Determinants of Bus Rapid Transit Ridership: System-Level Analysis

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Abstract: As one type of transit mode, bus rapid transit (BRT) systems have gained popularity worldwide for providing fast and easy access for citizens to fulfill their transportation needs. Current literature in the field does well in covering the identification and discussion of different elements of BRT systems and their effects, but the literature falls short of exploring factors that affect BRT ridership. Based on available databases, this study presents system-level macroscopic analyses that identify factors affecting the daily ridership of 111 BRT systems worldwide. Obtained from statistical models, including two-stage least-squares models, the results indicate that BRT system elements that are capable of improving travel-time reliability, such as passing lanes and median bus lanes, together with system supply size, may positively impact ridership. In addition, the analyses show that the existence of multimetro lines can increase BRT ridership by 41% and that the operation of both integrated fare collection and real-time information systems can boost ridership by 47%. Finally, it is shown that BRT speed may be associated with ridership. **DOI: 10.1061/(ASCE)UP.1943-5444.0000506.** © *2019 American Society of Civil Engineers.*

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Introduction

Rising urbanization trends over the last decades have called on transportation engineers and planners to better consider and more ably provide transportation services for the mobility needs of urban communities. Personal vehicles, as the predominant mode of transportation in many areas of the world, have often been a focal point in developing metropolitan areas. With increasing environmental and traffic congestion concerns plaguing urban communities, however, transportation authorities have tried to provide better alternative modes of public transportation with improved technologies and superior service quality.

As a mode of transit with high service quality (i.e., reliability and speed), bus rapid transit (BRT) has been adopted widely all over the world (Wirasinghe et al. 2013; Nikitas and Karlsson 2015). Due to relatively low capital and operational costs in comparison to metro or rail systems, BRT systems are capable of efficiently meeting the transit needs of urban communities. In addition, as a high-capacity transit mode, BRT stands to significantly decrease personal vehicle mode share, thereby effectuating environmental and economic benefits (Wirasinghe et al. 2013).

The concept of BRT was formed in Chicago in 1937, where it was proposed that three west-side rapid rail transit lines be converted to express bus lines in central and downtown areas of the city (Nikitas and Karlsson 2015). The first introduction and implementation of the modern concept of BRT, however, took place in Curitiba, Brazil, in 1974. The project was regarded as successful and subsequently inspired many other similar systems around the world. Bogota, Colombia, started a more advanced BRT system in 2000 with dedicated busways, enhanced stations, smart fare collection, and affordable ticket prices (Estupinan and Rodriguez 2008). In 2005, Los Angeles started an advanced-featured BRT system, Metro Orange Line, with similar characteristics to light rail transit (LRT) in terms of installed park-and-ride facilities, automated ticket machines, and two dedicated lanes (Cain and Flynn 2013). In preparation for the 2010 FIFA World Cup of soccer, Johannesburg, South Africa, also commenced operation of the first phase of its BRT system, which used fully dedicated bus lanes with prepaid platform-level stations (Wirasinghe et al. 2013; Walters 2008). As of 2014, there were 186 cities in 41 countries with known BRT systems or corridors, serving almost 32 million passengers every day (Nikitas and Karlsson 2015).

The growing popularity of BRT systems requires researchers to evaluate BRT effectiveness under various circumstances for the development of better systems. Indeed, the existing literature is fairly rich in research that aims to evaluate the performance and impact of BRT systems, focusing in particular on cost-effectiveness (Wirasinghe et al. 2013; Cervero and Dai 2014; Deng and Nelson 2011). Also important is identification of factors affecting BRT ridership at system or city levels in order to provide insights to attract more passengers (Currie and Delbosc 2011); however, such research efforts appear to be limited. Previous studies along these lines have considered only small numbers of cities and/or associated factors (Cervero and Dai 2014; Currie and Delbosc 2011; Hensher and Golob 2008; Hensher et al. 2014).

In this context, the current study intends to enhance the understanding of potential factors affecting BRT ridership on a system level. For this purpose, statistical models explaining the relationship between daily BRT ridership and potential influencing factors such as population, fare, system size, and the existence of advanced features are developed using information collected from 111 cities with BRT systems. The results are expected to help policymakers build successful BRT systems insofar as ridership is one of the key performance measures of transit systems.

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Literature Review

Identification of factors affecting transit ridership has been a major research topic in the field of public transportation. Pertinent studies can be generally grouped into two categories: descriptive analyses and causal analyses (Taylor et al. 2009). Descriptive analyses usually focus on traveler attitudes and perceptions, with travelers and/or transit managers as the unit of analysis. This approach relies on surveys or interviews, potentially incurring disadvantages of subjective outcomes and insufficient consideration of external factors. On the other hand, causal analyses examine environmental, system, and behavioral characteristics that affect transit ridership, employing more objective and diverse data than the data utilized in descriptive studies. Previous studies indicate that causal analyses often use multivariate regressions with aggregate-level explanatory variables (Ko et al. 2011).

Studies have conducted a wide range of causal analyses at three different scales: stop (station), route, and system levels. Regardless of scale, most studies have applied built environment and socioeconomic characteristics of the areas where the stops, routes, and systems are located as explanatory variables. For station-level analyses, an individual station's degree of connectivity to other stations is considered an important factor for explaining ridership (Sohn and Shim 2010; Kerkman et al. 2011; Kuby et al. 2004). Route-level analyses demand different types of factors, including vehicle capacity, stop spacing, and vehicle speed (Currie and Delbosc 2011, 2013). System-level studies show that fare level and system size (e.g., system length and the number of stations) explain to some extent variances in ridership (Cervero and Dai 2014; Hensher and Golob 2008; Hensher et al. 2014).

