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ABSTRACT

A Direct Ridership Model (DRM) for predicting Bus Rapid Transit (BRT) patronage in Southern California is estimated. Attributes of bus stops and their surroundings constitute the data observations of the DRM, enabling a fairly fine-resolution of analysis to be carried out on factors that influence ridership. The best-fitting DRM revealed that service frequency strongly influences BRT patronage in Los Angeles County. High intermodal connectivity, with both feeder bus routes and rail-transit services, also significantly induces BRT travel. Population densities also contribute to BRT patronage and in the case of exclusive-lane BRT services, higher employment densities further increase higher daily boardings. The strong statistical fit of the model bodes well for DRM as a platform for estimating BRT patronage in coming years.

DIRECT RIDERSHIP MODELING

Direct modeling of transit ridership has emerged as an alternative to traditional four-step travel-demand modeling for corridor and station-level analyses (1). Direct models estimate ridership as a function of station environments and transit service features rather than using mode-choice results from large-scale models. This provides a fine-grain resolution suitable for studying relationships between built environments, transit services, and ridership. Because of the focus on bus stops and their surroundings, direct ridership models have found particular favor for estimating the ridership bonus of a transit-oriented developments (TOD) (2).

Because direct models predict demand for a specific node or location versus the origin-destination attributes of a trip, some variables normally found in mode-choice models, such as comparative travel times and prices of transit versus auto, are conspicuously absent. The comparative accessibility of station-area residents to jobs and shops via transit versus auto are included in some direct models in imbed the performance attributes of transit services versus its chief competitor, the private automobile.

Direct ridership models generally have small sample sizes since observations consist of transit stations or stops. Thus degree of freedom constraints often limit the number of variables that can be included as well their specifications (e.g., inclusion of interactive terms). It is because of these limitations that direct models fall under the rubric of sketch-planning tools. They provide order-of-magnitude insights for testing of various system designs and land-use scenarios.

To date, direct modeling has been used to estimate station- and corridor-level ridership for rail transit investments and expansion proposals in areas as diverse as Charlotte-Mecklenburg County (NC), St. Louis (MO), the East Bay of the San Francisco Bay Area, Fairfax County (VA), and Boise (ID) (3-6). For a host of reasons, including fiscal constraints and development densities that are too low for rail investments, more and more U.S. cities and regions are turning to Bus Rapid Transit (BRT) as a cost-effective alternative to rail transit (7). As far as we know, no direct ridership model has been estimated to date for a BRT proposal.

This paper presents a Direct Ridership Model (DRM) for BRT services based on experiences in Los Angeles County. The paper is organized as follows. First, we discuss the sample frame used to conduct the analysis as well as candidate variables that were considered for entry into the DRM. This is followed by a presentation of a best-fitting regression model that conforms with travel-demand theory and yields interpretable and statistically significant results. The paper concludes with discussions on the policy implications of the research and opportunities for advancing BRT direct ridership models in coming years.

MODELING APPROACH AND SAMPLE

Limited real-world experiences with BRT in the U.S. limits the ability to draw upon empirical experiences to inform ridership estimates. While foreign cities like Curitiba, Brazil, Adelaide, Australia, and Bogota, Colombia have accumulated considerable experiences with dedicated-lane BRT operations, vast cultural, socio-economic, and institutional differences with the U.S. limit the use of empirical evidence from such settings.

In the United States, one of the most proactive regions in advancing BRT services has been Southern California. The Metropolitan Transportation Authority (MTA) phased in the Metro Rapid Program in 2000 with the goal of improving bus speeds within urbanized Los Angeles County. Four pilot routes -- along Wilshire Boulevard (720), Broadway (745), Vermont Avenue (754) and Ventura Boulevard (750) -- used Next Bus (real-time passenger information) technology at most stops to inform waiting customers of estimated bus arrival times. Metro Rapid buses consist exclusively of low-floor buses and have their own distinctive color scheme and markings. Other features include signal prioritization, frequent headways, and comparatively long spacings between bus stops.

