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Performance Evaluation for Fixed Route Transit: The Key to Quick, Efficient and Inexpensive Analysis

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Institute of Transportation Studies University of California, Irvine Irvine, CA 92697-3600, U.S.A. http://www.its.uci.edu ABSTRACT

This research uses FY 1980 Section 15 data to identify and test a set of seven key performance indicators that are useful for nationwide, fixed route, motor bus transit performance evaluation. These indicators can be used together or individually to assess transit performance, for a single system or for cross-system comparison. The second year of Section 15 data is also used to evaluate the validity of an earlier analysis based on the first year data.

Rigorous cleaning, verifying and grooming procedures carried out before analysis insured that the current input data was as complete as possible. Careful decisions regarding which variables to keep and/or drop from the analysis provided the best possible set of performance indicators available in the FY 1980 Section 15 data.

Use of four parallel data sets and several exploratory factor analyses detected the simple underlying structure of the data. Rigorous testing verified the structure as the most salient performance dimensions. The small subset of seven key performance indicators was identified and tested as representative of these dimensions.

Results here are compared to the earlier analysis. The strength of the current research lies in both the quality of the data used and the rigor with which it was tested throughout. A strong case is made for using the seven identified performance indicators for motor bus transit performance evaluation.

INTRODUCTION

Section 15 of the Urban Mass Transportation Act of 1964, as amended, has provided for the collection of a unique set of comparable transit statistics by requiring all urban transit applicants for operating assistance to provide a uniform set of information about their transit systems. The first year of Section 15 reported statistics [FY1978-79] was used by Fielding and Anderson (2) to test the performance concept model developed by Fielding, and Glauthier and Lave (3). The results were not satisfying. A set of nine performance indicators were selected representing the three dimensions of transit performance. However, serious questions were raised about the validity and completeness of the first year's data. Only 98 agencies out of 311 could be used in the final factor analysis. The rest were dropped because of missing and imprecisely reported data. Other questions were raised by reviewers about the validity of the indicators selected based upon a single factor analysis solution. Although the results were not satisfying, the method of using factor analysis to identify clusters of variables and performance indicators held promise. If the data set could be improved, more rigorous factor analytic solutions could be applied on different versions of the data to test the validity of the performance model.

This paper analyzes data from the second year of reported statistics [FY1979-80]. It replicates the methods and revises the results from the first year (FY 1979-1980) statistics ($\underline{1}$). A thesis is advanced that

there exists a highly consistent set of performance concepts relevant to fixed route transit operators and a small, unique subset of performance indicators that are useful for performance evaluation by individual transit managers for systems of all sizes. Results from these analyses are compared to previous research and suggestions are offered for the use of the seven identified key performance indicators.

Emphasis is given to describing the sequence of steps used to explore the thesis that a highly consistent set of performance concepts exists and that they can be represented by a small, unique set of performance indicators. Results from previous research have been controversial ($\underline{3}$). Therefore, we have endeavored to explain how:

- variables were selected, verified and groomed
- performance indicators were selected and calculated in alternative ways to minimize bias
- ` different methods of factor analysis were used to explore the structure of performance concepts
- tests were used to verify the structure of performance concepts.

PERFORMANCE EVALUATION VIA SECTION 15 DATA

The prime objective of performance evaluation is to identify and assess the most salient features of a transit system that are relevant to performance. When individual system managers have questions on performance vis-a-vis decisions about resource allocation, immediate, accurate and reliable answers are necessary. Transit analysts have a



FIGURE 1. FRAMEWORK FOR TRANSIT PERFORMANCE CONCEPTS

minimum amount of time and money with which to provide key pieces of information on performance.

Further, performance has a comparative function. A system may desire to evaluate its own performance over time or, more typically, to evaluate its own performance against those systems it regards as peers. In order to do such cross-system analyses, the analyst must use a set of performance statistics that would be equally valid for each system to be analyzed.

Section 15 data has been crucial to the analysis; it is only through the use of a nationwide set of comparable data that identification of globally-oriented performance indicators can be assessed. A wide variety of Section 15 statistics was evaluated as performance indicators. Three categories of statistics--service inputs, service outputs and service consumption--provided the framework to organize the much larger set of data ($\underline{2}$).

Figure 1 portrays the organizing framework developed in the Fielding et al. performance concept model. Cost-efficiency indicators measure service inputs (labor, capital, fuel) to the amount of service produced (service outputs: vehicle hours, vehicle miles, capacity miles, service reliability). Cost-effectiveness indicators measure the level of service consumption (passengers, passenger miles, operating revenue) against service inputs. Finally, service-effectiveness indicators measure the extent to which service outputs are consumed.

