WORKING PAPER

ITLS-WP-18-02

Determinants of Bus Rapid Transit (BRT) system revenue and effectiveness – A global benchmarking exercise

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January 2018

ISSN 1832-570X

INSTITUTE of TRANSPORT and LOGISTICS STUDIES

The Australian Key Centre in Transport and Logistics Management

The University of Sydney

Established under the Australian Research Council's Key Centre Program.

NUMBER: Working Paper ITLS-WP-18-02

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ABSTRACT: Bus rapid transit systems (BRT) have evolved in all shapes and sizes around the world in the last 30 years motivated by providing greater efficiency and value for money than potential alternatives. This paper aims to explore and compare the effectiveness (including its determinants) and revenue potential of 58 BRT systems globally. A key research question for this paper is to what extent there is a trade-off between long term capital expenditure and short term operating cost. The results suggest that BRT systems located in developing countries or countries that have high population densities are successful in generating higher revenues per passenger and unit of input than their conventional bus counterparts but are from a community perspective not more cost effective in doing so. Better BRT standards and hence higher capital expenditure, while significantly increasing patronage and input effectiveness do not have a significant impact on either yields or cost effectiveness. In contrast, public ownership and the number of stations are on average associated with higher cost effectiveness scores.

KEY WORDS: ***BRT, Effective bus service operation, Benchmarking, Performance measurement, DEA***

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Acknowledgements: The authors would like to thank the many managers from the analysed BRT firms and their associated agencies for providing the data and investing their time to support this research. This research would not have been possible without the support of the Across Latitudes and Cultures – Bus Rapid Transit (ALC-BRT) Centre of Excellence for Bus Rapid Transit development, centred in Santiago, Chile, and financed by the Volvo Research and Educational Foundations (VREF). We are also grateful for useful comments from David Hensher, John Stanley, David Levinson and three anonymous reviewers on previous versions of the paper.

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DATE: January 2018

1. Introduction

The extent to which a transport system is considered to be cost inefficient and/or cost ineffective is of concern to transport operators, public transport (PT) authorities and regulators as PT systems play a significant role in the urban areas throughout the world (Mulley et al., 2014). Evaluating the operational performance of PT provides information on which to understand how potential improvements in efficiency, service quality/quantity (effectiveness) and financial plans can be implemented with potential implications for fare determination.

In common with other approaches to measuring performance, this paper compares multiple transport systems. However, there is a specific emphasis on how the transport operator performs in terms of their service outputs relative to physical inputs and costs for the set of transport systems under consideration. Moreover, this paper is concerned with a comparison of the efficiency of Bus Rapid Transit (BRT) systems globally which is new to the literature in terms of mode and spatial coverage. The evaluation of BRT performance is important and timely as BRT systems have evolved from their early implementation in Lima (Peru) and Curitiba (Brazil) in the early 1970s to systems being built around the world in very different shapes and sizes. There are now over 190 cities with BRT systems of one form or another, carrying over 32m passengers daily (BRTdata, 2015). Yet, many scholars still exclude BRTs when evaluating the use and performance of rapid transit systems (e.g., Shyr et al., 2017). This makes studying the efficiency of BRT systems both interesting and worthwhile as a basis for identifying best practice and providing opportunities for benchmarking.

BRT is a rapid mass transit mode of PT which combines the speed and dependability of rail service through having access to dedicated infrastructure with the operating flexibility and cost effectiveness of a conventional/regular bus service[1] (Deng and Nelson, 2011). BRT systems have now emerged as a leading and popular mode of urban transport in many cities in the world (Darido, 2006; Wright and Hook, 2007; Hinebaugh and Diaz, 2009; Deng and Nelson, 2011; Vermeiren et al., 2015). As of August 2015, the cities implementing BRT have a combined total of 5112 km total system length (BRTdata, 2015). Beyond the cities already implementing a BRT system, there are many cities considering BRT as a cost effective and flexible way of rapid transit system given the lower initial capital cost, in relation to comparable rail based PT. However, significant differences exist among the BRT systems in terms of standard and practices. In particular, open systems have a framework where patronage is fed from neighbourhoods and funnelled onto dedicated trunk sections of the route (using the same bus) in contrast

[1] In the remainder of the paper we use the term conventional buses which is interchangeable with the term regular buses and essentially represents bus operations that are not BRT.

to a closed BRT system where passengers take conventional/regular buses to the dedicated BRT infrastructure and use interchanges to board vehicles using the dedicated trunk sections of the BRT system. Compared to conventional bus transport, BRTs are successful at offering speed, reliability and comfort improvements with these improvements being achieved by all or parts of the BRT trunk routes being operated on segregated infrastructure so that services are not affected by congested car traffic. Other elements of full BRT usually include high-frequency, high-capacity bus services, bus stop designs which emulate rail stations, off-vehicle fare payment and intelligent transportation systems both for informing passengers (e.g. real-time information), or for prioritising vehicles at junctions. These different levels of BRT characteristics come, of course, not only with benefits but also with costs. While BRTs cost more than conventional bus services, the cost is less than light rail solutions for equivalent contributions to the PT network. This is the rationale for considering BRT implementation (as compared to conventional bus) at different levels of infrastructure implementation so as to identify the determinants of BRT revenue generation and effectiveness. This work will support the work of ITDP (2014) which has attempted with their BRT Standard, underpinned by a scoring system, to provide a fairer and more transparent comparison of standards of different BRT systems.

Benchmarking reports for BRT systems around the world (such as Menckhofff, 2010, LeighFisher, 2011 or Nabavi and Leurent, 2011) have not delivered a comprehensive empirical performance analysis of BRTs that combines various inputs and outputs of such systems, with a particular focus on capital and ongoing costs and changes to revenue potential that comes with improved BRT standards/scores associated with higher standard systems. This means that there is no opportunity for systems within the set under consideration be able to learn from best practice. The analysis of BRTs to date is in the main based on published data, primarily the published data collected by the Observatory of the BRT Centre of Excellence (BRTdata, 2015), supplemented with data from other sources in the public domain and confidential data provided by the operators. The paper aims to identify what data is available and to contribute to the development of a methodological framework (extending Fielding's, 1985 work) that provides stakeholders with an opportunity to achieve international performance benchmarking of BRTs, including a better understanding of the determinants of BRT system effectiveness.

From a policy perspective, such benchmarking is important as, at the end of the day, it reveals whether stakeholders benefit from value for money. Particularly relevant are questions around the extent (if any) to which improved BRT standards generate additional revenues/patronage and how effectiveness gains can be made by a trade-off between one-off capital (fixed) costs of infrastructure and on-going revenue generating (variable) cost.

The paper is organised as follows. Section 2 presents the literature review and the identified gaps in the literature addressed by this paper. This is followed by the methodology and details of the sample used in this paper in section 3. Section 4 discusses the results with section 5 summarising the findings of the analysis and offering policy recommendations.

