Evaluating the ability of transit direct ridership models to forecast medium-term ridership changes: Evidence from San Francisco

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Submitted for Presentation and Publication

97th Annual Meeting of the Transportation Research Board

Word count: 5734 Words + 7 Tables and Figures = 7484 Total Words

Submitted: August 1, 2017

Revised and Resubmitted: October 11, 2017

Abstract

Transit direct ridership models (DRMs) are commonly used both for descriptive analysis and for forecasting, but are rarely evaluated for their ability to predict beyond the estimation data set. This research does so, using two DRMs estimated for rail and bus ridership in San Francisco. The models are estimated from 2009 data, applied to predict 2016 conditions, and compared to actual 2016 ridership. Over this period in San Francisco, observed rail ridership increased by 9% while observed bus ridership decreased by 13%.

The results show that the models predict 2016 ridership about as well as 2009. The rail model correctly predicts the direction of change, but underestimates the magnitude of change. The bus model predicts the direction of change wrong, with a predicted 2% increase.

A series of sensitivity tests are conducted to better understand the factors driving the ridership changes. These tests produce reasonable rail sensitivities, but reveal that the bus model is too sensitive to frequency, potentially due to the difficulty of estimating the coefficient from cross-sectional data where high-frequency transit also occurs in high-density locations.

As the travel forecasting community increases its focus on empirically evaluating forecasts beyond a base year, DRMs must be a part of that.

Key Words: Direct Ridership Model, Direct Demand Model, Transit Ridership, San Francisco, Bus, Rail

1. Introduction

Transit direct ridership models (DRM), sometimes referred to as direct demand models, are often used for transit planning applications [1]. A DRM is a sketch planning model that reflects the notion that ridership is the sum of riders boarding at each stop. Rather than estimating trips on all modes and then applying a mode choice, as is done in the 4-step modeling paradigm, DRMs estimate transit ridership "directly" as a function of station or stop environments and transit services. Essentially each station becomes a node and a unit of analysis, which provides fine-grained spatial analysis of factors influencing ridership.

A hybrid between a DRM and a 4-step model is the Federal Transit Authority's (FTA) Simplified Trips on Stops (STOPS) model [2], which estimates rail and bus rapid transit (BRT) project ridership. It is similar to a DRM in that it predicts only the ridership on the rail or BRT, but it considers more information than most DRMs, including the Census journey-to-work flows, and highway level-of-service skims from a regional travel model.

DRMs have been developed for both rail and bus transit, and used for a variety of applications. The models are used both as descriptive tools to understand the factors that influence ridership, and as predictive tools to forecast the ridership at new stations or in response to changes in service or other attributes.

For example, Cervero et al [3] estimate a DRM of bus rapid transit ridership in the Los Angeles area. They argue for the application of DRMs as a complement to 4-step models, to generate first-cut ridership estimates, and to conduct sensitivity tests of key variables. Pulugurth and Agurla [4] estimate DRMs using different spatial modeling methods in Charlotte, North Carolina. They find that using a spatial weight method does not yield better results over a spatial proximity method, a buffer. Kepaptsoglou et al [5] predict ridership for a new light rail transit system in Cyprus using a DRM. The transit system had not been built yet, so there was not any comparison to observed ridership.

While the goal of the previous papers were to forecast transit ridership, the following papers explore the effects of various factors on transit ridership. Lee et al [6] studies the relationships between heavy and light rail ridership and socio-economic characteristics in Korea. They find that heavy rail ridership is correlated with the number of businesses and households, while light rail ridership is correlated with the number of economically active population and businesses. Liu et al [7] estimate a DRM of rail ridership in Maryland to suggest improvements that will boost ridership. Holmgren [8] determines what factors are affecting transit ridership in Sweden and does this by estimating an econometric first-difference model. Estupian and Rodriguez [9] estimate a DRM of Bogota's BRT ridership to quantify the effect that the built environment has, in particular environmental supports for walking. Dill et al [10] describe the effects that transit service characteristics and urban form have on local bus ridership. They find that socio-demographic characteristics seem to have a larger effect on ridership in large urban areas rather than small urban areas.

In nearly all of the above cases, the DRM is estimated from cross-sectional ridership data using ordinary least squares (OLS) regression. An exception is from Kerkman et al [11] who use data from both 2012 and 2013, during which significant service changes occurred. They estimate cross-sectional models and compare those models to a fixed-effects panel data regression model where the dependent variable is the change in ridership from 2012 to 2013. They find notably different sensitivities between the two models, with the panel data models showing the elasticity of ridership with respect to changes in stop frequency as about half of what the cross-sectional models show. They suggest that the panel data models do a better job of mitigating endogeneity where transit agencies tend to run higher frequency service in locations with higher potential demand.