The overriding goal of this research was to identify those key performance statistics: 1) that provide transit analysts with the most

salient performance information and 2) that target information which is equally valid for each transit agency and thus for cross-system analysis.

One result of the analyses that follow was the identification of a small, unique set of key performance indicators that met the overriding goal of this research. Seven performance variables from a much larger data set were identified. These can be used to assess the performance of any fixed route, motor bus, transit system. A minimum of three of the seven variables will provide key information on cost efficiency, cost effectiveness and service effectiveness. Further, all seven of these performance indicators and a parallel set of "alternates" can be used for cross-system comparisons with peers.

The following sections describe, in detail, how Section 15 data was used to identify these seven performance indicators, how these variables were identified, and how they were rigorously tested to ensure their validity for use. The main focus of this research has been to provide transit analysts with a set of easily accessible statistics with which to do individual and peer group comparisons of performance. The body of this paper explains how this was done.

DATA PREPARATION

The Section 15 data base includes information from fifteen separate required forms and three voluntary levels of reporting. At the Required Level of reporting, information is available for revenues, subsidies, expenses, wages and benefits, service schedules, maintenance performance,

energy consumption, accidents, employee counts, service supplied and service consumed. For many purposes the level of detail is excessive and key pieces of information are often fragmented into tiny units which must first be aggregated before analysis. Many of the variables relevant to the Fielding, et al., model refer to different units of analysis; e.g., economic data is fiscal year based while service consumed and service supplied information is reported for an "average" weekday, Saturday and Sunday. Further, revenue data and subsidy data are not disaggregated by mode; they are reported for the entire system. This requires the development of weighting strategies for single mode performance analysis as many performance indicators like fuel efficiency and revenue generation differ by mode. Data organization, verification and correction techniques used in this research are described in a companion paper ($\underline{4}$).

The first task of analysis, then, entailed a detailed compilation and assessment of each of the basic variables that would later be included in the conceptual model's performance indicator ratios. Some of the basic variables available in the Section 15 data base are better than others; some present unique problems for multivariate statistical analysis ($\underline{4}$).

Revenue and expense data are fairly complete while operator's wage, state and local subsidies, maintenance and passenger data present particular problems. Systems differ as to how local versus state subsidy is defined; the same funding source may be designated differentially by several transit systems. Maintenance data is often suspect; systems using outside contract maintenance labor often claim zero maintenance

personnel and cost. Finally, passenger data is the weakest part of the Section 15 data base; between 13% to 25% of the data is missing.

Missing Data Procedures

Missing information in Section 15 data, at present, poses a unique analytical problem. Both valid zeros and "no information reported" codes are represented by zeros. Whenever possible, other information available in the data base was pieced together to provide for missing data or to distinguish between valid zeros and failure to report (5).

Strategies for detecting real zeros are especially crucial for statistical analyses of the type used here. The basic variables used to calculate performance indicator ratios were compiled from several pieces of information. Each performance indicator was calculated as a ratio of two basic variables. Although multivariate analyses were performed on the performance ratios to detect the underlying performance data structure, several hundred variables went into the creation of these ratios.

Missing values encountered at any point in the computation of basic and ratio variables and during the multivariate statistical procedures cause a "snowball" effect of missing information to occur. The assumption in the computation and analysis procedures is that every case has information for all of the variables. If any case is missing even one piece of information it is thrown out of the computations and subsequent analyses. The missing values problem has a cumulative effect as cases are dropped from the analysis. Thus, from a total of 304 transit systems running fixed route motor bus service, only two-thirds of the cases--198 systems--had enough information available to use in the analysis. However, this is a vast improvement over the 98 systems which could be used from the FY 1979 data.

SELECTING PERFORMANCE INDICATORS

A wide variety of performance indicator ratios was available from the Section 15 data base. In selecting the set of performance indicators to be used for further analysis, the data included variables that would relate to the conceptual model i.e., those that would best represent the three categories of performance concepts--cost-efficiency, costeffectiveness and service-effectiveness. Particular attention was given to the availability and reliability of the data from which the ratios would be calculated. As noted, some of the Section 15 data variables were more complete or more reliable than others.

Table I lists the initial set of forty-eight variables selected for further multivariate analysis. The variables are organized under the performance concept to which they relate. This set of forty-eight variables in most cases (other than passenger data) represent the most complete, generally reliable and non-redundant performance indicators available in the current (FY 1980) Section 15 data set.

