EFFICIENCY OF BUS PRIORITY INFRASTRUCTURE

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ABSTRACT

This paper estimates the impact of bus priority infrastructure on bus speeds using GPS data from approximately 660 routes daily between 2016 and 2019, resulting in over 48 million observations. The longitudinal structure of the data allows us to analyze year-to-year variation in the proportion of priority bus infrastructure, with a specific focus on two infrastructures with limited evidence regarding their effectiveness: bus lanes and corridors. Providing priority through a bus corridor to a bus trip increases its speed by 20 %. On the other hand, bus lanes are found to be substantially less effective than corridors. Back-of-the-envelope calculations reveal that providing priority infrastructure to a 5km corridor saves over US$1.2 million per year, solely due to shorter travel times.

1. INTRODUCTION

Road congestion is a significant challenge that adversely affects the quality of life for urban dwellers in large cities. This issue has been extensively studied, and the detrimental effects of congestion are well documented. Couture et al. (2018) estimated that the annual deadweight loss resulting from congestion is around US$30 billion in major US cities. This significant economic impact is due to increased travel times, fuel consumption, and emissions, resulting in lost productivity, increased health costs, and reduced economic growth.

The negative effects of congestion on employment growth are also well-documented. Hymel (2009) demonstrated that high congestion levels dampen employment growth, particularly in industries dependent on fast and reliable transportation. Congestion pricing, which charges drivers for using congested roads during peak hours, has been proposed as a solution to reduce congestion and restore economic growth. Hymel and Small found that congestion pricing could yield substantial returns in restoring growth and mitigating the negative impacts of congestion on employment. According to The Economist, the congestion cost in Great Britain, Germany, and the United States was estimated at US$461 billion in 2017. This high cost highlights the urgent need for policy interventions to mitigate congestion and its associated economic and social impacts, particularly in urban areas where congestion is most prevalent.

Congestion affects commuters directly but also imposes other social costs on the rest of the population, such as pollution and noise. Transportation is one of the main sources of greenhouse emissions in the world. For example, in 2020, transportation activities accounted for 36 percent of U.S. CO_2 emissions from fossil fuel combustion and the transportation sector generated the largest share (27 percent) of greenhouse gas emissions EPA (2022). Greenhouse gas emissions from transportation primarily come from burning fossil fuel for vehicles, as over 90 percent of the fuel used for transportation is petroleum-based, primarily gasoline and diesel.

However, after more than a century of economists advocating for road congestion charges, there are only a handful of examples where it has been implemented. These include London, Stockholm, Singapore, Milan, and Gothenburg. One explanation for the lack of implementation is the distributional concerns among drivers, as the benefit comes at the expense of those who desist from driving (see, e.g., De Borger y Proost, 2012, for a discussion).

More recently, theoretical articles with simulations have suggested that providing bus infrastructure may achieve similar benefits as second-best congestion pricing. For example, Basso y Silva (2014) find that providing bus infrastructure optimally may reap over 80 % of the benefits that car congestion pricing would bring in the case of London. Using data from Santiago, they show that it may even surpass congestion pricing from a welfare standpoint. A similar analysis is conducted by Börjesson et al. (2017). However, this strand of the literature assumes that bus lanes and corridors perfectly segregate buses from traffic and significantly improve travel times.

The bus rapid transit (BRT) system is a particularly attractive alternative to subways in developing country cities since it delivers similar reductions in commute times at a fraction of the cost and is much faster to build. These features have led to systems being built in more than 200 cities, the vast majority constructed over the past 15 years in Latin America and Asia (BRT Data 2017). The US is also embracing this alternative, as in 2020, the Federal Transit Administration awarded $375 million to build bus rapid transit infrastructure.

This paper estimates the impact of providing bus priority infrastructure on bus speeds. We use GPS data to obtain the average speed of every bus trip of the approximately 660 routes each day between 2016 and 2019, yielding over 48,000,000 observations. For each route, we compute the share of km traveled by type of road: mixed traffic, bus lane, segregated corridor, or others.

