modes, such as fares, service levels and gasoline price. Population data were not included because information on a monthly, quarterly or annual basis was not very accurate. Retail sales data were not included because they were very highly correlated with employment and did not add new information. Service levels were investigated but later discarded because no consistent relationships could be found.

In addition to the time series data that were available, special events such as strikes, dock outages and the Hood Canal bridge destruction in 1979 were found to be important. This winnowing process left six major categories of data to deal with: patronage, fares, special events, employment, gasoline price and weather data.

PATRONAGE

Summary Data File

All patronage data were derived from the summary data file compiled by the WSF and recorded in machine-readable form since 1977. This data file included 38 categories of ridership. Some of these categories were used for only a short time and were not considered in this analysis. Other categories involved such small numbers that it was not possible to find reliable relationships. Total ridership was taken to be the sum of total passengers (PASS-TOTAL) and total vehicles (VEH-TOTAL). Total ridership was divided into two classifications: type of ticket and travel mode. The first class distinguished between commuter and non-commuter patronage. Commuters were composed of the sum of commuter passengers (PASS COMM) and commuter vehicles (AUTO COMM). Non-commuters were the difference between total riders (defined above) and commuter riders.

The second classification was by mode of travel and included vehicles (with driver), passengers in vehicles and walk-on passengers. Walk-on passengers was a separate classification in the summary data file (WALK-ON). Vehicles (with driver) was simply the total vehicle (VEH-TOTAL) classification, and passengers on vehicles was total ridership minus the walk-ons and total vehicle counts.

A special analysis was performed of commercial and over-sized vehicles using the classifications for under (TRK-REG) and over 48-foot (TRK-EX) trucks, recreational vehicles ()-S-REG) and trailers (TRAILER). This analysis is reported separately from the main analysis of fare elasticities.

Data were also classified according to route group. The summary data file contained patronage data for each route in the system. However, because of the variability in patronage it was difficult to find consistent relationships on a route-by-

route basis. By combining similar types of routes together, some of the wide fluctuation in data was reduced and the underlying relationships were more readily apparent.

Three route groups were employed: Vashon, Cross-Sound and San Juan routes. Vashon routes included the following:

Fauntleroy-Vashon,

Vashon-Southworth and

Tahlequah-Point Defiance.

These routes were thought to be similar since they all involved trips to and from an island accessible only by ferry.

Cross-Sound routes included

■ Fauntleroy-Southworth,

- Seattle-Bremerton,
- Seattle-Winslow,
- Edmonds-Kingston and

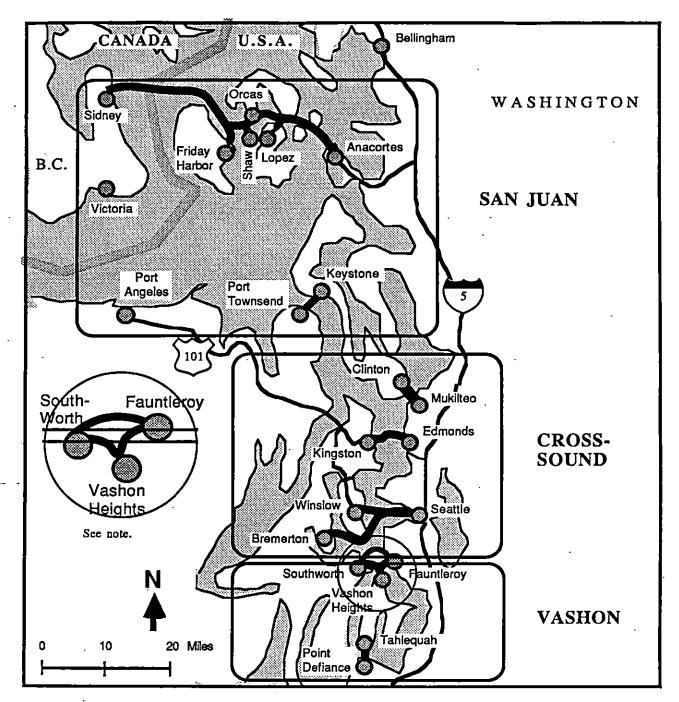
Mukilteo-Clinton.

These routes included destinations that were accessible by land, so that competing modes of transportation were feasible. In addition, they tended to have a high degree of commuter and residence use, as opposed to tourist use.

San Juan routes included all routes between and among Anacortes, the San Juan islands and Sydney. In addition, the Keystone-Port Townsend route was included in this group. The latter route could be considered a Cross-Sound route, but it had a high percentage of tourist use, which made it more like the other San Juan routes. Figure 2-1 shows the route groups.

Downloading and Data Reduction

The summary data file was stored on the IBM 370 mainframe computer at Service Center 5 in files formatted for access by COBOL. The data were reduced and



Note: The direct crossing between Fauntleroy and Southworth is in the Crosssound group. The crossing via Vashon is in the Vashon group.

Figure 2-1. Route Groups.

downloaded to floppy disks for analysis on a microcomputer. The daily data were collapsed into monthly records for each route. Four monthly records were produced:

- average data for Monday through Thursday,
- average data for Fridays,
- average data for Saturdays and
- average data for Sundays.

The averages excluded holidays and days that might be affected by holidays. There were 16 routes, 115 months, four types of days and 38 classifications of data, for a total of 280,000 data points.

These data points were further collapsed to get weekly numbers for the three route groups, reducing the total number of data points to about 13,000. Only ten types of ridership classification are used in the fare elasticity analysis, leaving a total of about 3,450 data points.

There were some anomalies in the data for February through October 1980 that were corrected before further analysis was performed. Missing data in that period for some classifications were replaced with the averages for the same months in 1979 and 1981. In some cases, only one-way data were recorded during that period, so the numbers were doubled before further analysis was performed.

The resulting data were average weekly ridership figures during the time period of interest. Figures 2-2 through 2-11 show seasonally-adjusted total ridership figures for each classification.