Variables based on revenue capacity miles were not included because of a detected inconsistency in the measurement of that variable across systems. Ratios based on population data were not included because

Table I. Performance Indicators by Concept

COST EFFICIENCY MEASURES

Labor Efficiency

Vehicle Hours per Employee Revenue Vehicle Hours per Operating Employee Hour Vehicle Miles per Employee Peak Vehicles per Executive, Professional and Supervisory Employees Peak Vehicles per Operating Personnel Peak Vehicles per Maintenance, Support and Servicing Personnel

Vehicle Efficiency

TVH/AVEH
TVH/PVEH
TVM/AVEH
TVM/PVEH
RVM/TVM

TVH/EMP

RVH/OEMP

TVM/EMP

PVEH/ADM

PVEH/OP

PVEH/MNT

RVM/FUEL TVM/FUEL

Fuel Efficiency

Revenue Vehicle Miles per Gallon Diesel Vehicle Miles (Bus) per Gallon Diesel

Maintenance Efficiency

Total Vehicle Miles per Maintenance Expense	TVM/MEXP
Vehicle Miles per Maintenance Employee	TVM/MNT
1,000,000 Vehicle Miles per Roadcall	TVM/RCAL

Output per Dollar Cost

Revenue Vehicle Hours per Total Labor and FringeRVH,ExpensesRVH,Revenue Vehicle Hours per Operations Labor andRVH,Fringe ExpensesRVH,Revenue Vehicle Hours per Vehicle MaintenanceRVH,Labor and Fringe ExpensesRVH,Revenue Vehicle Hours per Administrative LaborRVH,Revenue Vehicle Hours per Administrative LaborRVH,	Reve Vehi	enue Vehicle Hours per icle Miles per Operati	• Operating Expense ng Expense	RVH/OEXP TVM/OEXP
Revenue Vehicle Hours per Operations Labor and Fringe Expenses RVH, Revenue Vehicle Hours per Vehicle Maintenance Labor and Fringe Expenses RVH, Revenue Vehicle Hours per Administrative Labor and Fringe Expenses RVH,	Reve Expe	enue Vehicle Hours per enses	• Total Labor and Fringe	RVH/TWG
Revenue Vehicle Hours per Vehicle Maintenance Labor and Fringe Expenses Revenue Vehicle Hours per Administrative Labor and Fringe Expenses RVH,	Reve Frir	enue Vehicle Hours per nge Expenses	Operations Labor and	RVH/OWAG
Revenue Vehicle Hours per Administrative Labor and Fringe Expenses RVH,	Reve Labo	enue Vehicle Hours per or and Fringe Expenses	Vehicle Maintenance	RVH/VMWG
	Reve and	enue Vehicle Hours per Fringe Expenses	Administrative Labor	RVH/ADWG

SERVICE EFFECTIVENESS MEASURES

Utilization of Service

·	Passenger Trips per Revenue Vehicle Hour Passenger Trips per Revenue Vehicle Mile Passenger Trips per Peak Vehicle Passenger Trips per Passenger	TPAS/RVH TPAS/RVM TPAS/PVH PASM/TPS
0per	ating Safety	
	1,000,000 Vehicle Miles per Accident Revenue Vehicle Hours per Accident	TVM/ACC RVH/ACC
Reve	nue Generation	
	Passenger Revenue per Peak Vehicle Passenger Revenue per Revenue Vehicle Hour Operating Revenue per Revenue Vehicle Hour Passenger Revenue per Passenger	REV/PVEH REV/RVH OREV/RVH REV/TPAS
Pub1	ic Assistance	
	Revenue Vehicle Hours per Local Capital and	

Operating Assistance RVH/LSUB Revenue Vehicle Hours per State Capital and Operating Assistance RVH/SSUB Revenue Vehicle Hours per Total Operating Assistance RVH/OSUB Revenue Vehicle Hours per Total Capital and Operating Assistance RVH/TSUB Passengers per Local Operating Assistance TPAS/LOA Passengers per Total Operating and Capital Assistance TPAS/TSUB Passenger Revenue per Total Operating and Capital Assistance REV/TSUB Passenger Revenue per Total Operating Assistance Passengers per Total Operating Assistance REV/OSUB PAS/OSUB

COST EFFECTIVENESS MEASURES

Service Consumption per Expense

Passengers per Operating Expense	PAS/OEXP
Passenger Miles per Operating Expense	PASM/OEX
Passengers per Total Labor and Fringe Benefits	PAS/TWAG
Passengers per Gallon Diesel Fuel	PAS7FUEL
Passenger Miles per Total Expense	PASM/TEX
Revenue Generation per Expense	

Ratio Operating Revenue to Operating Expense Ratio Total Revenue to Total Expense REV/OEXP TREV/TEX available population information reflected total urban population rather than service area population. Otherwise, performance indicator ratios comparable to the 1979 data analyses were selected for use. This facilitated comparison with previous results and identification of shifts due to the better-collected, cleaner and more complete data.

