

Transit Ridership Efficiency as a Function of Fares
For
Public Transportation Systems in Washington State for 1994

By

Gerrit R. Moore

Moore Planners and Consultants

East 2820 SR-302
Belfair, WA 98528
Phone: 360-275-5130
Fax: 360-275-5130
E-Mail: GRMoore@prodigy.net

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TRANSIT RIDERSHIP EFFICIENCY AS A FUNCTION OF FARES

Gerrit Moore

ABSTRACT

The purpose of this study is to assist in the development of transit fares policies which exploit the benefits of public transit in the mix of transportation options for Washington State. The study relates fares to *Ridership Performance* and *Farebox Recovery* parameters.

The *Ridership Efficiency* of each transit system is estimated by multiplying the ridership (unlinked trips) by the median income, and dividing by the urban population of the service area and the service investment (peak seats) of the system. A mathematical model is developed which relates fares to *Ridership Efficiency*. The *Ridership Efficiency* function follows a Weibull distribution with the tail being reached at \$0.41. Higher fares have little impact on *Ridership Efficiency*. An operating cost model is developed from the transit data in which the independent variables are ridership and revenue distance traveled. This model is used to estimate the farebox recovery and operating cost subsidy.

Ridership and Farebox Recovery estimates are made for selected transits. *Farebox Recovery* reaches a maximum at \$0.30, then decreases to a minimum at \$0.50. With Urban systems, fares above \$0.30 appear to result in a nearly constant subsidy requirement.

The conclusion of the study suggests that a significant percentage of urban trips can be captured by transit if appropriate fares policies are established. A reduced fare experiment is recommended for a congested service area or traffic corridor to determine the effect on traffic counts and ridership to form the basis of traffic management policies by government agencies.

Key Words: Transit, Ridership, Fares, Regression, Cost

BACKGROUND

The thrust of most investigations is to improve the farebox contribution to meeting operating costs rather than finding a balance between fares and overall community benefits. Reference (1) discusses various fare options but only addresses ridership impacts in an anecdotal manner. It mentions that "Ridership increases of 20 – 40% have been seen with free fares ... however, that such a policy does not by itself generate long-term increases in ridership, but loses considerable revenue as well." On the other hand, K. Grace King, *et al.* in, "Long-term Impact of Fare Free Policy on Bus Ridership: A Case Study of WRTD Bus Service," University of Connecticut Departments of Civil and Environmental Engineering and Statistics, Storrs, Connecticut, describe the long term impact of fare-free policy on bus ridership for a mid-sized Connecticut bus service as providing a sustained ridership increase.

Generally, investigators in (2) and (3) have identified values of fare elasticity varying from -0.17 to -0.4. These studies mostly have been longitudinal. That is, they have examined single transit systems with relatively small fare changes over limited durations. This has the advantage of studying a system with consistent marketing methods in a defined community. However, these studies have the disadvantage of examining a narrow range of fares and might miss regions of high volatility where blocks of rider population choose or reject transit over time on the basis of fares.

SOURCE DATA

The source data for this study are given in TABLE I.

greater than one thousand persons per square mile. Ridership is generated in areas which have a high number of trip origins and destinations. The inverse of median income, M_i , is part of the potential driver of Ridership because lower income people are less likely to afford a choice in transportation mode.

S , the service infrastructure, is the capacity of the system to meet the ridership demand of the population (P_u). The studies, referenced above, generally use *revenue service miles* for the measure of service infrastructure. For all the Washington agencies, *peak seating* capacity has a slightly higher correlation to ridership than *revenue service miles*.

The constant of proportionality (A_0) and the fare functions are determined as a part of the data analysis, described below.

The complicated fare pricing policies with zone pricing, congestion pricing, transfers, etc., have been simplified by using the farebox revenue divided by the ridership. This is called *Effective Fares*.

Table II shows the input data, and the calculation of *Effective Fares* and *Ridership Efficiency* from the basic input data. The table column headings show the calculation steps. Here, the constant of proportionality, A_0 , is selected so that the ridership efficiency has an average value of one where the *Effective Fares* are zero.