BRT systems are a focus of ridership studies. Cain and Flynn (2013) conducted a descriptive analysis that investigates the impacts of image and user perceptions of BRT systems in Los Angeles on ridership attractions by employing a focus group survey. Wang et al. (2013) studied the mode choice behaviors of travelers in Chinese cities with BRT systems, revealing that travel time savings is a crucial factor for mode shifts toward BRT. Estupinan and Rodriguez (2008) conducted a causal analysis to explain the boardings of 79 BRT stations in Bogota, Colombia, emphasizing the impacts of built environments surrounding stations. A similar approach was applied in a ridership study targeting 69 BRT stations in Los Angeles County, California (Cervero et al. 2010). The study pointed to the importance of intermodal options at stations, as well as neighborhood characteristics, such as population density. Multiple BRT routes in Australia were compared to identify factors that influence route-level ridership (Currie and Delbosc 2011, 2013). In those studies, the ridership of conventional bus and LRT routes was contrasted to that of BRT routes as a way to identify the significance of BRT design components (e.g., high service frequency).

Despite these numerous BRT ridership studies, system-level causal analyses appear to be limited insofar as only Cervero and Dai (2014), Hensher and Golob (2008), and Hensher et al. (2014) have handled the topic. More specifically, Cervero and Dai (2014) explored factors affecting BRT ridership for 119 cities. They considered only two factors, however, BRT route length and population density, resulting in a relatively low explanatory power ($R^2 = 0.286$) of the developed model. Hensher and Golob (2008) investigated the potential sources of influence on BRT ridership in terms of the number of total system passenger trips per day per kilometer, identifying statistically influential factors including the number of stations, headway, vehicle capacity, and fare. Although the estimated model explained 65.9% of the variation in ridership, the model considered only a limited number of BRT systems (37 systems worldwide), rendering the findings of the study less applicable to a larger context. Similarly, Hensher et al. (2014) utilized only 54 BRT systems worldwide for developing a patronage model with a dependent variable of daily passengers. Table 1 summarizes the modeling approaches, factors, and number of systems considered in the three studies mentioned previously. Currie and Delbosc (2011) also attempted to identify factors affecting BRT ridership, but the scope was confined to Australian systems and route-level analyses. The current review suggests that previous studies have failed to explore and consider wide ranges of influential factors and BRT systems worldwide.

Regarding analytical approaches, previous studies have argued that service supply-level variables can suffer from a degree of endogeneity because extra service may be added when ridership becomes higher (Currie and Delbosc 2011). It is understood that endogeneity may result in erroneous interpretations of estimated models and/or may obscure the roles of important factors. To tackle this issue, studies have attempted to develop causal relationship models by considering various options, including exclusion of service supply variables (Currie and Delbosc 2011), application of panel data (Kerkman et al. 2011), employment of relative ridership to service levels for response variables (Currie and Delbosc 2011, 2013), and application of advanced estimation models (Estupinan and Rodriguez 2008; Hensher et al. 2014; Taylor et al. 2009). These approaches stand to be applied when service levels are believed to reciprocally interact with ridership.

Data

To identify factors affecting BRT ridership at a system level, this study utilized the Global BRT Database (BRTdata.org. 2015) for cities' BRT system-related information worldwide, supplemented by the Bus Rapid Transit Information Database (Worldbrt.net. 2015). In addition, the World Metro Database (Metrobits.org. 2015) and cities' official websites were referred to for metro and socioeconomic data. Initially, the collection of information on numerous potential factors was attempted by referring to previous research, but due to data availability, only a limited number of factors were considered. In addition, missing variables prevented this study from using all 187 cities contained in the Global BRT Database, resulting in analysis of 111 systems from 30 countries in the final data set.

Table 1. Summary of previous system-level BRT ridership studies

Study	Statistical model	Factors considered	Number of systems considered
Cervero and Dai (2014)	OLS regression	Population density, BRT kilometers	119
Hensher and Golob (2008)	OLS regression	Number of stations, peak headway, trunk vehicle capacity, fare	37
Hensher et al. (2014)	Random effects regression (by nation)	Fare, frequency, mode share by car, number of BRT stations, vehicle characteristics (number of doorways for passengers), existence of bus priority facilities	54

Note: OLS = ordinary least squares.

Table 2. Descriptive statistics of considered factors ($n = 111$)

Variables		Mean	Standard deviation	Minimum	Maximum	Data source
City-level	Population[a] (million)	2.64	3.36	0.03	13.62	*A*, *D*
	Population density[a] (people per kilometer squared)	4,675.98	4,865.61	133.54	26,409.31	*A*, *D*
	Gross Domestic Product per capita (USD 2012)	25,695.70	20,934.30	1,299.00	80,528.00	*A*
BRT components	Number of passengers per day (thousand)	249.08	546.66	1.80	3,164.00	*A*
	Total BRT length (kilometers)	33.33	35.88	3.70	206.75	*A*
	Number of corridors	2.29	2.86	1.00	16.00	*A*
	Fleet size[b]	236.12	557.76	5.00	3,966.00	*A*, *B*
	Standard fare (USD 2012)[b]	1.35	1.24	0.00	6.93	*A*, *B*
	Number of stations[b]	43.69	45.03	3.00	240.00	*A*, *B*
	Number of stations per length in kilometers[b]	1.58	0.75	0.18	4.50	*A*, *B*
	Existence of median bus lanes[c,d]	0.40	0.49	0.00	1.00	*A*
	Existence of passing lanes[c]	0.11	0.31	0.00	1.00	*A*
	Existence of real-time information systems[c]	0.32	0.47	0.00	1.00	*A*
	Existence of integrated fare-collection systems[c]	0.47	0.50	0.00	1.00	*A*
Metro components	Number of metro lines	1.37	3.03	0.00	16.00	*C*
	Total metro length (kilometers)	31.91	76.61	0.00	442.00	*C*

Note: *A* = BRTdata.org. (2015); *B* = Worldbrt.net. (2015); *C* = Metrobits.org. (2015); and *D* = official website of the city or Demographic Statistics Database provided by United Nations Statistics Division (2018).
[a]Missing values in Global BRT Database were supplemented by the official website of the city or Demographic Statistics Database provided by United Nations Statistics Division (2018).
[b]Missing values in Global BRT Database were supplemented by Bus Rapid Transit Information Database.
[c]Value of one was assigned when the lane or system exists and zero otherwise.
[d]Median bus lanes include median, partial median, separated right-of-way, and partially separated right-of-way lanes.