2. Literature review

In recent years, a considerable amount of research has been carried out in the area of efficiency and effectiveness of different transit systems (e.g. Chu et al. 1992; Kerstens, 1996; Viton, 1997; Mulley, 2003; Karlaftis 2004; Hirschhausen and Cullmann, 2010; Jarboui et al., 2013; Munoz et al., 2013; Tsai et al., 2015). At the early stage of PT performance research, Tomazinis (1977) measured the performance of PT systems by using simple indicators and evaluation of efficiency, productivity and quality of services. Fielding et al. (1978, 1985) adopted a framework and set service indicators (inputs, outputs and consumption) to evaluate the efficiency and effectiveness of PT performance as schematically shown in Figure 1 (see next section). Efficiency in this framework refers to the total service outputs, usually measured by car-km travelled or car-hour operated with respect to service inputs (labour, fuel consumption, or operating cost) for rail-based systems, whereas effectiveness represents the service consumption by passengers, such as number of passengers, or passenger-km against service inputs. Cost efficiency is also referred to as supply-side efficiency in contrast to cost effectiveness which is also referred to as demand side efficiency. The ratio of service consumption to service outputs is defined as service-effectiveness, with the distinction between efficiency and effectiveness highlighting the different aspects of performance evaluation from the operator and consumer perspective, respectively. In a recent literature review on performance evaluation research in the context of PT Daraio et al. (2016) presented a similar framework confirming the importance of both efficiency and effectiveness in the sense of accounting for the relevance of different viewpoints of producers (efficiency), users (quality) and the community (effectiveness).

In terms of performance measurement approaches, scholars (e.g., Windle and Drenser, 1992) have used Partial Productivity Measures (PPM) which are intuitively easy for policy decision makers to understand and or communicate since they revolve around a ratio of a single output to a single input in the PT system context. However, even with multiple formulations, PPMs consider only a subset of inputs and outputs and can potentially produce a misleading overall indication of productivity and can even lead to conflicting results if multiple PPMs are used. Total Factor Productivity (TFP) methods have also been used to evaluate the efficiency and effectiveness of PT systems (Benjamin and Obeng, 1990; Karlaftis and McCarthy, 1997) but as a methodology it requires very significant resources to be devoted to wide scale data collection.

The advance of computing power and the development of more sophisticated methods have meant that new approaches have become more common for evaluating PT performance, most notably

Stochastic Frontier Analysis (SFA) (e.g., Cambini et al., 2007; Lin et al., 2010; Sakai and Shoji, 2010; Holmgren, 2013; Jarboui et al., 2013; Ayadi, and Hammami, 2015) and Data Envelopment Analysis (DEA) (e.g., Viton, 1997; Cowie and Asenova, 1999; Pina and Torres, 2001; Boame, 2004; Karlaftis, 2004; Odek, 2008; Chiu et al., 2011; Caulfield et al., 2013; Georgiadis et al. 2014; Zheng et al., 2014). Both SFA and DEA use multiple inputs and outputs to estimate a single efficiency indicator thus providing an improvement over the multiple indicators required for PPM monitoring. In SFA, a production or cost function is estimated using econometric (parametric) methods to obtain productivity based on service inputs. This method requires large (often longitudinal/panel) data sets to deliver robust results (Karlaftis and Tsamboulas, 2012) and also requires the assumption of cost minimisation as the key objective of all firms under evaluation. This may well be unrealistic as an objective in the context of many PT systems. DEA does not require this assumption and is also less demanding in terms of sample size for yielding robust results. DEA is a non- parametric method and uses linear programming to identify the efficient production frontier and then estimates inefficiency by determining the distance of individual observations from the efficient frontier (Farell, 1957; Charnes et al., 1978).

In the PT context, DEA has been primarily used to understand the determinants of inefficiency. As such Chu et al. (1992) were able to demonstrate a negative correlation between PT system efficiency and effectiveness; so systems with higher effectiveness ratings were identified as having low efficiency scores and vice versa. More recent papers have identified the drivers of PT firms' inefficiency by using second-stage regression models (e.g. Tsai et al., 2015 in the metropolitan train operation context). In a very recent paper, Obeng et al. (2016) separated stochastic and systematic technical inefficiencies and analysed determinants for the latter, most notably subsidies and regulation. Their results suggest that capital expenditure subsidies for single mode bus PT systems have a very significant positive impact on PT efficiency. This leads to the question as to whether the same applies to BRT systems which typically exist in a multi-modal environment (which would be reflected by high BRT standards having a positive impact on BRT efficiency) or whether this trade-off behaves differently in the BRT context.

Although, the implementation of BRT systems has increased globally (as discussed above and also summarised in Finn and Munoz, 2014), research and academic journal papers on BRT benchmarking efficiency are scarce (for a comprehensive review on efficiency and effectiveness studies related to urban PT see Daraio et al., 2016). Wright and Hook (2007) documented cost and performance based information of selective BRT systems but did not apply econometric methods. Hensher and Golob (2008) evaluated 44 BRT systems in operation throughout the world by comparing infrastructure costs and a range of design and service specifications through a formal statistical analysis but relied on PPM measures only. Hidalgo and Graftieaux (2008) reviewed BRT systems of 11 cities in Latin America and Asia and found that improved speed had a positive impact on ridership of BRT systems. Hensher and Li (2012) assessed 46 BRT systems in 15 countries and found price elasticity, frequency of service, offered capacity and connectivity are the most important impact factors for increasing ridership. Currie and Delbosc (2014) reviewed BRT system performance in Australasia and revealed that BRT ridership growth had surpassed non-BRT transit ridership changes in all of their analysed cities, with significant impact factors being high service levels, speed of vehicles, shorter station spacing, segregated rights of way, modern accessible vehicles, lower fares, system integration and pre-boarding ticketing. Whilst this literature relies either on PPM or even simpler ratios, a good range of potential explanations of efficiency or inefficiency in BRT operation are provided. In this paper, these factors are used in a second-stage regression model to determine underlying causal explanations for efficiency scores estimated in the first stage (DEA) of the analysis.

Overall, the existing literature lacks international comparison on a single comprehensive measure of performance for BRT systems. A key aim of this paper is to contribute a first attempt of benchmarking in the BRT context, which includes providing evidence on what data is actually available and what methods can therefore be deployed. This includes potentially extending existing frameworks by evaluating, in addition to cost effectiveness, input effectiveness. BRTs are a very heterogeneous set of PT with considerable differences in standard of service and it is hoped that looking at the BRT systems using DEA methods will reveal determinants of both revenue/patronage potential and effectiveness (and trade-offs between these) of interest to both BRT operators and the jurisdictions in which they are located. In addition, such analysis could enhance the value of the scoring system of different BRT standard elements proposed by ITDP (2014) so that both operators and transport authorities have a better sense as to whether they achieve their desired goals.

3. Methodology and sample

To meet the aim of the paper, the analysis is divided into two parts, one investigating the revenue potential of BRT systems and the other being focused on performance. Of particular interest is the impact of BRT standard of service on both revenue potential and effectiveness. We use the definition and BRT standard data established by ITDP (2014). IDTP have classified as Gold, Silver and Bronze systems, depending on complex point system, the majority of BRT systems around the world with at least 3km length of dedicated BRT lanes.[2]

[2] In this definition systems have points added to their BRT standard (up to 100 points) through performing well in regard to BRT basics (such as Dedicated Right-of-Way, Busway Alignment, Off-board Fare Collection, or Platform-level Boarding), Service Planning aspects, Infrastructure characteristics, Station characteristics, Communication aspects and Access and Integration aspects. Further details are provided in the next section.