Our econometric strategy relies on novel data with the repeated observation of 665 bus routes between 2016 and 2019. The longitudinal structure of this information allows us to exploit year-to-year variation in the proportion of priority bus infrastructure. We focus on two infrastructures lacking evidence of their effectiveness: bus lanes and corridors. We exploit this variation within routes over time using two-way fixed effects. Using fixed effects by bus routes and years ensures that we compare bus speeds in the same route after it experienced variation in the proportion which prioritizes buses. To assess potential threats to identification, we show that changes in bus infrastructure are unrelated to prevailing bus speed. We also show the robustness of results to control for underlying factors which could have been driving the implementation of related policies.

Providing priority in the form of a bus corridor to a bus trip increases its speed by 20 %. To put this number in perspective, the impact of the London Congestion Charge in 2003 has been estimated to be approximately a 20 % increase in speed. Our analysis also reveals that bus lanes are substantially less effective than corridors. Our main estimates indicate a positive yet small and not statistically significant speed increase from bus lanes.

Our results have important policy implications. First, we make a back-of-the-envelope calculation of the value of travel time saved (VTTS) should a typical corridor without priority be provided with a 20 % speed increase. Using data from 2019, we estimate that giving the average priority infrastructure to the 5.4 km corridor "La Florida" saves over US$ 1.2 million per year only due to shorter travel times. Therefore, bus corridors can bring substantial welfare gains. Another implication is that bus lanes, often considered a reasonable alternative to bus corridors, cannot bring significant travel time savings. This informs policymakers to prioritize place-based transportation policies.

Our paper contributes to the recent literature on the effectiveness of bus-priority infrastructure. Adler et al. (2021) and Russo et al. (2021) report positive effects of bus lanes when estimating the marginal external cost of road travel and the benefit from transit provision in Rome. Russo et al. (2022) directly estimate the elasticity of bus travel time with respect to traffic density for regular roads and bus lanes. Using different demand elasticities, they evaluate the counterfactual reduction in bus travel time due to the introduction of separate dedicated bus lanes by assuming that the motor-vehicle density is reduced towards zero. We add to this literature by directly estimating the effect on travel times.

We also contribute to the literature on the welfare gains and distributional impacts of implementing BRT systems. Tsivanidis (2022) shows that implementing the bus rapid transit (BRT) system in Bogotá brought substantial welfare gains and can account for between 2.83-12.06 % of GDP growth in Bogotá from 2000 to 2016 and up to 29.24 % of the observed population growth. Balboni et al.

(2020) finds a large positive impact of Dar es Salaam's bus rapid transport system. Gaduh et al. (2022) study the expansion of the TransJakarta bus system in Jakarta, Indonesia, and find that it reduces travel time on the bus by about 13 percent, in addition to eliminating a transfer.

2. BACKGROUND

2.1. Transportation in Santiago

Transantiago is a multimodal transportation system in Santiago de Chile implemented in 2007. The system has been constantly reformed and improved and currently serves a population of over 8 million inhabitants and includes a combination of buses, metro and light rail services. The Metropolitan Public Transport Directory (DTPM), a state agency that depends on the Ministry of Transport and Telecommunication (MTT), coordinates and supervises the system. Bus services are contracted to six private companies, while publicly-owned companies operate the Metro and rail. Additionally, four other companies provide complementary services such as financial administration, smart card management, technological services for bus and Metro companies, and the smart card sales and charging network.

The Transantiago system has over 6,500 buses equipped with GPS devices. It operates daily in a network with 87 km of segregated busways, 300 km of bus lanes, and over 11,000 bus stops (DTPM, 2021). The integrated Metro network consists of 7 lines, 140 km of rails, and 136 stations, with plans for further expansion (DTPM, 2021). The fare scheme is based on trips, with a flat fare applied to trips of up to three stages within two hours. A small surcharge, larger during peak hours than other periods, is applied to Metro network trips. The payment system is based on a contactless smart card called "bip!,"the only payment method in buses and the most commonly used in the Metro, accounting for 97 % of payment transactions. Tapping off is not required in buses or the Metro due to the fare structure.