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TABLE II - 1994 Fixed Route Service for Washington State - Ridership Efficiency Calculation								
Agency Ref. 3	Farebox Income <i>FBI</i>	Ridership <i>R</i>	Effective Fares <i>FBI/R</i>	Urban Population <i>P_u</i>	Peak Seats <i>S</i>	Median Income <i>M</i>	First Calculation <i>R*M_i/Pr/S</i>	Ridership Efficiency <i>R*M_i/Pr/S/A₀</i>
Community Transit	\$4,898,088	5,143,782	\$0.95	311,133	7,890	\$44,326	92.88	0.0256
King Metro	\$50,227,554	79,854,571	\$0.63	1,513,824	49,891	\$44,682	47.24	0.0130
Prosser Rural	\$15,036	26,744	\$0.56	4,630	128	\$43,684	1979.05	0.5463
Spokane	\$3,885,765	7,485,275	\$0.52	349,690	4,690	\$32,808	149.74	0.0413
Jefferson*	\$73,292	169,420	\$0.43	8,337	332	\$29,065	1781.73	0.4918
Pierce	\$4,940,013	12,077,931	\$0.41	541,037	6,460	\$37,057	128.06	0.0353
Pacific	\$67,101	178,827	\$0.38	6,115	281	\$22,414	2336.75	0.6450
Intercity	\$1,019,116	3,064,508	\$0.33	83,383	1,420	\$37,620	973.68	0.2688
C-TRAN	\$1,580,573	4,806,285	\$0.33	211,606	2,180	\$39,485	411.39	0.1136
Kitsap	\$1,055,758	3,616,581	\$0.29	97,720	1,380	\$36,832	987.78	0.2727
Pullman	\$279,807	1,018,460	\$0.27	23,770	332	\$27,007	3490.66	0.9635
Clallam	\$182,177	675,531	\$0.27	26,898	478	\$28,758	1511.00	0.4171
Everett	\$392,687	1,763,750	\$0.22	78,225	1,320	\$44,326	757.14	0.2090
Grays Harbor	\$305,650	1,384,869	\$0.22	33,184	842	\$25,692	1274.17	0.3517
Whatcom	\$426,056	2,067,000	\$0.21	72,718	730	\$34,922	1359.80	0.3754
Yakima	\$265,454	1,376,797	\$0.19	59,725	900	\$27,895	714.50	0.1972
Ben Franklin	\$521,702	2,865,294	\$0.18	113,184	2,171	\$40,327	470.24	0.1298
Twin Transit	\$41,037	232,593	\$0.18	19,260	180	\$28,239	1894.60	0.5230
Cowlitz	\$63,422	369,105	\$0.17	44,985	145	\$32,813	1856.78	0.5125
Valley	\$127,337	754,213	\$0.17	38,705	434	\$29,866	1342.50	0.3706
Mason	\$0	103,901	\$0.00	7,440	102	\$30,569	4185.31	1.1553
Island	\$0	543,094	\$0.00	21,881	230	\$35,389	3827.32	1.0565
Skagit	\$0	490,392	\$0.00	26,118	145	\$34,045	4408.54	1.2169
Link	\$0	1,468,601	\$0.00	50,515	432	\$30,754	2069.67	0.5713
A ₀ (Average Zero Fares)				=	3622.71			

There are five transit systems in TABLE II which were not used in the subsequent regressions. These are agencies which are identified in (4) as having school or college transportation functions or where the fixed route component is not clear. Data points from these agencies do not represent a free market for fixed route service.

The transit agencies listed in TABLE II which charge the highest fares serve the highly urbanized regions. These are regions with the highest congestion and the most limited parking. The transit agencies that charge the lower fares serve communities which do not have high congestion and have the easiest parking. Yet, these are the transit agencies with the highest Ridership Efficiency. Therefore, the examination of such typical cross products as congestion and parking costs is not relevant to this study.

Ridership Efficiency and Fares Relationship

The relationship between *Effective Fares* and *Ridership Efficiency* is defined by a function which is fitted to these data points by Ordinary Least Squares techniques. Equation 2 is a function which fits a wide range of geometries including linear functions and cumulative probability functions.

$$R_n = B_1 \exp(B_2 F^{B_3}) + B_4 \quad \text{Equation 2}$$

Where:

B_n are constants which are determined in the least squares fitting operation,

$\exp(f)$ = the base of the natural logarithm raised to the “f” power,

F = effective fare cost,

$B_1 + B_4$ = fraction of rides which take place if fares are charged,

B_4 = the minimum fraction of rides which take place if any fares are charged, and

B_2 and B_3 define the geometry of the function.

The *Ridership Efficiency* relationship to *Effective Fares* data might be considered in two ways:

- There is a sensitivity to the confrontational act of collecting fares and to the fare price or
- The only sensitivity of ridership efficiency to fares is in the price.