3.1 Determinants of the revenue potential of BRT systems

The first step of the analysis is to establish whether the standard of the BRT system (IDTP, 2014) and other factors have a significant impact on the revenue potential of global BRT systems. Revenue potential is thereby defined as a combination of average fare revenues (yields), patronage per network-km and total farebox revenues. Initially the analysis focused on yields but this approach is extended to account for, and to be able to reward systems that aimed for higher effectiveness (increasing the passenger per network-km) giving rise to eventually higher total farebox revenues rather than simply higher yields.

The analysis thus evaluates the role of the determinants of BRT systems on revenue potential and tests the hypothesis that full or higher standard BRT systems generate on average higher fare revenues per passenger, higher patronage per network-km and higher total farebox revenues than systems of lower standards. The following four OLS regression models (equations 1-3) were investigated:

$$\frac{FAR\_REV_i}{PAXi} = \alpha + \beta_1 START\_YEAR_i + \beta_2 OWNERSHIP_i + \beta_3 BRT\_STANDARD_i + \beta_4 GDP\_CAP_i + \beta_5 POP\_DENSITY_{\ i} \tag{1}$$

$$\frac{FAR\_REV_i}{PAX_i} = \alpha + \beta_1 START\_YEAR_i + \beta_2 OWNERSHIP_i + \beta_3 BRT\_STANDARD_i \tag{1a}$$

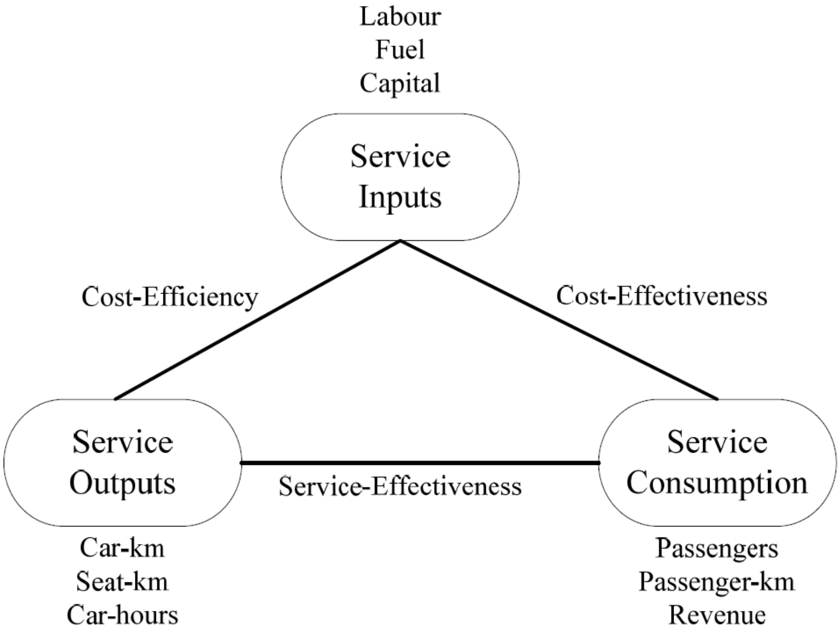
$$\frac{Pax_i}{Network\_km_i} = \alpha + \beta_1 START\_YEAR_i + \beta_2 OWNERSHIP_i + \beta_3 BRT\_STANDARD_i + \beta_4 GDP\_CAP_i + \beta_5 POP\_DENSITY_{\ i} \tag{2}$$

$$FAR\_REV_i = \alpha + \beta_1 START\_YEAR_i + \beta_2 OWNERSHIP_i + \beta_3 BRT\_STANDARD_i + \beta_4 GDP\_CAP_i + \beta_5 POP\_DENSITY_{\ i} \tag{3}$$

where $START\_YEAR_i$ is the year the *i*th BRT system in the sample commenced operation and is a measure of the maturity of the system. Many BRT systems in are still in transition as they upgrade from lower standards to full or higher quality BRT or are extended by one or more BRT corridors or stations. $OWNERSHIP_i$ is a dummy variable representing ownership (1 is private operational ownership of the system and 0 being public operational ownership of the system). $BRT\_STANDARD_i$ is the most important variable in this model, reflecting the level/standard of the BRT system in question. For this variable data provided by ITDP (2014) which categorises BRTs around the world into four categories are used: gold (85–100 points), silver (70–84 points), bronze (55–69 points) and basic (less than 55 points) with higher scores being associated with "fuller" or higher standard systems. The scoring system recognises that there are many dimensions to establishing the standard of a BRT system and that different systems are made up of a combination of features. Thus each system has a final score based on points for desirable attributes and points deductions for the absence of some desirable attributes which make up a BRT system. The scoring system covers dedicated right-of-way (maximum score 8), off-board fare collection (8 points), service planning including integration with other PT (19 points over a number of categories), infrastructure overall (14 points) including pavement quality (maximum score 2) and deductions (such as Significant Gap Between Bus Floor and Station Platform (-5) or Poorly Maintained Busway, Buses, Stations, and Technology Systems (-10)), only relevant to systems in operation, are introduced to mitigate classifying a BRT system that has design, operational or performance weaknesses such as low peak frequency (maximum score -3) (ITDP, 2014). As not all the systems analysed in this paper had an exact verified BRT score, they have been allocated a numerical score equal to the average of the achieved category (e.g. a gold scoring BRT was allocated 94 points). In the initial model a measure of the country's economic activity, GDP_CAP_i, the Gross Domestic Product per capita in \$US, and $POP\_DENSITY_i$, million inhabitants per km^2, for population density are used to capture elements that economic theory would suggest as being determinant of revenue potential and that are regularly deployed as determinants of transport efficiency in the extant literature (Daraio et al., 2016). A sub-model of model 1 (1a) which excludes the demographic variables from the analysis is focussed entirely on system variables. All models (models 1-3) contain a range of BRT system attributes through the use of the variable $BRT\_STANDARD_i$. Variables representing specific features of BRT systems such as the number of stations ($STATIONS_i$), $PEAK\_FREQ_i$ (buses per hour in the peak), PRE_BOARD_i (dummy variable for pre-boarding fare collection) and $ST\_DISTANCE_i$ (station distance in m) were found to be insignificant but had been initially included because of the way in which the literature identified their importance to efficiency.

3.2 Determinants of BRT system effectiveness

In order to examine the determinants of BRT effectiveness, the analysis must first establish a comprehensive single performance indicator which accounts for various inputs and outputs of the BRT provision process. Whilst the choice of and specification of the methodology to determine the single performance indicator has potential impact on the findings (as discussed in the literature review section and detailed in Karlaftis and Tsamboulas, 2012), the availability, selection and appropriate use of input and output data may have even larger consequences on the effectiveness of performance benchmarking of BRT systems. As schematically shown in Fig. 1, the extant literature has predominantly focused cost-efficiency, cost-effectiveness and services-effectiveness when assessing PT performance.



Source: Reproduced from Fielding *et al.* (1985, p.75).