While DRMs are routinely promoted as tools for forecasting [2, 4], they are rarely evaluated for their ability to forecast. In fact, many of the published DRMs evaluate the models exclusively on the goodness of fit against the estimation data set, without any validation against independent data in either location or time [2, 3, 4, 5, 6, 7, 8, 9]. An exception to this is Upchurch and Kuby [12] where a DRM is estimated from data in 9 (other) cities, applied to predict the ridership on a new light rail line in Phoenix, and compared those predictions to actual ridership. The comparison allowed the authors to understand how well the model could be applied to a new data set, and to understand what caused over/under predictions.

Beyond the efforts of Upchurch and Kuby, there remains a sparsity of evidence on the ability of DRMs to forecast changes in transit ridership. This research contributes to filling that gap by estimating both a rail and bus DRM using 2009 data, applying that model to forecast 2016 ridership, and comparing the forecasts to actual 2016 conditions. It does this using the example of the MUNI light rail and bus system in San Francisco, California. The analysis goes on to examine the magnitude of factors affecting the change in modeled ridership between these two years. Together, this allows us to evaluate how well the models perform in a predictive way, what they are able to capture in drivers of transit ridership trends, and what they may be missing.

The remainder of this paper is structured as follows. Section 2 describes the context of the San Francisco transit system. Section 3 explains the data sources and data processing. Section 4 presents the model estimation results for both the rail and bus models. Section 5 shows the application of the models to predict 2016 conditions. Section 6 examines the factors driving the change in modeled ridership. Finally, conclusions and next steps are considered.

2. Context

The 9-county San Francisco Bay area covers approximately 7,000 square miles with a population of 7.5 million residents. San Francisco is one of the core counties and has a population of 850,000 residents. The major transit systems operating in San Francisco are San Francisco Municipal (MUNI), Bay Area Rapid Transit (BART), and Caltrain. The system of interest for this paper is MUNI, in particular the bus and light rail systems.

The MUNI system experienced significant service cuts in 2010 due to budget constraints. Since then, there have been incremental service improvements, which have accelerated from about 2014 as the agency implements its MUNI Forward program [13], focused on deploying Rapid (skip-stop service with associated operational improvements) bus routes in high-use corridors.

During the past decade transit ridership in the area has experienced diverging growth, with bus ridership declining while rail ridership is growing significantly [14]. Our data show that between 2009 and 2016, Muni rail ridership increases from 147,500 to 161,400, while MUNI bus ridership decreases from 515,000 to 450,000. The employment and population in San Francisco has increased significantly, so it would be natural to expect a corresponding growth in transit ridership. By quantifying the factors that contribute to ridership changes, and comparing the total observed and modeled change, this research provides insight into both the accuracy of the model and explanations for these divergent trends.

3. Data

Direct ridership models estimate boardings or exits or both at a stop for defined periods of time, daily for this paper, as a function of variables related to the stop. This paper uses the standards previous research has set for DRMs with slight modifications to improve the models performance in San Francisco. The first modification is that the data are aggregated to the (directional) route-stop level rather than the stop level. That means that if two different transit routes stop at the same location, they are treated as separate observations. While the locational attributes of each record are the same, this allows the service attributes to be tracked separately. Second, bus stop-area data are tabulated for tenth-mile buffers instead of the more common quarter-mile buffers. This reflects the high density of stops in the network and avoids excessive overlap between adjacent buffers. Rail stations use the larger 0.25 mile buffer. Both were tested with a range of buffer sizes.

Previous research was used to determine what other data should be collected and included in the model [5, 6, 7, 8, 9]. Table 1 shows an overview of significant influencers of transit ridership with previous models. These variables were used as a starting point to guide the data collection process. Table 2 shows a list of the variables considered in this research, along with their calculation method. The remainder of this section describes the data and how it is processed in further detail.