Distribution of Data

One of the first tasks for exploring the data set was to search for extreme outliers and to remove them from the analysis. Extreme outliers could force the analysis to focus on the inflated variance due to the presence of an outlier, rather than the more true-to-data variance present across the range of the other cases. Four cases were dropped from the analysis because of the outlier quality of their reported statistics.

The next task was to check the univariate descriptive statistics for each of the selected performance indicator ratios to evaluate the distribution of the case values across the variable range. Most commonly used bivariate and multivariate procedures assume a normal-like distribution of the case values in each variable.

Two descriptive statistics that provide information on how far a variable deviates from a normal-like distribution of values are skewness and kurtosis. For a normal distribution of data, both skewness and kurtosis equal zero; for each statistic the further from zero the value, the less normal-like is the data distribution. The less normal-like the distribution, the more questionable the statistical results.

The skewness and kurtosis values for the list of forty-eight variables ranged from -5.212 to 16.098 and from 1.373 to 263.908 respectively, indicating that the distributions were far from normal. The proposed multivariate procedures to be used on the performance indicator data set were considered relatively "robust," i.e., valid even under deviations from normality. However, the goal of this research was to provide a highly reliable set of consistent analytical findings that could serve as a benchmark for cross-year comparisons.

To counter any possible bias in the analyses and to provide a comparable set of more normally distributed performance indicator variables, the base 10 logarithms of the forty-eight performance indicators were calculated. Logarithms preserve the essential data structure of the variables from which they arise while shifting the distribution of the data to a more normally shaped curve ($\underline{6}$). This provided two sets of comparable data--the forty-eight performance indicator ratios calculated from the Section 15 reported data and a set of forty-eight logarithm variables calculated from these.

In aiming to develop the strongest set of data on which to base analytical findings, a second question arose. As mentioned above, revenue data is reported as a total for the whole system; it is not broken down by mode when more than one mode exists. Local and state subsidies are not consistently defined and calculated across systems. A third set of performance ratios was developed using basic variable data and revenue statistics that were weighted to eliminate revenue from modes other than bus transit. Then, a full set of forty-eight base 10

logarithms was calculated on the weighted data, again, to provide more normally-distributed data.

As a result of the cleaning, verifying and grooming, four somewhat different sets of performance indicator data were available: a) ratios from reported data, b) logs of reported data variables, c) ratios from the weighted reported data, d) logs of the weighted data variables. The purpose for developing these four sets was to ensure that when final results from multivariate analyses were reported, most contingencies for possible bias in the data had been addressed. Consistent results across the four data sets would provide evidence that, indeed, a stable performance concept structure had been found in the data.

EXPLORATORY ANALYSES

Multivariate analyses were used to search for a highly consistent set of performance concepts relevant to fixed route transit and for a small, unique subset of conveniently useable performance indicators. Factor analysis is ideal for detecting the most salient features of a set of data and for determining those few key variables with which a whole range of information can be represented. The prime objective in this research was to search for the minimum amount of data necessary to convey the maximum amount of performance information. Parsimony and consistency were the key criteria; factor analyses was the most efficient means.

Factor Analysis Defined

The most distinctive characteristic of factor analysis is its ability to reduce a large set of data to a smaller set of "components" or "factors" which portray the underlying structure of relationships among a set of variables. Based upon the correlation patterns of a large number of variables, the objective of the factor analytic technique is to group together those variables which are highly correlated with each other. Then the analyst inteprets each factor according to the variables belonging to the group. The idea is to summarize many variables by using a few representative factors.

There are two main types of factor analyses, principal components analysis and inferential or "classical" factor analysis ($\underline{7}$). The former works from the assumption that the entire population of cases--not a sample--is being analyzed. Analytical solutions describe the data at hand and the relationships among the variables as represented in the input data. Inferential factor analysis, however, adjusts analytical solutions to make predictions about a larger, ideal population. Because the entire population of motor bus systems was represented in the data, principal components factor analysis was used.

The basic factor analysis model assumes that in any set of variables, there exists two main types of variation or variance: variance commonly shared by all the variables in the set and variance unique to each individual variable. Commonly shared variance contributes to the intercorrelations of variables. The patterns of intercorrelations are used to group variables into a smaller number of factors. The number of factors necessary to portray this underlying data structure depends on how much more commonly shared variance continues to be detected with the addition of each new factor. The order in which the factors emerge from the data is important. The first factor accounts for the largest portion of shared variance in the data. With each successive factor, less and less of the shared variance is accounted for. At the point where little more explained variance is detected, the procedure halts and the factor structure is considered complete.

