Efficiency of Bus Priority Infrastructure*

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Abstract

We use bus GPS data across 600 routes to estimate the impact of priority infrastructure on buses' speed in Chile. Almost 100 million observations allow us to leverage within-route variation in the proportion of the route with bus lanes or Bus Rapid Transit (BRT) corridors. Corridors increase bus speeds by 20% at peak hours. A rough estimation of the travel time savings yields that an average kilometer of corridor saves approximately US$ 300,000 per year in Santiago. However, bus lanes, often seen as an equally effective but cheaper alternative to a BRT corridor, are, on average, ineffective. We find that only when fully isolated from private vehicles coupled with monitoring cameras and enforcement bus lanes achieve the same travel time savings as BRT corridors. Importantly, those bus lanes cost only a fraction of the BRT corridors because the isolation is made by forming a bus-only street, which does not require significant capital investment. They use the same (regular) bus stops and do not feature off-board payment or platform-level boarding and alighting.

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1 Introduction

Bus Rapid Transit (BRT)[1] is gaining popularity as a cost-effective way to improve commuting, especially in developing countries. Compared to subways, BRT offers similar time savings at a significantly lower price and can be built much quicker. These benefits have led to a boom in BRT systems, with nearly 200 cities (mainly in Latin America and Asia) implementing them in the past 15 years. More recently, in 2023, the U.S. Department of Transportation's Federal Transit Administration announced awarded grants of over US$450 million to support bus rapid transit lines.[2] However, the worldwide upsurge of BRT corridors has faced opposition and criticism, too. For example, Gaduh et al. (2022) documents that Indonesia's TransJakarta, one of the world's largest BRT systems, did not reduce travel times but exacerbated congestion along service corridors. An explanation often provided for the lack of positive effects is the so-called "BRT Creep", a term coined to describe a phenomenon of downgrading an initially intended higher-quality BRT due to budgetary pressures during project implementation (Borsje et al., 2023).

In this paper, we offer new evidence of the impact of providing different types of bus priority infrastructure, including BRT corridors, on bus speeds. We rely on bus-level GPS data across 665 bus routes between 2016 and 2019 in Santiago, Chile, adding up to almost 100 million bus trips. The longitudinal structure of this information provides us with the extraordinary opportunity to exploit year-to-year variation in the proportion of priority bus infrastructure within routes over time. We study the performance of BRT corridors, (dedicated) bus lanes along private vehicles' lanes, and bus lanes that are fully isolated from other traffic implemented as bus-only streets. The main difference is that BRT corridors require substantial capital investment, and bus lanes are regular lanes with pavement markings. The difference between types of infrastructure can be seen in Figure 1.

Our econometric strategy is twofold. First, we exploit the infrastructure variation within routes over time using fixed effects by bus routes and years. The fixed effects ensure that we compare bus speeds on the same route after the route experiences variation in the proportion

[1]According to the Institute for Transportation and Development Policy (ITDP), Bus Rapid Transit (BRT) is a high-quality bus-based transit system that delivers fast, comfortable, and cost-effective services at metro-level capacities. It does this through the provision of dedicated lanes, with busways and iconic stations typically aligned to the center of the road, off-board fare collection, and fast and frequent operations.

[2]The announcements are to support BRT lines by the Twin Cities Metropolitan Council (Gold Line Bus Rapid Transit project), the Pittsburgh Regional Transit (Downtown-Uptown-Oakland line), and the Seattle Department of Transportation.

that prioritizes buses. To assess potential threats to identifying the impact of priority infrastructure, we show that changes in bus infrastructure are unrelated to previous bus speeds. We also show the robustness of results to control for underlying factors that could have been promoting the implementation of related policies.