A new stage in BRT services was reached in 2005 when MTA's Metro Orange Line opened. The Orange Line is one of the first "full-service" BRT systems in the United States, featuring a dedicated busway (running on a disused rail corridor), high-capacity articulated buses, "rail-like" stations (incorporating level boarding and off-board fare payment), and headway-based schedules. The 14-mile route connects the western terminus of the Red Line subway at North Hollywood with Warner Center, the third largest employment center in Los Angeles County. As of 2009, Southern California's Metro Rapid Program consisted of 28 routes in total, providing 450 directional miles of service. MTA buses operate all but two of the routes. The Santa Monica Big Blue Bus (BBB) operates a BRT service as well: Rapid Blue Line 3, which runs along Lincoln Boulevard, and Rapid Blue 7, which connects downtown Santa Monica to the Rimpau Transit Center in the eastern part of the city. The Rapid Blue 3 line is slated for conversion to a higher end BRT service with a dedicated bus lane, and is the focus of ridership forecasts presented later in this paper.

Sample Selection

In order to obtain a sample of sufficient size to draw statistically reliable inferences, 50 MTA bus stop locations were sampled across 20 different Metro Rapid lines. Each location had

a stop on each side of a road, meaning ridership as well as service-level data were compiled for both stops at each location. In addition, data were collected for six bus stop locations of BBB's Rapid Blue line 3. Lastly, to reflect the relationships between services and ridership for "high end" BRT services, data for 13 Orange Line stops were obtained. Figure 1 shows the locations of the 69 total bus stop locations that constituted the sample frame for Direct Ridership modeling. Average daily ridership data were obtained for each stop for October 2008. Accordingly, data for explanatory variables were obtained for time periods as close as possible to the October 2008 date.

Model Specification and Variables

Direct Ridership models estimate boardings (and/or exits) at a stop or station for defined periods of time (e.g., daily) as a function of 3 key sets of variables related to stops or stations:

(1) *Service Attributes* – e.g., frequency of buses (headways, buses per hour), operating speeds, feeder bus connections (number of lines or buses), dedicated lane (0-1), vehicle brand/marketing (0-1), etc.;

(2) *Location and Neighborhood Attributes* – e.g., population and employment densities, mixed land use measures (0-1 scale), median household incomes and vehicle ownership levels (as proxies for levels of "transit dependence"), distance to nearest stop (as a proxy for catchment size), accessibility levels (e.g., number of jobs that can be reached within 30 minutes over transit network in peak periods), terminal station (0-1), street density (e.g., directional miles of street divided by land area), connectivity indices (e.g., links/nodes of street network), etc.; and

(3) *Bus Stop/Site Attributes* – e.g., bus shelters (0-1), Next Bus passenger information (0-1), bus benches (0-1), far-side bus stops (0-1), park-and-ride lots (0-1, or number of spaces), bus bulbs (0-10), etc.

Often, service attributes like bus headways do not vary within a bus line though they can and often do vary across lines. Travel-demand theory holds that transit riders, particularly choice users, are more sensitive to service quality and operating features than other factors (8, 9). Accordingly we expected some measures of a bus stop's service quality to enter the Direct Ridership Model. Other attributes of the operations, like fare levels, are usually so similar across passengers who board buses at each stop that they are not of much use for DRMs. The one service-related variable that we felt would significantly enter a model of BRT ridership in Southern California was whether a stop received an exclusive-lane service. No factor can make bus-transit more time-competitive with the private car as operating in a bus-only lane (7, 10). Accordingly, MTA's 13 Orange Line bus stops were dummy-coded (0-1) to denote their qualitatively higher service levels than the other bus stops in the data base.