FARES

Data on fares were collected directly from schedules provided by the WSF since 1977. Since all fare increases (with one exception) have been the same across the board since 1977, only the fare levels from the route with the highest patronage in each route

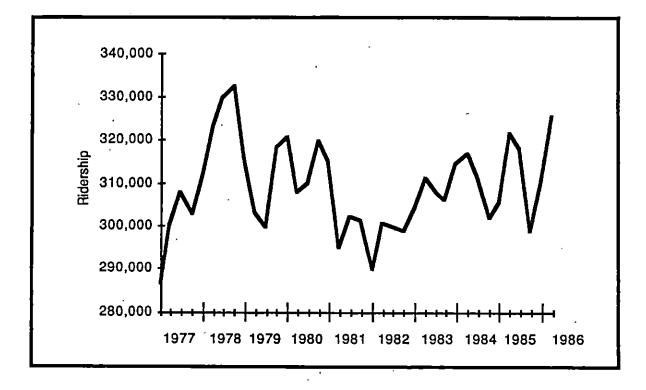
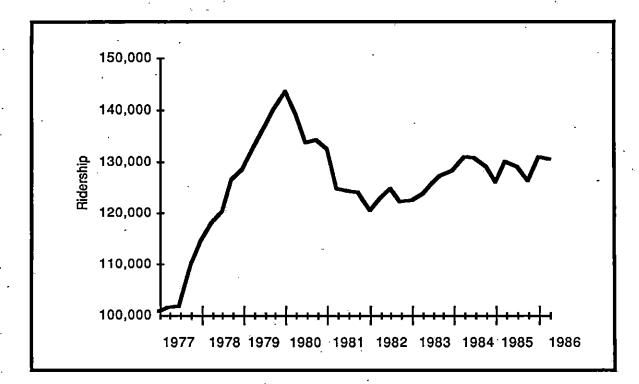


Figure 2-2. Average Weekly Ridership.





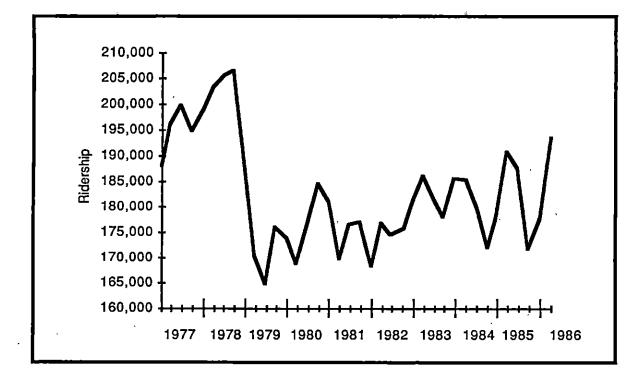


Figure 2-4. Average Weekly Non-commuter Ridership.

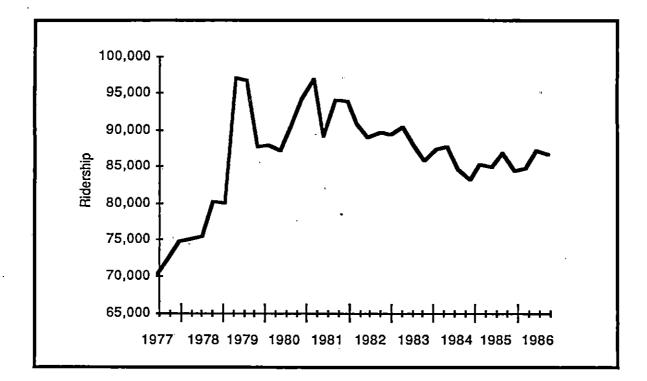


Figure 2-5. Average Weekly Walk-on Ridership.

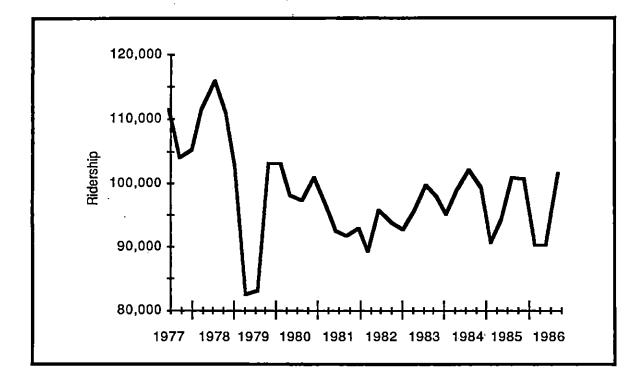


Figure 2-6. Average Weekly Vehicle Passenger Ridership.

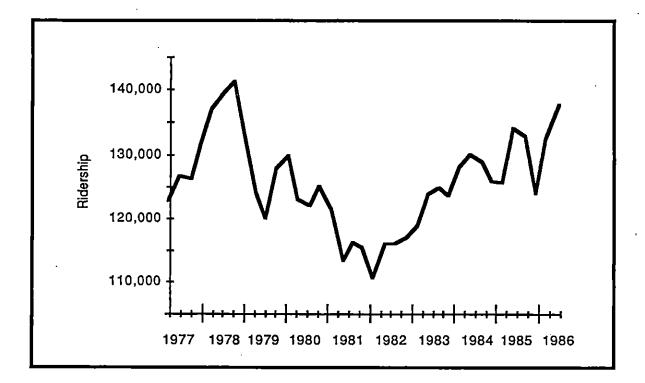


Figure 2-7. Average Weekly Vehicle Driver Ridership.

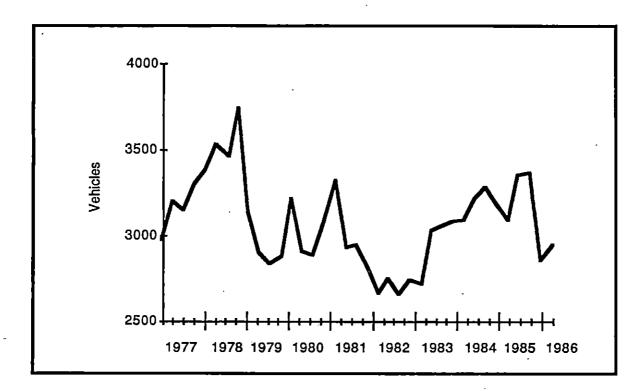


Figure 2-8. Average Weekly Oversized Vehicles Under 48 Feet Long.

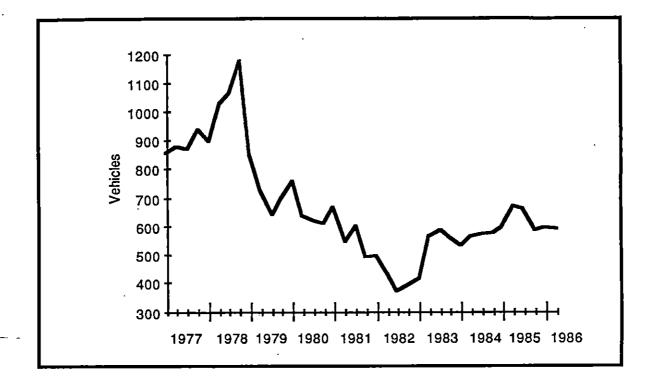


Figure 2-9. Average Weekly Oversized Vehicles Over 48 Feet Long.

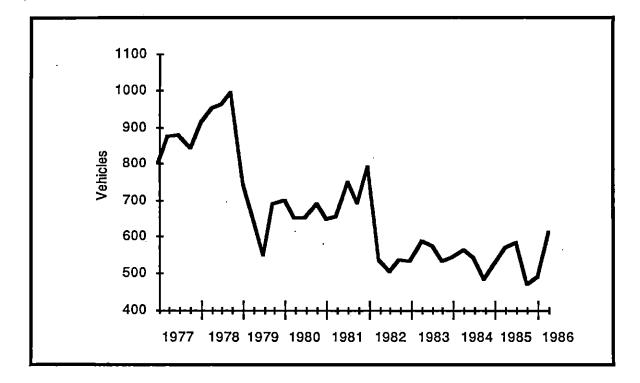


Figure 2-10. Average Weekly Recreational Vehicles.