The main result is that providing priority in the form of a BRT corridor, physically segregated from traffic to a bus trip, increases its speed by 20% at peak hours and by 15% at off-peak hours. According to the BRT Standard developed by the Institute for Transportation and Development Policy (ITDP), Santiago's corridors reach the minimum conditions to be defined as BRT corridors but are on the lower end of the quality spectrum. Nevertheless, they decrease travel times substantially. To put the 20% speed increase 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, often seen as an equally effective but cheaper alternative to a BRT corridor, are significantly less effective than corridors. Our main estimates indicate a positive yet small and not statistically significant speed increase from bus lanes. This result aligns with the anecdotal evidence that low-quality BRT corridors are ineffective.

We complement our primary empirical analysis described above with a difference-in-differences propensity score matching approach. We estimate the impact of two sets of events that help us uncover the variation in the average effect of bus lanes on bus speeds. The motivation is that we might observe imprecise estimates due to differences across bus lanes in Santiago. The first event is the implementation in March 2017 of a new bus lane supported by monitoring cameras.[3] A 1.5 km section of the "Santo Domingo" street was transformed into a bus-only two-lane street during workdays from 7:00 a.m. to 9:00 p.m. Except for residents, private vehicles were not allowed to use the street at all. The second event is the installation of monitoring cameras in June of 2018 on two already existing bus lanes ("Vespucio" and "Bilbao" avenues). These bus-only lanes are along two lanes for unrestricted traffic and are marked with painted pavement. This complementary analysis uncovers whether the lack of effect of bus lanes we find is due to a lack of enforcement or other reasons.

The inauguration of the bus-only street with monitoring cameras increased bus speeds, on average, by 3.6% and 7.8% at peak and non-peak hours, respectively. However, in our

[3] These bus lanes were part of the "Plan Centro" (Center Plan), implemented by the local government—the plan aimed to promote sustainable transport modes like walking, cycling, and public transport.

second event study, bus speeds are unaffected by the installation of monitoring cameras and enforcement on regular bus lanes. Importantly, these null results can confidently reject that the average bus speed increases by more than 4%. The seemingly contradictory results can be explained by the fact that most of the city's bus lanes, particularly those that received the installation of cameras in 2018, are alongside unrestricted traffic lanes. This induces the possibility of private vehicles congesting buses because they are permitted to use the bus lane to make right turns, which can be especially problematic at intersections with high pedestrian volumes. On the contrary, for the 2017 implementation, the entire two-lane street was restricted to buses only. Contrasting this coefficient with the estimates from a non-linear specification for corridors, we safely conclude that the 2017 bus lanes with monitoring cameras have a similar impact as the standard installation of BRT corridors observed in 2016-2019.

Our results have important policy implications relevant to the design and implementation of bus-priority infrastructure. 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 BRT corridor's 20% and 15% speed increase at peak and off-peak hours, respectively. Using a typical value of travel time savings for Chile (US$ 3 per hour), we estimate that a BRT corridor saves approximately US$ 300,000 per year per kilometer only due to shorter travel times.[4] Therefore, bus corridors can bring substantial welfare gains. However, the cost of implementing BRT corridors can be significant, too. The latest BRT Corridor in Santiago was reported to cost over US$ 10 million per kilometer by the Ministry of Transportation[5] This figure suggests that the investment could yield net benefits over a very long period.

Another implication is that bus lanes, often considered a reasonable alternative to bus corridors, do not necessarily bring significant travel time savings. Our analysis documents that the coexistence of bus and mixed traffic lanes, even when adequately enforced with monitoring cameras, inhibits the increase in the buses' speed. Therefore, the lack of dedicated right-of-way unexposed to mixed traffic can cause poor performance in some systems. This result is especially relevant for implementing the so-called BRT-Lite system, which, according to Kim and Ewing (2024), is the most common style of BRT in North America.

[4]For the calculation, we assume the following. The corridor has a load of 9,000 passengers per hour at peak times and 2,000 at off-peak. There are 260 working days per year and, as in our data, the peak period lasts four hours (6:30 to 8:30 and 18:00 to 20:00), and the off-peak lasts six hours (9:30 to 12:00, 14:30 to 17:00 and 21:30 to 22:30).