If the regression is made with the consideration that *ridership efficiency* sensitivity is related to the confrontational aspect of demanding fares as well as the fare price, the confrontational change component is along the zero-fares axis. The fare price sensitivity component is in the region where the fares are greater than zero. Then the regression of *Ridership Efficiency* as a function of *Effective Fares* does not include the \$0.00 fare subset. The difference between the average of the zero fares R_n values (in this case, one) and the intersection of the regression with the \$0.00 fare axis would be the estimate of the fare demand loss because of the confrontational aspect of demanding fares. TABLE III lists the result of fitting Equation 2 to the data set, excluding the zero fare data set.

TABLE III- Ridership Efficiency Model Smoothed on Non-Zero Fares (Monetary Component of the Confrontational Loss Model)				
Results				
$B_1 =$	0.32992	Sample Size =	15	
$B_2 =$	-555.8	Sample Standard Deviation =	0.11510	
$B_3 =$	6.16518			
$B_4 =$	0.0216			
Comparison				
Agency	Effective Fares Data	Ridership Efficiency Data	Regression Model Estimate	Residuals
Community Transit	\$0.95	0.02564	0.02160	0.00403
King Metro	\$0.63	0.01304	0.02160	-0.00856
Spokane	\$0.52	0.04133	0.02162	0.01971
Pierce	\$0.41	0.03535	0.05655	-0.02121
Intercity	\$0.33	0.26877	0.19788	0.07089
C-TRAN	\$0.33	0.11356	0.20540	-0.09184
Kitsap	\$0.29	0.27266	0.27079	0.00188
Clallam	\$0.27	0.41709	0.29934	0.11775
Everett	\$0.22	0.20900	0.33455	-0.12555
Whatcom	\$0.21	0.37535	0.34086	0.03449
Yakima	\$0.19	0.19723	0.34442	-0.14720
Ben Franklin	\$0.18	0.12980	0.34652	-0.21671
Twin Transit	\$0.18	0.52298	0.34740	0.17558
Cowlitz	\$0.17	0.51254	0.34801	0.16452
Valley	\$0.17	0.37058	0.34837	0.02221
Mason	\$0.00	1.15530		
Island	\$0.00	1.05648		
Skagit	\$0.00	1.21692		
Link	\$0.00	0.57131		

If the regression is made with the consideration that *ridership efficiency* sensitivity is related only to the fare price, the following are the sample standard deviation of regression residuals:

- Over the total data set = 0.1613399,
- Over the non-zero fare data set = 0.1190923.

The standard deviation of regression residuals is slightly less for the non-zero regression than for the regression which smoothed over the total data set. This suggests that the confrontational-price loss model is a better reflection of the input data.

FIGURE 1 is a plot of the *Ridership Efficiency* data set and the regression curve.