All variables with log+1 in parenthesis is the log-transformed version of the data. The transformation includes taking the natural log of the data plus one. The plus one is to avoid errors when the data is 0. A sample calculation can be found below.

$$Data_{Log-Transformed} = Ln(1 + Data_{original})$$

3.1 Bus Ridership (Dependent Variable)

A portion of the San Francisco Municipal (MUNI) bus fleet is equipped with automated vehicle location / automated passenger counter (AVL/APC) technology. The AVL equipment records the latitude and longitude along with a timestamp every time a vehicle arrives or departs a stop. Busses are randomly assigned the AVL/APC equipment at the depot each day, but over a number of days all routes have been observed. The data are scaled up to cover the entire system by applying the ratio of total trips over observer trips to the observed data using a previously developed process [14]. In addition to ridership, the data provides other performance metrics, including runtime, speed, on-time performance, and crowding measures. This analysis considers average weekday conditions (excluding holidays) for the fourth quarter of 2009 and 2016.

Table 1: Significant Variables in Previous Rail and Bus DRMs

Variables		
Service Attributes	Location of Stop Attributes	Bus Stop or Site Attributes
Primary	**Primary**	**Primary**
• Presence of dedicated-lane services (0-1)	• Population density (US census)	• Presence of bus benches (0-1)
• Run Speed (Actual)	• Employment density (US census)	• Presence of a passenger information system (0-1)
• Reliability	• Total urban density (persons plus workers)	• Presence of a bus-stop shelter or canopy (0-1)
• Bus-stop ridership (log) (dependent variable)	• Distance to the nearest rapid transit stop	• Distance to urban center
• Fare	• Income	• Bus terminus (indicator) (start/end of stop)
• Service Miles (Scheduled)	• Competitive bus-stops	
• Dwell Time	(two levels: opposing and same route)	
• Crowded hours		
	Secondary	**Secondary**
Seconday	• Percent of population that are elderly	• Transer stop (indicator) (can transfer to at least
• Rear Door Boardings	• Land Use (residential/agriculture/etc.)	two other routes)
• Number of daily Connecting rail-transit lines	• Street connectivity	•Park-and-ride lot (0-1)
• Supply demand match index (how well demand matches supply)	(# of nodes divided by # of links)	•Number of park-and-ride spaces
• Stop frequency (log)		• Presence of BRT-branding or logo at stop (0-1)

3.2 Rail Ridership (Dependent Variable)

Light rail cars are not equipped with APCs. Instead the San Francisco Municipal Transportation Authority (SFMTA), relies on occasional manual counts. They provided boarding and alighting counts at the station level for average weekday conditions in both 2009 and 2016. Due to the limited ridership data in 2009, some routes (the J, KT and L) were supplemented with 2008 counts.

3.3 General Transit Feed Specification (GTFS)

GTFS [15] allows transit operators to publish their schedules in a standard format. Only the current schedule is published, but when a new version is published, the old is archived [16], so the differences can be used to systematically identify transit service changes. The GTFS provides service attributes for both the rail and bus models, such as scheduled headways, and is used as trip totals when the APC data is scaled up.

3.3 Employment Development Department (EDD)

EDD data for the 4th quarter of 2009 and 2016 were used as the measure of employment. The data are segmented by industry, and are spatially detailed. Longitudinal Employer-Household Dynamics (LEHD) [17] was considered, but not used because it is currently only available through 2014.

3.4 Housing Inventory and Decennial Census

The San Francisco Planning Department provided housing inventory data, which tracks the completion of housing developments in the city with the address, completion date, and net change in housing units. The housing inventory was used to pivot from the 2010 Census blocks to obtain an estimate of the housing stock in each year.