Some relevant variables including vehicle characteristics (e.g., capacity, number of doorways for passengers), station boarding level, preboard fare collection, user rating, number of transfer stations, and modal shares were available in the data sets, but information about these features is provided for only a portion of the systems and cities constituting the sample. There exists a tradeoff between variable extension and sample size (number of systems). This study intends to identify key factors without a significant loss of sample size in order to obtain generalizable relationships between BRT ridership and key influencing factors.

Table 2 shows descriptive statistics of the considered explanatory variables in this study. The variables include city characteristics [population, gross domestic product (GDP) per capita], BRT components (system length, number of corridors, fleet size, fare, number of stations, median bus lanes, passing lanes, real-time information systems, integrated fare-collection systems) and metro components (number of metro lines, metro length). The distribution of the variables shows a wide dispersion across the cities. Regarding population, Maubeuge, France, has only around 30,000 people, whereas Istanbul, Turkey, has more than 13 million inhabitants. The same spectrum can be seen in BRT system length. Bradford, United Kingdom, has only 3.7 kilometers of BRT system, whereas the length of the system in Jakarta amounts to 206 kilometers over 12 corridors. Fare levels appear to differ significantly between cities, with the system in Merida, Venezuela, providing citizens with a free-of-charge service, whereas Kent, United Kingdom, provides services at a standard fare of around USD 6.9. Fig. 1 illustrates the distribution of daily ridership by continent, showing higher ridership for systems in Latin America, with average values of 578,934 and 12,730 for daily ridership and its normalized value by length in kilometers, respectively.

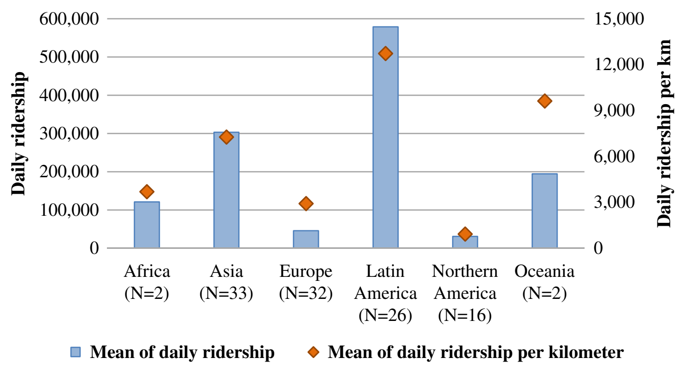

Fig. 1. Daily ridership by continent.

Analytical Approach

This study develops two BRT ridership models with dependent variables of total daily ridership and its normalized ridership by system length (i.e., daily ridership per kilometer). Multiple regression models were tested, specifically with extensive trial-and-error experiments, by taking various forms of the explanatory variables: for example, fare divided by GDP, fleet size divided by system length, system length divided by the number of corridors, or the combination of integrated fare collection and real-time information systems. In addition, the dependent variables were transformed by taking a natural logarithm as a way to cancel out their biased distribution effects. Indeed, Fig. 2 illustrates that following transformation, the distributions approximately correspond to the normal distribution.

To identify the appropriate specifications of the models, a Pearson correlation test was performed to measure the linear associations between variables. As seen in Table 3, as expected, the test revealed that daily BRT ridership has a strong association with fleet size, system length, and number of corridors and stations, suggesting that daily BRT ridership can be sufficiently explained by the variables. It was highly suspected, however, that service supply variables have a reciprocal effect on daily BRT ridership. This bidirectional relationship between the dependent variable and regressors may cause a serious regression estimation problem, violating a key