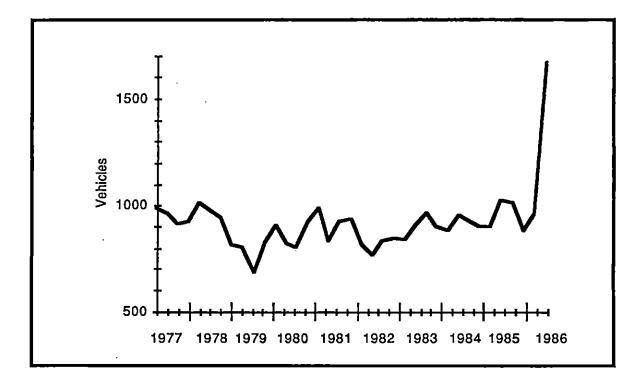


Figure 2-11. Average Weekly Vehicles with Trailers.

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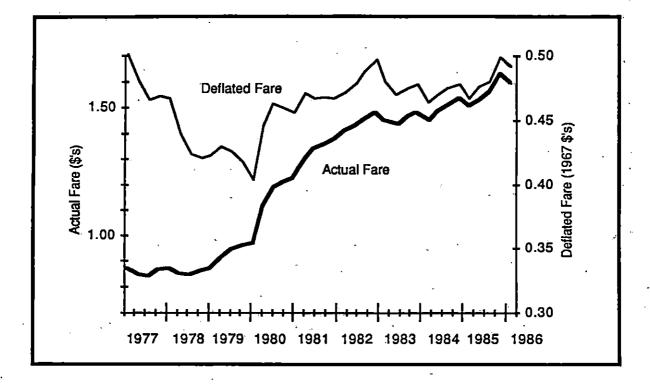
group were used in the analysis. (Slight differences in fare changes among the routes were produced by the requirement to round off fares to the nearest five cents.)

The one exception to the across-the-board fare increases was in 1977 when the vehicle toll for the Anacortes to Sydney was the only increase. In 1981, all fares increased, except for that route. Since the Anacortes- Sydney route was a relatively small part of the total patronage in the San Juan route group, these differences were ignored in the analysis.

The fare levels were adjusted for inflation by dividing by the Consumer Price Index (CPI) for the Seattle-Everett area and multiplying by 100. This adjustment converted the fares to 1967 dollars. Adjustment for inflation is supported by economic theory, since the adjusted value reflects the cost relative to other expenditures that a potential ferry patron can make. Preliminary analysis confirmed that the deflated fare was a better predictor of ridership than the inflated fare. Figure 2-12 shows the undeflated and deflated fares for passengers on the Scattle-Winslow route. All others look very similar.

SPECIAL EVENTS

Several events occurred during the ten years of analysis for this study that could potentially have had an effect on ridership. The primary ones were the destruction of the Hood Canal Bridge by a windstorm in February 1979 and the imposition of a 90-day period for commuter tickets to be valid in 1980. Other events included strikes and dock outages, but these were not very visible in the data since they were of short duration or only affected one particular route. Major weather events such as the snow storm of November 1985 were also represented in the model separately from the weather variables that reflected longer term influences on ridership.





EMPLOYMENT

Employment data were derived from data published by the Washington State Employment Security Department. Estimates were made on a monthly basis for each county in the state. Data were analyzed for King, Snohomish, Pierce and Kitsap counties from January 1977 through July 1986. Figure 2-13 shows total employment for these counties after seasonal adjustments have been applied.

GASOLINE PRICE

Gasoline price represents one of the major costs for operating automobiles and usually has an effect on overall travel levels. This impact can affect ferry ridership. Monthly data were derived from the Lundberg letter for the time period of interest. The Lundberg association publishes data on the average price of gasoline at the pump for several regions in the United States and for each type of gasoline. For this study, the average price of unleaded gasoline for the Seattle area was used.

As with fares, economic theory justifies the adjustment of gasoline prices for inflation. The gasoline price data were deflated using the Consumer Price Index for the Seattle-Everett area. Figure 2-14 shows the deflated gasoline price for this area.

WEATHER DATA

Variations in weather have not often been used in travel forecasting except for major storms. However, in order to analyze the patronage on the WSF, the study team hypothesized that longer-term weather trends might have significantly impacted ridership, since much of ferry travel is discretionary. Long periods of good or bad weather conceivably could have affected the level of out-of-state tourist traffic on the ferries and most likely did affect the discretionary use of the ferries by Puget Sound residents.

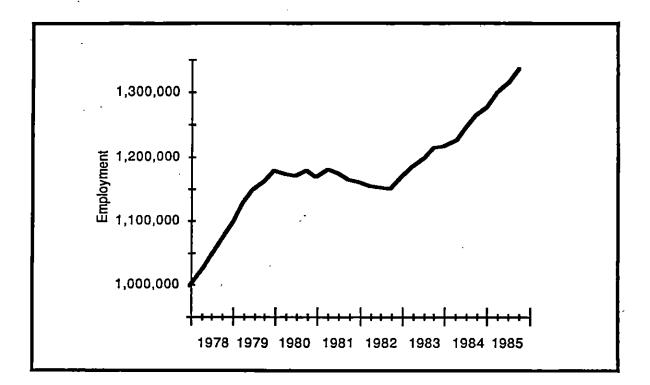


Figure 2-13. Total Area Employment.

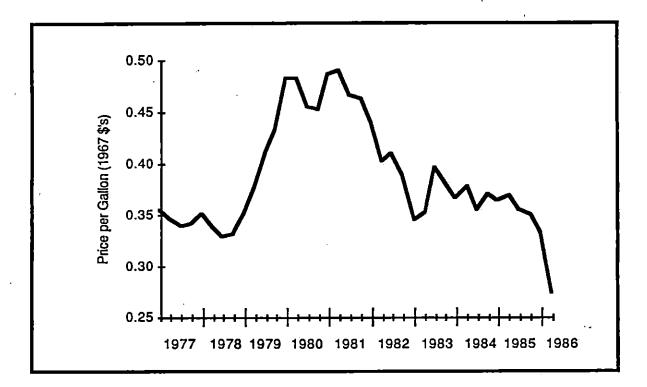


Figure 2-14. Average Gasoline Price (1967 \$'s).