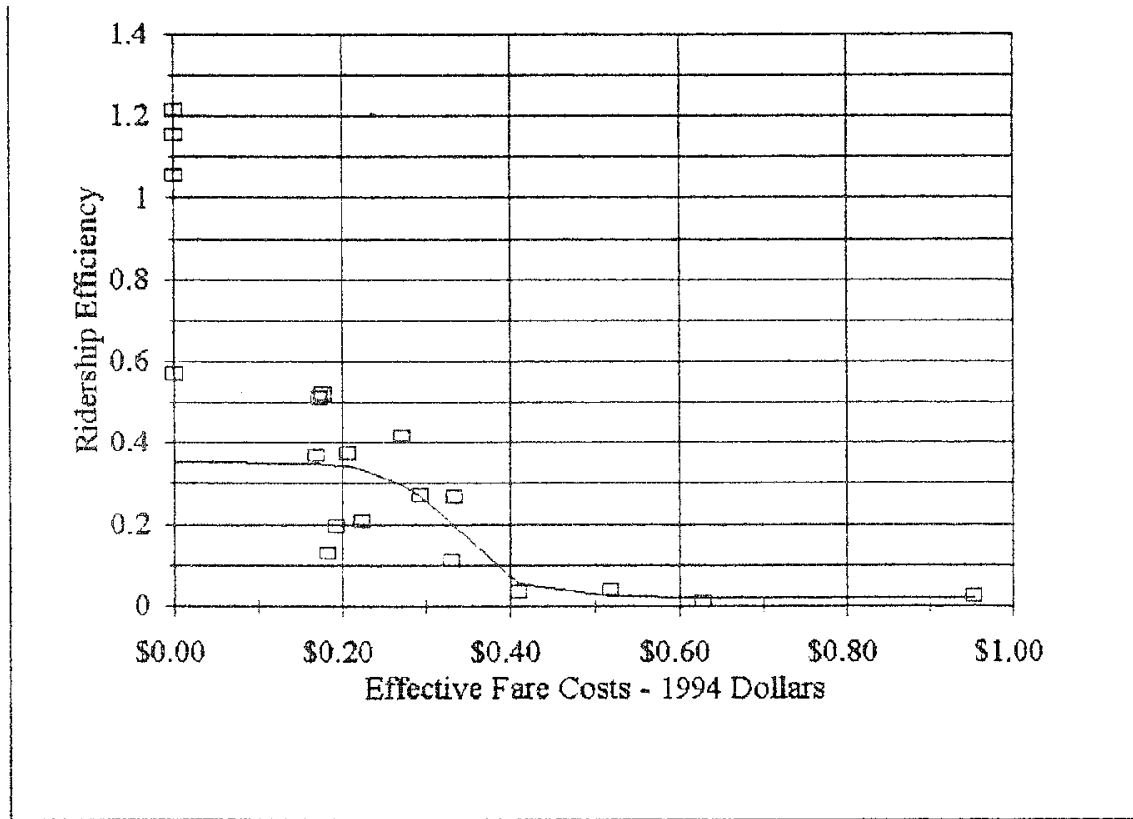


FIGURE1 – Ordinary Least Squares Fit of Equation 2 to Normalized Ridership Data, Excluding the \$0.00 Fares Points

There appears to be four different regions of fare impact:

- The first region is along the zero fare axis where the ridership efficiency changes with the confrontation of fare demand.
- The second region extends from \$0.00 to \$0.21 fares. Ridership seems fairly insensitive to fare changes (everyone has two dimes or a quarter).
- The third region extends from \$0.21 to \$0.41 fares. Here, ridership is very sensitive to the fare levels charged.
- The fourth region, the toe of the curve, extends from \$0.41 to \$0.95 fares. The slope is nearly zero. People seem willing to pay any fare demanded. Probably, this is because the agencies charging these fares are the larger urban systems where the passenger loads are defined by the diurnal commute patterns. Here, patrons consider the fare costs as a part of the employment investment or they are the patrons who do not have the means to invest in other transportation options.

The third and fourth regions in the fare function are suggested in (3), Appendix A. This quotation is from a paper given by Daniel K. Boyle in 1985 at the 64th Annual Meeting of the Transportation Research Board, Washington, DC:

“A second interesting point concerns the concept of a fare threshold. This concept postulates that, as fares rise beyond a certain threshold level, ridership behavior changes significantly [...] Elasticities are increasingly negative at higher values of the original fare up to the “over 60 cent” category. In this category, ridership response becomes less elastic than the “51 to 60 cent” category. The explanation driving this version would be that by the time a relatively high fare level is reached, most of the “choice” riders have already abandoned transit for another mode, and so further increases have less impact on ridership. While the data in Table 1 does not provide conclusive proof that a fare threshold of this nature actually exists, further research into this concept would be useful.”

In Washington State, the less elastic response region begins at \$0.41 rather than \$0.60, as discussed above. This difference might be due to the increased competition between modes because of the more automobile centered community design in the Western states.

The regression function follows a Weibull distribution. This would imply that the transportation mode choice should be modeled as a probability function. Equation 2 could be considered a cumulative probability function that transit is chosen by the transit using population if the fare costs are less than a given value.

Operating Cost Model

An operating cost model is required to evaluate the fiscal impacts of changes in ridership. The four fare-free transits are not included in this analysis. The cost model used in this analysis is regressed from Ridership (R) and Revenue Service Miles (RSM). The source data are given in Table I. The operating cost model is given in Equation 3.

$$Cost = RSM^{C_1}(C_2 + C_3R^{C_4}) + C_5 \quad \text{Equation 3}$$

The concept for this regression model is as follows:

- If RSM approaches zero, then $Cost$ approaches a minimum (the only costs being overhead, C_5),
- If R approaches zero, then $Cost$ approaches a function of RSM (the vehicles would still operate over the designated routes, but with the number of passengers approaching zero),
- Economies of scale might be expected with RSM and R so those parameters are allowed to be raised to some exponent (C_1 and C_4 , respectively).

The results of the operating cost regression are given in Table IV. In addition, the *Operating Cost per Person* (Operating Cost divided by Served Population, Table 1) and *Subsidy per Person* (the difference between Operating Costs and Farebox Income, divided by Served Population) are given to show the relative cost and tax burden carried by the service area populations. The subsidy in Washington State is achieved through a special sales tax and a portion of the motor vehicle excise tax collected in the transit service area.