Table 2: Variables and Data Sources

Variable	Variable Name	Description	Data Source	Calculation Method
Ridership (Dependent Variable)				
Bus/Rail Route-Stop Ridership (Log+1) *	LOG_RIDERS	Daily average number of Bus/Rail passengers boarding and alighting a bus at each specific route-stop.	MUNI (Bus Operator)	APC and GTFS Data Fusion
Potential Demand (Independent Variables)				
EDD Employment (Log+1)	EDD_EMP LOG	Total employment within walking distance of a stop.	Employment Development Department (SFCTA)	Buffer Aggregation
LEHD Employment Density	EMP WAC DEN	Employment per acre within walking distance of a route-stop.	Longitudinal Employer-Household Dynamics	Buffer Aggregation
Income (2009 $)	SHR INCOME 100P **	Distribution of income for a census tract that a route-stops falls within. Incomes are in 2009 dollars for both 2009 and 2016.	American Community Survey	Spatial Join
Housing Density (Log+1)	HOUSING DEN LOG	Housing units per acre within walking distance of a route-stop.	Census and Housing Inventory (SFCTA)	Buffer Aggregation
Population Density	POP DEN	Population per acre within walking distance of a route-stop.	Census	Buffer Aggregation
Population	TOTAL POP	Total population for a census tract that a route-stop falls within.	American Community Survey	Buffer Aggregation
Share of Households with 0 Vehicles	SHR HH 0VEH	Share of households with 0 vehicles for a census tract that a route-stop falls within.	American Community Survey	Spatial Join
On-Street Parking Cost (Log +1) (2014 $)	PARK HOURLY AVG ON LOG	Hourly cost of on-street parking in 2014 $	SFCTA	Buffer Aggregation
Transit Supply (Independent Variables)				
Frequency (Log+1)	FREQ S LOG	Average number of buses per hour scheduled to serve each route-stop on a typical weekday.	GTFS	Freq = 1/(Headway*60)
Competitive Stops	COMP STOPS	The number of stops within walking distance of a route-stop.	GTFS	Buffer Aggregation
Bus Terminus	EOL SOL	Whether or not a route-stop is the start or end of a route.	GTFS	N/A
Transbay Terminal (Bus Station)	TRANSBAY	Whether or not a route stop is within walking distance of the Transbay Terminal.	Google Earth	Buffer Aggregation
Reliability	ONTIME5	The on-time share of a route-stop, specified as either 1 minute before or 5 minutes after the scheduled time.	GTFS	N/A
BART Ridership	AVG_BART_LOG	The average number of BART passengers boarding and alighting within walking distance of a route-stop.	BART OD Matrices	Buffer Aggregation
Route Configuration	LIMITED / EXPRESS	A variable to separate out the limited/rapid and express routes from the rest of the bus fleet.	GTFS	N/A
Bus/Rail Ridership *	MUNI BUS AVG / MUNI_RAIL_AVG	The average number of Bus/Rail passengers boarding and alighting within walking distance of a route-stop.	MUNI (Bus Operator)	Buffer Aggregation

* For the bus model the bus ridership is the dependent variable with the rail ridership as an independent variable, and vice-versa for the rail model.

** This is one category of income, includes the share of households with an income of over $100k.

3.5 American Community Survey (ACS)

To test the possible effect of demographics and socio-economic characteristics, we used American Community Survey (ACS) data [18]. For the 2009 data set, we used the 5-year estimates, from 2005-2009. For 2016, we used the 5-year estimates from 2011-2015, the most recently available. The 5-year estimates are more suitable for our purpose because they provide more spatial detail than the 1-year estimates. In tracking demographic changes, we did not use a stop-buffering approach, but instead tagged each stop with the attributes of the Census tract in which it lies. The income variable for 2015 had to be adjusted to 2009 dollars, to account for inflation. Meaning the share of households above $100k in 2009 dollars is the share above $115k in 2015 dollars. The 2009 income variable is kept at $100k, since it is already in 2009 dollars. The $115k was found by multiplying $100k, the 2009 original amount, by the ratio of the 2016 consumer price index (CPI) over the 2009 CPI.

3.6 BART Monthly Entry and Exit Matrices

The Bay Area Rapid Transit (BART) system is a heavy rail system serving four counties in the San Francisco Bay Area. Commuters are a large share of the users because it provides an alternative to the heavily congested Bay Bridge. BART serves as a potential competitor to MUNI for certain trip interchanges within San Francisco, but also serves as a complement because many regional BART trips transfer to MUNI for the “last-mile”.

BART uses distance-based fares, so passengers have their tickets read upon both entering and exiting the system. Knowing the number of entries and exits for each station allows BART to publish monthly matrices showing the number of trips to and from each station. [19] There are nine BART stations in San Francisco that are of interest: Embarcadero, Montgomery, Powell, Civic Center, 16th, 24th, Glen Park, and Balboa Park. The Daly City station was included, due to a few of the buffers reaching across the county line.

3.7 Hourly On-Street Parking Cost

Parking data was provided by SFCTA and came in the form of hourly on street parking prices throughout the day. The prices were averaged to obtain an average hourly price for a meter on a typical weekday. The data was then attached to Micro-Analysis Zones MAZ to give the data a spatial component and then assigned to a stop by using a buffer around the stop. These data are only available for 2014, and are not collected annually. The hourly prices are kept in 2014 dollars because that is the year the data is observed. Since the data was only available for one year the same prices are used for 2009 and 2016. Thus the parking prices can only be used to look at the relationship between it and transit ridership, and not how it influences change in transit ridership.