Data on average temperature, average percentage of sunshine, rainfall and snowfall were taken from National Oceanographic and Atmospheric Administration information collected at SeaTac Airport. Time series data on rainfall and snowfall did not explain a significant amount of the variance in ridership, except for a few major storms. Those were considered special events and analyzed accordingly. Temperature and sunshine were included in the main analysis of the fare elasticity. Figures 2-15 and 2-16 show the quarterly variation in these data after seasonal adjustment.

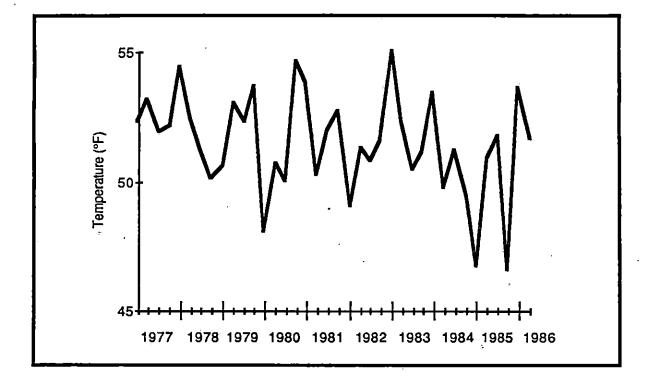


Figure 2-15. Average Temperature (seasonally adjusted).

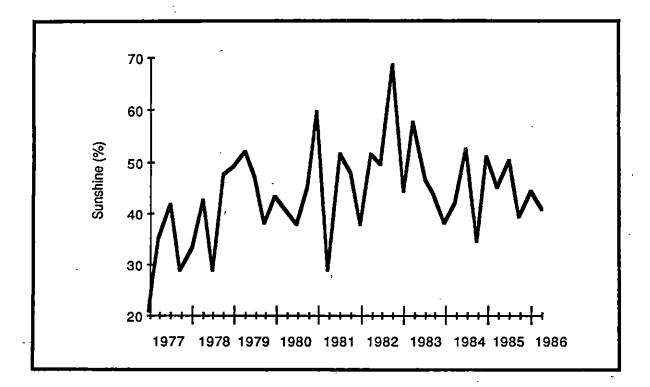


Figure 2-16. Average Percent Sunshine (seasonally adjusted).

CHAPTER 3 DATA ANALYSIS

The data analysis in this project involved a variety of statistical techniques that may be unfamiliar to the reader. The use of the study results does not necessitate understanding all of the techniques involved. Basically, the aim of the analysis was to determine how changes in different categories of ridership were affected by changes in fares. Other variables were included in the analysis to explain changes in ridership that could not be explained by changes in fares alone. The most important results are reported at the end of this chapter as fare elasticities. The interpretation of these results may be found in Chapter 4. This section contains a short introduction to time series analysis, results and implications of the preliminary analysis and the final results of the analysis.

TIME SERIES ANALYSIS

The analysis of time series is the same as the analysis of any other kind of data set, except that it must consider that data are measured in a continuous set of time periods. There are important differences between the analysis of a time series, such as monthly ferry ridership, and a cross-sectional set of data, such as the percentage of households owning a car in each county in the state. In a time series, successive measurements are probably (but not necessarily) related to each other. In a crosssectional data set of county car ownership levels, arranged in alphabetical order, a relationship probably does not exist between adjacent values.

The basic statistical analysis method employed in this study is regression analysis. The reader should be familiar with a few terms to understand the discussion in this section of the report. The <u>dependent variable</u> is the one that is to be predicted (ferry patronage, in this case). The <u>independent variables</u> are the ones used to make the

predictions (in this case, fares, gasoline price, employment and weather variables). <u>Residuals</u> are the differences between the actual values of the dependent variables and the predicted values. <u>Regression coefficients</u> are the values that relate the independent variables to the dependent variable. The prediction of the the dependent variable is a constant plus a linear combination of the independent variables, as follows:

$$Y = C_0 + C_1 * X_1 + C_2 * X_2 \dots$$

where Y is the dependent variable, the X's are the independent variables and the C's are the regression coefficients.

Pitfalls in Time Series Analysis

In time series analysis, one characteristic of the data that the researcher must deal with is that successive values usually depend on previous ones. Unless this characteristic of time series is accounted for, successive residuals will be statistically related to each other (serially correlated), and one of the assumptions of least squares regression will be violated. On the other hand, methods exist to take advantage of this characteristic of time series data, and these are described in the next section.

A second issue to deal with is that the independent variables may not affect the dependent variable immediately. In standard regression techniques, only concurrent effects of independent variables on the dependent variables are taken into account. In a time series, however, the impact of a change in an independent variable can be detected after a lag in time and may continue to be effective for some period after the initial change.

Box-Jenkins Approach

The Box-Jenkins, or ARIMA, approach to time series analysis takes advantage of some of the characteristics of time series to improve forecasts and to avoid methodological faults in the use of least squares regression analysis. That approach has been followed in this study. There are three basic elements or tools used in this

approach: autoregressive terms (AR), integrated terms (I) and moving average terms (MA). Hence, the approach is called ARIMA.

The autoregressive term uses a lagged value of the dependent variable to help predict future values. The lags can be of any order, but three or four lags tends to be the limit of useful autoregressive terms. This tool minimizes the serial correlation of residuals and takes advantage of the structure of time series data to explain and forecast the dependent variable.

The integrated term is used to handle a time series that tends to drift over time. The use of it entails replacing the values in the time series with the differences between adjacent terms (for a first-order integrated term). A second-order term is composed of the differences of the first-order terms. In other words, X_0 is replaced with $X_0 - X_{-1}$ for a first order difference. The first order difference is replaced with $(X_0 - X_{-1}) - (X_{-1} - X_{-2})$ or $X_0 - 2X_{-1} + X_{-2}$ for the second order difference. Often, the use of an integrated term eliminates the serial correlation of residuals. If the original data are replaced by their natural logarithms and a first order difference is applied, the resulting regression coefficients may be interpreted as elasticities. The analysis in this study employed this technique.

The moving average term uses the lagged values of the residual (rather than the dependent variable) to improve the explanatory power of the regression. It is useful when the autocorrelation of the dependent variable dies out very quickly.

The Box-Jenkins approach addresses seasonal effects in the data by employing the three tools using appropriate seasonal lags. However, this dealt only with seasonally adjusted data in order to simplify the presentation of the results (see the section on seasonal adjustments, below).

Description of MicroTSP

MicroTSP is a time series analysis package designed for use on microcomputers. The program was written by David M. Lillien and is distributed by Quantitative Micro Software in Irvine, California. It is a very useful tool for the present analysis since it can easily transform and manipulate time series data sets and perform regression analysis using autoregressive terms and moving average terms.

PRELIMINARY ANALYSIS

A preliminary analysis was performed on the data to answer several questions before the final analysis was performed. Although most of the time series used for this analysis were available on a monthly basis, it was not clear if one month was the appropriate time period to employ. Determining the seasonality of the data and the best way to deal with that factor was also important. Some variables were eliminated from the analysis, since they showed little, if any, relationship to ridership. An investigation of the effects of lags confirmed that lags had to be taken into account in the analysis.