TABLE IV - Operating Cost Model Smoothed on Ridership and Revenue Service Miles					
Results					
$C_1 =$	0.97671	Sample Size =	15.00000		
$C_2 =$	0.54618	Deg. of Frdm =	3.00000		
$C_3 =$	0.29991	Sample Std. Dev. =	\$2,536,376		
$C_4 =$	0.19350				
$C_5 =$	0.39105				
Comparison					
Agency	1994 Operating Cost	Model Estimate	Residuals	Cost Per Person	Subsidy Per Person
Community Transit	\$28,647,785	\$22,144,956	\$6,502,829	\$84.40	\$69.97
King Metro	\$218,755,172	\$217,975,452	\$779,720	\$136.76	\$105.36
Pierce	\$31,713,305	\$34,313,934	(\$2,600,629)	\$53.12	\$44.85
Spokane	\$21,731,478	\$24,514,184	(\$2,782,706)	\$62.14	\$51.03
C-TRAN	\$10,811,498	\$12,353,505	(\$1,542,007)	\$38.52	\$32.89
Kitsap	\$9,400,000	\$9,426,583	(\$26,583)	\$54.57	\$48.44
Whatcom	\$5,771,689	\$4,384,377	\$1,387,312	\$46.89	\$43.43
Ben Franklin	\$5,630,533	\$7,967,718	(\$2,337,185)	\$42.16	\$38.26
Everett	\$6,241,285	\$4,384,377	\$1,856,908	\$79.77	\$74.75
Intercity	\$11,305,403	\$13,643,850	(\$2,338,447)	\$60.81	\$55.33
Yakima	\$3,472,633	\$2,508,397	\$964,236	\$58.13	\$53.69
Cowlitz	\$1,069,612	\$815,194	\$254,418	\$23.81	\$22.39
Valley	\$1,712,312	\$1,482,387	\$229,925	\$37.71	\$34.90
Clallam	\$3,213,961	\$3,473,803	(\$259,842)	\$51.42	\$48.51
Twin Transit	\$708,799	\$699,614	\$9,185	\$36.80	\$34.67
Mason	\$630,492	\$585,320	\$45,172	\$14.23	\$14.23
Island	\$1,463,618	\$1,929,456	(\$465,838)	\$22.94	\$22.94
Skagit	\$908,169	\$1,235,763	(\$327,594)	\$32.49	\$32.49
Link	\$4,587,995	\$4,037,219	\$871,935	\$56.42	\$56.42

ESTIMATES

Methods

Ridership estimates for particular transits are made from the Ridership Efficiency (R_n) function. The base ridership value (in this case, 1994) is divided by *Ridership Efficiency* (Equation 2) for the corresponding *Effective Fare*. This gives the estimate for zero-fare ridership. The ridership as a function of a fare price is estimated by multiplying the zero-fare ridership by the *Ridership Efficiency* (Equation 2). The following estimates are based on the 1994 ridership performance as the point of departure. They are statements of what might have happened with the particular agencies under different fare policies.

Farebox Recovery is calculated by dividing the product of *Effective Fares* and the resulting ridership estimates by Operating Cost (Equation 3). R , required in this model, is given by the ridership estimate. The *RSM* estimate requires a further assumption.

In the ridership estimate, the *urban population* and *median income* are functions of the served community so a change in R_n , for a community is a change in the ratio of ridership to seats (see Equation 2 description, above). The number of seats, or vehicles remains constant in this estimate. It is the way they are used that changes. As R_n increases with decreasing fares, more vehicles are used in the non-peak parts of the day until all vehicles (and all seats) are used throughout the service period. RSM increases with the increased utilization of vehicles. This can be estimated from the transit Peak to Base Ratio. Appendix A, *The National Transit Profile*, of (7) gives the value for the peak to base ratio as 1.8. This is used in the following estimate. RSM is assumed to change according to Equation 4.

$$RSM(F) = RSM(d) * (1 + (P-1) * (R_n(F) - R_n(d))) \quad \text{Equation 4}$$

Where:

- $RSM(F)$ = Revenue Service Miles at Effective Fare (F),
- $RSM(d)$ = Revenue Service Miles input value (TABLE I),
- P = Peak to Base Ratio
- $R_n(F)$ = Ridership Efficiency at Effective Fare (F) (Equation 2 with regressed constants),
- $R_n(d)$ = Ridership Efficiency input value (TABLE II).