Factor analysis not only provides information on the number of factors underlying the data, it also determines which variables grouped on a particular factor are most highly related or representative of the identified factor. The <u>factor loading</u> of each variable on the respective factors can be interpreted as the correlation of the variable with the factor; high factor loadings represent high correlations.

In performing any factor analysis, there are several problem areas that could exist in the data and obscure the underlying data structure $(\underline{7})$:

- 1) two variables carry highly redundant information (colinearity)
- a variable loads across several factors equally well (poorly defined structure in the variable)
- 3) one factor has all or most of the variables weighting heavily on it (poorly defined structure in the data set)

The first exploratory factor analysis was begun with the most complete set of performance indicator ratios available in the Section 15 data. It remained necessary to assess how well these variables measured

the target information and how relevant the indicators were for cross-system analysis. The next task involved determining from the set of forty-eight variables, which subset of variables provided the best cross-system measures and best defined the structure in the data while testing the data for the three possible contaminating problems listed above.

As four parallel sets of performance indicators were available, the same type of exploratory factor analysis was carried out on each set. Finding similar results across the four data sets would signal detection of the consistency in the data which would point to the "true" underlying structure in the variables.

Variable Elimination

In the first exploratory analysis on the full set of forty-eight performance indicators, a total of 128 cases were included in the analysis. As mentioned earlier, factor analysis will drop from the analysis every case missing any piece of information. Because the missing values were scattered throughout the forty-eight variable set, the snowball effect had eliminated nearly two-thirds of the cases from the analysis. Thus, in the next exploratory pass through the data, it was decided to drop those variables that compounded the missing data problem and those that were still somewhat questionable as to the quality and comparability of reported information.

Fuel related variables (RVM/FUEL, TVM/FUEL) were eliminated because with four different types of fuel listed for motor bus operations it was

difficult to validly compare fuel efficiency across systems. Local and state subsidy related variables (e.g., RVH/LSUB, RVH/SSUB) were dropped because definitions of local versus state subsidies were inconsistent. Capital subsidy variables were dropped because they can greatly shift from year to year.

The passenger miles (PASM) variable was missing from almost 20% of the cases. To increase the number of cases entering into the analysis, variables based on PASM (e.g., PASM/OEX, PASM/TPS) were eliminated from the data set.

Variables related to active vehicle counts were also dropped because about a third of the cases have a problem of some sort. A distinction was not always made between school buses, charter buses and other motor buses. Some cases listed more active vehicles than total vehicles and vehicle inventories were incomplete for some companies.

The variable RVM/TVM was eliminated because sixty-five of the cases had revenue vehicle miles equal to total vehicle miles, a strong indication of a definitional problem, which greatly inflated the kurtosis value of the variable. The roadcall related variable, TVM/RCAL, was dropped because the definitions for what makes a true roadcall were unreliable. The variables related to total expense (e.g., PASM/TEX, TREV/TEX) were dropped because total expense is not truly comparable across systems; there are no set parameters for depreciating capital costs. Finally, REV/RVH was so highly correlated with OREV/RVH that it was eliminated. With each exploratory factor analytic pass through the data sets, the variables were checked against the factor structure to determine if remaining variables presented any of the structural problems mentioned above. With each pass through the data, the underlying structure became more clearly defined. The number of cases entering into the analysis had increased from 128 to 198 and the same general solution appeared across the four different sets of data.

The final set of thirty performance indicators that emerged after the fourth pass through the data reflected a strong set of performance indicator variables. These portrayed such highly consistent factor loadings across all data sets that it was evident that the most salient features of the performance concept model had been identified.

Table II lists the forty-eight performance indicator variables selected for analysis from the Section 15 data base. They are portrayed within the framework of the Fielding et al. conceptual model. Those variables eliminated prior to the final analysis are marked with an asterik to offset them from the final set of thirty performance indicators used in subsequent analyses.

FINAL FACTOR ANALYSIS ON THIRTY PERFORMANCE INDICATOR RATIO VARIABLES

The final factor analysis was carried out on the cleaned set of thirty performance indicator ratio variables. After all the data cleaning and verifying strategies, after all the exploratory passes through the data and after all the considerations for data quality, these

COST EFFICIENCY MEASURES

TVH/EMP	*RVM/FUEL
RVH/OEMP	*TVM/FUEL
TVM/EMP	TVM/MEXP
PVEH/ADM	TVM/MNT
PVEH/OP	*TVM/RCAL
PVEH/MNT	RVH/OEXP
*TVH/AVEH	TVM/OEXP
TVH/PVEH	RVH/TWG
*TVM/AVEH	RVH/OWAG
TVM/PVEH	RVH/VMWG
*RVM/TVM	RVH/ADWG