Monthly versus Quarterly Analysis

In the first series of analyses that were performed, monthly time periods were employed. The pattern of relationships between fares and ridership was very unclear. There tended to be significant but small elasticities using lags distributed throughout a 12-month period preceding the period of interest. These were interspersed with insignificant negative and positive elasticities and occasionally with significant positive elasticities.

These results implied that the effects of fare changes were felt for some months after they occurred, but that unexplainable noise in the data was making the pattern difficult to decipher. In order to reduce this noise, monthly data were converted to quarterly data by averaging over the three months in each quarter. The use of quarterly data resulted in more consistent fare elasticities since the extraneous variation evened

out when three months of data were combined into one data point. After this discovery, all subsequent analyses were performed on quarterly data.

Seasonal Adjustments

There were very clear seasonal patterns in ferry ridership, with the greatest ridership occurring in the summer months. Since most of the fare increases occurred just prior to the summer months, detecting the impact of the fare changes on ridership by visually inspecting graphs of data that were not seasonally adjusted was very difficult. Although it would have been possible to account for seasonal effects in ridership using autoregressive or moving average terms in the regression, the study team believed that this method would have unnecessarily complicated the presentation of results.

As an alternative, the data were seasonally adjusted using the seasonal adjustment option available in MicroTSP <u>before</u> the logarithmic transformations, differencing, autoregressive and moving average terms were applied. MicroTSP employs a traditional method to perform seasonal adjustment. For each period in the time series, the program computes the ratio between the value for that period and the average of the period around it that comprise one year's worth of data. An average factor for each corresponding time period in a year is computed and the time series is adjusted using these average factors.

The seasonally adjusted time series showed clearly the relative changes in data over the time period. For instance, a dip in summer ridership indicated that, compared with other summer quarters, that summer had lower ridership, even though ridership did go up that summer compared to the spring and fall quarters surrounding it.

Significant Variables

Some variables that were initially thought able to explain some of the variance in ridership were eliminated from further consideration after the preliminary analysis.

These included employment data other than King County's, service levels, rainfall, snowfall and indicators of tourism levels.

Employment data were collected for King, Kitsap, Pierce and Snohomish counties. Different combinations of these data series were tried for each of the route groups. King County employment was found to be more strongly related to the ridership data. The vast majority of the commuter traffic was generated by employment in King County, so it was not surprising that commuter traffic was related to that time series. In addition, King County employment was a good indicator of regional economic activity in general. Changes in the smaller counties reflected economic activity in those counties, but the base was small enough not to have as strong a relationship with ridership as King County employment did.

Service levels were obtained for all route groups being analyzed. Preliminary analysis showed no relationships between service levels and ridership except for unusual circumstances like strikes, dock outages and the destruction of the Hood Canal bridge. These occurrences were represented separately in the analysis.

Rainfall and snowfall data were collected from NOAA as well as average sunshine and temperature. No significant relationships were found between the time series representing rainfall and snowfall with the ridership data. In a quarterly time series, a winter quarter with a two foot snowstorm appeared the same as one with six four-inch snowstorms. However, the impact of the snowfall in these two quarters on ridership was quite different. Major storms were better represented as special events rather than as a time series.

Since much of the ferry ridership was tourist oriented, an attempt was made to obtain an independent measure of tourism. One commonly used time series for this purpose is employment in the hotel and motel sector. These data were obtained from the Washington State Employment Security Department. However, all attempts to relate the

data to ridership failed. This was probably due to the inclusion of gasoline price and employment data that were related to tourism levels already. Another effort was made to use data on hotel and motel occupancy. However, the available data sets were found to be inadequate for this study.

Analysis of Lags

1

People are not always able to change their traveling behavior immediately in response to environmental changes. This is especially true for ferry patronage. When fares increase, commuter trips are not likely to change for quite a while. People may decide to relocate, change jobs or buy an extra car so they can leave one at either end of the ferry route. New potential riders may not develop when the economic conditions are unfavorable. In any case, the full response to a fare change may not occur for several months. Preliminary analysis of the data revealed that response to fare changes occurred for up to one year afterward. Responses to changes in gasoline price or employment usually occurred within two quarters. Responses to weather conditions (represented by average temperatures and percentage of sunshine), as well as special events, occurred immediately. The final analysis examined all possible lags that were uncovered in the preliminary analysis.

FINAL ANALYSIS

The preliminary analysis showed that five independent variables (plus intervention variables to represent special events) should be used in the final analysis to explain the dependent variable, ferry ridership. Ridership was disaggregated in three ways. First, it was separated into three route groups: Vashon, Cross-Sound and San Juan routes. Secondly, it was separated into commuter and non-commuter use, according to the use of the frequent traveler coupon books. Thirdly, the ridership was separated by mode: walk-on, passenger on a vehicle and driver of a vehicle.

None of the variables were stationary. In order to induce stationarity, first differences were employed in all the analyses. In order to be able to interpret regression coefficients as fare elasticities, a logarithmic transformation was applied before differences were computed.

The preliminary analysis also identified the range of lags that should be considered. The discovery that fare changes could have effects up to one year after they occurred meant that lags of up to four quarters would have to be investigated for the fare variables. Changes in gasoline price and employment had little effect after three months, so no lag greater than one quarter was investigated for those variables. The weather variables, average sunshine and temperature would only have concurrent effects. The same applied to intervention variables representing the effects of special events. Where a moving average or autoregressive term could improve the explanatory power of the regression equation, terms of order one were used. Higher order terms were not significant in any of the equations.

Interpretation of Confidence Intervals

Results for all of the elasticities are reported using confidence intervals. Since the data used in this analysis represents only a sample of all possible time periods, the resulting fare elasticities are <u>estimates</u> of the actual fare elasticities. By using the standard error of the coefficients, a confidence interval for each elasticity can be computed. In results for this study, 90 percent confidence limits are reported. The proper interpretation of these limits is that the reader can be 90 percent sure that the actual fare elasticity falls within the reported intervals.

In cases where a fare elasticity was significantly different from zero for successive lags, elasticities were summed and the standard error for the sum was computed from the individual standard errors. While the total impact of a fare change may not have occurred immediately, this sum of fare elasticities represents the effect

that would have been felt after <u>n</u> lags, where <u>n</u> is the number of successive significant fare elasticities.

Fare Elasticity Results

Figures 3-1, 3-2 and 3-3 show the confidence intervals for fare elasticities for each of the route groups and for each of the methods of disaggregation.