[5]Accessed on April 4, 2024..

Our results inform policymakers to prioritize place-based transportation policies. Bus lanes, the cheaper alternative to BRT corridors, may only work effectively when private vehicle presence is minimal. For example, Minnesota's first bus rapid transit line, the Gold Line, is 10 miles long and has a budget of $505.3 million. The Environmental Assessment's scenarios assume that buses run at least 27 kilometers per hour (16.9 mph). Our estimations suggest that this could only be achieved if the bus lanes' interaction with traffic is the least possible.

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 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 add 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 sizeable positive impact of Dar es Salaam's bus rapid transport system. Kreindler et al. (2023) 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.

Our work complements the literature on policies to deal with traffic congestion. Parry and Small (2009) and Hall (2021) make a strong case for pricing transit optimally and for implementing congestion pricing, respectively. On the other hand, studies such as Kutzbach (2009), Basso and Silva (2014), and Basso et al. (2019) find through numerical simulations that bus lanes and BRT corridors can yield similar benefits as second-best pricing measures. Gu et al. (2021) find that subways in China reduce traffic congestion substantially on initially congested roads, and Kreindler et al. (2023) studies the optimal bus network, including BRT corridors as part of the solution.

Finally, we contribute to the literature that leverages high-frequency big data in urban transportation. Examples include Kreindler and Miyauchi (2023), who estimates the spatial distribution of income in Dhaka from cell phone records, Gu et al. (2021), who estimates the impact of the opening of subway lines on pollution in China using real-time speed information at the road segment level, and Chaves Maia (2022) who studies the impact of high-intensity rain on bus speeds in Rio de Janeiro using, as we do, the city buses' GPS information.

2 Background

We study the effect of bus priority infrastructure in the Greater Santiago Area (henceforth, Santiago) between 2016 and 2019. Santiago is the capital and largest city of the country, accounting for over 40 percent of the country's population and GDP (Banco Central, 2017). It has an extension of approximately 838 km^2 (INE, 2018), slightly larger than New York City, and is inhabited by more than 8 million people. In October 2019, several protests disrupted the entire city of Santiago for months (González and Prem, 2023). To avoid possible confounding effects, we use the data until September 2019.

Santiago's current multimodal public transportation system was implemented in 2007 under the name of *Transantiago*, inspired by Bogotá's *TransMilenio*, the world's first large-scale Bus Rapid Transit system. The reform included the implementation of 225 km of segregated bus corridors. Still, when Transantiago was introduced, there were only 13 km of bus corridors, 11 km of bus lanes, and 8 kilometers of roads that could only be used by public transport during peak hours (Gómez-Lobo, 2012). Since then, several Public Transport Infrastructure Master Plans have been approved to catch up with the original promise. By 2011, there were 90 km of bus corridors and 101 km of bus lanes (Muñoz et al., 2014).

The Metropolitan Public Transport Directory (DTPM) is the state agency (within the Ministry of Transport and Telecommunication) that coordinates and supervises the system. In our study period, bus services were contracted to six private companies, while publicly-owned companies operated the Metro and rail lines. Additionally, four other companies provide complementary services such as financial administration, smart card management, technological services for bus and metro companies, and smart card sales and charging networks.

Currently, 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). In 2019, the system transported an average of 5.8 million people monthly (DTPM, 2019). 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 used for 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 metro, accounting for 97% of payment transactions. Due to the flat fare structure, there is no tapping-off system.

Engineering studies about Santiago's bus priority infrastructure have shown that buses traveling in mixed traffic have a larger mean travel time and variability than buses in bus lanes and corridors. For example, Durán-Hormazábal and Tirachini (2016) combines GPS data with data from surveyors performing and recording trips on several days between 2007 and 2011. Their study focuses on estimating the probability distributions for travel time by car, bus and metro. Still, they do report different mean travel times for bus trips with and without priority. Gibson et al. (2016) estimates an engineering model for passenger bus travel times and simulates scenarios to evaluate the potential benefits of implementing a dual carriageway median busway.

