Better, or Just Different?

Examining Operational Efficiency on Commuter Rail and Hybrid Rail Systems in the US

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Introduction

The last several decades have seen a remarkable resurgence in public transit in the United States. As traffic congestion increases and many metropolitan areas continue to sprawl, policymakers have increasingly looked to increase the number of mobility options available to their constituents. One of the most popular ways to do this has been to implement a regional, or commuter, rail system.

Commuter rail is a uniquely American mode that evolved to cope with high peak-hour demand from low-density areas surrounding a major urban center. Commuter rail trains can cover long distances at high speeds, and are is relatively cheap to implement if using existing rights of way. However, commuter rail trains are expensive to operate because of staffing requirements and generally run infrequently at off-peak times as a result, leading to significant emphasis on peak service. The US has five major "legacy" commuter rail systems (systems of significant size that have been in continuous operation from the pre-World War II era to today), in New York City, Boston, Philadelphia, Washington, DC, and Chicago. While other systems (including those in Detroit, Pittsburgh, and Milwaukee) have come and gone over the years, since the 1980s a number of "new" commuter rail systems have opened in cities like Seattle, Los Angeles, Albuquerque, and Miami. Ridership

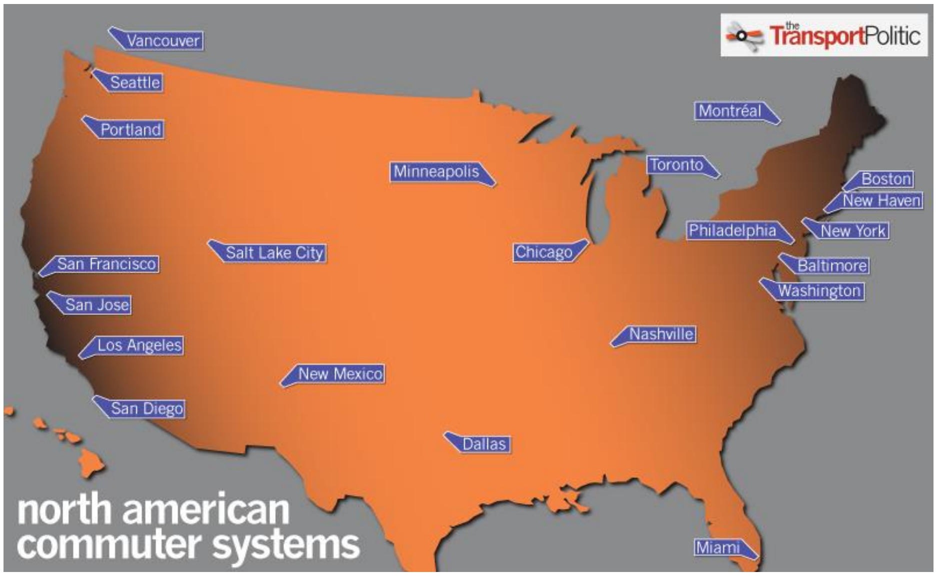

Figure 1: Existing commuter rail systems in North America, from The Transport Politic (http://www.thetransportpolitic.com/existing-systems/existing-commuter-rail-systems)

levels on these systems, however, remain uneven, leading some metro areas to seek other solutions.

Recently, several cities have experimented with a form of transit known to the Federal Transit Administration as "hybrid rail." The foundations for this kind of operation were laid with the release of Transit Cooperative Research Program (TCRP) report 52, "Joint Operation of Light Rail Transit or Diesel Multiple Unit Vehicles with Railroads," in 1999. Often known popularly as "diesel light rail," and first defined by the FTA in 2011[1] (although systems were in operation before then) "hybrid rail" is best understood as a cross between light rail and commuter rail. "Hybrid rail" systems generally run with self-propelled cars (like light rail), but propelled by diesel, rather than electric, motors (like most commuter rail). For a variety of technical and regulatory reasons, "hybrid rail" systems generally import European vehicles known as Diesel Multiple Units, or DMUs[2]. With streamlined staffing and lower fuel consumption, these systems can and do operate more frequently than commuter rail, though they generally serve a suburb-to-city routing and do not run as frequently as urban light rail. As a

Figure 2: Coaster commuter rail (left) and Sprinter hybrid rail (right) share a station, but not tracks, at Oceanside, CA. Difference in size and design between the two modes is apparent. Source: http://www.trainweb.org/chris/13nps4.JPG

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[1] Federal Register /Vol. 76, No. 103 / Friday, May 27, 2011 /Notices

[2] Several of the systems have used "FRA-compliant" American-made DMUs, but these have generally been unsuccessful in the market.

result, many transit advocates have hailed DMU-based “hybrid rail” as the wave of the future in American transit[3].

Hypothesis and Research Question

At this point in time, “hybrid rail” systems have been in operation in the US for a period of time long enough to begin the process of examining their efficiency benefits. The earliest such line, New Jersey Transit’s River Line between Trenton and Camden, opened in 2004. It was followed by the North Country Transportation District (CA) Sprinter in 2008, Oregon’s Westside Express in 2009, Capital MetroRail in Austin, TX in 2010, and the A-Train in Denton County, TX in 2011. Three more California projects, SMART in Sonoma County, eBart in the East Bay, and the Redlands Line from San Bernardino to Redlands, will open using the mode in coming years. As “hybrid rail” proliferates, the time has come to examine to what extent its cost efficiency promises relative to commuter rail have been born out.

This paper examines a snapshot of data from the National Transit Database (NTD) related to commuter and hybrid rail systems, with the goal of measuring relative efficiencies given a number of physical and operational factors. Given the expectations of advocates and the growing popularity of the mode, it seems reasonable to hypothesize that **hybrid rail systems will be more efficient on an operational cost basis than commuter rail systems.** This paper uses the statistical software SPSS to conduct several analyses on the dataset, including descriptive statistics, hypothesis testing, and creation of a correlation matrix. The paper also seeks to establish regression models that can be used not just to observe, but to predict, operational costs and efficiencies. One set of regression models will help stakeholders decide

[3] See for example http://seattletransitblog.com/2014/01/03/the-cheaper-brighter-future-of-american-passenger-rail/ and http://capntransit.blogspot.com/2009/03/feds-relax-restrictions-for-light-rail.html

between commuter rail and hybrid rail systems based on expected dimensions of service, and the other will predict service costs and efficiencies based on mode.

About the Data

This paper relies on data compiled from the National Transit Database. Established by Congress in 1974, NTD "collects annual transit performance and financial data, monthly ridership, and safety and security data."[4] The data is used to support benchmarking and research and calculate federal funding; all urban and rural transit agencies that receive Federal funding are required to report data to NTD. The data tables—currently up-to-date through 2013—are accessible online through the Federal Transit Administration[5] or the American Public Transit Association[6] and can be downloaded in Excel format.

NTD tables allow sorting and filtering by a number of variables, including mode (meaning, in transit parlance, roughly what kind of vehicle is being used). For the following analysis, results from several tables were filtered to present only the "CR" (commuter rail) and "YR" (hybrid rail) modes. The filtering returns 28 results, of which one, representing the *Downeaster* Amtrak service from Boston to Portland, ME, was manually excluded because it is an intercity, not a commuter, service (despite being classified as CR in NTD) and presented as an extreme outlier in data analysis. It is presumably included in NTD because it receives some FTA funding. Another semi-intercity Amtrak route, the *Keystone Service* between Philadelphia and Harrisburg, is also presented in the 2013 NTD data, but was retained because its stop spacing and frequency are more equivalent to a commuter rail route and fall within the norms of such

[4] Background information on NTD from: http://www.apta.com/members/memberprogramsandservices/international/Documents/U.S.%20National%20Transit%20Database.pdf
[5] www.ntdprogram.gov
[6] http://www.apta.com/resources/statistics/Pages/NTDDataTables.aspx

operations. Thus the full dataset of commuter rail and hybrid rail operations in the US contains 27 operations, 22 classified as CR and 5 as YR; a full list may be found in Appendix A below.