The highest (most negative, that is) fare elasticities occurred for the San Juan routes, followed by the Cross-Sound routes and the Vashon routes. The confidence interval midpoint for the San Juan routes' total ridership was -1.14; the midpoint for the Cross-Sound route was -0.80 and the midpoint for the Vashon route was -0.47. These differences were expected, since a much higher percentage of passengers ride ferries on a discretionary basis on the San Juan routes than the other two route groups. These data showed that there is a better than 50 percent chance that San Juan ridership is elastic with respect to fares. In other words, fare increases on those routes would likely reduce total revenue. The other two route groups are probably inelastic, but individual categories of ridership must be examined to determine the impact on total revenue.

For the Cross-Sound and San Juan routes, commuter ridership is highly elastic with respect to fares. For Vashon routes, it is negative, but inelastic. For all three route groups, there are significant fare elasticities for commuter ridership for lags of up to four quarters. Losses in ridership after a fare increase tend to come from commuters to a greater extent than non-commuters, but the effect is not felt immediately.

These results should not be interpreted as a shift from commuter to noncommuters as a result of a fare increase, for two reasons. First, all fare elasticities for non-commuters are negative, meaning that a fare increase results in ridership loss in that category, as well as for commuters. Secondly, commuters would probably not buy an even more expensive ticket when the cost goes up. However, higher prices possibly lead

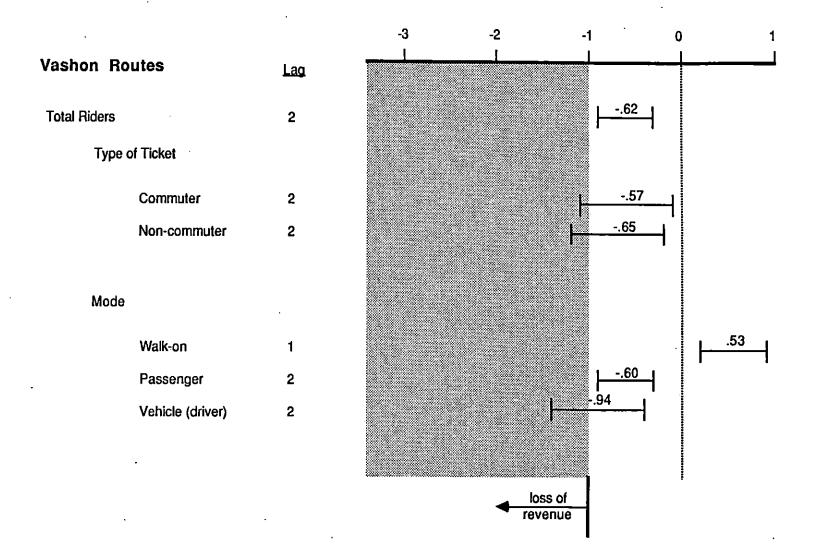


Figure 3-1. Fare Elasticity on Vashon Routes.

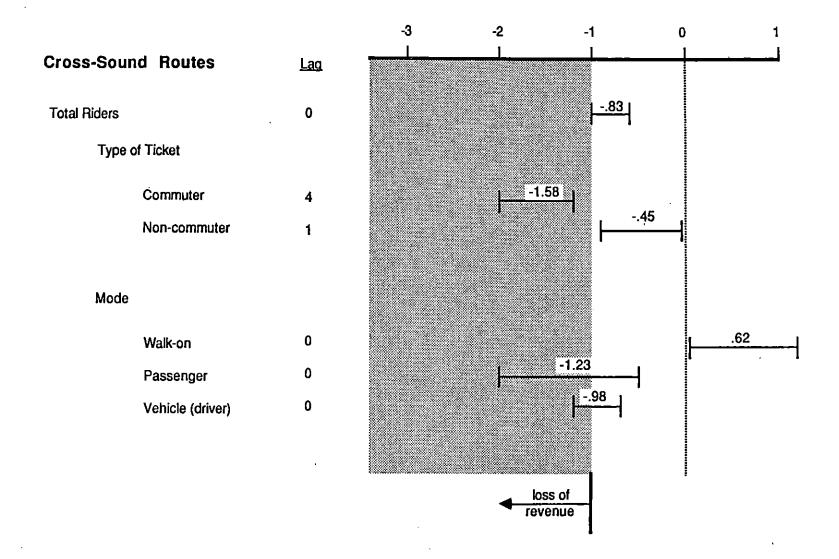
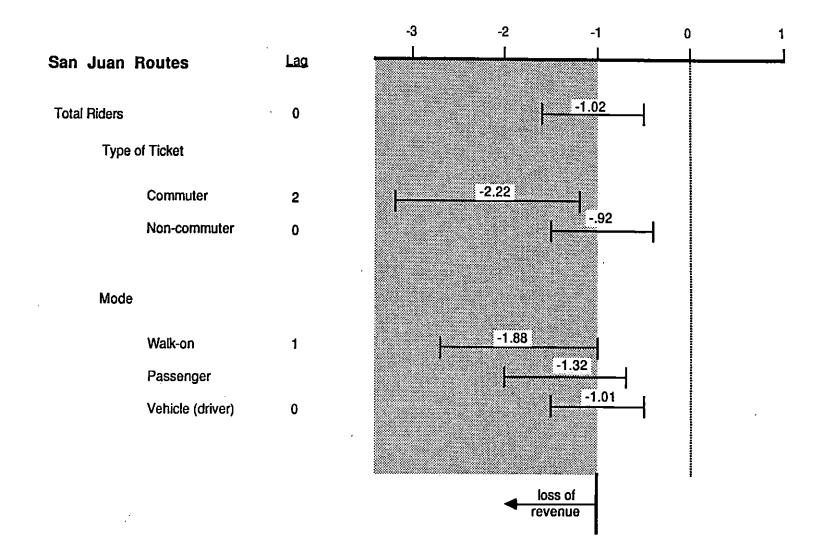


Figure 3-2. Fare Elasticity on Cross-Sound Routes.





language of ARIMA analysis, the factors are represented as <u>intervention variables</u>. They are quite similar to the dummy variables used in standard regression analysis.

For the purposes of this study, the special events that were explored included

- the 1978 strike (third quarter),
- the destruction of the Hood Canal bridge in February 1979,
- the 1980 strike (April 5-17),
- the 1981 strike (May 20-22),
- the construction of the Mukilteo dock in 1982 (first quarter), and
- a record snowfall in November 1985.

Only three of these special events had a significant impact on changes in quarterly ridership. These were the destruction of the Hood Canal bridge, the construction of the Mukilteo dock and the snowstorm in 1985. They were not used in all of the regressions, but they did serve to reduce the error in several of the estimates of fare elasticity.

Employment had an uneven relationship with ridership. When there was a significant relationship between employment and ridership it was positive. That is, higher employment was associated with higher ridership. It was consistently related with walk-on riders and commuters on the Vashon and Cross-Sound route groups. This implies that when employment goes up in King County, the ferry system can expect to see more people commuting, especially as walk-on passengers.