SERVICE EFFICIENCY MEASURES

TPAS/RVH	*RVH/LSUB
TPAS/RVM	*RVH/SSUB
TPAS/PVH	RVH/OSUB
*PASM/TPS	*RVH/TSUB
TVM/ACC	*TPAS/LOA
RVH/ACC	*TPAS/TSUB
REV/PVEH	*REV/TSUB
*REV/RVH	REV/OSUB
OREV/RVH	PAS/OSUB
REV/TPAS	

COST EFFECTIVENESS MEASURES

PAS/OEXP *PASM/OEX PAS/TWAG *PAS/FUEL *PASM/TEX REV/OEXP *TREV/TEX

* Variable dropped prior to final analysis

thirty variables were chosen to represent the best possible information on performance currently available in the Section 15 data base.

Principal component factor analysis with varimax orthogonal rotation was carried out on the four different sets of thirty performance indicator variables. Two different computer routines were used--SPSS-PA1 ($\underline{8}$) and BMDP-P4M ($\underline{9}$). The latter was used to compare as closely as possible the current analyses with the previous work.

The patterns of factor loadings were so similar between the reported data, weighted data and the two sets of logs that it appeared very convincing that the underlying structure in the data set had, indeed, been found.

Seven factors, accounting for approximately 85% of the variance emerged from the analysis. Table III shows the pattern of factor loadings for the final weighted data set. Factors one, two and three represent output per dollar cost, utilization of service and revenue generation per expense, respectively. These first three factors directly relate to the three major categories of the performance concept model--cost efficiency, service effectiveness and cost-effectiveness outlined by Fielding, et al. (2).

Factors four, five and six represent labor efficiency, vehicle efficiency and maintenance efficiency respectively. Finally, factor seven is clearly related to safety.

TABLE III.

ROTATED ORTHOGONAL FACTOR LOADINGS MATRIX



TOTAL AMOUNT OF VARIANCE EXPLAINED: 83.2%

NOTE: * = FIRST MARKER VARIABLE ** = Second marker variable A cut-off value of .5 used throughout.

VERIFYING THE FINAL 1980 FACTOR ANALYSIS

The adequacy and strength of the final solution were determined by Thurstone's five criteria for detecting simple structure solutions in factor analysis results (<u>10</u>). The rotated factor loading structure was compared against Thurstone's criteria for evaluating structure for its "simpleness" and met each of the qualifying conditions. This was convincing evidence that a clear, underlying structure in the data had been found.

In interpreting and portraying the factor loading pattern, an arbitrary cut-off of .5 had been used as a factor load value. The high-loading, i.e., representative variables for any factor were identified with a .5 factor load. It was felt that a high cut-off value would make for easier and clearer interpretation of the factors.

The next point investigated was how much of the variance of the final factor solution was not being accounted for by those identified "high-loading" variables. The data were tested and it was found that for each factor, approximately 95% of the information was still being represented while overall, 86% of the variance of the original factor structure was represented in the subset of high-loading variables.

<u>Reliability</u>

A third question regarding the set of high-loading variables defining the factor structure centered on the reliability--in a statistical

sense--of the grouped variables. Cronbach's Alpha was calculated for each group of variables gathered together on a particular factor.

Cronbach's alpha can be used to evaluate the internal consistency of a group of variables to see if they essentially target the same underlying information (<u>11</u>). Alpha values range from zero to one with a value equal to one representing perfect reliability, or internal consistency in this case. An alpha value of .8 is considered very reliable.

Standardized item alpha was calculated for each group of high-loading variables on each factor, and for each of the four sets of slightly different performance indicators. The alpha values hovered around the .8 criterion on the weighted data set and were all well above .8 on the log set of the weighted data. This was true on all Factors except Factor 5 which produced an uninterpretable alpha value. Factor 5 measures the positive and negative poles of the vehicle efficiency concept as shown in the negative and positive factor loadings. Thus, it confounds the calculation of standardized item alpha.

Factor Structure Stability

Two final questions were raised regarding the 1980 final factor analysis. They both focused on a single concern--how globally relevant was the final factor structure? Would the underlying structure of the data remain stable over different theoretical assumptions or an increase in data cases?

Classical inferential factor analyses were carried out on the four performance indicator variable sets. As noted previously, this type of analysis assumes that the data comes from a sample of cases from a larger population. All solutions and reported statistics are mathematically adjusted to predict values as they would exist in a larger population. Thus, it is conceivable that if a factor structure is somewhat weakly defined, a different structure could emerge from an inferential solution than from a principal components analysis. However, results from both the inferential and principal components analyses were consistent across the four data sets.