This paper uses a number of variables from NTD to define and analyze operational factors and efficiency. Some of these variables are taken directly from NTD tables, and others are secondarily computed from variables contained in NTD tables. Future versions of this work could expand the list of variables to include measurements and factors not included in NTD, especially crew requirements and density of the area along the route. A full list of variables may be found in Appendix B below. This paper will particularly stress three dependent variables that measure operational efficiency: operational expense per vehicle hour, operational expense per passenger mile, and operational expense per passenger trip (unlinked). The most important independent variables are stop spacing (the distance between stops on a given line) and trains per route mile, a crude proxy for frequency of service, which is not directly measured by NTD. Another variable, passenger trips per vehicle revenue hour, can occupy either a dependent or an independent role.

Descriptive Statistics

This section provides an overview and numeric and visual presentations of the data covered in this paper. Not all variables present in Appendix B are presented here; some are filtered out based on irrelevance to the research question. Data is presented with a particular eye towards defining the differences between CR and YR systems. Visual representations are available in Appendix C below.

	Mean	Median	Variance	SD	Min	Max	Range	IQR
Variable: VOMS								
CR	277.05	64.0	171667.0	414.33	7.0	1230.0	1223.0	330.0
YR	7.4	6.0	20.800	4.56	4	15	11	7.5
Variable: Number of Trains								
CR	39.46	12.0	2410.74	49.1	2.0	143.0	141.0	61.75
YR	5.4	4.0	13.80	3.72	3.0	12.0	9.0	4.50
Variable: Stop Spacing								
CR	4.60	4.63	3.69	1.92	1.45	8.60	7.15	2.95
YR	2.79	2.92	1.41	1.19	1.47	4.26	2.79	2.31
Variable: Trains per Route Mile								
CR	.0928	.0701	.004	.06429	.02	.26	.24	.09
YR	.1044	.0939	.002	.04081	.06	.17	.11	.06
Variable: Passenger Trips Per Revenue Hour								
CR	46.06	43.66	217.1	14.73	17.0	87.34	70.34	14.33
YR	58.80	58.92	508.447	22.55	22.90	82.68	59.78	37.10
Variable: Operational Expense per Vehicle Hour								
CR	548.16	505.65	29978.69	173.143	326.30	1087.50	761.20	200.20
YR	688.82	674.30	27225.76	165.0	465.60	868.60	403.0	313.0
Variable: Operational Expense per Passenger Trip								
CR	14.66	12.95	45.796	6.77	6.20	30.8	24.6	5.32
YR	14.72	15.90	30.72	5.45	7.40	22.20	14.80	9.75
Variable: Operational Expense per Passenger Mile								
CR	.541	.40	.065	.256	.30	1.30	1	.20
YR	1.22	1.00	.272	.522	.8	2.0	1.2	.95

Relationships Between Variables (t-tests)

We have seen thus far that many, but not all, of the variables examined show apparently large differences between YR and CR systems. But are these differences *statistically significant*? We use paired-sample t-tests, grouped by the "type" variable, to determine. It should be kept in mind that the sample size is relatively small—22 CR systems and just 5 YR systems—so statistical significance at high levels of confidence will be hard to achieve.

Variable	Levene's Test	t	DF	Sig. (2-tailed)
Stop Spacing	Sig.=.226; equal variances assumed	1.992	25	0.057
Pax Trips/Revenue Hour	Sig.=.434; equal variances assumed	-1.583	25	0.126
Trains/Route Mile	Sig.=.162; equal variances assumed	-0.381	25	0.706
OpEx/Vehicle Hour	Sig.=.972; equal variances assumed	-1.652	25	0.111
PaxTrips/Vehicle Hour	Sig.=.434; Equal variances assumed	-1.583	25	0.126
OpEx/PaxTrip	Sig.=.737; Equal variances assumed	-0.2	25	0.984
OpEx/PaxMile	Sig.=.013; Equal variances NOT assumed	-2.835	25	.042

Correlations

Constructing a correlation matrix allows us to immediately see statistically significant relationships between ratio variables. While the sample size is small and statistical significance could therefore be hard to tease out, this exercise is important for two reasons:

a) It allows us to see relationships between dependent and independent variables, previewing the construction of linear regression models in the next section

b) It establishes relationships or lack thereof between independent variables, warning about potential multicollinearity problems.

It is important to recognize that this matrix represents correlations for *all of the data points in the set*, and is not sorted by type (YR vs. CR). Statistically significant correlations are marked in red.

Correlation Matrix (n for all=27)

		OpEx per Vehicle Hour	**OpEx per Unlinked Pax Trip**	**OpEx per Pax Mile**	**Stop Spacing**	**Trains Per Route Mile (proxy for frequency)**	**PaxTripPerRevHr**
OpEx per Vehicle Hour	Pearson Correlation	1	.386*	.421*	.170	-.134	.353
	Sig. (2-tailed)		.047	.029	.396	.505	.071
OpEx per Unlinked Pax Trip	Pearson Correlation	.386*	1	.405*	.553**	-.442*	-.611**
	Sig. (2-tailed)	.047		.036	.003	.021	.001
OpEx per Pax Mile	Pearson Correlation	.421*	.405*	1	-.094	-.095	-.060
	Sig. (2-tailed)	.029	.036		.643	.637	.765
Stop Spacing	Pearson Correlation	.170	.553**	-.094	1	-.705**	-.477*
	Sig. (2-tailed)	.396	.003	.643		.000	.012
Trains per Route Mile	Pearson Correlation	-.134	-.442*	-.095	-.705**	1	.323
	Sig. (2-tailed)	.505	.021	.637	.000		.101
PaxTrips per Revenue Hour	Pearson Correlation	.353	-.611**	-.060	-.477*	.323	1
	Sig. (2-tailed)	.071	.001	.765	.012	.101	

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

Operational expense per vehicle hour:

- Moderately positively correlated with operational expense per passenger trip
- Moderately positively correlated with operational expense per passenger mile

Operational expense per unlinked passenger trip:

- Moderately positively correlated with operational expense per vehicle hour
- Moderately positively correlated with operational expense per passenger mile
- Moderately positively correlated with stop spacing (as distance between stops INCREASES, costs increase)
- Moderately negatively correlated with frequency
- Moderately to strongly negatively correlated with passenger trips per revenue hour

Operational Expense per Passenger Mile:

- Moderately positively correlated with operational expense per vehicle hour
- Moderately positively correlated with operational expense per unlinked passenger trip

Stop Spacing

- Moderately positively correlated with operational expense per passenger trip
- Strongly negatively correlated with frequency
- Moderately negatively correlated with passenger trips per revenue hour

Passenger Trips per Revenue Hour

- Moderately to strongly negatively correlated with operational expense per revenue hour
- Moderately negatively associated with stop spacing

Linear Regression Modeling

With an idea of the relative efficiencies of the two modes from descriptive statistics, and having established between which variables statistically significant correlations exist, we now turn to predictive functions. Creating linear regression models that can predict our various dependent variables will allow future policymakers who wish to establish a commuter rail or DMU service to predict the operational efficiency (and therefore, costs) with some accuracy, given the several inputs.

There are two kinds of regression models in this section. The first includes regression models for each of the three primary dependent variables measuring operational efficiency, using up to four independent variables: stop spacing, frequency of service, passengers per revenue hour, and a dummy variable representing the binary choice between YR and CR service, where YR=1 and CR=0. These models allow direct prediction of the relative efficiencies of YR and CR service. A fourth model calculates the anomalous variable passengers per vehicle revenue hour, here treated as a dependent variable though it may be regarded as an input as well. Each model incorporates the full sample size of data from NTD, so n=27 in all cases.

The second set of nesting models represents an attempt to create operational cost and efficiency tests for each of the two modes separately, using exclusively their own data. For each of the three dependent variables measuring operational efficiency, we have created one set of nested models based on YR data exclusively and one set of nested models based on CR data exclusively, all using the same independent variables. Although the sample sizes are very small (n=5 for YR and n=22 for CR), this is at least a beginning to work that will allow future decision makers to predict operational costs. Using nested models allows us to control for different variables and make observations about the relative importance of various independent variables. Ultimately the goal is the selection of the best model(s) for operational efficiency for both YR and CR; since the dependent variables are largely interchangeable in terms of predictive value, this can be any of them.