Since changes in transit performance with changes in Effective Fares (F) involve people moving in and out of the transit riding population set, it must be assumed that there is a lag between a change in F and a change in R . There is a paucity of data on these phenomena. However, the time constant, with 63% of the change, appears to be around 2.5 years (if an exponential model is assumed). This is not an accurate estimate but it gives some idea of the time involved.

Examples

In Washington there are four transits which operate with zero-fares. The oldest of these is Island Transit which serves Whidbey and Camano Islands in Puget Sound. The fare-free transits are the most efficient systems as measured by Ridership Efficiency. The prepaid fares policy promotes an egalitarian operation; everybody is invited. Upon entering the vehicle, the patron has only a welcoming experience. There is no question of having the exact change or speaking English when the fare is to be paid. The service tends to be Spartan. Island Transit has next to the lowest *cost per person* of Washington State transits (TABLE IV). There is a high community involvement in support of the fare-free agencies.

FIGURE 2 shows the performance estimate for Island Transit.

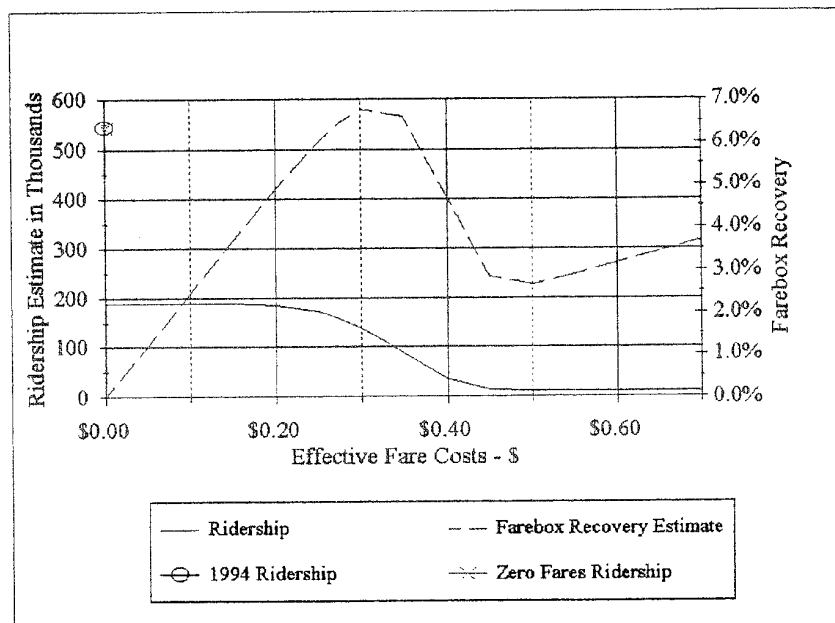


FIGURE 2 - 1994 Performance Estimates as a Function of Effective Fares for Island Transit

Except for the vertical scales, the Ridership Estimate and Farebox Recovery curves shown in Figure 2 are typical for all transits. The Operating Cost Estimate is not shown but it has the same shape as the Ridership Estimate curve relative to the *Effective Fare Cost*.

In the Fare region of \$0.00 to \$0.21, the *Farebox Recovery* increases in proportion to *Effective Fare Cost* because, here, *R* and *Cost* undergo little change. Between \$0.21 and \$0.30, *R* begins its sharp decline as *Effective Fare Cost* increases. The first maximum in *Farebox Recovery* occurs at \$0.30. It then decreases to a minimum at \$0.50. Here, *R* becomes asymptotic with the *Effective Fare Cost* axis so there is slight change to both *R* and *Cost* with increasing fares. From this point the *Farebox Recovery* increases as a near linear function of *Effective Fare Costs*. A transit system operating in this fare's region could increase farebox recovery by increasing fare prices without a significant decrease in ridership.

References (9) and (10) estimate the cost of fare collection varies from 3 percent to 7 percent of the operating cost. Island Transit could charge fares and have sufficient Farebox Recovery to cover the cost of collection. However, the ridership as a minimum would be reduced to 35 percent of the fare-free ridership.

Figure 3 shows the ridership and farebox recovery estimate for C-TRAN, which serves all of Clark County, including the City of Vancouver. The actual 1994 Farebox Recovery point, 14.6%, is greater than the estimate curve. This is because the 1994 operating cost is less than the *Model Estimate* value given in TABLE IV. The *Costs per Person*, and the *Subsidy per Person* (TABLE IV) are also significantly lower than the other urban transit agencies in Washington State. These three conditions suggest that C-TRAN is under-funded for the population being served and, therefore, cannot deliver the service which would result in the expected normalized ridership of 0.2 rather than the actual 0.11136.