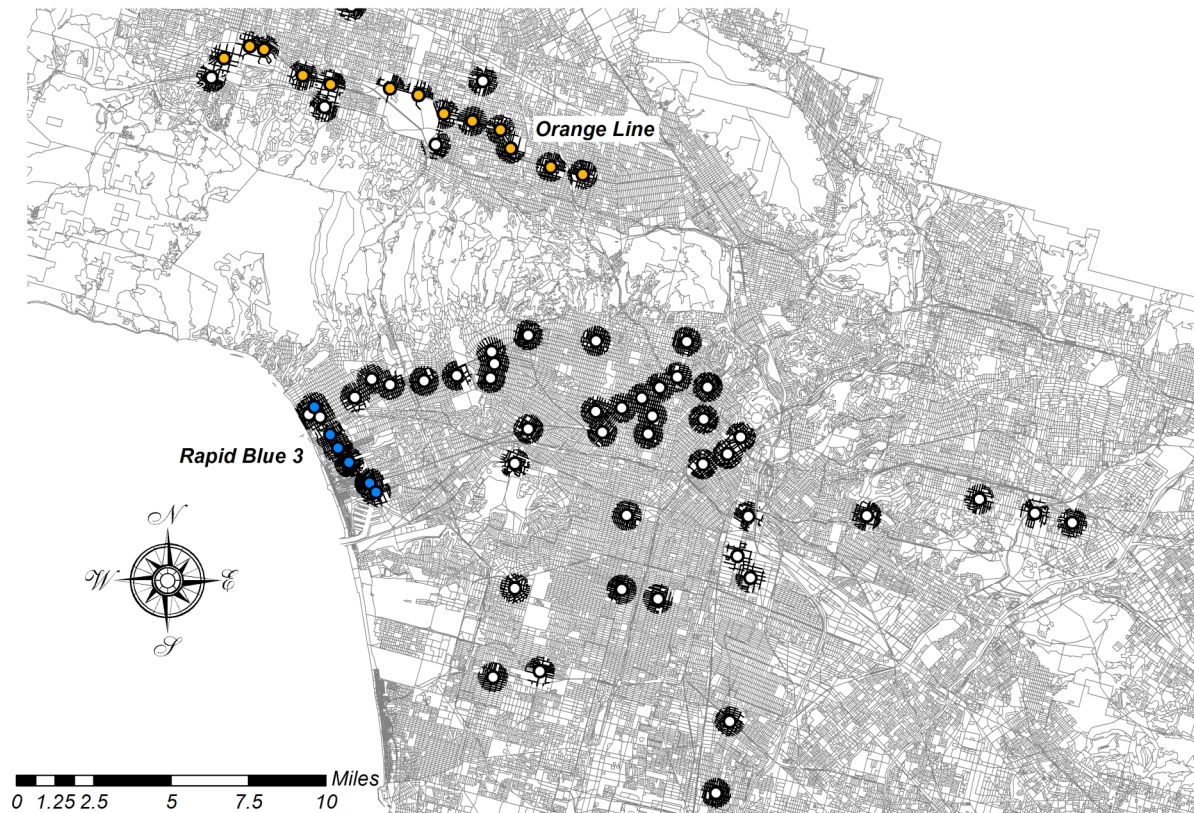


Figure 1. Locations of 69 BRT bus stop observations used for estimating Direct Ridership Model: 50 Metro Rapid stops, 13 Orange Line stops, and 6 Rapid Blue 3 stops

Location variables aim to capture attributes of the immediate operating environment, such as nearby densities and distances to nearest stop. The farther a bus stop is from the next nearest stop, for instance, typically the stop's geographical catchment area increases in size. Being a terminal station often boosts ridership even more since end-line stations typically serve big geographic catchments. If stops with large catchments average high population densities, boardings at the stop should go up even more. And if nearby residents average relatively low incomes and car ownership rates, then boarding can be expected to further rise. Factors like dense street networks with high connectivity (i.e., link-to-node ratios) can bump up ridership, at the margin, by expediting pedestrian flows to stops.

One measurement issue all direct ridership models face is the appropriate size of the geographic buffer drawn around bus stops to capture neighborhood attributes. In keeping with other research on the walkability to transit (11, 12), we opted to create $\frac{1}{2}$ mile buffers around stops. Overlaying these buffers onto census tract polygons allowed variables like population density within $\frac{1}{2}$ mile of a stop to be estimated using GIS techniques.

Lastly, some of the bus-stop attribute variables – such as the presence of bus shelters or far-side bus stops – are binary (0-1) and thus are used in the models as dummy variables. These variables largely represent the presence of passenger amenities and relative to variables that

traditional choice theory holds influences utility are thought to have fairly marginal influences on ridership levels. While the availability of a bench at a bus stop might be appreciated by a waiting customer, its presence or absence is unlikely to cause or deter most people from making a transit trip. In light of the relatively small sample size, we were prepared for such variables not to enter the best-fitting model.

One other possibility we allowed for in direct ridership modeling was interactive terms – specifically, the interaction between operating on a bus-only lane and other factors, like urban densities. That is, does the combination of having an exclusive bus lane and high nearby densities give a proportionally bigger boost in ridership than the sum of these two individual influences? Accordingly, we created a number of variables that interacted the presence of bus-only services with other predictors like population densities and feeder bus connections.