Combined/Comparative Models[7]

Dependent Variable:	Operational Expense per Vehicle Hour							
Independent Variable	**Model 1**	**sig.**	**Model 2**	**sig.**	**Model 3**	**sig.**	**Model 4**	**sig.**
Stop Spacing	15.698	0.396	13.987	0.6	39.626	0.125	59.555	0.976
Trains per Route Mile			-81.908	0.923	-36.388	0.961	383.871	0.027
Passengers/Revenue Hour					5.975	0.011	5.327	0.6
Dummy for Type							175.615	0.05
Constant	507.346	0	522.787	0.008	119.582	0.584	-6.355	0.976
R^2	0.029		0.029		0.273		0.393	

Dependent Variable:	Operational Expense per Unlinked Passenger Trip							
Independent Variable	**Model 1**	**sig.**	**Model 2**	**sig.**	**Model 3**	**sig.**	**Model 4**	**sig.**
Stop Spacing	1.854	0.003	1.607	0.056	0.856	0.281	1.437	0.084
Trains per Route Mile			-11.199	0.666	-12.525	0.592	-0.277	0.99
Passengers/Revenue Hour					-0.174	0.016	-0.193	0.006
Dummy for Type							5.118	0.006
Constant	6.772	0.15	8.885	0.121	20.66	0.005	16.99	0.018
R^2	0.305		0.311		0.468		0.544	

Dependent Variable:	Operational Expense per Passenger Mile							
Independent Variable	**Model 1**	**sig.**	**Model 2**	**sig.**	**Model 3**	**sig.**	**Model 4**	**sig.**
Stop Spacing	-0.02	0.643	-0.068	0.264	-0.083	0.214	0.005	0.066
Trains per Route Mile			-2.176	0.262	-2.202	0.263	-0.353	0.924
Passengers/Revenue Hour					-0.003	0.541	-0.006	0.815
Dummy for Type							0.773	0.147
Constant	0.751	0.001	1.162	0.009	1.396	0.02	0.841	0.066
R^2	0.009		0.06		0.076		0.511	

[7] Full SPSS output for all tables is attached in Appendix XXX below

Dependent Variable:	Passengers/Revenue Hour					
Independent Variable	Model 1	sig.	Model 2	sig.	Model 3	sig.
Stop Spacing	-4.139	0.012	-4.306	0.061	-3.481	0.173
Trains per Route Mile			-7.602	0.915	7.842	0.916
Dummy for Type					6.379	0.464
Constant	66.047	0	67.482	0	61.319	0.002
R^2	0.228		0.228			0.246

Differential Models

YR

Dependent Variable:	Operational Expense per Vehicle Hour					
Independent Variable	Model 1	sig.	Model 2	sig.	Model 3	sig.
Stop Spacing	-8.015	0.927	-31.015	0.806	282.484	0.306
Trains per Route Mile			-1275.091	0.731	4883.675	0.367
Passengers/Revenue Hour					15.667	0.256
Constant	711.197	0.059	908.511	0.731	-1530.83	0.393
R^2	0.003		0.075		0.858	

Dependent Variable:	Operational Expense per Passenger Trip					
Independent Variable	Model 1	sig.	Model 2	sig.	Model 3	sig.
Stop Spacing	4.493	0.009	5.237	0.004	4.549	0.118
Trains per Route Mile			41.256	0.052	27.741	0.374
Passengers/Revenue Hour					-0.034	0.538
Constant	2.176	0.395	-4.208	0.138	1.145	0.886
R^2	0.926		0.992		0.996	

Dependent Variable:	Operational Expense per Passenger Mile					
Independent Variable	Model 1	sig.	Model 2	sig.	Model 3	sig.
Stop Spacing	0.238	0.347	0.261	0.482	0.114	0.929
Trains per Route Mile			1.312	0.896	-1.588	0.896

Passengers/Revenue Hour					-0.007	0.899
Constant	0.556	0.447	0.353	0.844	1.502	0.875
R^2	0.293		0.3		0.317	

Dependent Variable:	**Passenger Trips per Vehicle Hour**			
Independent Variable	**Model 1**	**sig.**	**Model 2**	**sig.**
Stop Spacing	-12.919	0.207	-20.01	0.092
Trains per Route Mile			-393.106	0.174
Constant	94.869	0.029	155.7	0.044
R^2	0.462		0.829	

CR

Dependent Variable:	**Operational Expense per Vehicle Hour**					
Independent Variable	**Model 1**	**sig.**	**Model 2**	**sig.**	**Model 3**	**sig.**
Stop Spacing	33.392	0.089	50.39	0.092	56.626	0.05
Trains per Route Mile			681.071	0.432	360.294	0.665
Passengers/Revenue Hour					4.745	0.083
Constant	394.805	0	253.507	0.219	36.082	0.873
R^2	.137		.166		.298	

Dependent Variable:	**Operational Expense per Passenger Trip**					
Independent Variable	**Model 1**	**sig.**	**Model 2**	**sig.**	**Model 3**	**sig.**
Stop Spacing	1.984	0.006	1.745	0.097	1.455	0.116
Trains per Route Mile			-9.58	0.752	5.319	0.845
Passengers/Revenue Hour					-0.22	0.085

Constant	5.544	0.101	7.532	0.297	17.631	0.026
R^2	0.317		0.321		0.507	

Dependent Variable:	**Operational Expense per Passenger Mile**					
Independent Variable	**Model 1**	**sig.**	**Model 2**	**sig.**	**Model 3**	**sig.**
Stop Spacing	0.022	0.456	0.002	0.97	-0.004	0.929
Trains per Route Mile			-0.824	0.545	-0.526	0.705
Passengers/Revenue Hour					-0.004	0.321
Constant	0.439	0.007	0.609	0.068	0.812	0.042
R^2	0.028		0.047		0.099	0.028

Dependent Variable:	**Passengers per Revenue Hour**			
Independent Variable	**Model 1**	**sig.**	**Model 2**	**sig.**
Stop Spacing	-2.001	0.072	-1.314	0.586
Trains per Route Mile			67.601	0.353
Constant	59.845	0	45.821	0.013
R^2	0.153		0.192	

Discussion

This research has examined the comparative operational efficiencies of commuter rail and hybrid rail, using data from the National Transit Database. We hypothesized that, given the expectations of its backers and proponents, hybrid rail would, as a mode, be found to be more efficient in operation than commuter rail. This was analyzed using three primary dependent variables: operational expense per vehicle hour, operational expense per passenger trip, and operational expense per passenger mile. These variables were analyzed using two primary independent variables, stop spacing and trains per route mile, a proxy for frequency of service. Analysis was also conducted using the important ridership measure of ridership per vehicle revenue hour, which can serve either as an independent or a dependent variable, since ridership is both a result of good service and an input into the calculation of how much service is required.

The results of this statistical examination are, on the whole, mixed. We expected that YR systems would show closer stop spacing than CR systems, to take advantage of the lightweight- and faster-accelerating (in theory) nature of their equipment. Indeed, YR stop spacing is considerably closer than that of commuter rail systems—logical, considering the proposed benefits of the mode. The difference between the two modes comes very, very close to achieving the 95% confidence threshold (p=.057). With a median of 2.79 miles, YR stop spacing does not, however, approach the generally considered best practice for urban rapid transit of stations located every half mile to 1 mile. Indeed, the longer end of YR stop spacing overlaps with CR stop spacing, again suggesting a convergence between the modes. The minimum stop spacing on a CR system, SEPTA's 1.45 miles, actually is the single lowest result regardless of mode, and suggests that that entire system should be run as a rapid transit system rather than "commuter rail"—a longtime cause among transit advocates. It is worth remembering that, according to our hypothesis, stop spacing would be expected to show an *inverse relationship* with efficiency measures—that is, closer (smaller) stop spacing should make for lower costs.