4. Model Estimation

This section presents the model estimation results for the bus and rail models.

4.1 Bus Model

A 2009 base year model was estimated for each of the modes. The python statsmodels package [20] was used to run OLS regression on the data. The dependent variable was the log transformed average of the number of passengers boarding and alighting at each route-stop. The log transformation was made due to the ridership data being skewed towards 0. Table 3 shows the results of the 2009 bus model.

Table 3: 2009 MUNI Bus Direct Ridership Model Results

Variable	Variable Name	Coefficients	T-Statistics	Observations
Intercept		-0.8151	-6.25	6261
Potential Demand (Independent Variables)				R-squared
EDD Employment (Log+1)	EDD_EMP_LOG	0.1337	15	0.515
Housing Density (Log+1)	HOUSING_DEN_LOG	0.1056	8.45	
High Income Households (2009 $)	SHR_INCOME_100P	-1.2371	-14.71	
On-Street Parking Cost (2014 $)	PARK_HOURLY_AVG_ON_LOG	0.0231	3.44	
BART Ridership (Log+1)	AVG_BART_LOG	0.059	6.87	
Rail Ridership	MUNI_RAIL_AVG	7.40E-05	3.04	
Transbay Terminal (Bus Station)	TRANSBAY	0.8029	3.72	
Transit Supply (Independent Variables)				
Frequency (Log+1)	FREQ_S_LOG	2.8359	57.78	
Reliability	ONTIME5	0.5476	5.96	
Close Route-Stops	CLOSE_STOP	-1.2928	-25.80	
Bus Terminus	EOL_SOL	0.7281	12.75	
Limited Route Configuration	LIMITED	-1.2006	-18.35	
Express Route Configuration	EXPRESS	-1.911	-38.63	

Each of the terms included in the model are significant at the 95% level or better. For those variables that are log-transformed, the coefficients can be interpreted directly as an elasticity, since the left-hand side is also log transformed. Attributes that are measured based on the area (total employment, housing density, etc.) are calculated within a tenth-mile buffer of the stop. Attributes associated with the service itself (frequency, on-time performance, etc.) are measured at the route-stop itself. Demographic measures from the ACS (income shares) are measured based on the census tract that contains the stop.

The intercept can be interpreted as scaling the riders. The scaling value is found by taking the exponent of the intercept, which is found to be 0.44.

The positive employment coefficient is expected, indicating that ridership grows with increasing employment. We also tested employment segmented by different industry categories, including retail, hotel and restaurant, and education and health, but found that these specifications did not result in logical coefficients.

Higher frequency service (measured in average vehicles per hour) is associated with higher ridership. This relationship is logical, but the model appears to be quite sensitive to frequency, with a 1% increase in frequency associated with a 2.8% increase in ridership. For comparison, other studies have found this elasticity to be within the range from 0.1 to 1.04. [21] This high sensitivity may occur due to endogeneity with the dependent variable, or due to collinearity with other descriptive variables. Either way, the highest frequency service, the highest employment densities and the highest ridership all occur in downtown San Francisco, making it difficult for any cross-sectional model to parse out the differences. Headway, a linear treatment of frequency, and several piece-wise linear specifications were also tested, but with no better results.

Ridership is higher at the start and end of lines, in areas with denser housing, and in areas with higher parking costs, all of which we would expect.

Stops in areas with a higher share of households earning $100,000 or more per year tend to have fewer riders per transit stop. This may be because wealthier households have more options to take other modes. It is also noteworthy because virtually all of the net growth in households over the 2009 through 2016 period has been through an increase in households earning $100,000 or more per year [14].

We measure reliability as the share of buses on that route arriving at that stop on-time, where on-time is defined as no more than one minute early and no more than 5 minutes late [22]. This is of particular interest, as reliability has been an important focus of MUNIs operational efforts in recent years.

We measure BART ridership as the log transformed Bart ridership calculated as the average of BART boardings and alightings within the buffer area. The positive coefficient indicates net complementarity between BART and MUNI, with transfers between the two. Boardings and alightings on MUNI light rail stops within the buffer area also have a positive and significant coefficient. Stops near the Transbay Bus Terminal, which serves AC Transit commuter buses from the East Bay, also have higher ridership, likely due to a similar transfer effect.

CLOSE_STOP is a dummy variable representing whether or not the previous stop on the same route is within 0.2 miles. It is included to account for competition with other stops on the same route, and the negative coefficient indicates that closely space stops have lower ridership per stop, as we would expect.