In all, three classes and 22 candidate variables, listed in Table 1, were available for model entry were: (1) Service Attributes – 8 variables; (2) Location and Neighborhood Attributes – 6 variables; and (3) Bus Stop/Site Attributes – 8 variables. Thus, for each bus stop studied, data were compiled on each of these 22 variables. The general modeling approach involved including variables that traditional travel-demand theory holds are significant predictors of transit ridership – namely, some measures of service quality (e.g., number of daily buses, number of feeder connections), location (e.g., distance to the nearest bus stop), and neighborhood density. Once a best-fitting “core” model was developed, we then stepped in other variables related to bus-stop attributes (e.g., bus shelters, far-side bus stops) to see if they provided marginal explanatory benefits to the core model. Last, we sought to introduce interactive terms that captured potential boosts in ridership from combining dedicated-lane services with other predictors. Only interactive terms that marginally improved the predictive power of the model were added. In all cases, variables were retained in the model if the signs on coefficients met a prior expectations and the t statistics were reasonably significant, preferably with probability values less than 0.05.

Table 2. Candidate Variables Available for Entry into Direct Ridership Model

Variable Class	Variable List
BRT Service Attributes	<ul style="list-style-type: none"> • Daily number of buses in both directions • Daily number of hours of service • Daily number of perpendicular feeder buses • Number of perpendicular feeder bus lines • Number of daily connecting rail-transit train units • Number of daily parallel rail-transit lines • Number of daily perpendicular rail-transit lines • Presence of dedicated-lane services (0-1)
Location and Neighborhood Attributes (within ½ mile buffer of stop)	<ul style="list-style-type: none"> • Population Density, in 2000 (number of persons within ½ mile radius, from U.S. census) • Employment Density, in 2000 (number of workers within ½ mile radius, from U.S. census) • Total Urban Density, in 2000 (number of persons plus workers within ½ mile radius, from U.S. census) • Street Connectivity Index (number of intersections divided by number of links; a high value denotes high connectivity and in general, more navigable walking environments) • Distance to the nearest BRT stop (in miles) • A terminal (end-of-line) stop (0-1)
Bus Stop/Site Attributes	<ul style="list-style-type: none"> • Park-and-Ride Lot (0-1) • Number of Park-and-Ride spaces • Presence of bus benches (0-1) • Presence of bus schedule information (0-1) • Presence of a Passenger Information System (NextBus) (0-1) • Presence of a bus-stop shelter/canopy (0-1) • Presence of a far-side bus stop (0-1) • Presence of BRT-branding/logo at stop (0-1)

DIRECT MODEL FOR ESTIMATING BRT RIDERSHIP

Ordinary least squares (OLS) regression was used to estimate a BRT direct ridership model based on Southern California experiences. Since a number of BRT bus stops in the data base share the same bus line, we also attempted Hierarchical Linear Model (HLM) estimates to account for the nested nature of the data. In theory, HLM accounts for the statistical non-independence of bus stops that share the same bus lines. Although interclass correlations suggested significant nesting of bus stops within bus lines, the HLM models yielded results with poorer fits than OLS and more limited set of predictive variables with statistical significance.

Table 2 presents descriptive statistics for the dependent variable (average daily boardings) and eight explanatory variables that entered into the Direct Ridership Model. (Interactive variables that entered the model are not presented in Table 1.) Among predictor

variables, the largest variation (standard deviation/mean) was with the number of feeder rail trains (only 3 of the 63 Metro Rapid stops had rail connections) and in park-and-ride capacity (10 of the 69 bus stops had nearby parking lots). Bus service frequency varied least across the 69 bus-stop observations.

Table 2. Descriptive Statistics for Dependent Variable and Independent Variables that enter the Direct Ridership Model. All values are for bus stop observations.

	Minimum	Maximum	Mean	Std. Deviation	Coefficient of Variation
<i>Dependent Variable:</i> Average Number Daily Boardings	0	8,703	743.9	1,194.9	1.61
<i>Independent Variables:</i>					
Number of daily buses (each direction)	40	185	88.6	40.9	0.46
Number of perpendicular daily feeder bus lines	0	7	1.56	1.29	0.83
Number of perpendicular daily rail feeder trains	0	100	5.49	22.31	4.06
Distance to Nearest BRT Stop (in miles)	0.17	1.48	0.73	0.277	2.63
Park-&-Ride Lot Capacity (number of spaces)	0	1,205	76.2	231.6	3.04
Population density (people within 1/2-mile buffer)	19.4	53,488.8	13,809.5	9,300.5	0.67
Total density (population + employment within ½ mile buffer)	6,238.0	115,808.4	24,746.6	18,409.1	0.74

The best performing multiple regression model for directly measuring BRT ridership is shown in Table 3. From the summary statistics, a model with good overall statistical fit was obtained: 95 percent of the variation in average daily boardings across the 69 bus stop locations was explained by the nine variables in the model.