To test whether the final structure in the analyses would remain stable over an increase in data cases, an estimation procedure for missing data was used. The BMDP statistical computing package includes a program whereby missing data values can be estimated. Multiple regression on the variables with data is used to predict a "most likely estimate" for any case missing data on some subset of the variables in the analysis. When no prediction can be made from other available data, the mean of the variable of interest is used to replace the missing value. When any case is missing too much of its data, it is not used in the estimation procedure.

A final set of factor analyses was carried out on the four sets of performance indicators where missing values had been replaced with estimates. The number of cases then being analyzed increased from 194 to 280.

It was plausible that an increase in the number of cases being analyzed could shift a weak or unstable factor solution to a different factor structure. The final set of factor analytic solutions carried out from the data sets which included estimated values were entirely consistent with the earlier results.

Thus, after rigorous testing of the final 1980 factor analysis, it was found that: 1) the same general underlying structure had consistently appeared across all checking routines; 2) not only the same factors appeared, but they also appeared in the same order; 3) with minor fluctuations, the factor loading patterns were generally the same. Therefore, it was concluded that a stable, consistent and reliable simple structure had been detected out of the larger group of performance indicators.

COMPARISON OF 1980 FINAL FACTOR ANALYSIS TO 1979 ANALYSIS

One of the motivations in analyzing this data in this way was to provide a comparison with the previous attempt to use Section 15 data for performance evaluation (1).

The earlier attempt was carried out on the first year (FY1979) data. As might be expected, there were many more problems with the first year of collected data than with the second year of data. The former data set was fraught with missing data problems, imprecisely reported data, and less careful checking procedures before and after analysis. For the final factor analysis on the 1979 data, one set of raw reported data consisting of thirty-six performance indicator variables was analyzed. A total of ninty-eight cases (out of 311) were in the analysis; the rest dropped out due to the snowball effects of missing data. Only a superficial grooming of the data was done. Thus, many erratic values and questionable zeros remained in the data.

For the final factor analysis on the 1980 data, four sets of similar data consisting of thirty performance indicator variables were analyzed. The data was carefully groomed for accidental or inconsistent values and strategies were developed to differentiate valid zeros from "missing data zeros." All in all, there was much greater confidence in the 1980 data set by the time the current set of factor analyses was begun than was possible for the 1979 data set.

Comparison of the two final factor structures--from the FY 1979 data analysis and from the FY 1980 data analysis--shows that the same first two factors emerge in the same order in both years. Output per dollar cost and utilization of service are Factors one and two respectively for both factor analyses. Since the first few factors usually account for a large amount of the total variance in the data set, it was clear that the first two key features of performance had been identified in both years.

From that point on, the factor structures diverged across years. The remaining seven factors from the total of nine factors in the earlier analyses were as follows: vehicle efficiency, fuel efficiency, public assistance, social effectiveness, maintenance efficiency, revenue per expense and safety. Because the set of performance indicators used in

the analyses had differed across years, it was difficult to compare the two any further.

Fuel efficiency and social effectiveness related variables had been dropped in the current analysis. The former did not lend themselves to valid cross system comparisons and the latter were not valid when based on other than service population data. Thus, the two data sets differed somewhat in the variables used for the analyses.

In the 1979 data, weighting strategies had not been used to disentangle the aggregated revenue and subsidy information. Thus, variables relevant to those areas were clearly contaminated and invalid for cross-system single mode analyses. The pattern of variation in such variables would have clearly been different from the other variables in the analysis, and the identification of a public assistance factor in the earlier analysis attests to that fact.

The 1979 analysis, when compared with the current set of analyses, shows that the underlying structures are not so different, but that the two data sets from which the analyses began were clearly different. In the research at hand there was a great deal more confidence concerning the variables chosen and especially regarding the quality of the data itself. It was strongly felt that the 1980 data analyses had, in fact, detected the key underlying concepts of performance for this data. The increase in number of cases analyzed, the many analyses on the four parallel sets of data, and finally, the rigorous verifying and validating procedures provided a great deal of confidence in the final results.

Further, the fact that both years of data had detected many of the same concepts, despite the poorer quality of the 1979 data, provided stronger validation for the conceptual model of transit performance. However, the final structures detected with the FY 1979 and FY 1980 data were different. The order in which factors emerged from the data was not the same. This was partly due to the use of somewhat different sets of performance indicator variables and partly the result of using the much cleaner and more complete set of FY 1980 data. Since the 1980 data had been so carefully cleaned and verified, it was evident that in the current analyses not only the underlying concepts had been detected, but their relative importance to each other and across the larger set of available data had been determined.