For almost all categories of ridership, there was a negative relationship between gasoline price and ridership. As gasoline price goes up people generally travel less. This apparently leads to less travel on the ferries as well. Since there were no positive relationships between ridership and gasoline price for any category, there was no support for the contention that riders switch to the ferry when the competing mode of driving becomes more expensive.

In virtually every category of ridership, a strong positive relationship existed between average temperature and ferry ridership. In a few cases there was also a positive relationship between average sunshine and ridership. Although a positive relationship between good weather and ridership was not surprising, it was surprising that such strong and consistent relationships existed even when the weather variables were averaged over a whole quarter.

CHAPTER 4 APPLICATION OF RESULTS

The quantitative results of this study are itemized and discussed in the previous three sections of this report. The purpose of this section is to discuss policy implications of these results. In this section, the results of the study are first discussed in a qualitative sense. The meaning behind the numbers is presented. The second part of this section covers the use of the data for numerical forecasting. The presentation shows how the study results can be translated into specific forecasts for revenue using different assumptions for fare structure.

GENERAL INTERPRETATIONS

The major results of the study (the fare elasticities) were reported using three different classification methods: type of route, type of ticket and type of mode. In this section, results are interpreted using these three classifications.

Route Group Differences

The three route groups (Vashon, Cross-Sound and San Juan) were defined in order to represent different types of service and patronage. They were also defined so that they would be relatively homogeneous within themselves.

The Vashon routes are unique because they provide transportation to places accessible only by ferry. No highway alternatives exist. They are different from the San Juan routes because of the proximity of Vashon Island to Seattle, meaning that a high percentage of the trips are work-oriented. The routes are also shorter (in general) than the San Juan routes. However, the ridership shows significant seasonality due to the attractiveness of the island as a destination for mainland-based tourism during the summer months. The Cross-Sound routes also carry some summer tourists, but the bulk of the ridership is related to the work commute for the people who live in Kitsap County and commute to King or Snohomish county to work. Another distinguishing feature of the Cross-Sound routes is the fact that people can drive around Puget Sound and reach the same destinations served by these routes.

The San Juan routes serve some work commute trips, but the bulk of the trips are recreation- or shopping-related. This applies both to residents of the islands and visitors from the mainland. These routes show a high degree of seasonality.

The differences among the routes accounts for differences in response to changes in fares and to other factors used in the analysis. A major difference is the overall response to fare changes. The San Juan routes, which serve the highest number of discretionary trips, has the strongest relationship between fares and ridership. The relationship is so strong that a change in fares results in an even larger change in ridership. This means that a fare increase will actually reduce the total revenue on these routes. Conversely, a fare reduction would, theoretically, increase revenue from these routes.

The Cross-Sound and Vashon routes have similar relationships between fare changes and ridership, but the Cross-Sound routes show a slightly stronger relationship between fares and ridership than do the Vashon routes. This variance is probably due to the fact that a greater percentage of riders on the Vashon routes are captive riders than on the Cross-Sound routes.

The relationships for employment and weather variables are related to the percentage of discretionary trips in the route groups. A greater percentage of discretionary trips leads to a smaller relationship with employment and a correspondingly stronger relationship with weather variables.

Commuter vs. Non-commuter

The patterns of responses to fare changes by commuters and non-commuters vary by route group. On the Vashon routes, the commuters respond slightly less strongly to fare changes than do non-commuters, probably because commuters are captive riders. They have no other way to get to work. If they do make fewer trips, they probably cut out the discretionary recreational or shopping trips that they had been taking with their commuter tickets.

On the other hand, Cross-Sound commuters show a much stronger reaction to fare changes than do non-commuters on the same routes. The response to fare changes is not immediate, but the end effect of a fare increase is a large reduction in commuter trips on these routes. Three explanations can probably account for this reduction. First, for some commuters, the alternative of driving around is available and no doubt happens when fares increase. Second, with the 90-day limit on the use of commuter tickets and a reduction in the use of commuter trips for trips other than work trips, many riders probably shift from the commuter to the non-commuter type of ticket. Third, since fare increases tend to be related to ridership reductions for as long as one year after the reductions have occurred, some people eventually make different choices in location of employment or residence as a result of the fare increases.

The pattern in commuter/non-commuter responses to fare changes for San Juan routes is the same as the pattern for Cross-Sound routes. The explanations are probably also the same, except for the fact that San Juan residents have no highway alternatives available.

As would be expected, relationships between employment and commuter ridership is stronger than those between employment and non-commuter ridership, for all routes. Higher employment levels lead to higher ridership, especially for commuters.

Conversely, non-commuter ridership is more strongly related to weather variables than is commuter ridership. Discretionary, recreation trips occur more often when the weather is especially good.

<u>Mode</u>

Fare changes have an interesting effect on the mode of ridership on the ferries. For Vashon and Cross-Sound routes, the number of walk-on riders actually increases when fares go up. However, clearly the additional riders come from the other two modal categories, vehicle drivers and passengers. A major response to fare changes is for people to ride the ferries without a vehicle. This is especially true for routes with a high percentage of commuter use.

The San Juan routes display a different reaction pattern. Walk-on passengers have a slight tendency to respond <u>more strongly</u> to a fare change than do vehicle passengers. This is probably because walk-on passengers on San Juan routes are more likely to be making discretionary trips that those on other routes.

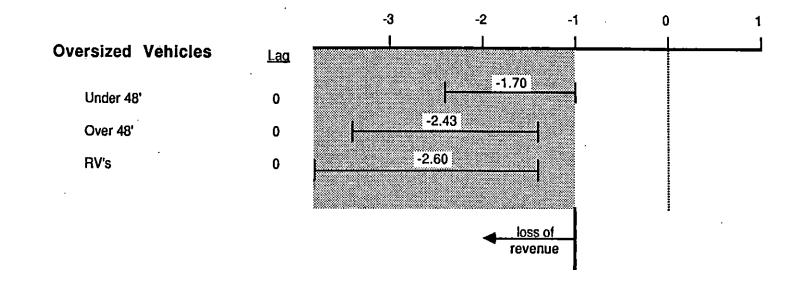
Oversized Vehicles

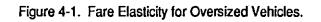
The fare clasticity for three classes of oversized vehicles was investigated for this project:

- commercial vehicles under 48 feet long,
- commercial vehicles over 48 fect long, and
- recreational vehicles.

Other classes of oversized vehicles, such as those with trailers and buses, had frequencies too low to detect significant relationships. For the three vehicle classes that were investigated, the frequencies were too low for significance on the Vashon and San Juan routes. Only results for the Cross-Sound routes are presented here.

Figure 4-1 shows the fare elasticity confidence intervals for three classes of oversized vehicles on the Cross-Sound routes. The fare elasticities are highly elastic.