3 Priority Infrastructure and Bus Speed

This section presents our data, econometric strategy, and estimates for the effect of bus priority infrastructure on bus speeds. We leverage the observation of the speed of thousands of buses in almost 665 routes over four years. This information, coupled with annual measurements of infrastructure for each route, allows us to examine changes in bus speed within routes over time as a response to changes in bus priority infrastructure.

3.1 GPS and infrastructure data, 2016-2019

We combine two administrative datasets. First, we employ official GPS data for the universe of public buses in the city capital of Santiago for the 2016-2019 period. The Ministry of Transportation, which is part of the central government, originally collected this data. 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 day, and multiple buses operate on a given route. This leads to over 95 million observations. Days are categorized into workdays (Monday-Friday) and weekends (Saturday and Sunday). A day is divided into morning, afternoon, and night, and each is further divided into peak and off-peak hours with a transition period between them. The peak hours go from 6:30 a.m. to 8:30 a.m. and 6:00 p.m. to 8:00 p.m. on workdays. Off-peak periods are from 9:30 a.m. to 12:00, 2:30 p.m. to 5:00 p.m. and 9:30 p.m. to 10:30 p.m. on workdays. Second, we use annual data on bus priority infrastructure in the same period. In particular, we observe the total distance of each route (in kilometers) and the share of the route corresponding to mixed traffic, bus lanes, and BRT corridors. Figure 1 displays the difference between the types of bus priority infrastructure that we study.

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 is 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 95 million bus trips to a dataset recording information for 665 routes hosting trips during four years for a total of 2,419 observations. Our primary 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 all hours during the weekend.

Columns 1-3 in panel A of Table 1 present descriptive statistics for the 665 routes in the main dataset. Buses travel at an average speed of 19.2 kilometers per hour at peak periods. The average route is 17 kilometers, but some are shorter than 8 kilometers, and some are longer than 30 kilometers. The existing length of routes implies that, on average, a bus takes 1.8 hours per round trip during peak hours on workdays. Routes host more than 7,800 trips during peak hours in the 2016-2019 period, a little more than 1,900 per year. The remaining columns provide similar statistics for non-peak hours (columns 4-6) and all hours during the weekend (columns 7-9). As expected, the speed of buses increases in non-peak hours and during the weekend, which allows them to make more trips per route. Panel B presents descriptive statistics for priority infrastructure. On average, a route has 11 percent of bus lanes (2 km), almost doubling the availability of BRT 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. Columns 4-9 show that the routes used during non-peak hours and weekends are essentially the same as those used during peak hours.

3.2 Econometric strategy

Our first econometric estimation relates bus priority infrastructure (BRT corridors or bus lanes) and average bus speed in a route-year using the following regression equation:

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

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 bus lanes or corridors, depending on the specification. We exploit the construction of corridors and bus lanes in the 2016-2019 period by estimating β using within-route variation. Operationally, we can 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. We allow the error term ε_{rt} to be arbitrarily correlated within routes (i.e., we use route-level clustering). 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 BRT corridor. We estimate equation (1) by weighted least squares, using the number of bus trips as weights, and estimate it separately for peak, non-peak, and all weekend hours.

The causal interpretation of β requires primarily two identification assumptions. First, we must assume the absence of unobserved variables correlated with 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 bus lanes and corridors over time have not been driven by bus speeds in the preceding years. This threat is more straightforward to analyze because we can empirically check whether infrastructure changes correlate with past bus speeds. Table A.1 supports our econometric analysis by showing that changes in infrastructure (corridors and bus lanes) between year t and $t + 1$ are empirically unrelated to bus speed in year t.

3.3 Results

Column 1 in Table 2 presents estimates of equation (1) for workday peak hours. Panel A shows that a 10 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 bus lanes are uncorrelated with bus speed. However, the latter empirical relationship is notably noisier; thus, we cannot rule out that some bus lanes in the city could significantly increase bus speed. We further study this hypothesis by examining different types of bus lanes in the following section. The patterns documented for peak hours are smaller during non-peak hours (column 2) and absent during the weekend (column 3) when buses approach their maximum speed and traffic is notoriously lower.[6] Overall, corridors increase bus speed, with traffic being a likely mediator variable.