Perhaps the most important result is that YR systems decisively outperform CR systems on the cherished operating efficiency measure of passengers carried per vehicle hour; though the difference does not quite achieve significance at a high level of confidence (p=.126), that level of confidence is hard to achieve with such small sample sizes. The mean (58.80) is well higher than that of CR (46.06), and indeed aside from one lower outlier (DCTA), the entire distribution of YR systems lies above the CR mean. The single most heavily used system in the country, though, is #4, Caltrain on the San Francisco peninsula—a strong corridor anchored by San

Francisco on one end and San Jose on the other, running through Silicon Valley in between. On the whole, though, YR systems clearly make better use of their equipment than do CR systems. This is not a surprise given that CR systems often run long trains at off-peak times with only one or two cars open since breaking up trainsets midday is difficult, while YR systems use self-propelled cars that can be more easily mixed and matched to meet demand.

NTD does not measure frequency of service directly (and indeed, that would be difficult to do on a system-wide basis for systems that have more than one line). As such, since frequency of service is an important determinant of efficiency of service and of passenger utility, this paper uses the number of trains in operation on an average weekday divided by the system's overall route mileage as a crude proxy for frequency of service. The results are interesting: YR systems are actually, on the whole, more frequent than CR services. That is how it should be; the promise of YR is that is can offer more frequent service at lower cost. The single most frequent system, though, is point #16, New York and Connecticut's Metro-North Railroad. As one of the two largest systems in the country, that is not a surprise. When measuring all 27 systems, frequency of service is moderately to strongly negatively correlated with operational expense per revenue hour and moderately negatively associated with stop spacing. In other words, systems with closer stop spacing generally have more frequent service, although it is hard to state the direction of causation. Frequency is also associated with lower operational expense on one measure—a potentially important result. However, regression shows that slopes related to the crude frequency proxy used here generally struggle to achieve statistical significance, so a more thorough analysis using actual schedule data to more accurately estimate frequency, though outside the scope of this project, would likely prove a strong next step.

If passengers per vehicle revenue mile indicated that YR systems are more productive, the various dependent variables indicating operational expense show that the mode has not yet conquered the bug of massive operational expense that plagues American commuter rail. YR's mean for operating expense per passenger mile mean is higher than that of CR systems, as is almost the entire distribution (though the highest single expense belongs to Minnesota's Northstar commuter rail, a prime example of wasteful commuter rail spending). Based on averages and distributions, operational expense per passenger trip is virtually identical for CR and YR systems. Cost per passenger mile, too, is much higher—both in averages and in distribution—for YR than CR systems. In part, this is surely because YR lines are typically shorter than CR equivalents, which typically carry passengers for long distances. The cost efficiency measures—our dependent variables—suggest that, on the whole, YR systems have not accomplished the cost control they have potential to provide.

Of the variables examined, difference in only one, operational expense per passenger mile, achieves full statistical significance at the .95 confidence level. One other, stop spacing, comes very close (sig.=.057), while several—passenger trips per revenue hour, operational expense per vehicle hour, and passenger trips per revenue hour—come close to achieving significance at the .90 confidence level. This is a fascinating result as it seems to indicate that operational practices on YR systems are not very different from those on CR systems, perhaps accounting for some of the YR mode's apparent operational inefficiencies.

Analysis of descriptive statistics and hypothesis tests allow us to analyze currently existing differences between YR and CR systems; regression allows us to project those differences into the future. Since all of the dependent variables are highly correlated with each other, and largely interchangeable in planning for overall costs, we can afford to pick the strongest models of each type to represent overall costs. For the comparative models, those measuring directly the differences between YR and CR systems, this takes the form of Model 4 analyzing Operational Expense per Unlinked passenger trips, all of whose slopes are highly significant by the standards of this exercise, and whose r^2 is .544:

$$
\begin{aligned}
&\mathit{Operational\ Expense\ per\ Unlinked\ Passenger\ Trip} \\
&\qquad = 16.99 + (1.437 \times \mathit{Stop\ Spacing}) + (-0.277 \times \mathit{trains\ per\ route\ mile}) \\
&\qquad + (-0.193 \times \mathit{passengers\ per\ revenue\ hour}) + (5.118 \times \mathit{TYPE})
\end{aligned}
$$

Where TYPE is a dummy variable representing mode type, with CR=0 and YR=1. In this function, operational expense has a positive relationship with stop spacing—meaning that as stop spacing gets *wider*, expenses will go up. Expense has a negative relationship with frequency, meaning that as frequency grows, expense goes *down* (although at a low rate), which would be somewhat surprising to operators, though not to advocates. And, of course, expense goes up as ridership goes down, which is to be expected, since expenses are largely fixed for a given level of operation. When the mean input variables from our data are plugged into this equation, YR expense per passenger trip comes to $14.74, and CR to $14.69—virtually identical to the means of the variable in NTD data. Regression thus again confirms that YR has, on this measure, not achieved the significant operational savings promised, despite higher productivity in terms of ridership.

This research also seeks to present regression models tied directly to the individual types, to allow policymakers who have already decided on their mode type to predict costs to some extent. Given the small sample sizes, the models struggle to achieve much significance. Of all the YR models presented, it seems that #2 of operational expense per passenger trip is the overall strongest. The model boasts an impressive r^2 of .992 and looks like this:

$$Operational\ Expense\ per\ passenger\ trip$$
$$= -4.208 + (5.237 \times stop\ spacing) + (41.256 \times Trains\ per\ Route\ Mile)$$

This conclusion suggests that policymakers must establish a sense of what ridership will be before seeking to measure future efficiency on a YR service. There is also significant room for additional research on the effect of frequency and span of service on efficiency, beyond the use of a crude proxy such as NTD is able to provide.

For CR systems, it is clear that the most reliable relationship is between stop spacing and operational efficiency. Overall, the best model of those tested is likely model #1 of those measuring operational expense per passenger trip. The resulting equation would be:

$$Operational\ expense\ per\ passenger\ trip = (stop\ spacing \times 1.984)$$

Between r^2 and its adjusted equivalent, we can surmise that stop spacing accounts for around 30% of the variation in operational expense per passenger trip—a not insignificant amount. As with the YR systems, there is clearly much more work to be done here, particularly with regard to the effects of frequency on efficiency. Interestingly, the lack of reliable results with regard to operational cost per passenger *mile* suggests that the wide variability within CR systems on distance may make constructing cost-predictive functions difficult.

Conclusions and Further Research Needed

This analysis has come to several primary, and important, but limited conclusions:

- Hybrid rail systems can and do outperform their commuter rail counterparts on a ridership-per-vehicle-hour basis
- Hybrid rail operational costs are equivalent to or higher than commuter rail costs
- With all systems analyzed together, closer stop spacing generally correlates to more efficiency (reduced costs and higher ridership)
- While the crudeness of the representation used may obscure the results, frequency of service may also correlate with more cost-efficient service

Taken together, these conclusions point in the direction that technically-minded transit advocates have long advocated: commuter and regional rail systems in the US need significant labor reform to increase operating efficiency.[8] Systems that break the 9-to-5, peak-focused, mold of typical US commuter rail can and do perform well on ridership metrics—but they have not yet solved the problem of high operational costs. DMU advocates often point to the mode as being lightweight, easy, and cheap to implement—and that can be true in terms of capital costs, although due to their rarity DMUs still often cost significantly more in the US than in Europe, where they are more common[9]. It seems, though, that hybrid rail systems have not yet broken through the cost barrier of reducing crewing requirements, the single largest piece of the transit expenditure puzzle.

Trying to track labor efficiency, then, is probably the single largest piece of research that could supplement this analysis. NTD tracks a variable known as "Operating Expense per Employee Hour," but agencies are not required to report it, and in 2013 data only five agencies did so. One potential avenue forward on this measure would be to cobble together data from multiple years of NTD reporting and try to compile a larger sample size. Alternatively, an ambitious researcher could try to compile the data from agencies' own annual reports and other documentation.

The second primary way forward, as has been stated multiple times, is to better quantify the concept of frequency of service. In times past this would have required manual examination of timetables and schedules, and still might; but the introduction of General Transit Feed Specification, or GTFS, tools might allow automated quantification of frequency. On larger

[8] See, for example, Alon Levy's recent post "Why Labor Efficiency is Important." https://pedestrianobservations.wordpress.com/2015/07/26/why-labor-efficiency-is-important/
[9] See in particular https://systemicfailure.wordpress.com/2010/11/13/the-six-million-dollar-train/

systems with more than one route, especially those with multiple service patterns on the same route (say, the Long Island Railroad, which has very frequent service on the inner half of its network and relatively infrequent service on the outer part), there would be numerous complicating factors, but an enterprising researcher could surely make something work. A better measure for frequency than this paper's crude proxy would likely make the models much more robust.