Limited and express routes tend to have fewer riders per stop, which may be associated with relatively worse off-peak service on those routes.

The overall R^2 of the model is 0.515 relative to a constants-only model.

4.2 Rail Model

The rail model used the same unit of observation, route-stop. There are fewer observations because there are significantly less rail stops than bus stops within San Francisco. Table 4 shows the estimation results for this model.

Table 4: 2009 MUNI Rail Direct Ridership Model Results

Variable	Variable Name	Coefficients	T-Statistics	Observations
Intercept		2.1822	-6.245	315
Potential Demand (Independent Variables)				R-squared
EDD Employment (Log)	EDD_EMP_LOG	0.1607	4.29	0.482
Housing Density (Log)	HOUSING_DEN_LOG	0.2755	4.349	
BART Ridership (Log)	AVG_BART_LOG	-0.0652	-2.935	
Bus Ridership	MUNI_BUS_AVG	6.15E-05	4.452	
Transit Supply (Independent Variables)				
Frequency (Log)	FREQ_S_LOG	0.3042	1.686	
Close Stop	CLOSE_STOP	-0.3706	-3.18	
Bus Terminus	EOL_SOL	0.3129	1.89	
Route J Route-Stops	J	-0.6166	-5.158	

The rail model specification broadly follows that of the bus model, although it is simplified both as some insignificant variables drop out of the model, and because we also lack some of the operational measures, such as on time performance, that are available through the automatic passenger counter (APC) data on the buses. Station-area attributes for the rail model are tabulated using a 0.25 mile buffer, reflecting a higher willingness to walk to rail and longer distances between the stations. 0.1 and 0.33 mile buffers were also tested and rejected. All variables included in the model are significant at the 90% level.

The intercept can be interpreted as scaling the riders. The scaling value is found by taking the exponent of the intercept, which is found to be 8.87.

The coefficient on the log transformed employment is 0.16, slightly higher than what is found in the bus model. Specifications that segmented the employment by industry were unsatisfactory. Housing density is also positive and significant.

The log of transit frequency in the rail model is 0.3, and significant at the 90% level. This is much lower than what is found in the bus model, and may reflect that there is less variation in frequency between the more sparse stops.

Unlike with the bus ridership, BART boardings in the buffer area are negatively correlated with MUNI rail ridership. This may reflect stronger competition and less complementarity between the two rail systems. The model does still show complementarity with MUNI bus boardings and alightings within the buffer area. That symmetry is encouraging.

As with the bus model, a nearby rail stop on the same route draws down the ridership at the stop in question. Both end of line and start of line stations tend to have higher ridership as expected.

A constant on the J line is negative and significant. Constants tested on each of the other lines were insignificant and left out of the model. The negative coefficient could be associated to the J line competing with BART more directly. This would be due to the J line having stations in close proximity of nearly all of the BART stations. In the model application results section figure 2 shows the accuracy of the model, and the rail stops that the J line uses are highlighted.

The overall R^2 of the model is 0.482 relative to a constants-only model.

4.3 Other Variables Tested

There were numerous variables included in the estimation file, but were not included in the final model. A few of importance are the share of households with 0 vehicles and fares. The share of households with 0 vehicles is potentially explained with other variables, such as housing density. However, fares only change 25 cents between 2009 and 2016. After accounting for inflation the change is only 6 cents, which was considered to be negligible.

5. Model Application Results

To evaluate the forecasting ability of the models, the 2009 bus and rail models were ran using an independent data set, 2016 data that was processed in the same manner as the 2009 data. In contrast to the model estimation, which limited the data set to route-stops with observed boardings, the models were applied to the full set of route-stops in San Francisco (a few outside the county were excluded). The focus of the examination focuses on how well the models predict change, more so than their cross-sectional fit.

Table 5 shows the system-level results. The 2009 bus model under-predicts total ridership by 11%, with the rail model under-predicting total ridership by 13%. Between 2009 and 2016, the data show that bus ridership decreases by 13%, whereas the model predicts a 2% increase. The data show rail ridership increasing by 9% over this period, while the model only predicts a 3% increase. For the rail model, the percent root mean square error (RMSE) is slightly better for the 2016 application than the 2009 application. The opposite result is found for the bus model. The percent RMSE are fairly large due to the disaggregate nature of a route-stop. The percent RMSE is given at two aggregated levels, stop and route. The general trend is that a better percent RMSE is found when more aggregated data is used. The average observed ridership for a bus route-stop is 70, a stop is 130, and a route is 5,500. For rail, the average observed ridership for a route-stop is 410, a stop is 530, and a route is 25,600.