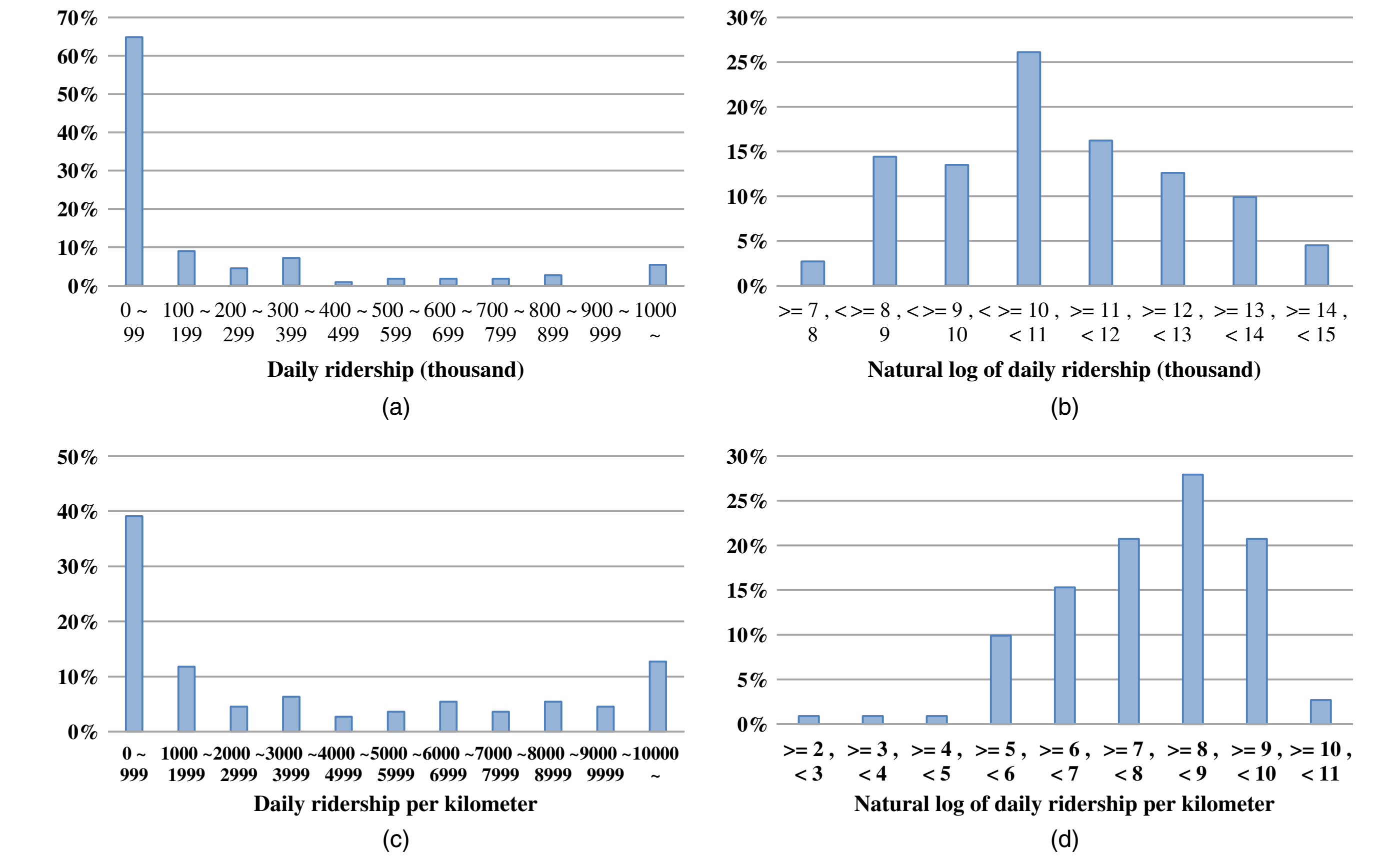

Fig. 2. Initial and log-transformed distributions of ridership: (a) total daily ridership; (b) log-transformed total daily ridership; (c) daily ridership per kilometer; and (d) log-transformed daily ridership per kilometer.

Table 3. Pearson correlation coefficients between the variables considered in the BRT ridership models

Variable	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17
V1	**0.71**[a]	**0.52**[a]	0.38[a]	−0.28[a]	**0.64**[a]	**0.75**[a]	**0.70**[a]	−0.14	**0.72**[a]	−0.12	0.08	0.10	0.08	0.30[a]	0.28[a]	0.25[a]
V2		0.44[a]	0.25[a]	−0.38[a]	0.27[a]	0.39[a]	**0.63**[a]	−0.23[b]	0.35[a]	−0.09[a]	0.28[a]	0.29[a]	0.09	0.30[a]	0.23[b]	0.23[b]
V3			**0.52**[a]	−0.47[a]	0.49[a]	0.40[a]	0.36[a]	−0.33[a]	0.43[a]	−0.31	0.27[a]	0.10	−0.05	0.18[c]	**0.53**[a]	**0.57**[a]
V4				−0.27[a]	0.31[a]	0.37[a]	0.30[a]	−0.21[b]	0.31[a]	−0.07[b]	0.16	0.04	0.01	0.19[b]	0.37[a]	0.29[a]
V5					−0.26[a]	−0.26[a]	−0.24[b]	**0.77**[a]	−0.25[a]	0.22[a]	**−0.59**[a]	−0.07	0.07	−0.10	−0.08	−0.10
V6						**0.78**[a]	0.43[a]	−0.13	**0.85**[a]	−0.34	0.04	0.03	−0.01	0.16[c]	0.25[a]	0.21[b]
V7							**0.54**[a]	−0.13	**0.78**[a]	−0.15	−0.04	0.03	0.03	0.28[a]	0.19[b]	0.19[b]
V8								−0.08	**0.58**[a]	−0.03	0.07	0.11	−0.04	0.26[a]	0.19[b]	0.14
V9									−0.10	0.11	−0.48[a]	0.07	0.04	−0.01	−0.03	−0.05
V10										0.03[a]	0.04	−0.02	−0.02	0.20[b]	0.25[a]	0.18[c]
V11											−0.17[a]	−0.20[b]	−0.01	−0.01	−0.10	−0.12
V12												0.19[b]	0.08	0.09	0.00	0.03
V13													0.26[a]	0.25[a]	−0.02	0.00
V14														0.41[a]	0.07	0.04
V15															0.20[b]	0.13
V16																**0.91**[a]

Note: V1 = daily ridership; V2 = daily ridership per kilometer; V3 = population; V4 = population density; V5 = GDP per capita; V6 = system length; V7 = number of corridors; V8 = fleet size; V9 = standard fare; V10 = number of stations; V11 = number of stations per kilometer; V12 = median bus lane; V13 = passing lane; V14 = real-time information system; V15 = fare integration system; V16 = number of metro lines; and V17 = metro length. Values in bold indicate a Pearson correlation value of greater than 0.5.
[a]Significant at 1%.
[b]Significant at 5%.
[c]Significant at 10%.

assumption of regression that regressors and disturbances are uncorrelated (Washington et al. 2010). To mitigate this issue, this study considered two modeling approaches: (1) excluding the service supply variables (i.e., fleet size, system length, number of corridors and stations) and (2) developing two-stage least-squares (2SLS) models, which have been commonly applied as a way to remedy interactions between supply- and demand-side factors (Wooldridge 2009).