3. EMPIRICAL FRAMEWORK

3.1. Data

We combine two administrative datasets. First, we employ official GPS data for the universe of public buses in the city capital of Santiago—the largest in the country and inhabited by more than 8 million people—for the 2016-2019 period. These data were originally collected by the Ministry of Transportation. We observe the average speed (in kilometers per hour) of buses on each one of their trips. A trip is defined as the completion of a route. Buses make an average of 7 trips on the same route per working day, and multiple buses operate on the same route. Days are categorized into work days (Monday through Friday) and weekends (Saturday and Sunday). Days are divided into morning, afternoon, and night, and each is further divided into peak and non-peak hours. Peak hours are 7:30-9:00 A.M. and 6:00-7.30 P.M. on working days. Second, we use annual data on bus priority infrastructure in the same 2016-2019 period. In particular, we observe the total distance of a route (in kilometers) and the share of the route corresponding to mixed traffic, only bus lanes, and segregated corridors.

Given our interest in the impact of changing route infrastructure from year to year, we reduce the dimensionality of the bus speed data to the level of a route, and each one observed every year between 2016 and 2019. More precisely, we focus on a given day-time (e.g., peak hours on working days) and take the average bus speed across trips within route-year pairs, keeping track of the number of trips per route-year. This process reduces the number of observations from more than 100 million bus trips to a dataset recording information for 665 routes hosting trips during four years for a total of 2,419 observations. Our main estimating dataset measures the average bus speed per route during peak hours on working days each year from 2016 to 2019. We apply the same strategy to construct datasets for non-peak hours and subsets of days such as weekends for econometric exercises.

Table 1 presents descriptive statistics for the 665 routes in the main dataset. Buses travel at an average speed of 19.3 kilometers per hour. The average route has 17 kilometers, but some are shorter than 8 kilometers and some longer than 30 kilometers. The length of routes means that, on average, a bus takes 1.8 hours per round trip during peak hours on working days. Routes host more than 7,200 trips during these hours in the 2016-2019 period, a little more than 1,800 per year. Regarding infrastructure, on average, a route has 11 percent of bus lanes (2 km), almost doubling the availability of corridors at 6 percent. There is substantial heterogeneity in this priority infrastructure across routes, with many having none at all and some having more than one-third of their routes with this priority. More importantly, there is significant variation in infrastructure within routes without any particular trend: Bus lanes and corridors remain relatively constant at around 11 and 6 percent, respectively.

Tabla 1: Descriptive statistics for bus routes, 2016-2019

	Peak hours			
	Avg.	p10	p50	p90
	(1)	(2)	(3)	(4)
Speed (km/hr)	19.28	15.78	18.28	23.43
Distance (km)	17.03	8.01	15.26	30.04
% only bus	0.11	0	0.04	0.32
% bus corridor	0.06	0	0	0.23
Number of trips	7,234	4,198	6,572	11,319
Bus routes	665			
Observations	2,419			

Notes: This table shows annual descriptive statistics for 665 bus routes in 4 years (2016-2019) during peak hours in working days. The average route has 7,234 bus trips in four years, approximately 7 bus trips per working day.

3.2. Econometric Strategy

The core of our strategy focuses on peak hours in working days to relate bus priority infrastructure (e.g., corridors) and bus speed using the following econometric equation:

$$\log\left(\overline{Y}_{rt}\right) \quad = \quad \beta\, T_{rt} + \phi_r + \phi_t + \varepsilon_{rt} \tag{1}$$

where $\overline{Y}_{rt}$ is the average bus speed in route r during year t. The main right-hand side variable of interest is $T_{rt} \in [0, 1]$, which measures the percentage of the route with only bus lanes or corridors, depending on the specification. We exploit the construction of corridors and only bus lanes in the 2016-2019 period by estimating β using within-route variation. Operationally, we are able to compare routes with themselves in nearby years by including route fixed effects ϕ_r. In addition, we control for temporal shocks to the speed of buses—e.g., policy changes that affect the entire city—with year fixed effects ϕ_t. Below we show that results are also similar if we control for temporal shocks to a subset of observations, such as long routes. We allow the error term ε_{rt} to be arbitrarily correlated within routes. The coefficient of interest is β and measures the percentage increase in average bus speed after transforming the entire route to a bus lane or corridor. We estimate equation (1) by weighted least squares, using the number of bus trips as weights.