The BRT direct ridership model for Southern California yielded results that conform to expectations. All of the service quality variables positively contribute to ridership. As Metro Rapid bus service frequency increases, so does ridership – each Metro Rapid bus arriving at a bus stop increases average daily boardings at that stop by 5.1 passengers (or stated another way, the average number of boardings per bus at a stop was a little over 5 passengers). In addition, daily boardings increased with the intensity of both bus and rail-train feeder services. Also notably significant were the two interactive terms for bus service quality: BRT & Feeder Bus as well as BRT & Feeder Rail. (In Table 3, “BRT” is used to denote dedicated-lane services, notably MTA’s Orange Line operations.) Based on the beta weight (standardized regression coefficient), the combination of dedicated-lane services and rail connections had the strongest predictive power of any variable in the model (reflecting the ridership boost received at two Orange Line stops served by rail). For example, the model results indicate that each feeder train that arrives increases average daily ridership by 6.7 passengers. However, if the daily train connects to a stop with a dedicated-lane Metro Rapid service, it increases average daily

ridership by another 52.8 passengers, for a total of nearly 60 passengers. Clearly, the ability to make a rail-bus intermodal transfer has significantly increased BRT ridership in Los Angeles County. While BRT no doubt supplements rail services in parts of Los Angeles County, for dedicated-lane services on MTA's Orange Line, it without question has been a complement as well.

Table 3. Direct Ridership Model for BRT in Los Angeles County. Estimated using OLS for 69 Bus Stop Locations in Los Angeles County

	Coefficient	Std. Error	Beta	t statistic	Sig.
<i>Service Attributes</i>					
Number of Daily Metro Rapid Buses (both directions)	5.103	1.353	.176	3.771	.000
Number of perpendicular daily feeder bus lines (both directions)	73.921	36.045	.080	2.051	.045
Number of perpendicular daily rail feeder trains	6.722	1.934	.126	3.476	.001
<i>Neighborhood Attribute</i>					
Population density (1/2-mile buffer)	0.017	0.004	.134	4.303	.000
Distance to nearest BRT stop (in miles)	261.705	150.751	.060	1.736	.088
<i>Interactive Terms:</i>					
BRT & Feeder Bus: Dedicated Lane (0-1) * Number of perpendicular daily feeder bus lines	124.557	62.121	.123	2.005	.050
BRT & Feeder Rail: Dedicated Lane (0-1) * Number of perpendicular daily rail feeder trains	52.891	3.831	.533	13.807	.000
BRT & Parking Capacity: Dedicated Lane (0-1) * Park-&-Ride Lot Capacity	0.514	0.249	.093	2.067	.043
BRT and Total Density: Dedicat eLane (0-1) * (Population + Employment density within 1/2-mile buffer)	.036	.011	.185	3.202	.002
Constant	-541.164	154.71	--	-3.50	.001
<i>Summary Statistics:</i> R Square = .952 F Statistic (prob.) = 129.011 (.000) N = 69					

The primary neighborhood attribute that influenced BRT ridership in Los Angeles County was population density within ½ mile of a bus stop (an area of around 503 acres in size). Metro Rapid stops surrounded by denser residential areas averaged appreciably higher ridership, controlling for other factors. This is consistent with a body of literature that shows density to be the most important built-environment attribute for predicting travel demand in general (13) and transit ridership in particular (2). As the saying goes, “mass transit” needs “mass”, or density. The model suggests that doubling the population within one-half mile radius of a Metro Rapid bus stop from 5000 to 10000 inhabitants (or from around 10 to 20 persons per gross acre) could be expected to increase daily BRT boardings by 170 passengers, holding all other factors constant. An interactive variable modified this relationship. If the Metro Rapid

stop had a dedicated-lane service, the combination of both population and employment densities further boosted ridership. We suspect the addition of employment counts in addition to residential population (as a measure of total density) was significant in this interactive form because workers were likely to respond to BRT services most noticeably only when dedicated-lane services that yielded significant commute-time savings were available.