Results

Total Daily Ridership Models

Table 4 summarizes the results of model estimations using the dependent variable of log-transformed total daily ridership. The explanatory variables of fleet size, population, and fare were also transformed by taking a natural logarithm. Regarding the fare variable, the impact of different income levels by country was reflected by normalizing fare by the fifth root of GDP per capita. The fifth root, which was taken to avoid an excessive variance of the normalized fare induced by the wide distribution of GDP per capita for the nations considered, was determined after numerous tests through the construction of preliminary models. Fare divided by the simple form of GDP per capita is significant in the work of Hensher et al. (2014), but simple normalization is found not to be effective in this study. A stepwise variable selection procedure was applied, capturing only significant variables at a level of 0.1.

First, an ordinary least squares (OLS) model (Model 1) was developed by considering all the factors in Table 2. The model identified that fleet size has a dominant impact on the total daily ridership as suggested by beta coefficients (also called standardized coefficients), which show the relative impacts of explanatory variables. In addition, the variables of population size, number of corridors, and fare were found to be significantly associated with the total daily ridership. Their resultant signs appeared to be intuitively correct.

Because BRT service supply levels are highly likely to interact with ridership, an additional model (Model 2) was developed by excluding supply-level variables including fleet size, system length, and the number of corridors and stations. The model captured an additional positive influential factor—namely, whether a city-level BRT system operates both integrated fare collection and real-time information systems—even after controlling the effects of population size and the geographic locations of BRT systems. Interestingly, the separate operation of the advanced systems was not significant. The significance of the geographic location variable indicates that BRT systems in developing countries tend to have higher ridership. This observation is somewhat intuitive insofar as other transportation options, such as private vehicles, are not easily available for citizens in developing countries, rendering them heavily dependent on public transit. Regarding this aspect, Hensher et al. (2014) showed that the car mode share of a city has a negative association with BRT ridership. Model 2 shows a moderate level of explanatory power ($R^2 = 0.450$), even without the supply variables.

As a second measure to protect against interaction effects, a 2SLS model was developed by considering the natural log of fleet size as a single endogenous regressor. It was assumed that fleet size would be strongly affected by demand levels given that BRT operators are easily able to adjust fleet sizes according to changes in demand. The number of corridors and system length may be considered to have endogeneity with ridership; however, it seems that these two system elements cannot be easily adjusted to meet changes in demand. Indeed, Model 1 proves the importance of fleet size for explaining ridership. Following the 2SLS modeling procedure, the endogenous variable, fleet size, was fitted with two instrumental variables (IVs) including the natural log of the population and the number of BRT corridors. These two variables were selected because they have a significant association with fleet size—explaining 44% of the variation of fleet size. Then, a second-stage model (Model 3) was developed by replacing the original values of fleet size with estimates from the first-stage model. Hausman tests (Hausman 1978) show that the fleet size variable is endogenous at a significance level of 0.05. In addition, the significance of the first-stage model with an F-statistic of 42.84 ($p < 0.01$) rejects the null hypothesis that the IVs are weak. These results support the adoption of the 2SLS model for the data set; however, the exogeneity requirement of IVs (Wooldridge 2009) was suspected because the coefficient of correlation between daily ridership and the number of corridors is 0.75. Nevertheless, this study adopted the 2SLS model specification by assuming that the number of corridors is related to daily ridership via fleet size, potentially determining fleet size to a substantial extent (i.e., the requirement of instrument relevance). The estimated model explained 78% of the variance in system-level ridership, showing a rather lower explanatory power in comparison to Model 1; however, this was expected given that, by definition, the 2SLS R-squared value is always smaller than the OLS R-squared value because OLS minimizes the sum of squared residuals. Considering all these aspects, the estimated 2SLS model seems to be the most preferred of the three

Table 4. Total daily BRT ridership models ($n = 111$)

Variable	Model 1 (OLS) Coefficient	Model 1 (OLS) Beta coefficient	Model 2 (OLS excluding supply variables) Coefficient	Model 2 (OLS excluding supply variables) Beta coefficient	Model 3 (2SLS) Coefficient	Model 3 (2SLS) Beta coefficient
Constant	13.315[a]	—	10.077[a]	—	13.824[a]	—
Log of fleet size[b]	0.837[a]	0.710	—	—	1.148[a]	0.973
Log of population[b]	0.206[a]	0.174	0.520[a]	0.439	—	—
Log of standard fare in USD/GDP per capita$^{0.2}$[b]	−2.933[c]	−0.080	—	—	−1.406[a]	−0.038
Number of BRT corridors	0.068[d]	0.108	—	—	—	—
Existence of two or more metro lines	—	—	—	—	0.343[c]	0.081
Operation of both integrated fare collection and real-time information systems	—	—	0.699[d]	0.168	0.387[d]	0.093
Developing countries (Asia, Latin America, Africa)	—	—	1.095[a]	0.306	—	—
	Adjusted $R^2 = 0.808$		Adjusted $R^2 = 0.450$		Adjusted $R^2 = 0.780$	
	F-statistic = 117.4[a]		F-statistic = 31.03[a]		First-stage F-statistic = 42.84[a]	
					Hausman p-value = 0.031	

[a]Significant at 1%.
[b]Natural logarithm transformations are applied after adding ones to handle zero values.
[c]Significant at 10%.
[d]Significant at 5%.