Clearly, the alternative of driving oversized vehicles around the Sound is an attractive one when fares are increased. In fact, fare increases appear to result in such a loss of use by these types of vehicles that total revenue from these classes is reduced when fares are increased.

The difference in fare elasticity between the under and over 48-feet commercial vehicles is insignificant. However, larger vehicles tend to opt for alternatives more when fares are increased.

NUMERICAL FORECASTING

Fare elasticities can be used to forecast <u>relative</u> differences in ridership, and therefore relative differences in revenue as a result of different fare structure changes. Forecasting total ridership requires other information and forecasts of other variables (i.e., employment or gas price), if those variables are found to be closely related to ridership. This section presents the use of fare elasticities to forecast marginal differences, rather than ridership as a whole.

Inflation Adjustment

The fare variable employed to estimate fare elasticities in this study was the deflated average fare. Forecasts should take this into account. For instance, if one is interested in the effect of a ten percent increase in fares, one needs also to estimate the change in inflation for the period under consideration. In this study quarterly data were used. Therefore, the proper fare change to employ is the nominal change (in this case ten percent) minus the change in inflation <u>during the quarter</u>. For instance, a prediction of an annual inflation rate of four percent means a probable change of one percent in the quarterly rate. The appropriate fare change to use in the calculation is nine percent.

An effective reduction in deflated fare (due to rising inflation) accompanies constant fares. Reduction does not have to be considered when no fare increase occurs

because the objective is to find marginal changes in ridership. The effective reduction in fare occurs whether or not there is a fare increase.

Influence of Lags

For many of the results reported above, a quarter to quarter change in fare resulted in changes in ridership for as long as a year afterwards. The elasticities reported are the sum of the elasticities during the time that the fare change had an effect. The relative differences in ridership with or without a fare increase, using the fare elasticities reported, are for the time after the last quarter that the fare increase had an effect on ridership. Figures 3-1 through 3-3 show the lags that should be considered. The effect on ridership during the intermediate quarters can be calculated by spreading the elasticity over all quarters when the lag has an effect.

Figure 4-2 shows how ridership forecast differences are calculated.

Dealing with Confidence Intervals

Given the fact that the data represent only a sample of all possible data sets, the fare elasticities reported here are estimates of the <u>actual</u> fare elasticity. The confidence intervals reported are 90 percent intervals. In other words, given the available data, there is a 90 percent chance that the true value for the fare elasticity falls within the reported limits.

The limits on the ridership differences can be calculated by using the fare elasticities at the extreme ends of the confidence intervals. Then there is a 90 percent chance that the ridership loss due to a certain fare increase will be between the calculated limits. For instance, consider the impact of a 10 percent increase in deflated fare on the total ridership of Cross-Sound routes. The confidence interval for the elasticity is -0.61 to -1.02. The ridership loss will be between 6.1 percent and 10.2 percent, with 90 percent certainty.

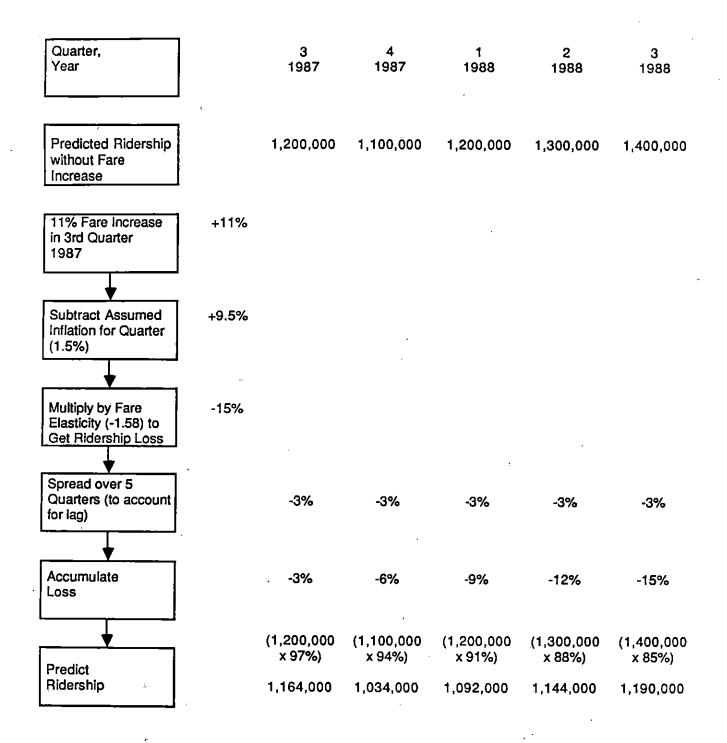


Figure 4-2. Calculation of Ridership for Cross-sound Commuters Assuming 11% Fare Increase.

RECOMMENDATIONS

Specific recommendations for an efficient and equitable fare structure requires knowing more than the fare elasticities. The fare structure needs to address factors such as policies concerning the provision of mobility for island residents, matching fares with operating costs, optimal vehicle and walk-on passenger mix, and the like. The fare elasticities can be used to explore the implications of different policies concerning these issues. However, a few recommendations from the fare elasticity research can be made if maximizing revenue is a major objective of changes in the fare structure.

The fact that ridership is elastic with respect to fares in several categories means that care should be taken when increasing the fares in those categories. The probable result will be a net loss in revenue. For instance, all ridership categories for San Juan routes have elastic relationships. Any increase in fares on those routes will probably mean a loss in total revenue.

The loss in commuter ridership on Cross-Sound and Vashon routes will probably be greater than any increase in fares. These riders constitute the bulk of ferry system ridership, so refraining from alienating these riders is important. A properly priced monthly pass may be a very good way to attract more of these riders. A reduction in fare may actually increase ridership enough to offset the loss. Theoretically, a fare reduction should increase net revenue. Note, however, that for both categories there is a lag in the effect of up to one year.

For the Vashon and Cross-Sound routes, riders a very strong tendency to shift from driving to walking onto the ferries when the fare increases. The fare structure can be used as a way to control the mix of vehicles and walk-on passengers. For instance, a fare increase applying to vehicle fares only will probably result in an increase in net revenue from vehicle passengers and an increase in revenue from walk-on passengers as a result in the shift from vehicles. The important point is that the total loss in ridership

from a vehicle-only fare increase would be minimal. The result would be a shift of passengers to the walk-on category and a net increase in revenue.

For all three categories of oversized vehicles included in this study, ridership is elastic with respect to fares. Increasing those fares apparently causes many people not to make their trips or diverts them around the Sound. The result of a fare increase in these categories will probably be a net loss in revenue. Conversely, a decrease in those fares will probably result in a net increase in revenue. This finding lends support to the idea of providing an off-peak discount for those vehicles.

One important aspect of ridership response to fare changes not covered in this research is the influence of time-of-day. In order to fully explore the possibility of imposing different fares by time-of-day, the research should be extended to include this factor.