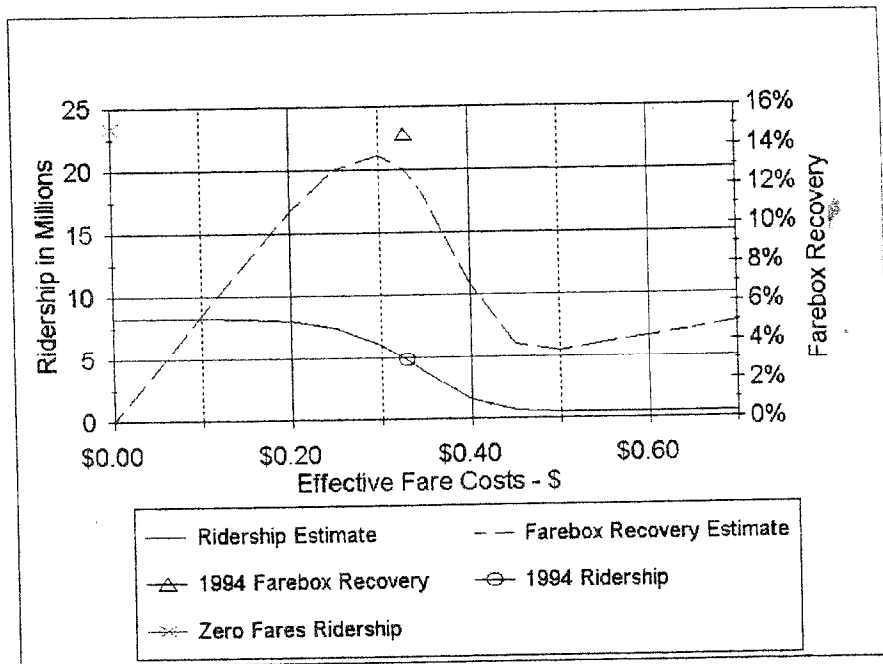


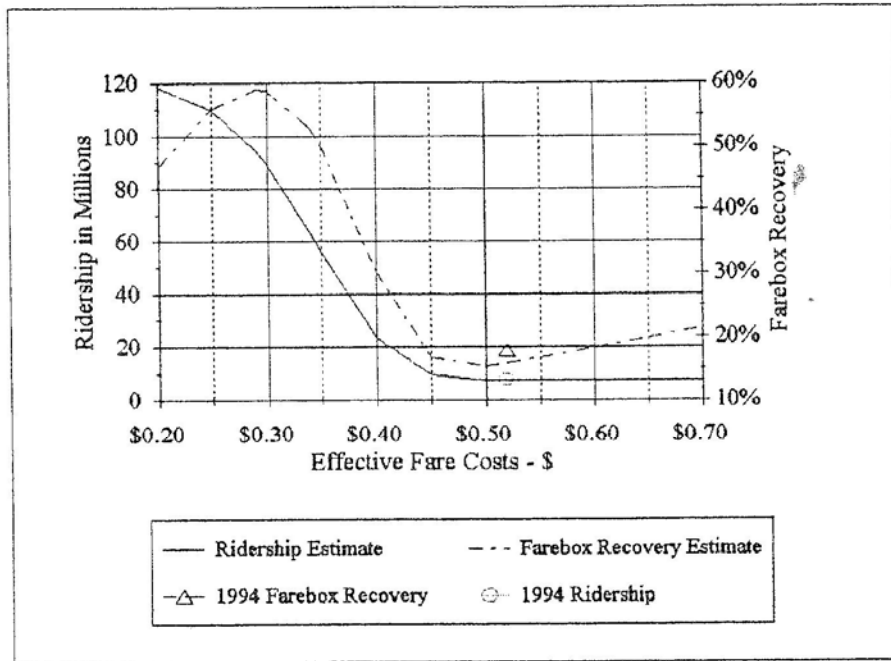
FIGURE 3 – 1994 Performance Estimate as a Function of Effective Fares for C-TRAN

Portland, across the Columbia River, has no sales tax, which places C-TRAN at a competitive disadvantage for subsidizing effective operations. If it did meet the average transit efficiency for

\$0.33 effective fares, the estimated ridership would be approximately 8,500,000, or twice the actual 1994 level. The \$0.33 *Effective Fare Cost* places C-TRAN *Farebox Recovery* near the first maximum value. A change in fares would require a corresponding change in the subsidy. The ridership range of C-TRAN is not large enough to offset the operating cost changes with the farebox income. However, if the fares were reduced, Figure 3 suggests improvement in ridership. The C-TRAN operating conditions are near optimum, given the financial constraints on this system.