Fig. 1. Public transport efficiency and effectiveness

Initially the aim was to evaluate all of these types of performance. However, it became apparent that benchmarking BRT systems globally is not straightforward as the availability, coherence and quality of data are problematic. For example, service outputs such as car-km or seat-km were, despite all efforts and support from international partners, impossible to obtain from most operators. The same applies to passenger-km and most cost data related to BRT systems, with the exception of BRT infrastructure cost which is available from BRTdata (2015). Whilst we expected that most data would not be available in the public domain, many operators were not only hesitant to share any data but more importantly claimed that they did not even possess that data themselves. This may be explained by the way in which most companies and/ or authorities run mixed BRT and conventional bus operations, making it not only difficult to for example separate/ allocate cost across the different types of operations but also problematic to share such data because of sensitivity issues related to public support, regulation or competitive advantage. As a result of an intense data collection the cost of capital for the BRT infrastructure was obtained which permits the partial assessment of cost-effectiveness. More interesting may be however the extension in this paper of Fielding et al.'s (1985) framework to consider the community perspective by adding a fourth key indicator, namely input-effectiveness (in addition to cost-effectiveness, both representing different aspects of demand side efficiency). Similar to the concept of productivity (or technical efficiency as opposed to allocative and cost efficiency of discussed of traditional production processes, for further details see Merkert and Cowie, 2018) this indicator does not require any cost or input price data and allows us to assess the effective use of physical measures of BRT capital inputs such as BRT network length and fleet size in relation to available BRT service consumption outputs such as number of passenger and revenues.

While focusing our analysis on partial cost-effectiveness and input-effectiveness, these first-stage single performance indicators are computed using the Data Envelopment Analysis (DEA) methodology and are then used in a second stage regression to systematically identify key determinants of BRT performance in terms of underlying characteristics such as BRT standard, design, management or demographic factors of the operating territory. As with Merkert et al. (2010), we argue that the use of two-stage DEA is superior to SFA in the BRT context as the latter does require much larger samples as well as cost minimisation assumptions that appear unrealistic for BRT systems (i.e. for those in public ownership).

3.2.1 Specification of the first stage DEA modelling

The first DEA stage consists of non-parametric bootstrapped and also non-bootstrapped/original[3] models to compute the efficiency of the relevant BRT systems. As with previous studies (e.g. Tsai et al., 2015), the DEA specifications in this paper focus on two important choices, firstly input versus output orientation, and secondly whether constant returns to scale (CRS) or variable returns to scale (VRS) are assumed. This paper focuses on the variable returns to scale (VRS) model, as the requirement for a CRS model is that all BRT systems in the sample are producing at their optimal size, an unrealistic assumption given the level of regulation and other constraints, such as financial constraints, in their operation. In terms of orientation, there is an on-going debate in the literature (e.g. Merkert and Assaf, 2015) as to whether input or output oriented models are more appropriate for the transportation sector. The input-oriented DEA model can be expressed as follows (based on Coelli et al.'s (2005) optimisation approach):

$$
\begin{aligned}
&\min_{\theta\lambda}\ \theta, \\
&st \qquad -q_i + Q\lambda \geq 0 \\
&\qquad\quad\ \theta x_i - X\lambda \geq 0 \\
&\qquad\quad\ \lambda \geq 0 \quad ,
\end{aligned}
\tag{4}
$$

where λ represents the weights for the inputs and outputs which is a $I \times 1$ vector of constants, X and Q are input and output matrices, and θ measures the distance between the observations x_i and q_i and

[3] Since the bootstrapped algorithm for DEA is now well established in the literature, we refer to Simar and Wilson (1998, 2007) for more details.

the frontier (where the frontier represents efficient operation). In other words, the distance (θ) represents the technical efficiency scores, and ranges between zero (i.e. least efficient) and one (i.e. most efficient). To account for the variable returns to scale (VRS) the term ($\mathrm{I}1'\lambda = 1$), is added as an additional convexity constraint which ensures that inefficient or in our case ineffective firms are only benchmarked against firms of a similar size. While it could be argued that the output oriented model would be preferable as it assumes that BRT operators can influence outputs more effectively than inputs (as modifying the one-off infrastructure capital cost of BRT infrastructure is difficult in the short to medium run), this paper follows the majority of extant studies that have applied DEA in the PT context (e.g., Georgiadis et al., 2014) and adopts an input-oriented framework. The justification is that BRT outputs are often heavily impacted by endogenous factors or substantially regulated or pre-specified by the procuring authorities (e.g. through managed contracts, fare regulation and subsidies). In addition, the aim is to evaluate the impact of different BRT standards and it is therefore by definition more interesting to evaluate the effect of minimising inputs or on other words levels of BRT infrastructure (as an indication of fixed cost) and/or fleet size (as an indication of variable cost) for a given quantity of outputs (observed demand).

The choice of inputs for the analysis is heavily influenced by the theoretical consideration of a trade-off between the one-off capital (fixed) cost of providing infrastructure and on-going (variable) costs associated with generating revenue. To compute partial cost effectiveness (PCE_{VRS}) $INFRACOST_i$ (m $US of infrastructure for the entire BRT network length) was chosen as the proxy for capital cost and $FLEET_i$ (fleet size measured in number of buses operating on the BRT system) as the on-going costs associated with generating revenue. In order to control for the potential distortion arising from a comparison of money costs across different jurisdictions, separate DEA models focused on input effectiveness (IE_{VRS}) were run using $NETWORK\_KM_i$ (the entire BRT network length in km) instead of $INFRACOST_i$ as the proxy for one-off capital (fixed) input. A capital and labour trade-off was frustrated by the lack of available data, particularly for staff numbers, and the way in which labour, represented by the number of drivers and $FLEET_{i,,}$ for capital, are highly correlated (which allows some conclusions on this trade-off anyway). The outputs are represented by PAX_i (passenger numbers in m) and $FARE\_REV_i$ (fare revenue in m $US). The attempt to evaluate the impact of the type of BRT system (closed versus an open system with the latter being characterised by dedicated trunk lines with feeder routes & conventional bus services), did not yield significant results.

3.2.2 The second stage analysis

As identified above, VRS demand side efficiency or effectiveness (E_{VRS}) scores are most appropriate for the BRT context and these are used in the second stage regressions for both partial cost effectiveness (PCE_{VRS}) and input effectiveness (IE_{VRS}). However, the analysis also estimates effectiveness scores under the assumption of constant (IE_{CRS}) and non-increasing economies of scale (IE_{NIRS}). Putting the IE_{CRS} and IE_{NIRS} effectiveness scores into a relationship with the estimated VRS effectiveness scores allows the scale demand side efficiency (*SE*) for each operator and its direction (*DIR*), increasing or decreasing returns to scale to be determined.