It may be ironic that this statistical analysis of operational efficiency ultimately comes down to, in large part, a qualitative rather than a quantitative measure. Yet it does seem that labor policy—in particular, the question of how many crew members must ride a particular train—is the single most important remaining question in the comparative analysis of hybrid rail vs. commuter rail systems. It is a question that remains unquantified because of NTD's (lack of) reporting practices, and one that is highly politicized. Labor unions remain extremely strong in the railroad sector, and often provide crucial political support for transit projects. That makes any talk of reducing crew sizes extremely touchy. Ultimately, it seems that the question of efficiency remains not just a technical one, but a political one—perhaps even more political than technical. And research on that front will continue in this author's senior paper.

Appendix A: Systems Studied

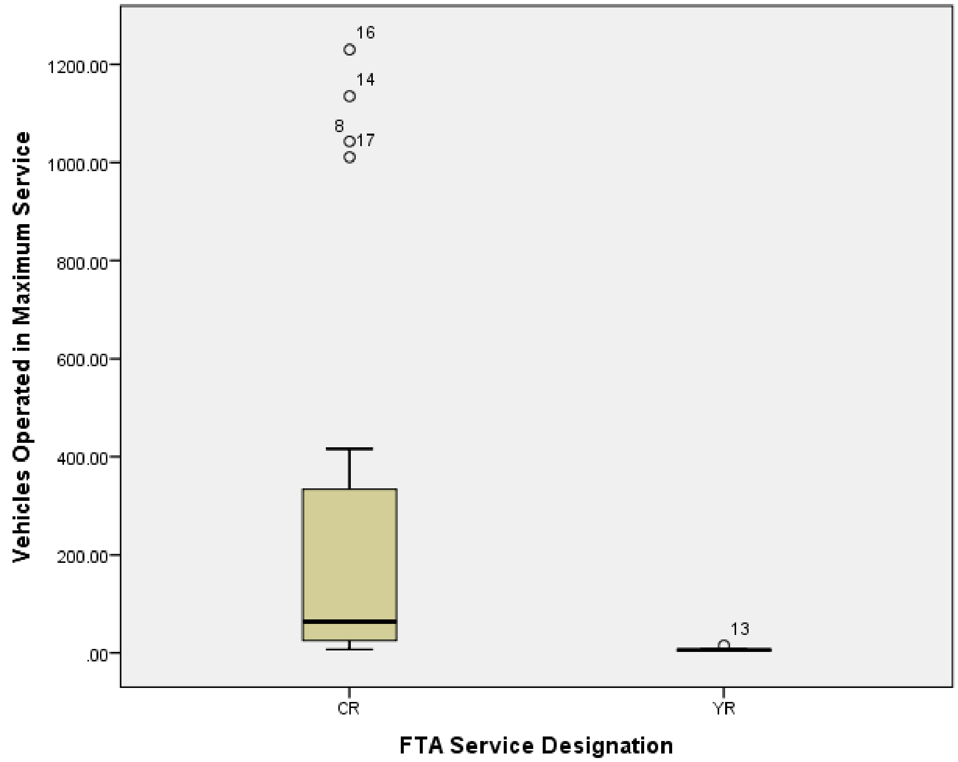
Service	Metro Area	Type	Dataset ID
Altamont Commuter Express	San Jose-Stockton	CR	1
Sprinter	San Diego	YR	2
Coaster	San Diego	CR	3
Caltrain	San Francisco-San Jose	CR	4
Metrolink	Los Angeles	CR	5
Shore Line East	Connecticut Shoreline	CR	6
Tri-Rail	Miami	CR	7
Metra	Chicago	CR	8
South Shore	Chicago/Northwest Indiana	CR	9
MBTA	Boston	CR	10
MARC	Washington, DC/Baltimore	CR	11
Northstar	Minneapolis/St. Paul	CR	12
River Line	Philadelphia/Trenton	YR	13
New Jersey Transit	NYC/Trenton	CR	14
RoadRunner	Albuquerque/Santa Fe	CR	15
Metro-North	NYC	CR	16
LIRR	NYC	CR	17
Westside Express	Portland, OR	YR	18
Keystone Service	Philadelphia/Harrisburg	CR	19
SEPTA	Philadelphia	CR	20

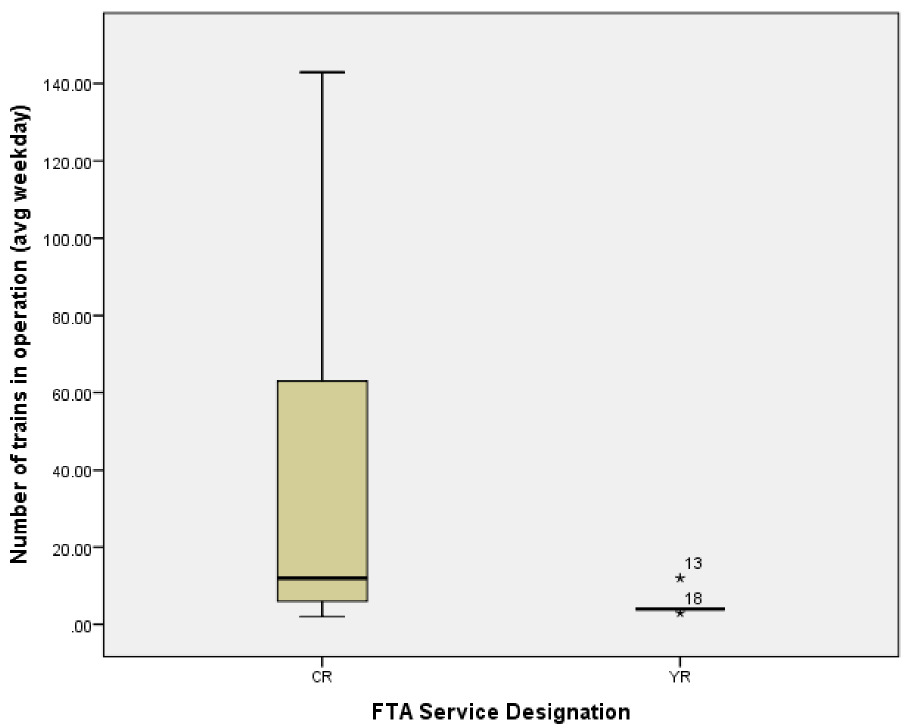
Music City Star	Nashville	CR	21
Capital MetroRail	Austin	YR	22
DART	Dallas	CR	23
A-Train	Dallas	YR	24
FrontRunner	Salt Lake City	CR	25
Virginia Railway Express	Washington, DC	CR	26
Sounder	Seattle	CR	27