The causal interpretation of β requires primarily two identification assumptions. First, we need to assume the absence of unobserved variables correlated with only bus lanes or corridors and average bus speed *within* routes. An example of this threat would be the implementation of another infrastructure project on the same route, which also changes the average bus speed. To assess this concern, we explore the relation of interest across different types of days. Second, we need to assume that changes in lanes and corridors over time are not driven by bus speed in preceding years. This threat is simpler to analyze because we can empirically check whether infrastructure changes correlate with past bus speeds. In what follows, we provide further empirical evidence to support these assumptions.

4. MAIN RESULTS

4.1. Infrastructure and Speed

Column 1 in Table 2 presents estimates of equation (1) using peak hours in working days. Panel A shows that a ten percentage points (pp) increase in corridors is associated with an increase of 2 percent in bus speed (p-value<0.01), approximately 0.4 kilometers per hour faster. In contrast, panel B shows that only bus lanes are uncorrelated with bus speed. These patterns are similar across peak hours in the morning and the afternoon and non-peak hours (columns 5-7). In days with pre-emergency pollution, a share of high-polluting cars cannot go out in the streets, decreasing traffic significantly. Yet, in the absence of traffic, corridors should not affect bus speed. Weekends and nights provide a good testing ground. Columns 8-9 confirm this intuition and show a significantly more limited impact of corridors on bus speed during these days. In all, traffic appears to be an important mediator for the impact of corridors.

4.2. Threats to Identification and Robustness

Table 3 shows that the relationship between bus infrastructure and the bus speed is not driven by any particular month, it is robust to the inclusion of important control variables, and it remains similar when changing somewhat arbitrary specification decisions. Panel A shows that the estimated coefficients are the same when we exclude from the sample all trips that took place during the summer months (January and February), winter holidays (July), Christmas holidays (December), or all of these months at the same time. Similarly, results remain unchanged with the inclusion of the following control variables: route distance (in kilometers), indicators for the private firms in charge of the management and operation of bus routes, and the proportion of the route which takes place on highways. The positive relation between corridors and bus speed is also robust to measuring speed in levels instead of in logarithms, or changing the weight from trips to kilometers traveled.

The construction of bus infrastructure is mostly uncorrelated with the prevailing bus speed. Table 4 shows the results of this econometric exercise.

5. CONCLUSION

We have estimated the impact of providing bus priority infrastructure, namely bus lanes and corridors, on bus speeds. To our knowledge, we are the first to measure this direct effect. Our econometric strategy relies on novel data with the repeated observation of 665 bus routes between 2016 and 2019. The longitudinal structure of this information allows us to exploit year-to-year variation in the proportion of priority bus infrastructure. We exploit this variation within routes over time using two-way fixed effects.

Providing priority in the form of a bus corridor to a bus trip increases its speed by 20 %. To put this number in perspective, the impact of the London Congestion Charge in 2003 has been estimated to be approximately a 20 % increase in speed. Our analysis also reveals that bus lanes are substantially less effective than corridors. Our main estimates indicate a positive yet small and not statistically significant speed increase from bus lanes. Back-of-the-envelope calculations show that travel time savings alone can bring benefits of over $1 million per year in a 5km corridor

The paper provides policy insights that are relevant to the design and implementation of BRT. We have shown that quality matters and that if segregation is not enforced properly, the benefits may well vanish. Studying the potential heterogeneous effects of bus lanes as a natural avenue of future research.