The second-stage regression models seek to evaluate the impact of several variables,[4] most notably BRT standards on the single effectiveness scores. For this the following truncated regression model (truncated at 0 as a result of the non-negativity of the input-oriented effectiveness scores) is used:

$$y_i = \alpha + \beta_1 START\_YEAR_i + \beta_2 OWNERSHIP_i + \beta_3 BRT\_STANDARD_i + \beta_4 STATIONS_i + \beta_5 DEVELOPED_i \quad (5)$$

where y_i represents *PCE* and PCE_{corr} (the original and bootstrapped/bias-corrected partial cost-effectiveness VRS scores) in the first model and *IE* and IE_{corr} (the original and bootstrapped/bias-corrected input-effectiveness VRS scores) in the second model. The interpretation in this paper is mainly on the bootstrapped models but both the original and bias corrected efficiency scores are used as the debate on the value of bootstrapping is ongoing (e.g. Simar and Wilson, 2008). This paper uses the smoothing homogenous bootstrap approach with 2000 iterations to overcome the potential problem of biased results in the second-stage regressions (Simar and Wilson, 2000, 2007, 2008). The hypothesis for the paper is that higher values of the $BRT\_STANDARD_i$ have a significant and positive impact on both cost- effectiveness and input-effectiveness. While there is no experimental evidence or literature supporting the claim that fuller BRT systems are more effective, the existing literature on general PT performance (e.g., Daraio et al., 2016) suggests such a relationship as for example segregated lanes will have an impact on commercial speed and hence fleet productivity. A more diverse set explanatory variables could have been used to include variables such as car ownership levels but the set employed were chosen as being the most appropriate given the need for comparability and the need to take account of a relatively small number of observations in the sample. This decision was also driven by that data for the selected variables are available from the BRTdata (2015) database for the majority of the operators thus offering a certain amount of comparability and meant that this study only needed to contact those operators where observations of these variables were not available from BRTdata (2015): this provided a more effective and consistent approach than trying to introduce more variables,

[4] For a definition of the exogenous variables see section 3.1 and models 1-4. $DEVELOPED_i$ is additional and is a dummy variably that identifies whether a BRT system is based in a developed (1) or developing (0) country.

especially as many of the analysed BRT systems are in developing countries where official statistics are not readily available or questionable in terms of their reliability.

3.3 Sample and data

This paper evaluates 58 BRT systems. While the sampling was partially driven by data availability (a number of systems such as Edinburgh were removed either because of missing data points or because the data was too far out of date), particularly regarding infrastructure cost. Nevertheless, the sample includes the largest and most heavily patronaged systems from around the world. The descriptive statistics presented in Table 1 show the sample spans 25 countries and is representative for global BRT systems through its inclusion of very large systems such as Sao Paulo but also relatively small systems such as Orlando, with an average fleet size of 370 buses (taking account of differences in open and closed BRT operation). There is significant variation in the one-off infrastructure unit cost with 7.24m $US per km being the average of the sample which is broadly in line with the previous literature (e.g. LeighFisher, 2011). Table 1 also illustrates that BRT systems are on average large in terms of passenger numbers but less so in regard to fare revenue: this suggests that some, if not most, of the systems will need to receive additional support from local or federal transport/public authorities. One system (Orlando) offers the BRT services free of charge (in terms of fare revenue) and to provide a fair comparison, the fare revenue in this case was proxied and replaced by the average fare revenue of similarly sized North American BRT systems. We also tried to run the model without Orlando but the aggregated results did not differ significantly, indicating that Orlando is a rather average system at neither end of the spectrum. The majority of the data for the sample comes from the publicly available BRTdata (2015). However, for some BRT systems this is not wholly reliable, coming from secondary sources such as research papers or newspaper items, or inconsistent with data sourced from various years. BRTdata also has many gaps. We therefore filled these gaps and verified many BRTdata observations with the help of the relevant BRT operators or BRT administrating authorities (via email data requests). All observations used in the analysis are the 2011-2014 average of the data, as some systems only have observations for say 2011 while others have 2013 data only and others again had observations for both or even all years. For most BRTs, data exists for 2013 across all variables. Overall, the data collection for this efficiency analysis was much more difficult than expected. The last two columns of Table 1 summarise the choice of inputs and outputs in the *IE* and *PCE* DEA models.

For the independent variables used in the second stage analysis, Table 1 illustrates that most systems in the sample are publicly owned. Developed countries are slightly under-represented with some countries being very poor while others are appearing at the relative upper end of economic activity per capita (GDP_CAP_i) globally. Approximately 50 percent of the analysed systems collect the fares pre-boarding and the average number of corridors at 2.8 per system and the average peak frequency, at nearly 70 buses per hour, is relatively high. Again, there is significant variation across the analysed operators with regard to all these variables.

Table 1. Descriptive statistics of DEA efficiency models & regressions (N=58; mean 2011-2014)

	Mean	Std. dev.	Min	Max	IE	PCE
	First-stage DEA variables					
Inputs						
$FLEET_i$	370.74	703.6	10	3966	x	x
$INFRACOST_i$ (m \$US)	244.24	429.01	2.76	2995.23		x
$NETWORK\_KM_i$ (km)	40.15	39.18	4.5	206.75	x	
Outputs						
PAX_i (m)	97.56	190.31	0.7704	949.2	x	x
$FARE\_REV_i$ (m \$US)	68.61	164.63	0.26	877.06	x	x
	Second-stage regression variables					
$START\_YEAR_i$	2002.74	9.62	1972	2013		
$OWNERSHIP_i$ (1=private)	0.14	0.35	0	1		
$BRT\_STANDARD_i$	63.32	13.72	50	92		
$STATIONS_i$	55.78	54.97	3	240		
$DEVELOPED_i$ (1=yes)	0.48	0.50	0	1		
	Dropped or yield regression variables					
GDP_CAP_i	26883.6	22538.3	1299	67468		
$POP\_DENSITY_i$ (m/km2)	1833.84	1888.26	28.8	7227		
$PEAK\_FREQ_i$ (buses/h)	69.62	107.51	5	600		
PRE_BOARD_i (1=yes)	0.58	0.45	0	1		
$CORRIDORS_i$	2.81	3.38	1	16		
$ST\_DISTANCE_i$ (m)	822.04	632.15	300	5000		

4. Results

4.1 Discussion of OLS regression results

The first part of the analysis focusses on evaluating the impact of BRT standards (ITDP, 2014) and other variables on the BRT system revenue potential or in other words yields (average fares), passengers per network-km and/or total farebox revenue. As shown in Table 2, in model 1, where the impact on average fare levels is evaluated, $BRT\_STANDARD_i$ only becomes significant once the demographic variables GDP_CAP_i and $POP\_DENSITY_i$ (both of which have the significant positive impact on yields as economic theory would suggest) are removed from the model. The negative direction of the $BRT\_STANDARD_i$ in the reduced model suggests higher standard BRT systems (gold/silver) are associated with lower fare revenues per passenger which may be a function of size as larger systems tend to have a higher $BRT\_STANDARD_i$ and lower fares since larger passenger numbers result in higher total revenue and break even points being achieved even with relatively lower yields. The volume trend is confirmed in model 2, as $BRT\_STANDARD_i$ is highly significant and positively impacting passenger per network-km numbers. The overall effect, as suggested by the results of model 3, is that $BRT\_STANDARD_i$ has a significant positive effect on total farebox revenue, although not quite as significant as this same variable in model 2 in explaining passengers per network-km as a result of the inclusion of the GDP and population density variables. While yields decrease with higher BRT standards (model 1a), increased patronage overcomes that effect and results in increased total farebox revenues (model 3). However, an alternative explanation might be just that the larger systems are more likely to have a high BRT standard as well as higher farebox revenues. A likely further contribution to this effect is that the regulatory or PT authority decisions may impact on the determination of fares particularly when such decisions may aim to increase patronage and affordability. All this highlights that sometimes statistical and practical significance are not aligned, likely as a result of not accounting for all potential endogenous variables. The range of model fit results of 0.82 for model 1 to 0.68 for model 3 are also indicative of this. Both GDP_CAP_i and $POP\_DENSITY_i$ appear to have no significant effect on either passengers per network-km or farebox revenues. As BRT systems with high standards also cost more to operate (both in terms of capex and opex) it is likely that, despite their overall potential for positive revenues (if they are able to materialise the expected passenger growth and are not just left with a decrease in yields) they will not break even. In these cases the systems will require additional public support, which would explain why so many of the analysed BRT systems are still in public ownership.