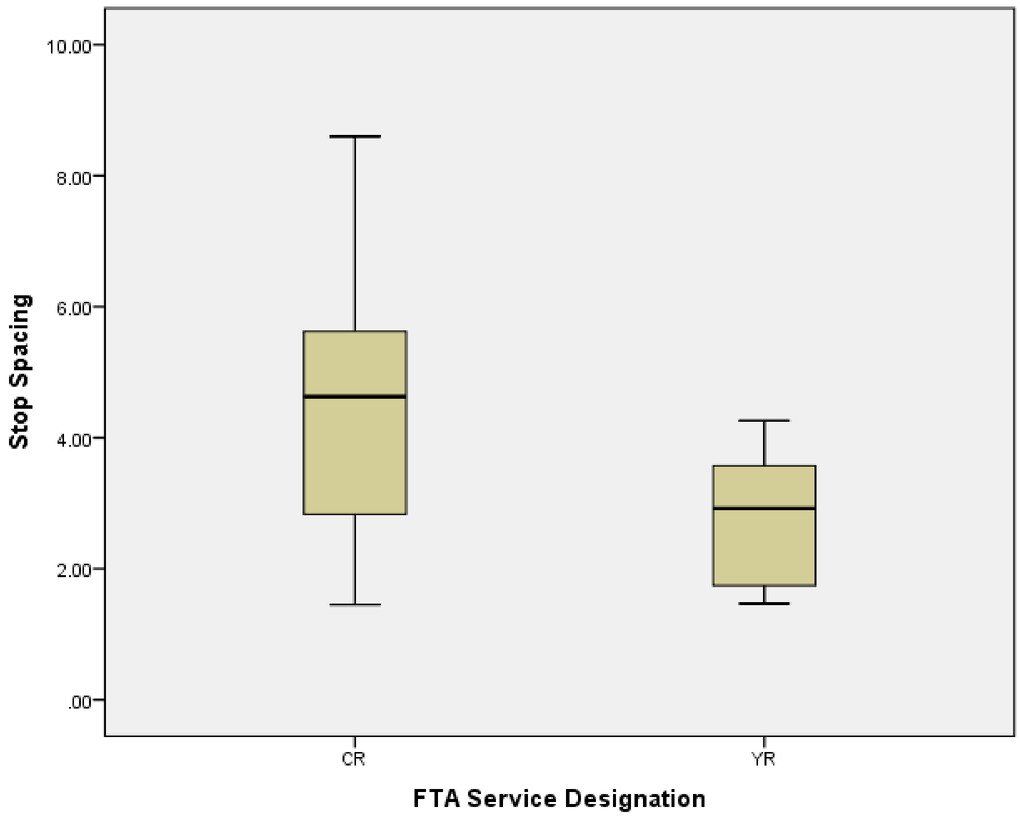
Appendix B: Variables

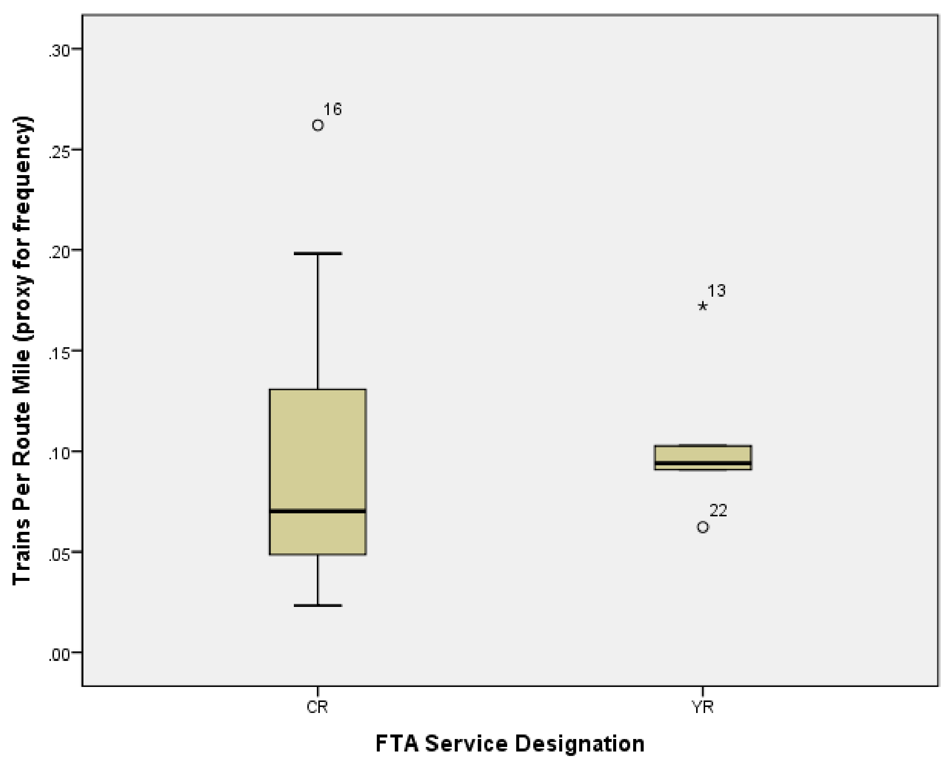
	NTD Table	Description	Units	Notes
Independent Variables				
VOMS	19	Vehicles Operated in Maximum Service—most vehicles (coaches) operated at busiest point of the day		
VehMi	19	Annual Vehicle Miles	Thousands	
RevMi	19	Annual Vehicle Revenue (in service, carrying passengers) Miles	Thousands	
VeHr	19	Annual Vehicle Hours	Thousands	
RevHr	19	Annual Vehicle Revenue Hours	Thousands	
PaxTrips	19	Annual Unlinked Passenger Trips	Thousands	
PaxMiles	19	Annual Passenger Miles	Thousands	
NumTrains	20	Number of trains in operation (Average weekday)		
Stations	21	Total Number of Stations		
RouteMiles	23	Round Trip Route Miles		All lines in system
StopSpace	n/a	Stations/(RouteMiles/2)		Average stop spacing for a one-way trip (entire system)
TrainsPerRouteMile	n/a	NumTrains/RouteMiles		Proxy for frequency
Dependent Variables				
OpExVoms	27	Operating Expense per Vehicles Operated in Maximum Service	Single dollars	
OpExVeHR	27	Operating Expense per Vehicle Hour		
OpExPaxTrip	27	Operating Expense per Passenger Trip		
OpExPaxMi	27	Operating Expense per Passenger Mile		
OpExEmHr	27	Operating Expense per Employee Hour		Only some agencies report
PaxTripPerRevHR	n/a	Unlinked Passenger Trips Per Vehicle Revenue Hour		Considered one of the most reliable indicators of performance efficiency

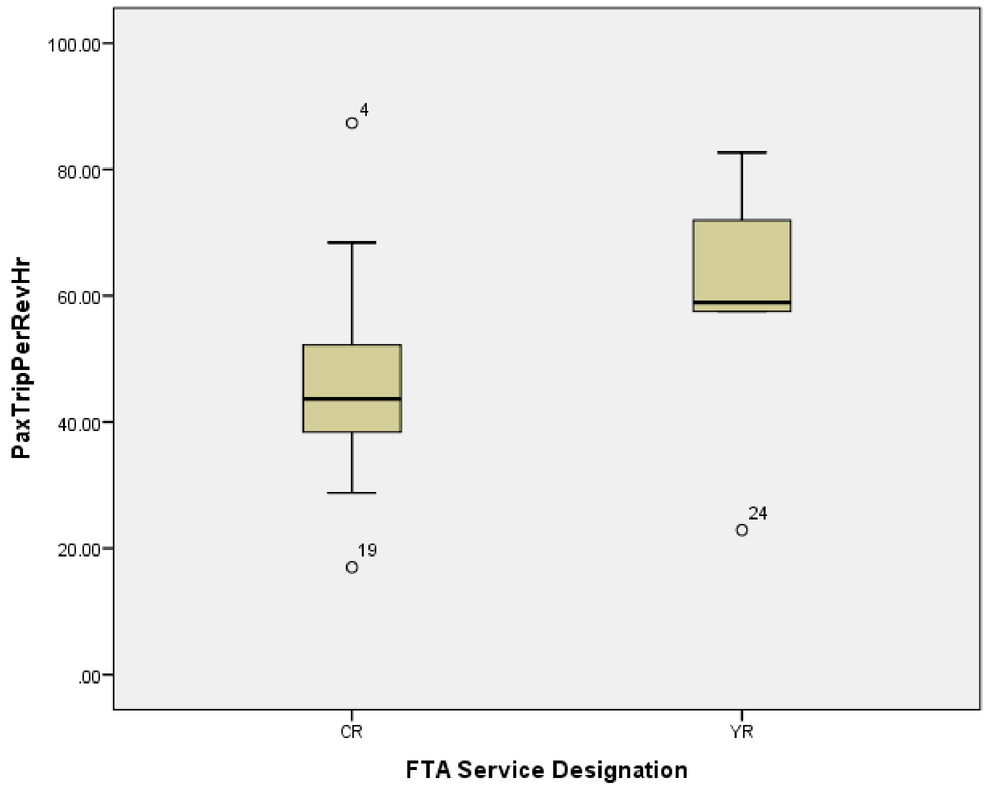
Appendix C: Visual Presentations of Descriptive Data