Tabla 2: Main estimates

	Dependent variable: Logarithm bus speed (km/hr)							
	Work day: Peak hours			*Work day*: Non-peak hours				*Weekend*
	Avg.	Morning	Afternoon	Avg.	Morning	Afternoon	Night	Avg.
Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Percentage of route with corridor	0.21***	0.20***	0.22***	0.17***	0.21***	0.22***	0.05	0.11**
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.03)	(0.04)
Panel B								
Percentage of route with only bus lane	0.03	-0.05	0.09	0.03	0.04	0.05	-0.00	-0.02
	(0.09)	(0.12)	(0.07)	(0.09)	(0.11)	(0.09)	(0.07)	(0.08)
Observations	2,419	2,400	2,375	2,395	2,351	2,375	2,250	2,424
Bus routes	665	661	653	661	655	654	624	666
Trips (in millions)	17.5							
Route fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Average of dependent variable	19.28	19.89	18.99	21.84	21.92	20.55	24.94	21.38

Notes: Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Tabla 3: Robustness

Dep. variable: Log bus speed (in kilometers per hour)		
	Treatment of interest	
	Corridor	Only bus lane
Panel A: Excludes Holidays	(1)	(2)
Excludes January	0.21***	0.03
	(0.04)	(0.09)
Excludes February	0.21***	0.02
	(0.05)	(0.09)
Excludes July	0.21***	0.03
	(0.04)	(0.09)
Excludes December	0.22***	0.03
	(0.04)	(0.09)
Excludes all	0.23***	0.03
	(0.05)	(0.09)
Panel B: Includes Additional Controls		
Distance	0.21***	0.03
	(0.04)	(0.09)
i.Unidad	0.20***	0.04
	(0.04)	(0.09)
Highways	0.21***	0.08
	(0.04)	(0.07)
Panel C: Specification decisions		
Dependent variable in levels (km/hr)	3.95***	0.66
	(0.85)	(1.98)
Weight by kilometers traveled	0.17***	0.02
	(0.05)	(0.11)

Notes: Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Tabla 4: Exogeneity test for the construction of bus infrastructure

	ΔCorridors				ΔOnly bus lane			
	All	2016	2017	2018	All	2016	2017	2018
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log average bus speed	-0.04*	0.00	-0.02***	-0.00	-0.02	-0.02***	-0.00	-0.01
	(0.02)	(0.01)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.01)
Log distance	-0.04	-0.00	0.01	-0.00**	-0.00	0.02***	-0.00**	0.00
	(0.06)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)
Observations	1,802	646	648	529	1,802	646	648	529
R-squared	0.255	0.002	0.009	0.008	0.299	0.064	0.004	0.006

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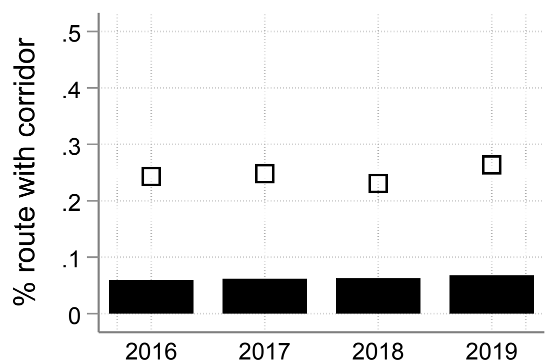
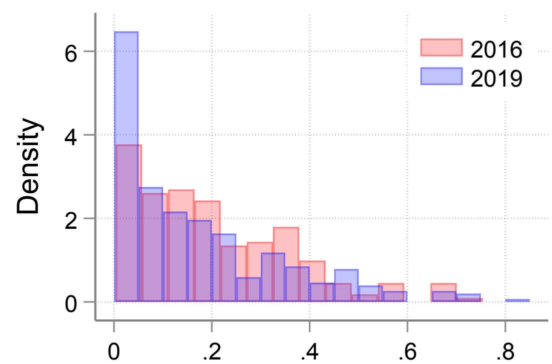
6. ADDITIONAL TABLES AND FIGURES

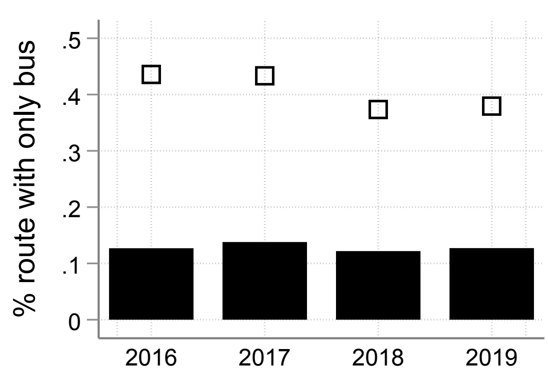
Figura 1: Corridors and only bus over time