FIGURE 4 gives the Ridership and farebox recovery estimate curves for Spokane Transit, which serves a 372.5 square mile area, including the City of Spokane. This is the second largest urban center in Washington and the transit reflects the characteristics of a larger urban system.

FIGURE 4 – 1994 Performance Estimate as a Function of Effective Fares for Spokane Transit



The 1994 Spokane Transit fare is at the toe of the ridership curve, where ridership becomes inelastic with fares. At this point, most of the ridership potential is lost. Also, the fare is near the minimum for *Farebox Recovery*. If the *Effective Fare* cost is decreased from \$0.52 to \$0.30, *R* and *Farebox Recovery* would be expected to increase. Spokane Transit has sufficient ridership to offset the operating cost changes with the farebox income so the change to the \$0.30 effective fare eventually would result in a slight reduction in the required tax subsidy. This occurs with Spokane and not with C-TRAN because of the economies of scale reflected in the operating cost model (Eq.3) TABLE V lists fares and the corresponding estimated tax subsidies and riderships. This performance is characteristic (with appropriate changes in scale) of the four largest transit systems in Washington. A \$0.52 fare places Spokane Transit performance at the least efficient locus. However, the 1994 Spokane *Ridership Efficiency* is almost twice the *Model Estimate* so it would appear there is very effective management of the system.

TABLE V – Spokane Transit Subsidy and Ridership Estimates		
Fares	Subsidy Estimate	Ridership Estimate
\$0.20	\$26,884,856	118,616,655
\$0.30	\$18,697,486	89,414,304
\$0.40	\$21,789,472	23,617,632
\$0.52	\$20,628,783	7,485,275

Conclusion

This study concludes that *Ridership Efficiency* is primarily a function of the fare charged. *Ridership Efficiency* function can be described as a probability function. This is the probability that people who are potential transit users will choose transit over other modes or not travel given particular fare values. This function has three components:

- 1) The probability that a trip by transit is chosen if any fares are charged (0.33, if fares are >0.00),
- 2) The probability that a trip by transit is chosen if the fare is a particular value (0.33 to 0.022, if fares are between \$0.00 and \$0.65),
- 3) The probability that a trip by transit is chosen if fares exceed a limiting value (0.022, if fares are \$0.65 and greater).

Fare-free transit agencies would experience a sharp decrease in ridership (67%) if any fares are charged. If it becomes agency policy to collect fares, the fare-free ridership should exceed 700,000 unlinked trips for a farebox recovery greater than 3 percent, the minimum estimate for fare collection costs given in (9) and (10). The maximum farebox recovery is achieved with a fare of \$0.30.

Transit agencies which collect fares in the \$0.20 to \$0.40 range are in the steepest part of the *Ridership Efficiency* curve given in Figure 1. Here, small increases in *effective fares* can result in marked decreases in ridership.

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Transit agencies which collect *effective fares* exceeding \$0.45 are the urban agencies service communities with heavy traffic and increased air pollution. A change in fares has little impact on ridership if the fare remains in excess of \$0.45. If an agency in this group were to adopt a policy to reduce traffic congestion and air pollution through increasing transit mode share, the most direct way is to reduce fares. The *Effective Fares* would have to be reduced below \$0.45 to have even a beginning effect on ridership. The *effective fares* for these transits could be reduced to \$0.30 (the maximum *Farebox Recovery* point) without a significant increase in tax subsidy support.

Regressions are tools for data summary and not prediction unless there is some knowledge of the similitude of each member of the data set. The assumption here is that the people in Washington have a common ethos about using transit. Before any heavy investment is made in radical fare change that assumption should be tested in a limited experiment. It might be implemented in a total service area of a medium size system, or in a definable service area sub-region or in a congested traffic corridor for a large transit system where the problems are most

egregious. Careful counts of ridership and traffic volumes would be made both before and during the experiment. The effective fares would be reduced in annual steps until the desired traffic and air quality goals are realized. For example, the fare might be reduced to \$0.40 for a year and then the results evaluated. About a third of the total expected increase in ridership should be realized in that period. Then, the fares might be held at that level or reduced another step, depending on the outcome. The results of the experiment could be applied to the regional systems with some confidence in the outcomes.

Any large scale capture of ridership from other modes can be done only through economic competition that is consistent with the public's perception of the transportation market. This study presents a measure of that perception with the variation of ridership efficiency over the regime of effective fares in Washington State for 1994.

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