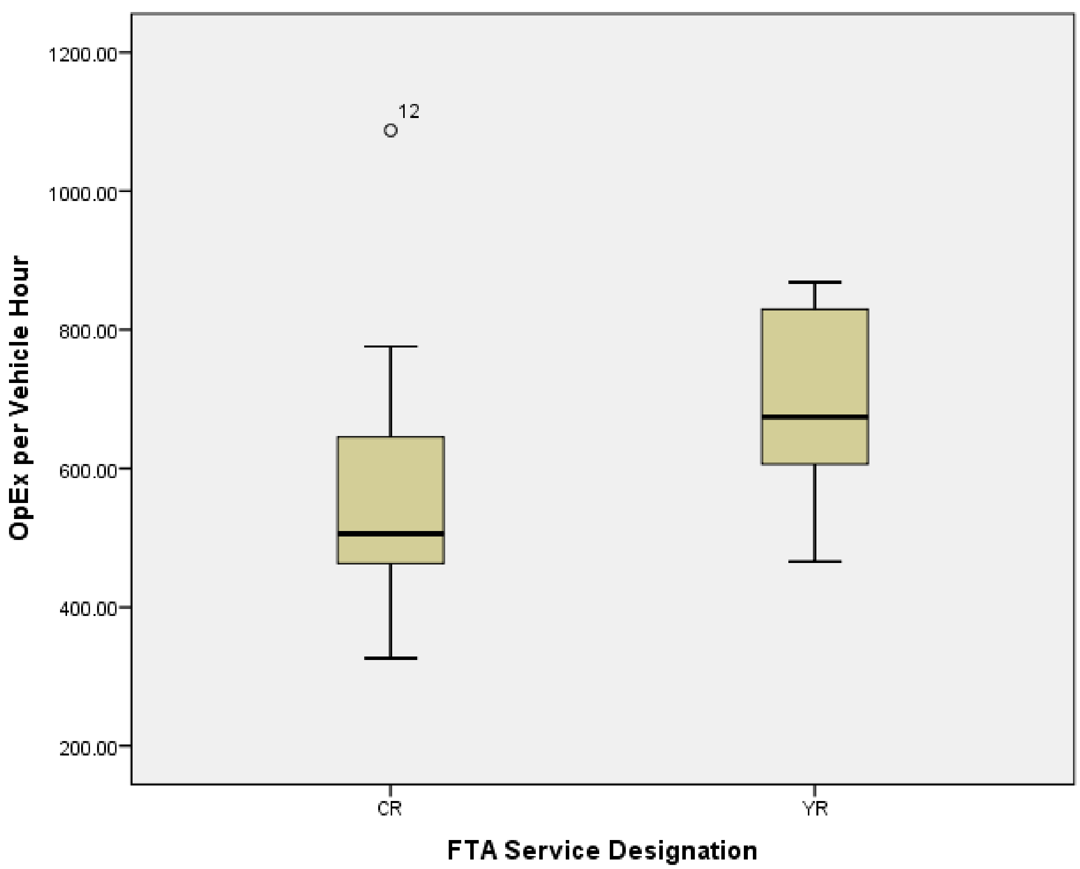



10.00
8.00
6.00
4.00
2.00
.00
Stop Spacing
CR
YR
FTA Service Designation

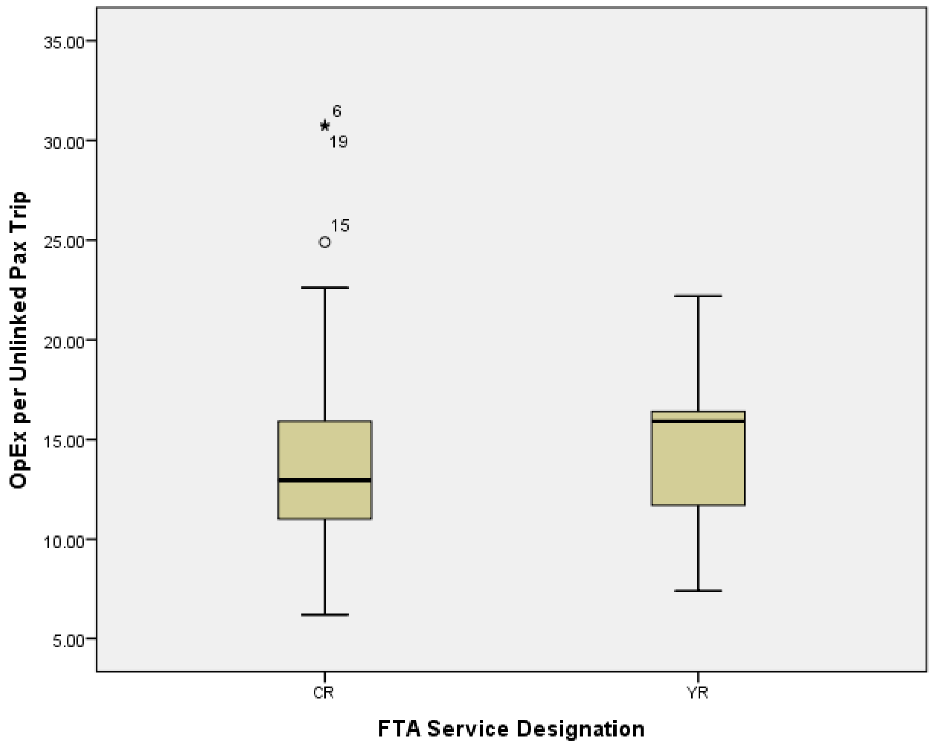

.30
.25
.20
.15
.10
.05
.00
Trains Per Route Mile (proxy for frequency)
16
13
22
CR
YR
FTA Service Designation



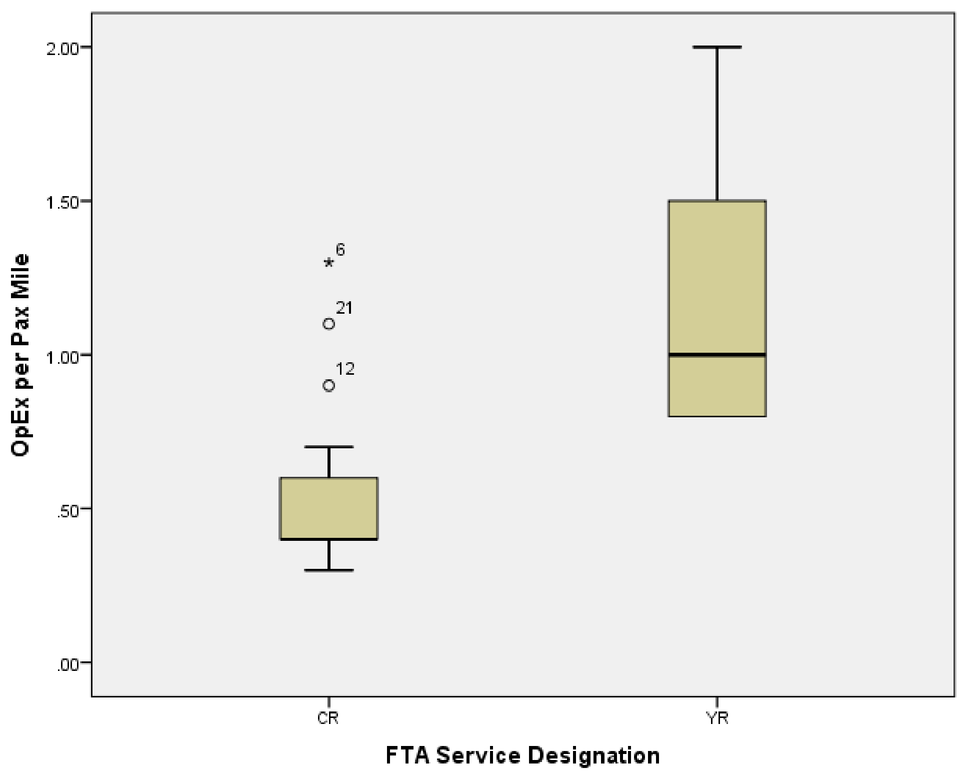
PaxTripPerRevHr
100.00
80.00
60.00
40.00
20.00
.00
4
19
24
CR
YR
FTA Service Designation