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models. After controlling the impact of fleet size, the model suggested that fare levels are negatively associated with ridership and showed that the operations of both integrated fare collection and real-time information systems can boost BRT ridership by 47% [this is known because $\exp(0.387) = 1.47$]. The existence of two or more metro lines, which was not found to be significant in Models 1 and 2, showed a positive influence on ridership (41% increase), implying the importance of transit network effects.

Distance-Normalized Ridership Models

Models with a dependent variable of log-transformed BRT ridership per kilometer were also developed as shown in Table 5. The estimated OLS model (Model 4) identified that variables such as fleet size per kilometer, population density, fare level, and the existence of multimetro lines are significantly associated with relative ridership to system length. Similar to the total daily ridership model, the fleet size variable displayed the strongest impact, and fare levels were negatively associated with ridership. The model implies that higher population density tends to induce higher ridership with an elasticity of 0.153. What is more, a doubling of population densities is associated with a 15.3% rise in ridership. This elasticity is rather lower than the elasticity of 0.393 found in the two-variable ridership model of Cervero and Dai (2014). That study's higher elasticity might be ascribed to a failure in sufficiently controlling the effects of other factors, thus causing an overestimated impact of population density. The metro line variable is significant because it suggests that BRT ridership can be positively affected by other transit systems that are well developed.

In line with Model 2, a model (Model 5) without service supply variables was developed. (Unlike in Model 2, the number of BRT corridors was retained in Model 5 because the variable was regarded not to have a reciprocal relationship with relative ridership.) The developed model revealed that GDP per capita is negatively associated with relative ridership, pointing to the poorer *service effectiveness* of BRT systems in wealthy cities, as mentioned in the research of Currie and Delbosc (2011). Although the cause is seemingly perplexing, characteristics of wealthy cities, such as higher car ownership and lower residential density, might partly explain the situation. The log-transformed model indicated that the elasticity of GDP per capita is −0.281. The number of corridors was also identified as an influential factor in the model, implying an 11.7% increase in ridership with a one-corridor increase per BRT system. Similarly, the model indicated that adding metro systems increases ridership with an elasticity of 0.127. This situation was expected because the average ridership of 35 cities with metro systems is much greater than the average ridership of 76 cities without metro systems (i.e., 8.6 thousand versus 4.1 thousand per day per kilometer). Note that the interpretation of metro length elasticity is rather tricky for cities without metro systems (zero values for length). Although the impact of metro systems on BRT ridership may need further investigation, these findings clearly emphasize that BRT service effectiveness can be substantially affected by network effects of BRT systems alone or coupled with metro systems. The positive signs of the existence of passing and median bus lanes imply that improved service reliability and speed, which can be obtained from installing these lanes, stand to significantly increase ridership. These findings are in line with the arguments of Wirasinghe et al. (2013).

A 2SLS model was also developed for distance-normalized ridership. For this, the fleet size variable was considered an endogenous variable and fitted by three IVs including logarithmic forms of population density, number of stations per kilometer, and BRT length per corridor. Although the first-stage model was significant at a level of 0.01, Hausman tests suggested that the fleet size variable is significantly endogenous only at a level of 0.119 or higher. This is somewhat expected because the dependent variable is relative ridership, which is likely to be weakly affected by service levels. Because of this, it cannot be easily concluded that the 2SLS approach is strongly preferred to other approaches. Nevertheless, the 2SLS model appears to be useful for the identification of meaningful variables considering its high R-squared and Hausman p-value close to 0.1. The developed model indicated that fare,

Table 5. Daily BRT ridership per kilometer models ($n = 111$)

Variable	Model 4 (OLS)		Model 5 (OLS excluding supply variables)		Model 6 (2SLS)	
	Coefficient	Beta coefficient	Coefficient	Beta coefficient	Coefficient	Beta coefficient
Constant	5.950[a]	—	9.820[a]	—	6.338[a]	—
Log of fleet size per kilometer[b]	0.903[a]	0.752	—	—	1.130[a]	0.948
Log of population density (persons per kilometer squared)[b]	0.153[c]	0.107	—	—	—	—
Log of GDP per capita[b]	—	—	−0.281[d]	−0.216	—	—
Log of standard fare in USD/GDP per capita[0.2b]	−4.283[a]	−0.142	—	—	−1.529[a]	−0.178
Number of BRT corridors	—	—	0.111[d]	0.215	—	—
Existence of passing lanes	—	—	0.723[c]	0.152	—	—
Existence of median BRT lanes	—	—	0.551[c]	0.183	—	—
Two or more metro lines	0.380[d]	0.109	—	—	0.410[d]	0.119
Log of metro length in kilometers[b]	—	—	0.127[d]	0.174	—	—
Operation of both integrated fare collection and real-time information systems	—	—	—	—	0.406[d]	0.118
	Adjusted $R^2 = 0.706$ F-statistic = 63.71[a]		Adjusted $R^2 = 0.241$ F-statistic = 7.99[a]		Adjusted $R^2 = 0.679$ First-stage F-statistic = 5.128[a] Wald-statistic = 20.69[a] Hausman p-value = 0.119	

[a]Significant at 1%.
[b]Natural logarithm transformations are applied after adding ones to handle zero values.
[c]Significant at 10%.
[d]Significant at 5%.

Table 6. BRT speed model

Variable	Coefficient	Beta coefficient
Constant	4.104[a]	—
Log of number of stations per kilometer	−0.612[a]	−0.576
Log of number of passengers per station	−0.063[a]	−0.304
Existence of passing lanes	0.188[b]	0.235
Operation of integrated fare-collection systems	0.109[c]	0.192
Number of observations = 76; F-statistic = 11.36[a]; adjusted $R^2 = 0.355$		

[a]Significant at 1%.
[b]Significant at 5%.
[c]Significant at 10%.

the existence of multimetro lines, and the operation of both integrated fare collection and real-time information systems are significant factors affecting relative ridership.