Table 2. Regression results for determinants of BRT system revenue indicators

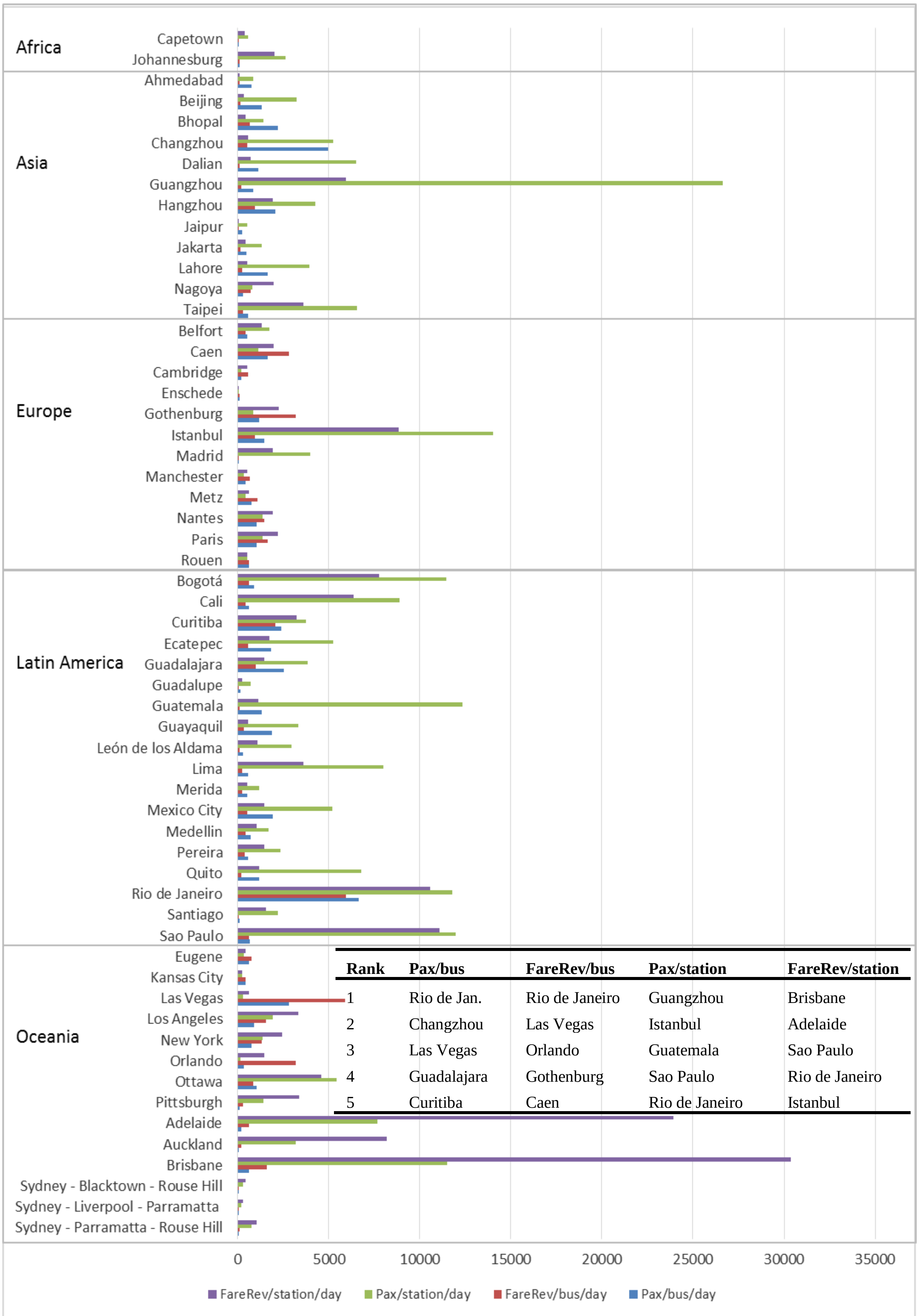
	Model 1 Yield ($/pax)	Model 1a Yield ($/pax)	Model 2 Pax/ Network-km	Model 3 Farebox Rev (m $)
CONSTANT	18.178	66.975*	4.52E+07	5656.29
$START\_YEAR_i$	-0.009	-0.032*	-23574.8	-2.93
$OWNERSHIP_i$ (1=private)	-0.472	0.248	-19948.7	-19.61
$BRT\_STANDARD_i$	-0.0006	-0.024*	70765.9***	4.47**
GDP_CAP_i	0.0001***	-	-21.6	-5.4E-05
$POP\_DENSITY_i$ (m/km^2)	0.0002*	-	-24.2	0.0003

Note: *p<0.1, **<0.05, ***p<0.01; these represent significant p values.

The initial hypothesis that the higher standard BRT systems achieve higher yields and total revenue is hence only partially supported, leaving the following question to answer "If BRT standards don't improve yields but increase passenger numbers per network-km, do they overall improve BRT system effectiveness?"

Figure 2 shows the various PPM results and orders the top 5 systems under different PPM measures. The results support the claim made in the literature review that while a PPM measure can in itself be useful for identifying a trend they can often be inconclusive and even misleading when trying to understand the overall performance of BRT systems. While Rio de Janeiro's BRT system appears to perform well in all the presented PPM measures, Changzhou's BRT is 2nd best ranked when measured by passengers per bus on an annual basis (bus productivity) but does not even make it into the top ten of the second indicator of bus productivity (Fare revenue per bus) or into any of the two station productivity PPMs. Brisbane on the other hand scores well on the fare revenue per bus and fare revenue per station.

The diversity of outcomes, depending on the PPM measure used, illustrated in Figure 2 reinforces the importance of the DEA methodology and a single effectiveness indicator that combines the various inputs and outputs which will add value to the overall understanding of the effectiveness of the BRTs under consideration.



Rank	Pax/bus	FareRev/bus	Pax/station	FareRev/station
1	Rio de Jan.	Rio de Janeiro	Guangzhou	Brisbane
2	Changzhou	Las Vegas	Istanbul	Adelaide
3	Las Vegas	Orlando	Guatemala	Sao Paulo
4	Guadalajara	Gothenburg	Sao Paulo	Rio de Janeiro
5	Curitiba	Caen	Rio de Janeiro	Istanbul

Fig 2. Partial productivity of analysed BRT

4.2 Discussion of two-stage DEA results

Table 3 presents the aggregated DEA effectiveness (demand side efficiency) scores. A comparison of the non-bootstrapped efficiency with the bias-corrected bootstrapped scores confirms (in line with the previous literature) that the original scores overestimate efficiency.

Table 3. DEA efficiency results by region

Region	obs	*IE*	IE_{corr}	*PCE*	PCE_{corr}
Africa	2	0.267	0.221	0.097	0.074
Asia	12	0.546	0.441	0.659	0.491
Europe	12	0.552	0.444	0.507	0.388
Latin America	18	0.526	0.414	0.585	0.448
Northern America	8	0.567	0.438	0.658	0.487
Oceania	6	0.601	0.479	0.219	0.166
Total average	58	0.540	0.429	0.539	0.408

Note: All DEA scores have been computed with Frontier Efficiency Analysis with R package FEAR 2.0 (Wilson, 2014).