SELECTING REPRESENTATIVE MARKER VARIABLES

A result of this research was the establishment of a small, unique subset of performance indicators that are particularly useful for performance evaluation by individual transit managers for systems of all sizes. The goal was to identify the minimum amount of data necessary to convey the maximum amount of performance information.

To accomplish this, the factor loading data in the rotated factor structure solutions on the final variable sets were used. High factor loadings represent a high correlation of a particular variable with a particular factor. When a variable has a high factor loading on only one

factor, it can be said to "represent" that factor both statistically and conceptually.

To select a small subset of easily accessible performance indicators from the final factor structure five criteria were used: 1) Representativeness of a variable vis-a-vis a Factor was reflected in a high factor loading on only one Factor. 2) The distribution of values in the variable had to be as close to normal-like as possible. 3) Ease of collection of the variable was assessed via the percentage of data missing. 4) The variable had to have been well captured by the factor structure in general (high communality). 5) The variable selected had to be easily understood by transit managers.

Seven representative or "marker" variables were selected from the final factor structure--one variable representing each factor. Seven "alternate markers" were also identified. These alternates could be used equally well for assessing performance.

The seven representative "marker" variables and their alternates include the following:

<u>FACTOR</u>	<u>"Marker" Variable</u>	<u>Alternate "Marker" Variable</u>
1	RVH/OEXP	TVM/OEXP
2	TPAS/RVH	TPAS/RVM
3	OREV/OEXP	REV/OSUB
4	TVH/EMP	RVH/OEMP
5	TVM/PVEH	TVH/PVEH
6	TVM/MNT	PVEH/MNT
7	TVM/ACC	RVH/ACC

The markers and the alternate set of markers are highly reliable (alpha range is from .802 to .937). Thus, with a maximum of seven variables from a much larger data set, performance of a transit system can be assessed. To assess the three major categories represented in the conceptual model, the first three "marker" variables would be sufficient. Further, any one of the seven factor concepts could be assessed via the relevant "marker" variable.

WHO IS NOT WELL REPRESENTED IN THE FACTOR ANALYSIS?

The FY1980 of Section 15 data is somewhat biased toward the larger systems. Although one-third of the systems reporting have twenty-five and under vehicles, it is this group which is consistently missing the largest percentage of its data.

Approximately 16% of this group's vehicle miles or vehicle hours data, 39% of its passenger data and 9% of its maintenance expense data is missing. In the final set of thirty performance indicator variables used in the factor analysis the small system group was missing from 7 % to 37% of its data.

Thus, the small systems group was not well represented in the factor analysis. This could have introduced a bias in the final solution. However, when the estimation of missing values procedure was used on the data, the factor structure that emerged was consisted with other results. Therefore, it was concluded that the final factor structure would remain stable even with increased representation from the smaller systems.

CONCLUSION

The FY1980 Section 15 data has been used to identify and test the most easily accessible and parsimonious set of performance indicators for fixed route transit. The research had two objectives: first to find the minimum amount of data necessary to provide solid and stable performance evaluation capability, and second to test the validity of results obtained from the previous analysis of FY1979 data.

The use of factor analysis on a large set of performance indicator ratios gleaned from the data the structure of the key underlying performance concepts. From the factor structure, a small subset of seven variables was identified and tested against the larger data structure. These seven variables are the most salient performance indicators currently available in the Section 15 data base. They can be used together or individually to assess fixed route transit performance.

There is a great deal of confidence in the data used and in the final results. Rigorous cleaning, verifying and grooming procedures carried out before analysis insured that the input data was as complete as possible. Careful decisions regarding which variables to keep and/or drop from the analysis provided the best possible set of performance indicators available in the Section 15 data. The use of four parallel data sets and several exploratory factor analyses detected the simple underlying structure of the data. Finally, the rigorous testing and validation of that underlying factor structure was convincing that the most salient performance indicator concepts had been found. The strongly

consistent and stable structure in the data led to identification of the key variables for evaluation. These too measured up to testing and verifying procedures. Given the quality of the Section 15 data at hand it is felt that the most salient features for performance evaluation have been determined.

A globally-relevant set of performance indicators has been detected. These variables can be used for peer group comparisons because variables that were problematic for such comparisons were detected then dropped from the analysis (e.g., fuel efficiency and social effectiveness variables, are not given to cross-system analysis).

The strength of this research lies in both the quality of the data used and the rigor with which the results were tested. A relevant set of performance concepts has been identified and linked to easily accessible "marker" variables which can be used for cross-system assessment. Future research should continue to test the simple structure underlying performance evaluation as the quality of Section 15 data improves over time.

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