BRT Speed Model

The developed models described in the previous section found that BRT systems with passing lanes, median bus lanes, and integrated fare-collection systems are likely to have higher ridership. Interestingly, this finding implies that BRT speed can be associated with ridership insofar as the operations of such facilities and fare-collection systems can positively influence speed, as has been also suggested in research by Wirasinghe et al. (2013) and Deng and Nelson (2011). To test the influence of such factors on speed, this study attempted to develop a speed model for 76 cities for which BRT speed data could be obtained.

Table 6 illustrates the developed model with a dependent variable of log-transformed BRT speed and four significant explanatory variables, including the operation of passing lanes and integrated fare-collection systems. Although the median bus lane variable was not captured, the model suggests that speed may have a positive influence on ridership in an indirect manner. The insignificance of median bus lanes may be partly attributed to the large variation of median bus lane performance because the lanes include a variety of types, such as full median, partial median, separated right-of-way, and partially separated right-of-way lanes; however, care should be taken in that higher ridership can negatively affect speed because the variable representing the number of passengers per station has a negative sign in the model. This is plausible because a high volume of passengers—entailing more boardings and alightings—tends to increase dwell times at stations. In ridership models, speed variables often have been found to have negative effects, even though the policy implications of this result are counterintuitive.

Conclusion

Summary and Findings

In cities, public transit has been developed as a way to improve mobility, provide transportation alternatives, and reduce negative environmental impacts from the excessive use of cars, thus enhancing sustainability and equity. As one mode of transit, BRT systems have gained popularity worldwide for providing fast and easy access for citizens to fulfill their transportation needs. A better understanding of performance levels of BRT systems and performance-influencing factors is expected to help transportation agencies make appropriate decisions about new BRT investments and better operation of existing systems. Accordingly, this study explores factors affecting system-level BRT ridership, one of the key performance measures of BRT systems, in 111 cities worldwide. Statistical models were developed by employing two dependent variables of total daily ridership and normalized ridership by system length. The normalized ridership models were expected to reveal factors affecting system effectiveness, regardless of system scales. The models tested the significance of potential factors including population, GDP per capita, BRT system characteristics, and metro service levels. Considering bidirectional relationships between ridership and service supply levels (specifically, fleet size), 2SLS models were also constructed for tests. Analysis showed that a bidirectional relationship exists notably in the modeling of total daily ridership, whereas the relationship was found to be rather weak in the normalized ridership model.

The developed models demonstrated that service supply levels, such as fleet size and the number of BRT corridors, are critical factors for determining ridership, as expected. Using supply variables, it was possible to explain 80% of the variation in total ridership and 70% of the variation in normalized ridership. After controlling the effects of service levels, the models revealed that factors such as population and fare affect total daily ridership. In particular, the 2SLS approach identified that the existence of multimetro lines can increase ridership by 41% and that the operation of both integrated fare collection and real-time information systems can boost ridership by 47%. In addition, the relative ridership models pointed to the importance of factors such as population density, GDP per capita, the length of metro systems, and the existence of passing and median bus lanes. Generally, these findings appear to coincide with the findings of previous BRT ridership studies (Cervero and Dai 2014; Currie and Delbosc 2011; Hensher et al. 2014; Currie and Delbosc 2013), suggesting that BRT elements of advanced technology (elements that support efficient and convenient intermodal systems in particular), as well as busways with passing lanes, stand to contribute to increased ridership. This study also shows that BRT elements have positive relationships with bus speeds, as supported by a regression model for 76 cities with available BRT speed data. This observation appears to indirectly demonstrate the positive influence of speed on ridership. The identification of network effects was noteworthy. Indeed, Model 5 identified that the inclusion of one additional BRT corridor in a city is likely to increase ridership by 11.7% and that a 10% increase in metro length tends to boost ridership by about 1.3% on average. Network effects might expand the usefulness of every corridor in a BRT network, thus increasing the ridership potential of each corridor. Network effects, however, still need further investigation of various aspects, including the extent of network effects and roles of integrated service and fare systems.

Future Research

Despite its meaningful findings, this study has limitations in its data extensiveness and analytical approaches. Regarding data extensiveness, the limited number of factors considered might weaken the explanatory power of the models, leaving about 20%–30% of the variance in ridership unexplained even with service supply-level variables. Potential factors not considered in this study include certain sociodemographic characteristics of cities such as the proportion of students and car ownership (Hensher et al. 2014; Ko et al. 2011) and walking conditions of the urban environment (Estupinan and Rodriguez 2008). Consideration of various operational characteristics, including service span (Currie and Delbosc 2011), vehicle type and capacity (Hensher et al. 2014; Currie and Delbosc 2013), and availability of intermodal connections (Sohn and Shim 2010; Cervero et al. 2010) would have improved the modeling results. In addition, there are numerous factors that are well understood to impact ridership, including service frequency, schedule reliability, preboard fare collection, station boarding level, city-wide modal shares, dedicated right-of-way length, transit signal priority, and user perceptions of BRT systems. Although the possibility of collecting all these potential influencing factors at a city level is questionable, extensive data-collection efforts are essential for future studies.

Although the linear regression approach was successfully applied in identifying important factors that affect ridership, the approach seems insufficient in capturing indirect and reciprocal relationships between variables (Sohn and Shim 2010). As shown in the relationships among ridership, BRT elements, and speed, the possibility that unknown relationships exist is high. This issue will be more critical when numerous variables are considered altogether. Accordingly, it is certain that larger databases and advanced analytical approaches such as structural equation models will add much value to the quality and strength of the findings herein. An effective treatment of endogeneity of some supply variables such as fleet size, number of corridors, and system length is another issue. Although this study rather simply assumed that fleet size has endogeneity with ridership, other supply variables may deserve to be tested for the endogeneity. Note that this study adopts city as the unit of analysis. Cities with different circumstances may have different endogenous variables.