Table 3 also shows while African systems have relatively low input effectiveness scores (IE_{corr}), the performance gets even worse once the cost of infrastructure is accounted for in partial cost effectiveness (PCE_{corr}). Given the strength and power purchasing parity of the Australian dollar it is not unexpected that also for Oceanian systems PCE_{corr} is smaller than IE_{corr}, however the magnitude of this effect is surprising. Interestingly all three Sydney BRTs (different parts of the Sydney Parramatta to Rouse Hill T-way) have relatively low PCE_{corr} scores which are perhaps explained by being operated as managed contracts and being located on the outskirts of Sydney, rather than forming the more usual key trunk route function of a BRT to the centre of the city. Given that the regional averages differ so little it is worth discussing some of the individual BRT system effectiveness scores, summarised in Table 4. Interestingly, Guangzhou comes out as the relatively most effective BRT system regardless of which indicator is used. Similarly, the Brazilian systems of Rio de Janeiro and Sao Paulo perform well across the board. In contrast, while smaller systems in developed countries such as Belfort, Brisbane and Auckland do well in regards to input effectiveness, they do not make it into the top 20 once partial cost-effectiveness is considered. Table 4 further identifies the reason for the difference between original and bootstrapped scores shown in Table 3 with many fully effective systems (score of 1), ranked by alphabetical order of the city name. This lack of variation makes the regression of the original scores in second stage regressions less reliable. However, given that the overall ranking does not change when applying the bootstrapping procedure (in contrast to when deploying output oriented models) there can be confidence that the DEA results are robust enough for a second-stage investigation.

Table 4. DEA technical efficiency score rankings

City/Rank	*IE*	City/Rank	IE_{corr}	City/Rank	*PCE*	PCE_{corr}
Belfort	1	Guangzhou	0.796	Guangzhou	1	0.754
Brisbane	1	Belfort	0.727	Gothenburg	1	0.733
Guangzhou	1	Orlando	0.726	Hangzhou	1	0.705
Las Vegas	1	Las Vegas	0.725	Jaipur	1	0.677
Orlando	1	Changzhou	0.702	Las Vegas	1	0.715
Rio de Jan.	1	Auckland	0.699	Manchester	1	0.714
Sao Paolo	1	Brisbane	0.697	New York	1	0.689
Changzhou	0.866	Sao Paolo	0.687	Orlando	1	0.702
Nantes	0.837	Rio de Jan.	0.674	Rio de Jan.	1	0.65
Auckland	0.835	Nantes	0.671	Sao Paolo	1	0.651
Gothenburg	0.776	Eugene	0.637	Taipei	1	0.651
Eugene	0.775	Gothenburg	0.619	Guadalajara	0.987	0.835
Nagoya	0.731	Sydney-BRH	0.605	Curibita	0.907	0.680
Jaipur	0.709	Nagoya	0.593	Mexico City	0.905	0.707
Sydney-BRH	0.703	Bhopal	0.583	Quito	0.894	0.707
Taipei	0.679	Jaipur	0.567	Changzhou	0.884	0.653
Bhopal	0.669	Ecatepec	0.546	Guayaquil	0.873	0.662
Bogotá	0.664	Guadalajara	0.541	Eugene	0.813	0.643
Caen	0.653	Taipei	0.520	Bhopal	0.769	0.622
Guadalajara	0.649	Enschede	0.519	Ecatepec	0.687	0.581

At the individual BRT system level it is further interesting to evaluate scale efficiency. Table 5 presents the scale efficiency and its direction (*Dir*) in relation to both input-effectiveness (*IE SE*) and partial cost-effectiveness (*PCE SE*). The results show why it is valuable to consider in addition to input-effectiveness some indication of infrastructure cost in the form of partial cost-effectiveness as for the former almost all systems would benefit from further growth (economies of scale) while for the latter many systems suffer from diseconomies of scale at their current size of operation (from fleets above approximately 300 buses). This becomes most notable for the top two systems Sao Paulo and Santiago (when using number of buses as an indication of firm size). At the other end of the spectrum all small BRT systems are associated with increasing economies of scale (starting from systems with 270 or less buses) suggesting benefits from economies of scale if the fleets were expanded, which is similar to other industries.

Table 5. DEA economies of scale results, ranked by fleet size

	Fleet #	Length #	Infco #	IE SE	DIR	PCE SE	DIR
Sao Paolo	1	3	6	1	E	0.800	D
Santiago	2	6	4	0.875	I	0.880	D
Madrid	3	42	41	0.547	I	0.801	I
Bogotá	4	4	1	0.968	D	0.882	D
Taipei	5	13	55	0.999	I	1	E
Guangzhou	6	34	31	1	E	0.663	D
Cali	7	20	14	0.933	I	0.848	D
Jakarta	8	1	17	0.818	I	0.846	D
León de los Aldama	9	24	50	0.765	I	0.936	I
Quito	10	11	25	0.947	I	0.600	D
Lima	11	30	18	0.856	I	0.951	D
Brisbane	12	28	3	1	E	1	I
Istanbul	13	15	5	0.936	I	0.885	I
Rio de Janeiro	14	2	2	1	E	1.000	E
Mexico City	15	5	15	0.939	I	0.764	D
Cape Town	16	39	44	0.206	I	0.547	I
Johannesburg	17	37	24	0.350	I	0.594	I
Pittsburgh	18	27	29	0.583	I	0.961	I
New York	19	9	42	0.872	I	1	E
Auckland	20	56	47	0.298	I	0.761	I
Ottawa	21	26	19	0.783	I	0.972	I
Curibita	22	7	26	0.903	I	0.995	D
Beijing	23	10	7	0.816	I	0.909	I
Pereira	24	46	34	0.566	I	0.817	I
Syd-Par-Rouse Hill	25	50	28	0.134	I	0.337	I
Syd-Liv-Parramatta	26	25	8	0.125	I	0.229	I
Ahmedabad	27	8	27	0.647	I	0.780	I
Guatemala	28	23	33	0.700	I	0.915	I
Syd-Blacktn-RouseHill	29	55	30	0.043	I	0.124	I
Adelaide	30	49	32	0.533	I	0.971	I
Guayaquil	31	17	45	0.786	I	0.990	I
Hangzhou	32	14	54	0.795	I	1	E
Guadalupe	33	51	36	0.127	I	0.250	I
Paris	34	18	9	0.827	I	0.851	I
Medellin	35	36	40	0.379	I	0.612	I
Rouen	36	21	12	0.446	I	0.460	I
Dalian	37	29	16	0.483	I	0.730	I
Lahore	38	47	48	0.620	I	0.659	I
Ecatepec	39	41	37	0.600	I	0.809	I
Changzhou	40	16	22	0.868	I	0.850	I
Belfort	41	58	46	0.292	I	0.498	I
Merida	42	48	52	0.229	I	0.428	I
Guadalajara	43	43	43	0.592	I	0.788	I
Manchester	44	45	57	0.304	I	0.769	I
Cambridge	45	19	21	0.325	I	0.327	I
Los Angeles	46	33	10	0.593	I	0.669	I
Metz	47	22	23	0.398	I	0.435	I
Kansas City	48	38	51	0.190	I	0.307	I
Bhopal	49	31	39	0.498	I	0.596	I
Nagoya	50	54	11	0.214	I	0.303	I
Caen	51	44	13	0.725	I	0.876	I
Jaipur	52	52	38	0.060	I	0.195	I
Nantes	53	53	58	0.309	I	0.402	I
Gothenburg	54	40	53	0.691	I	0.985	I
Enschede	55	32	35	0.032	I	0.032	I
Eugene	56	35	49	0.168	I	0.201	I
Las Vegas	57	12	20	0.993	I	0.993	I
Orlando	58	57	56	0.537	I	0.830	I

Note: All DEA scores have been computed with Frontier Efficiency Analysis with R package FEAR 2.0 (Wilson, 2014). E-Efficient, I=Increasing returns to scale. D= I=Decreasing returns to scale.