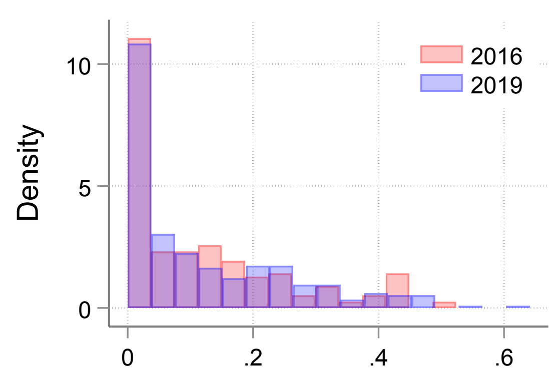
(a) Corridor



(b) Corridor



(c) Only bus



(d) Only bus

Notes: Panels A and C show the percentage of the route with bus corridors (panel A) and only bus lanes (panel B) every year in the 2016-2019 period. Vertical black bars show the average across 665 routes and the hollow squares show the 90*th* percentile. Panels B and D show the distribution of corridors and only bus in 2016 and 2019.

Tabla 5: Non-linear effects of infraestructure on bus speed

Dependent variable: Log bus speed		
	Corridor	Only bus
	(1)	(2)
Indicator for percentage $\in$ (0, 0.05]	0.00	0.00
	(0.01)	(0.01)
Indicator for percentage $\in$ [0.05, 0.10)	0.01	-0.01
	(0.01)	(0.01)
Indicator for percentage $\in$ [0.10, 0.15)	0.04***	-0.01
	(0.01)	(0.01)
Indicator for percentage $\in$ [0.15, 0.20)	0.05***	-0.01
	(0.01)	(0.02)
Indicator for percentage $\in$ [0.20, 0.25)	0.06***	0.00
	(0.02)	(0.03)
Indicator for percentage $\in$ [0.25, 0.30)	0.07***	0.00
	(0.02)	(0.02)
Indicator for percentage $\in$ [0.30, 0.35)	0.10***	-0.02
	(0.02)	(0.03)
Indicator for percentage $\in$ [0.35, 0.40)	0.09***	0.07
	(0.03)	(0.06)
Indicator for percentage $\in$ [0.40, 0.45)	0.09***	0.00
	(0.03)	(0.04)
Indicator for percentage $\geq$ 0.45	0.13***	0.06
	(0.02)	(0.04)
Observations	2,419	2,419
Bus routes	665	665
Route fixed effects	Y	Y
Year fixed effects	Y	Y

Notes: This table uses a panel data of routes observed yearly in the period 2016-2019 to estimate the impact of “bus only” and “corridors” lanes on the speed of public buses. All regressions are weighted by the number of trips in each route. Robust standard errors are clustered by bus route, i.e. 665 clusters. Statistical significance: *** p <0.01, ** p <0.05, * p <0.1.

Tabla 6: Heterogeneity by distance in route

	Dep. variable: Logarithm bus speed (km/hr)				
Distance in route (in km.):	<10	$\in [10, 15)$	$\in [15, 20)$	$\in [20, 25)$	>25
	(1)	(2)	(3)	(4)	(5)
Panel A					
Percentage of route with corridor	0.26***	0.34***	0.25**	0.22***	0.18
	(0.06)	(0.11)	(0.10)	(0.06)	(0.15)
Panel B					
Percentage of route with only bus lane	0.06	0.01	0.06	0.06	0.16
	(0.09)	(0.08)	(0.11)	(0.24)	(0.12)
Observations	727	580	423	290	317
Bus routes	204	165	125	90	98
Route fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Average of dependent variable in km/hr	18.77	18.96	19.51	20.05	19.86

Notes: Statistical significance: *** p <0.01, ** p <0.05, * p <0.1.