Table A.3 shows that all previously discussed results are robust to excluding specific months of the year (e.g., January), including important route-level control variables, and changing relatively arbitrary specification decisions related to measurement and weights. Panel A shows that the estimated coefficients are the same when we exclude from the sample all bus 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 ("Business Unit"), and the proportion of the route that takes place on highways. All results are also robust to measuring bus speed in levels instead of logarithms, not using weights, or changing the weights from trips to kilometers traveled.

4 Infrastructure Events

To uncover the variation in the average impact of bus lanes on bus speeds (see panel B in Table 2), we study the effect of two types of related infrastructure events. The motivation behind this section is that we might observe imprecise estimates in the previous section because bus lanes only increase bus speeds when the priority is adequately enforced. The primary enforcement method is to couple bus lanes with monitoring cameras that detect the

[6] Table A.2 presents estimates from a non-linear specification of equation (1) and shows that the effect of priority lanes is monotonically increasing in the percentage of the route with priority infrastructure.

presence of other vehicles (e.g., cars) using these lanes and allow the police to impose fines. Hence, the small positive but imprecise estimate in panel B of Table 2 might be the result of a minor impact of a large set of lanes that lack monitoring cameras and a larger effect of a small set of lanes that have supporting cameras to enforce priority. The imprecise estimate might also be due to the heterogeneity of the type of bus lane in place. The most common bus lane in the city is a single curbside lane alongside one or more unrestricted traffic lanes. This mix allows for congestion from private vehicles to buses because they are allowed to use the bus lane to make the right turns and stop temporarily. The second type, far less common, is to create a one- or two-lane street for buses only. The difference is that, except for residents, private vehicles are not allowed to use the street at all during working hours.

4.1 Inauguration and installations

We begin by estimating the effect of bus lanes forming a bus-only street whose enforcement is supported by monitoring cameras. These were inaugurated in locations that impacted a small number of routes. We use the variation introduced by the "Plan Centro" (Center Plan) policy implemented in March 2017. The local government of Santiago developed this initiative, and transportation-related institutions from the central government supported it. The plan's ultimate goal was to incentivize the use of sustainable transport modes, such as walking, cycling, and public transport. The part of the plan relevant to our study is the creation of bus lanes with camera enforcement. In March 2017, a 1.5km section of a street ("Santo Domingo") was changed from an ordinary mixed-traffic street to being available only for buses (bus lanes) during workdays between 7:00 a.m. and 9:00 p.m. We study 11 routes affected by this part of the plan.

The second set of events we studied was the installation of monitoring cameras on routes that already had bus lanes. The central government designed and implemented the plan to install 156 new cameras across six municipalities in June of 2018, after reports that bus lanes were ineffective due to the lack of monitoring. After one month of piloting the functioning of cameras, enforcement of traffic fines of approximately US$50 was given to people who were photographed driving cars into priority lanes in two consecutive cameras. The cameras are installed at intersections. We study how bus speed changed in 15 routes affected by these monitoring cameras.

4.2 Matched difference-in-differences

To estimate the average change in bus speed after the inauguration of bus lanes and installations of monitoring cameras, we estimate the following econometric equation:

$$Y_{rt} \;=\; \sum_{t=-6} \beta_t D_{rt} + \theta_r + \theta_t + \varepsilon_{rt} \tag{2}$$

where Y_{rt} is the logarithm of the average speed (in km/hr) of all buses operating in route r during month t. The sample period starts in January 2016 and ends in September 2019 to avoid confounding from the large protests that disrupted Santiago from October of that year onwards (González and Prem, 2023). Each indicator D_{rt} takes the value of 1 if route r is observed t months after the event of interest. We use the month before the event $t = -1$ as the omitted category. Our interest is in the parameters β_t, which, given the omitted category, measure the effect of the infrastructure event on bus speed t months after their inaugurations or installations. All specifications include fixed effects by route (ϕ_r) and month-year (θ_t). We allow the mean-zero error term ε_{rt} to be arbitrarily correlated within routes over time with the use of route-level clustering. We estimate equation (2) separately for peak hours during workdays, non-peak hours during workdays, and all hours during the weekend.