Table 5: System Level Model Application Results

		Observed Ridership	Modeled Ridership	Difference	Percent Difference	Route-Stop % RMSE	Stop % RMSE	Route % RMSE
Bus	2009	515,059	459,602	-55,456	-11%	409%	369%	150%
	2016	449,819	467,522	17,704	4%	424%	369%	72%
	Change	-65,240	7,920					
	P Change	-13%	2%					
Rail	2009	147,470	128,042	-19,428	-13%	67%	82%	20%
	2016	161,387	131,721	-29,666	-18%	60%	79%	21%
	Change	13,917	3,679					
	P Change	9%	3%					

Maps comparing the growth in observed ridership versus the growth in modeled ridership were made using python. Green circles indicated stops where the model predicted too much ridership growth (or too little decline), while red circles indicated stops where the model predicted too little ridership growth (or too much decline). Larger circles indicated a larger absolute difference between the observed and modeled change.

The bus map did not show an obvious pattern, beyond a general under-estimation of the decline in bus ridership, focused in particular along the Market Street corridor in the Northeast portion of San Francisco. The rail map showed that the model under-estimates the growth of rail ridership at all but a few stops. The J-line was highlighted and a possible explanation for the negative coefficient was found, which is the J-route is competing more directly with BART than other routes. After mapping the growth differentials it was clear that the J-route stops follow closely with the BART stops running through San Francisco.

6. Factors Affecting Change

To better understand the change in ridership between the two years, a series of sensitivity tests were conducted with the models. The tests focused on the subset of route-stops present in both 2009 and 2016, and each used 2009 data for all variables except for one isolation variable, for which 2016 data were substituted. This follows past work to understand the factors that drive changes in transit ridership [23], and provides a means for understanding the magnitude of change that can be attributed to that variable.

Table 6 shows the results of this exercise using the bus model. The coefficient for frequency was mentioned before to be high, and it shows up here again with a 3 percent increase in frequency resulting in ridership increasing by 21 percent. San Francisco has experienced favorable economic growth in recent years and that is picked up by the high income variable increasing 6 percent, resulting in a 4 percent decrease of bus ridership. MUNI rail ridership has grown significantly and is found to complement bus ridership leading to an increase of 8 percent. Close stops is picking up recent changes in route configurations where the MUNI forward program is reducing the number of stops along a route. Employment has grown resulting in bus ridership increasing 4 percent. The bus system overall has become more unreliable resulting in a decrease of 4 percent in ridership. The other variables do not experience much change and thus have a minimal effect on bus ridership. There is a decline in ridership associated with route-stops in 2009 but not 2016, and an increase associated with route-stops in 2016 but not 2009. Parking data was only available for 2014, so there was not any observed change in the data. This resulted in the on-street parking cost variable contributing no change in ridership.

Table 6: Factors Affecting the Change in Modeled Bus Ridership from 2009 to 2016

		Average Values (without log)			Associated Ridership Change		
Variable	Coefficient	2009	2016	% Diff	Absolute	Percent%	Elasticity
Intercept	-0.8151						
Potential Demand							
EDD Employment (Log)	0.1337	1197	1434	20%	10,403	4%	0.19
Housing Density (Log)	0.1056	384	396	3%	2,236	1%	0.26
On-Street Parking Cost (Log) (2014 $)	0.0231	94	93	-1%	(173)	0%	0.10
High Income Households (2009 $)	-1.2371	0.36	0.38	6%	(11,245)	-4%	-0.75
BART Ridership (Log)	0.059	282	294	4%	601	0%	0.05
MUNI Rail Ridership	7.40E-05	162	480	197%	21,959	8%	0.04
Transbay Terminal (Bus Station)	0.8029	0.002	0.008	278%	5,076	2%	0.01
Transit Supply							
Frequency (Log)	2.8359	3.93	4.05	3%	57,224	21%	6.89
Reliability	0.5476	0.63	0.58	-8%	(11,091)	-4%	0.49
Close Route-Stops	-1.2928	0.90	0.90	0%	18,458	7%	45.84
Bus Terminus	0.7281	0.05	0.05	1%	573	0%	0.16
Limited Route Configuration	-1.2006	0.02	0.03	18%	(589)	0%	-0.01
Express Route Configuration	-1.911	0.10	0.10	-2%	1,120	0%	-0.18
Total for Route Stops Present in Both Years--each term applied separately					94,553	35%	
Total for Route Stops Present in Both Years--all terms applied together					64,081	12%	
Total for Route Stops Dropped					(187,043)	-36%	
Total for Route Stops Added					130,882	25%	
System Total					7,920	2%	