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References

BRTdata.org. 2015. "Global BRT database." Accessed January 15, 2015. www.brtdata.org.

Cain, A., and J. Flynn. 2013. "Examining the ridership attractions potential of bus rapid transit: A quantitative analysis of image and perception." *J. Publ. Transp.* 16 (4): 63–82. https://doi.org/10.5038/2375-0901.16.4.4.

Cervero, R., and D. Dai. 2014. "BRT TOD: Leveraging transit oriented development with bus rapid transit investments." *Transp. Policy* 36: 127–138. https://doi.org/10.1016/j.tranpol.2014.08.001.

Cervero, R., J. Murakami, and M. Miller. 2010. "Direct ridership model of bus rapid transit in Los Angeles County, California." *Transp. Res. Rec.* 2145 (1): 1–7. https://doi.org/10.3141/2145-01.

Currie, G., and A. Delbosc. 2011. "Understanding bus rapid transit route ridership drivers: An empirical study of Australian BRT systems." *Transp. Policy* 18 (5): 755–764. https://doi.org/10.1016/j.tranpol.2011.03.003.

Currie, G., and A. Delbosc. 2013. "Exploring comparative ridership drives of bus rapid transit and light rail transit routes." *J. Publ. Transp.* 16 (2): 47–65. https://doi.org/10.5038/2375-0901.16.2.3.

Deng, T., and J. D. Nelson. 2011. "Recent developments in bus rapid transit: A review of the literature." *Transp. Rev.* 31 (1): 69–96. https://doi.org/10.1080/01441647.2010.492455.

Estupinan, N., and D. A. Rodriguez. 2008. "The relationship between urban form and station boardings for Bogota's BRT." *Transp. Res. Part A Policy Pract.* 42 (2): 296–306. https://doi.org/10.1016/j.tra.2007.10.006.

Hausman, J. A. 1978. "Specification tests in econometrics." *Econometrica* 46 (6): 1251–1271. https://doi.org/10.2307/1913827.

Hensher, D. A., and T. F. Golob. 2008. "Bus rapid transit systems: A comparative assessment." *Transportation* 35 (4): 501–518. https://doi.org/10.1007/s11116-008-9163-y.

Hensher, D. A., Z. Li, and C. Mulley. 2014. "Drivers of bus rapid transit systems—Influences on patronage and service frequency." *Res. Transp. Econ.* 48: 159–165. https://doi.org/10.1016/j.retrec.2014.09.038.

Kerkman, K., K. Martens, and H. Meurs. 2011. "Factors influencing stop-level transit ridership in Arnhem-Nijmegen city region, Netherlands." *Transp. Res. Rec.* 2537: 59–68. https://doi.org/10.3141/2537-03.

Ko, J., D. Park, and S. Lee. 2011. "Transit ridership evaluation using aggregate-level causal analyses of subway mode shares in Seoul, South Korea." *Transp. Res. Rec.* 2219 (1): 59–68. https://doi.org/10.3141/2219-08.

Kuby, M., A. Barranda, and C. Upchurch. 2004. "Factors influencing light-rail station boardings in the United States." *Transp. Res. Part A Policy Pract.* 38 (3): 223–247. https://doi.org/10.1016/j.tra.2003.10.006.

Metrobits.org. 2015. "World metro database." Accessed May 20, 2015. http://mic-ro.com/metro.

Nikitas, A., and M. Karlsson. 2015. "A worldwide state-of-the art analysis for bus rapid transit: Looking for the success formula." *J. Publ. Transp.* 18 (1): 1–33. https://doi.org/10.5038/2375-0901.18.1.3.

Sohn, K., and H. Shim. 2010. "Factors generating boardings at metro stations in the Seoul metropolitan area." *Cities* 27 (5): 358–368. https://doi.org/10.1016/j.cities.2010.05.001.

Taylor, B. D., D. Miller, H. Iseki, and C. Fink. 2009. "Nature and/or nurture? Analyzing the determinants of transit ridership across US urbanized areas." *Transp. Res. Part A Policy Pract.* 43 (1): 60–77. https://doi.org/10.1016/j.tra.2008.06.007.

United Nations Statistics Division. 2018. "City population by sex, city and city type." Accessed September 29, 2018. http://data.un.org/Data.aspx?d=POP&f=tableCode%3A240#POP.

Walters, J. 2008. "Overview of public transport policy developments in South Africa." *Res. Transp. Econ.* 22 (1): 98–108. https://doi.org/10.1016/j.retrec.2008.05.023.

Wang, Y., Z. Wang, Z. Li, S. R. Staley, A. T. Moore, and Y. Gao. 2013. "Study of modal shifts to bus rapid transit in Chinese cities." *J. Transp. Eng.* 139 (5): 515–523. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000523.

Washington, S. P., M. G. Karlaftis, and F. Mannering. 2010. *Statistical and econometric methods for transportation data analysis*. Boca Raton, FL: CRC press.

Wirasinghe, S. C., L. Kattan, M. M. Rahman, J. Hubbell, R. Thilakaratne, and S. Anowar. 2013. "Bus rapid transit—A review." *Int. J. Urban Sci* 17 (1): 1–31. https://doi.org/10.1080/12265934.2013.777514.

Wooldridge, J. M. 2009. *Introductory economics: A modern approach.* 4th ed. Mason, OH: South-Western Cengage Learning.

Worldbrt.net. 2015. "Bus rapid transit information." Accessed January 15, 2015. www.worldbrt.net.