The regression of equation (2) compares routes experiencing infrastructure events to a selected group of control routes. We carefully select the group of control routes using a propensity score matching algorithm. This data-driven method is particularly useful in our empirical context because of our dataset's availability of more than 750 bus routes and the observability of key route characteristics. We proceed in four steps. First, we focus on the cross-section of 750 routes in the period before the infrastructure events under study. Second, we estimate a linear probability model using as a dependent variable an indicator that takes the value of one if there is an infrastructure event in route r and zero otherwise (I_r). We employ the following covariates (x_r) as predictors: route distance (km), average bus speed in the route (km/hr), and the number of trips in the route. Third, we predict the probabiilty $\widehat{p}_r \equiv \widehat{p}_r(I_r = 1|x_r) \in [0, 1]$ that each route r has an infrastructure event. Fourth, we select ten control routes per each route that experiences an infrastructure event using (i) the Mahalanobis distance in $\widehat{p}_r$ as the matching criteria, and (ii) restricting attention to routes with common support in the propensity score distribution.[7] Overall, this procedure

[7] Lack of overlap in the propensity score distribution across treatment and control units leads to unstable estimators with variance that may explode in finite samples (Frölich, 2004; Khan and Tamer, 2010).

selects 81 and 121 control routes for inaugurations and installations, respectively.[8]

4.3 Results

Figure 2 presents our estimates for the effect of inaugurations on bus speed together with 95 percent confidence intervals. Overall, we find that the inauguration of bus lanes forming a bus-only street with monitoring cameras increased bus speeds. On average, bus speed increases by 3.6%, 7.8%, and 0.5% in peak, non-peak, and weekend hours respectively. The magnitude of this coefficient is similar to the construction of a corridor that changes the percentage of a route with a corridor from 5 to 10% (column 1 in Table A.2). Given that the events we study correspond to approximately changing 5% of the route, we can safely conclude that these bus lanes with monitoring cameras have a similar impact to the standard installation of BRT corridors observed in 2016-2019. Given the lower traffic and higher average bus speed, the lack of an effect of these infrastructure events during weekend hours is expected.

The dynamic impact of the infrastructure events in Figure 2 is also worth mentioning. Bus speed changes little in the first 5-6 months after the inauguration of these monitored lanes. The higher bus speed we have documented only begins to materialize six months after installation. In fact, bus speed slowly increases from month 7 to months 10-12 when it seems to reach a new speed equilibrium. Of course, these speed effects constitute the impact of bus lanes forming a bus-only street together with the monitoring cameras. Theoretically, the effect could be explained by one of these or by their combination.

Figure 3 examines the effect of monitoring cameras installed on top of already operating bus lanes alongside unrestricted traffic. In contrast to the previous findings, the estimates show that bus speed is unaffected by the installation of cameras. Importantly, these null results can confidently reject that average bus speed increases by more than 4%. The lack of an impact of cameras is similar during peak hours, non-peak hours, and all hours on the weekend.

[8] The average propensity score in the treatment group is 0.045 and 0.036 in the control group. Figure A.1 shows the probability that each one of the routes gets an infrastructure event $\widehat{p}_r$.

5 Discussion

Our research measures the direct causal effect of different bus priority infrastructures on bus speeds. We found that a BRT corridor can increase the speed of a bus trip by 20%, a significant finding. In contrast, our main estimates show a small and statistically insignificant speed increase from bus lanes. However, a deeper analysis reveals that implementing a bus-only street by converting mixed traffic lanes into bus lanes with monitoring cameras and enforcement increased bus speeds significantly.