Table 7 shows the sensitivity analysis for the rail model. The changes appear reasonable given the trends in the data, and are more modest than in the bus model. For the rail model, the bus ridership variable leads to a decrease in rail ridership, whereas the opposite effect is found for rail ridership in the bus model. This is because the rail system complements the bus system. Rail ridership has increased leading to an increase in bus ridership, while bus ridership has experience a decline resulting in a decrease in bus ridership.

Table 7: Factors Affecting the Change in Modeled Rail Ridership from 2009 to 2016

		Average Values (without log)			Associated Ridership Change		
Variable	Coefficient	2009	2016	% Diff	Absolute	Percent%	Elasticity
Intercept	2.1822						
Potential Demand							
EDD Employment (Log)	0.1607	11926	14933	25%	4,119	3%	0.13
Housing Density (Log)	0.2755	1789	1985	11%	5,116	4%	0.37
BART Ridership (Log)	-0.0652	1473	1348	-8%	-21	0%	0
Bus Ridership	6.15E-05	4297	3977	-7%	-3,959	-3%	0.42
Transit Supply							
Frequency (Log)	0.3042	4.5	4.83	7%	3,181	3%	0.34
Close Stop	-0.3706	0.83	0.86	3%	-3,290	-3%	-0.83
Rail Terminus	0.3129	0.08	0.08	-6%	-415	0%	0.05
Route J Route-Stops	-0.6166	0.16	0.16	0%	-	0%	0
Totals							
Total for Route Stops Present in Both Years--each term applied separately					4,733	4%	
Total for Route Stops Present in Both Years--all terms applied together					4,115	3%	
Total for Route Stops Dropped					-2,067	-1%	
Total for Route Stops Added					1,631	1%	
System Total					3,679	3%	

7. Conclusions

This research demonstrated the application of a rail and bus direct ridership model (DRM) estimated from 2009 data to predict 2016 conditions. This was for the MUNI transit system in San Francisco. The results show that the models predict 2016 ridership about as well as 2009. While this is encouraging (but not surprising for a mature system), we are also interested in how well the models predict the change in ridership over this period. The rail model correctly predicted the direction of change, but the modeled magnitude of change is about a third of the actual. The bus model predicted the wrong direction of change and is about 15% off from the true percent-change.

To better understand what factors drive the changes in transit ridership, a series of sensitivity tests were conducted to isolate the effects of each variable in the model. This analysis showed modest changes across a number of variables in the rail model. While these sensitivities appear reasonable, they do not capture all of the observed increase in rail ridership. The bus sensitivity tests show two variables that the model is very sensitive to: frequency and the presence of nearby stops on the same route. MUNI has increased service over this period, with a focus on implementing Rapid routes. The frequency increases and associated skip-stop service on high volume routes should result in a net increase in ridership, but the sensitivity to frequency in particular appears to be unreasonably high. We suspect that the cross-sectional estimation struggles to separate the effects of frequency versus employment density, parking cost and other factors which are all highest in the downtown area. Future research should look into panel data regression or other methods that may be better able to separate these effects.

Beyond these specific terms, it appears that there are real-world trends over this period that the models are not able to capture. The divergent rail and bus ridership trajectories are noteworthy, it would be valuable to understand what is driving that divergence. One possibility is that travelers are making an increased use of transportation network companies (TNCs) as a substitute for bus trips. TNCs have experienced noteworthy growth with the inception of the mode in 2009, in San Francisco. The current research suggests that TNCs complement transit, but the research has not focused on San Francisco. Future work should explore this issue.

Finally, we have found the exercise of evaluating DRMs in forecasting mode to be insightful, and would encourage other DRM users to conduct this type of exercise. Increasingly, travel forecasters are asked to evaluate how well their models predict, and DRMs are not exempt. A natural extension of this research would be to evaluate the ridership predictions of similar models, such as the STOPS model mentioned in the introduction. The forecasted ridership of the aforementioned model can be compared to observed ridership similar to how this paper evaluates DRM predictions.

Acknowledgements

This work was funded, in part, by the San Francisco County Transportation Authority (SFCTA). Staff at SFCTA and the San Francisco Municipal Transportation Agency supplied the data and provided valuable input and advice.

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