Two bus-stop attributes also entered the best-fitting ridership model. One was the distance to the nearest BRT stop. Lengthy spacing between stops enlarges a stop's catchment area which tends to increase daily boardings. In the case of Metro Rapid, a stop 1.5 miles from the nearest BRT stop could expect some 260 more daily boardings than one a half mile away, all else being equal. The second attribute of bus-stop settings that influenced patronage was the capacity of Park & Ride lots, though only in the case of Metro Rapid stops with dedicated-lane bus services. As shown in Table 3, this interactive term has a positive coefficient indicating that bundling high-quality BRT services with parking-lot capacity boosted ridership in Los Angeles County. Again, a BRT service's opportunities for inter-modality – be the connections with private cars, rail-transit cars, or surface-street buses – emerged as a significant predictor of BRT ridership in Southern California.

PREDICTION ACCURACY

Overall, the Direct Ridership Model's prediction of October 2008 average daily boardings corresponded fairly closely to actual boardings. This is reflected by both the high R-Square statistic in Table 3 ($R^2 = .952$) as well as the plot in Figure 2. The 45-degree angle of the data points (plotting predicted values on the vertical axis and actual boardings on the horizontal axis) reveals high prediction accuracy. Notably, this 45-degree angle and the absence of any notable outliers indicate that the DRM performed remarkably well at predicting BRT ridership for a range of services: from low-patronage stops with low-end, mixed-traffic services (i.e., BRT "lite") to high-patronage, exclusive-lane services (i.e., Orange-Line stops), including those with and without rail-transit connections.

As noted, Santa Monica's Big Blue Bus (BBB) aims to create an Orange-Line-like BRT service. This will be in the form of converting BBB's Rapid Blue Line 3 from its existing mixed-traffic operations to a high-end, dedicated-lane BRT service. Given that the Direct Ridership Model shown in Table 3 contained variables that captured attributes of "high-end", dedicated-lane BRT, it is well-positioned to estimate changes in ridership from the existing "low-end" BRT service. Producing ridership estimates involved adjusting values in Table 3 for the four interactive terms related to dedicated-lane BRT services. The difference in ridership estimates for Rapid Blue Line 3 between existing and upgraded service essentially involved "switching" the value of the dedicated-lane dummy variable from "0" to "1" (and multiplying this by the other values in the interactive model – namely numbers of daily feeder bus lines, number of daily rail feeder trains, Park-&-Ride capacity, and total density).