OpEx per Vehicle Hour
1200.00
1000.00
800.00
600.00
400.00
200.00
12
CR
YR
FTA Service Designation



35.00
30.00
25.00
20.00
15.00
10.00
5.00
6
19
15
OpEx per Unlinked Pax Trip
CR
YR
FTA Service Designation



2.00
1.50
1.00
.50
.00
6
21
12
OpEx per Pax Mile
CR
YR
FTA Service Designation

Appendix D: Analysis Dataset

Name	Type	VOMS	VehMi	RevMi	VeHr	RevHr	PaxTrips	PaxMiles	NumTrains	Stations	RouteMiles	OpExVOMS	OpExVeHr	OpExPaxTrip	OpExPaxMi	OpExEmHr	StopSpace	TrainsPerRouteMile	PaxTripPerRevHr	TypeDummy
Altamont Corridor Express(ACE)	CR	22.00	944.10	914.70	28.70	23.30	940.80	42140.30	4.00	10.00	172.00	678709.00	521.10	15.90	0.40	#NULL!	8.60	0.02	40.38	0.00
North County Transit District(NCTD)	YR	6.00	533.70	530.60	24.30	24.20	2000.90	18103.00	4.00	15.00	44.00	2454214.00	606.30	7.40	0.80	#NULL!	1.47	0.09	82.68	1.00
North County Transit District(NCTD)	CR	25.00	1470.70	1392.40	40.50	35.00	1629.20	44875.30	4.00	8.00	82.20	750679.00	462.80	11.50	0.40	#NULL!	5.14	0.05	46.55	0.00
Peninsula Corridor Joint Powers Board dba: Caltrain(PCJPB)	CR	100.00	6845.00	6590.70	199.40	187.60	16384.60	357919.10	20.00	32.00	153.68	1019919.20	511.50	6.20	0.30	#NULL!	2.40	0.13	87.34	0.00
Southern California Regional Rail Authority dba: Metrolink(M	CR	185.00	13460.00	13162.90	374.20	338.00	13444.80	464643.10	37.00	55.00	777.80	1023318.70	505.90	14.10	0.40	#NULL!	7.07	0.05	39.78	0.00
Connecticut Department of Transportation(CDOT)	CR	28.00	2008.90	1467.60	41.50	30.30	871.50	20872.20	6.00	9.00	101.20	957772.50	645.60	30.80	1.30	#NULL!	5.62	0.06	28.76	0.00
South Florida Regional Transportation Authority(TRI-Rail)	CR	40.00	3258.00	3164.50	115.70	102.50	4201.00	116122.40	10.00	18.00	142.24	1451297.30	501.80	13.80	0.50	#NULL!	3.95	0.07	40.99	0.00
Northeast Illinois Regional Commuter Railroad Corporation db	CR	1043.00	45217.40	43197.70	1458.60	1410.00	73603.20	1665749.70	141.00	241.00	975.40	636697.60	455.30	9.00	0.40	#NULL!	2.02	0.14	52.20	0.00
Northern Indiana Commuter Transportation District(NICTD)	CR	66.00	3835.90	3736.40	107.50	104.70	3606.90	104240.20	14.00	20.00	179.80	598529.10	367.40	11.00	0.40	80.00	4.50	0.08	34.45	0.00
Massachusetts Bay Transportation Authority(MBTA)	CR	416.00	22530.50	22072.60	753.60	742.30	35228.80	729585.70	63.00	137.00	776.08	844611.00	466.20	10.00	0.50	73.70	2.83	0.08	47.46	0.00
Maryland Transit Administration(MTA)	CR	175.00	6110.90	5687.40	156.80	147.10	9030.00	274231.00	28.00	42.00	400.40	694907.10	775.80	13.50	0.40	#NULL!	4.77	0.07	61.39	0.00
Metro Transit	CR	23.00	543.30	536.90	16.30	15.10	787.20	19877.40	4.00	7.00	77.90	771893.90	1087.50	22.60	0.90	#NULL!	5.56	0.05	52.13	0.00
New Jersey Transit Corporation(NJ TRANSIT)	YR	15.00	1253.30	1230.30	49.70	49.70	2859.20	41231.10	12.00	20.00	69.70	2236150.30	674.30	11.70	0.80	#NULL!	1.74	0.17	57.53	1.00
New Jersey Transit Corporation(NJ TRANSIT)	CR	1135.00	64130.40	60753.20	2193.40	1792.10	80136.40	2224999.20	131.00	164.00	1001.80	808051.30	418.10	11.40	0.40	94.40	3.05	0.13	44.72	0.00
Rio Metro Regional Transit District(RMRTD)	CR	25.00	1426.70	1398.30	38.10	36.10	1089.50	48413.10	7.00	13.00	193.10	1083428.20	711.50	24.90	0.60	#NULL!	7.43	0.04	30.18	0.00
Metro-North Commuter Railroad Company, dba: MTA Metro-North	CR	1230.00	73724.40	65213.20	2173.70	1955.20	83290.90	2501154.20	143.00	112.00	545.74	1205723.50	509.30	12.30	0.60	#NULL!	2.44	0.26	42.60	0.00
MTA Long Island Rail Road(MTA LIRR)	CR	1011.00	74456.10	64819.90	2393.40	2113.10	99256.00	2161002.90	113.00	124.00	638.20	871251.60	493.00	12.90	0.40	98.40	2.57	0.18	46.97	0.00
Tri-County Metropolitan Transportation District of Oregon(Tr	YR	4.00	164.30	162.10	8.50	7.50	441.90	3552.60	3.00	5.00	29.22	1759008.30	829.30	15.90	2.00	106.20	2.92	0.10	58.92	1.00
Pennsylvania Department of Transportation(PENNDOT)	CR	20.00	2146.10	2146.10	35.90	35.90	610.20	44623.40	4.00	12.00	144.40	936733.80	521.80	30.70	0.40	#NULL!	6.02	0.03	17.00	0.00
Southeastern Pennsylvania Transportation Authority(SEPTA)	CR	334.00	19990.20	18679.00	740.40	694.40	37167.70	502346.10	80.00	154.00	446.94	738994.10	333.40	6.60	0.50	#NULL!	1.45	0.18	53.52	0.00
Regional Transportation Authority(RTA)	CR	7.00	205.30	200.00	8.30	6.70	252.20	3917.50	2.00	6.00	62.80	597208.30	505.40	16.60	1.10	70.30	5.23	0.03	37.64	0.00
Capital Metropolitan Transportation Authority(CMTA)	YR	4.00	331.10	279.40	15.80	11.60	834.70	13281.90	4.00	9.00	64.24	3428112.30	868.60	16.40	1.00	#NULL!	3.57	0.06	71.96	1.00
Dallas Area Rapid Transit(DART)	CR	23.00	1351.60	1144.50	55.80	49.50	2092.80	40170.30	6.00	10.00	72.30	1172514.90	483.10	12.90	0.70	#NULL!	3.62	0.08	42.28	0.00
Denton County Transportation Authority(DCTA)	YR	8.00	624.60	598.10	24.30	22.30	510.70	7637.40	4.00	5.00	42.60	1414881.30	465.60	22.20	1.50	#NULL!	4.26	0.09	22.90	1.00
Utah Transit Authority(UTA)	CR	36.00	5126.10	5068.10	109.50	99.40	3816.40	108921.20	9.00	16.00	174.46	992619.30	326.30	9.40	0.30	#NULL!	5.45	0.05	38.39	0.00
Virginia Railway Express(VRE)	CR	89.00	2427.60	2081.20	81.00	66.50	4550.10	149745.10	32.00	18.00	161.48	682010.50	749.00	13.30	0.40	#NULL!	4.49	0.20	68.42	0.00
Central Puget Sound Regional Transit Authority(ST)	CR	62.00	1671.90	1636.80	54.50	49.30	2968.00	64702.00	10.00	12.00	163.84	622467.80	707.70	13.00	0.60	78.00	6.83	0.06	60.20	0.00

Appendix E: SPSS Outputs

<see digital attachments>