While this would justify an argument for larger fleets, it is not necessary an indication of benefits of larger networks in the sense of network length. For example, while Madrid has a large fleet, it is still associated with increasing returns to scale which may be a result from being one of the smaller systems in terms of network length. In contrast, Guangzhou is similarly large in fleet size and small in network length and infrastructure cost but associated with very significant decreasing returns to scale in relation to cost-effectiveness. This becomes even more noticeable in the context of Hangzhou, which has a relatively small fleet size and a medium sized network but one of the lowest infrastructure cost leading to scale efficiency in regards to partial cost-effectiveness, which suggests that big is not always beautiful and that context matters when evaluating BRT systems.

The second-stage truncated regressions results presented in Table 6 provide some explanation of the potential underlying reasons for BRT ineffectiveness. While the majority of the BRT systems do not significantly impact on either form of effectiveness, it is notable that the BRT standard has a positive impact on input-effectiveness which disappears once partial cost-effectiveness is considered. A similar effect occurs in regards to whether the BRT system in question is based in a developing or developed country with the latter type only benefiting until the costs of the BRT infrastructure are accounted for. This may also be a result of BRTs in developed countries competing with other lines or modes of transport of good quality, while in developing countries the BRT is often the only form of PT with good reliability and quality of service. In contrast, the number of stations and ownership is are only statistically significant in the partial cost-efficiency model which suggests that publicly owned BRT systems with a large number of stations are more partially cost-effective than their counterparts. While the findings in regards to ownership are contrary to economic theory predictions, the sample is dominated by systems in public ownership and, of course, the nature of ownership is a matter of political orientation, particularly in Europe but also in other regions. Moreover, ownership is typically not linked to the level of subsidies as both private and public entities can and often do receive some public support in the form of subsidies, transfer payments or contractual revenue guaranties.

Table 6. Second-stage truncated regression results

	IE_{corr}	PCE_{corr}
CONSTANT	-5.0700	-5.8715
$START\_YEAR_i$	0.0026	.00026
$OWNERSHIP_i$ (1=private)	-0.0024	-0.1621**
$BRT\_STANDARD_i$	0.0029*	0.0005
$STATIONS_i$	-0.0006	0.0007*
$DEVELOPED_i$ (1=yes)	0.0793*	0.0079

Note: *p<0.1, **<0.05, ***p<0.01; these represent significant p values.

5. Conclusions

This paper is a first attempt to evaluate the determinants of BRT system revenue/patronage potential and effectiveness. While the data collection for this analysis was more difficult than expected, by using BRTdata (2015) as a base and closing the gaps in this database with the help of BRT operators, it has been possible to establish sufficient data to evaluate not only input (and thereby extending existing PT performance measurement frameworks) but also partial cost effectiveness of BRT systems globally. This in itself is an important finding as it shows that the benchmarking of international BRT systems is possible and that such an exercise yields findings that are useful to operators, regulators transport authorities and policy makers.

The findings suggest that, in contrast to the two initial hypotheses, increasing the standard of the BRT system does not on average improve average fare levels (yields) but increases passenger numbers per network-km and thereby improves input effectiveness but not partial cost effectiveness. These results suggest that higher BRT standards would be favoured by operators (who are often regulated and therefore cannot set their fares freely) as this on average increases effectiveness (both when measured as PPM in terms of patronage per network-km and also as DEA input effectiveness) and total farebox revenues. In the discussion above, it was suggested that there might be a trade-off between capex (BRT standard) and revenue generating opex (Fleet). Whilst the analysis does not find that cost effectiveness is impacted by the BRT standard, the positive impact of BRT standard on input effectiveness suggests that the results for the BRT context are in line with already published literature around the performance measurement of conventional/ regular public bus transport (Obeng et al., 2016). Moreover, the results show similarity with heavy rail and metro systems (Tsai et al., 2015) with BRT systems generally benefiting from economies of scale, however also suffering from diseconomies of scale when cost effectiveness is considered (starting at BRT systems having an excess of 300 buses in their fleet).

Whilst the results presented in this paper are robust and provide useful insights to BRT system effectiveness across the globe, there are important limitations which present opportunities for future research. Most importantly, the analysis represents only a snapshot in time. It has become apparent, through talking to operators and examining individual BRT system data that many BRTs are still evolving or are in transition (being upgraded to a higher BRT standard or extended by one or more corridors). In the future it would be useful, data availability permitting, to evaluate the BRT system effectiveness and also efficiency over time and potentially also to treat different BRT corridors as separate businesses (assuming their accounts can be separated and appropriate control can be made for cross-subsidisation and network effects). Whilst great care was taken to ensure the sample of this analysis is representative in terms of size and spatial distribution, it does not include all BRT systems globally and the number of systems in existence is still growing. Future studies should aim to include more systems with all data for a consistent time period coming from the operators or their respective transport authorities, rather than secondary sources as this could improve data quality. In terms of our choice of input and output variables it is acknowledged that using monetary variables such as infrastructure cost and revenues instead of pure physical measures, may insert some bias to the model results. This follows from the way in which fare policies are often determined by PT contracts together with levels of subsidies (which are not always reflected by the status of the systems' ownership) and the way in which living costs, tax regulations, etc. greatly vary across different jurisdiction and are not captured by a simple conversion of local currency to $US. Once power purchasing parity (PPP) data of all countries in our sample becomes available the monetary values should be converted into PPP$ rather than US$ to account for these international differences. Moreover, the variable for fleet size does not account for the size of the buses and future research should attempt to use *"equivalent number of buses"* (as with *FTE*) once such data becomes available. Further research planned on comparing the results of our BRT analysis with the standards, level of services and effectiveness of cities and the PT system as a whole. In that sense our BRT analysis can be extended by analysing BRT synergies with the rest of PT lines, tariff integration, transfer points, etc.

Despite these limitations and suggestions for future research, the analysis shows that the existing data and proposed two-stage DEA benchmarking approach still produces valuable results which have the potential to improve the operation of current BRT systems, the planning and implementation of future systems and more generally to enrich the transport policy debate surrounding international BRT systems. Whilst the difficulty in obtaining data was initially a hurdle, the result has meant that this paper has developed an innovation in the extension of PT performance measurement frameworks by adding input effectiveness to the mix and perhaps more importantly, the analysis has demonstrated that this innovation contributes to knowledge and that there is a differentiation between input and cost effectiveness levels which is indeed useful to know but also that their determinants differ.

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