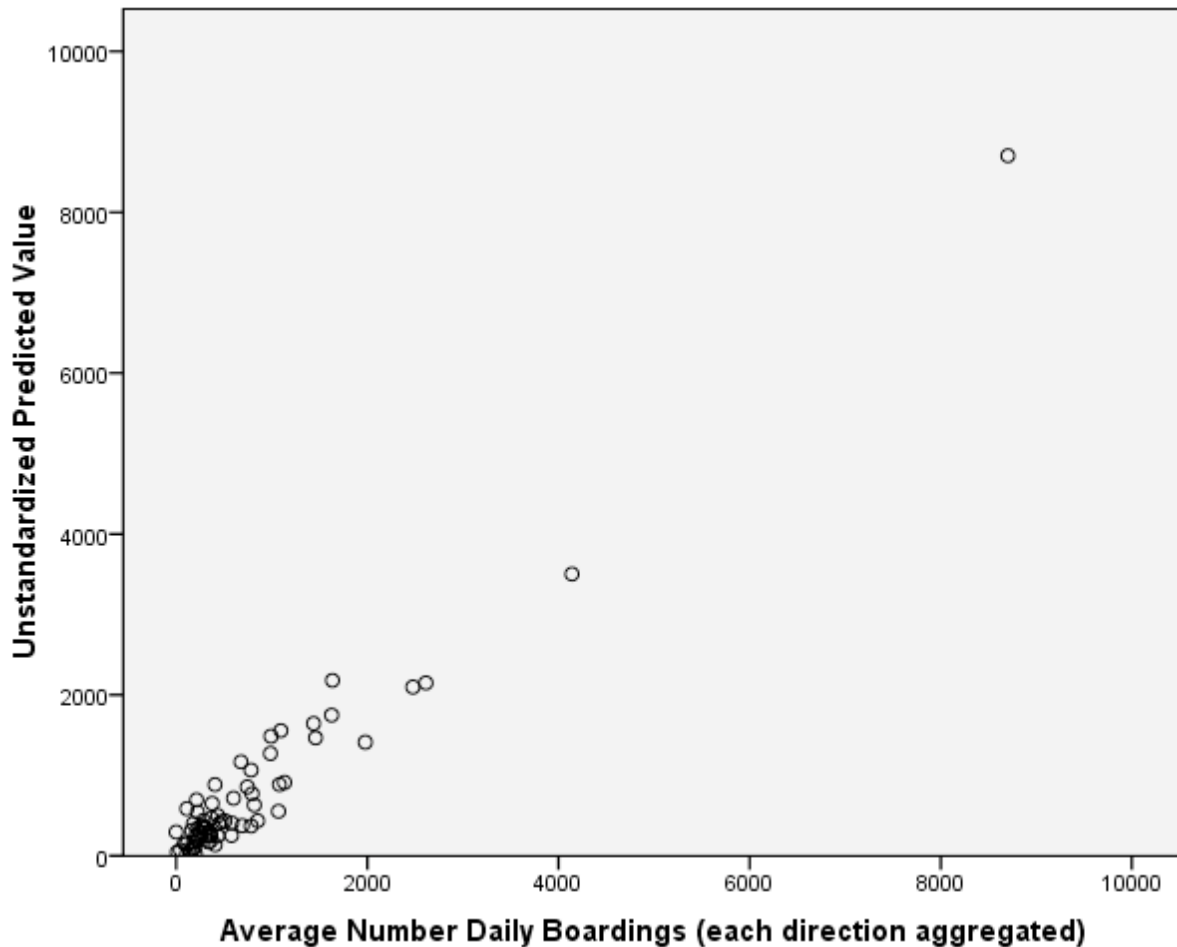


Figure 2. A Plot of Predicted Boardings (Vertical Axis) and Actual Boardings (Horizontal Axis) for 69 Metro Rapid Bus Stops.

For the 6 stops on Rapid Blue Line Line 3, the DRM estimates an increase in daily boardings from the existing (2008 daily average) of 857 customers to over 5,800 boarders with the conversion to high-end, dedicated-lane BRT service. This represents more than a six-fold increase in daily boardings. Such a surge in ridership is likely on the high side, reflecting the more transit-conducive environment of Metro Rapid services in denser, more congested Los Angeles City (that dominated the database) compared to the city of Santa Monica. While no one has a crystal ball and can predict with any precision what the future ridership will be on Rapid Blue Line 3, experiences with dedicated-lane services in Los Angeles County suggest that the impacts could be substantial.

CLOSE

BRT represents a fairly low-cost, fast-action way of introducing higher-quality transit services. In a way, a Direct Ridership Model (DRM) offers similar advantages to traditional large-scale travel-demand models – it is a fairly stripped down, sketch-modeling approach that allows empirically-informed estimates of patronage to be produced at a fraction of the cost. While not necessarily a substitute for more data-intensive and statistically sophisticated models, a DRM can provide a useful platform for generating first-cut ridership estimates and for conducting sensitivity tests of key explanatory variables like bus service frequency and station-area densities.

Data from 69 BRT stops in Los Angeles County – from mixed-traffic BRT operations to exclusive-lane services – revealed several important factors that are associated with high BRT ridership. One, service intensity matters. As the frequencies of both BRT and feeder bus services increase, so will BRT patronage. Second, high levels of intermodal connections can be a boon to BRT usage. The DRM for Southern California revealed that adding inter-modal options – notably, rail-transit connections and park-and-ride provisions in addition to surface-street feeder buses – is associated with significant gains in daily patronage. Third, surrounding population densities also matter. In the case of exclusive-lane BRT services, employment densities are also important contributors to ridership. Clearly, TOD can add riders to not only rail-transit operations but to BRT as well, something that is obvious to anyone who has ridden the exclusive busways of Curitiba or Ottawa.

In close, the state of practice in BRT ridership forecasting is still in its infancy. That said, we believe direct ridership modeling should be in the kitbag of tools available to planners for estimating patronage of future BRT services. When used as a complement to traditional four-step models and other more advanced forecasting tools, DRMs can provide useful supplemental insights into the likely ridership impacts of BRT service enhancements and neighborhood land-use changes. As with all sketch-planning tools, their value lies in the ability to quickly generate order-of-magnitude patronage estimates and to just as quickly probe the sensitivity of estimates to changes in key input variables.

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