While the average bus lane does not seem to improve speeds, the performance of the bus-only street is as good as the average BRT corridor. The critical difference between bus lanes is how they interact with traffic from private vehicles. Most of the city's bus lanes and those that received the installation of cameras in 2018 are alongside unrestricted traffic lanes. This mix allows for congestion from private vehicles to buses because they use the bus lane to make the right turns, which can be especially problematic at intersections with high pedestrian volumes. On the contrary, for the 2017 implementation, the entire two-lane street was restricted to buses only.

This paper provides critical policy recommendations directly applicable to designing and implementing adequate bus-priority infrastructure. Our analysis demonstrates that bus lanes, downgraded BRTs, or the so-called BRT-Lite, are significantly less effective than dedicated BRT corridors. Even when adequately enforced, the coexistence of mixed traffic and bus lanes can impede the increase in bus speeds and, therefore, the benefits from the infrastructure. This underscores the importance of dedicated right-of-way for bus lanes, as the lack of such infrastructure free from mixed traffic can lead to the underperformance of some systems.

Our results also help better interpret the implications derived in the literature based on numerical simulations. Several papers have suggested that providing bus infrastructure may achieve benefits similar to second-best congestion pricing. For example, Basso and Silva (2014) find that providing bus infrastructure may reap over 80% of the benefits that car congestion pricing would bring in the case of London. Using Santiago data, they show that bus lanes may even surpass congestion pricing from a welfare standpoint. Börjesson et al. (2017) conduct a similar analysis for Stockholm. With a different approach Basso et al. (2019) show that the implementation of BRT can benefit car drivers, bus users and operators if a fleet increase accompanies the policy. Our paper shows that the results in this strand of the literature may be valid only when bus lanes are fully segregated from private vehicles.

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Table 1: Descriptive statistics for bus routes and infrastructure, 2016-2019

	Peak hours			Non-peak hours			Weekend		
	Avg.	p50	St. dev	Avg.	p50	St. dev.	Avg.	p50	St. dev.
Panel A: Buses and routes	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Speed (km/hr)	19.2	18.2	4.2	21.7	20.4	5.4	25.0	23.4	6.2
Route distance (km)	17.0	15.3	8.5	17.0	15.3	8.4	17.2	15.4	8.5
Trips per route	7,818	7,088	3,319	10,107	10,162	5,752	8,919	9,355	5,036
Panel B: Infrastructure									
Percentage of route with bus lanes	0.11	0.04	0.15	0.11	0.04	0.16	0.11	0.04	0.16
Percentage of route with corridors	0.06	0.00	0.12	0.06	0.00	0.12	0.06	0.00	0.12
Bus routes	665			662			641		
Observations	2,421			2,400			2,285		

Notes: This table shows annual descriptive statistics for 665 bus routes in 4 years (2016-2019) during peak (columns 1-3) and non-peak (columns 4-6) hours in working days, and for all hours during the weekend (columns 7-9). The average route has approximately 7,000 bus trips in four years, or 7 bus trips per working day.

Table 2: Priority infrastructure and bus speed

Dependent variable: Logarithm bus speed (km/hr)			
	Work days		
	Peak hours	Non-peak hours	Weekend
Panel A	(1)	(2)	(3)
Percentage of route with bus corridors	0.20***	0.15***	-0.03
	(0.04)	(0.04)	(0.04)
Panel B			
Percentage of route with bus lanes	0.03	0.03	0.03
	(0.08)	(0.08)	(0.07)
Observations	2,421	2,400	2,285
Bus routes	665	662	641
Trips (in millions)	18.9	24.0	20.0
Avg. dep. variable (km/hr)	19.20	21.72	24.99
Route fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y

Notes: Each observation is a route in each of the four years between 2016 and 2019. All six regression estimates include route and year fixed effects. Peak hours go from 6:30 a.m. to 8:30 a.m. and 6:00 p.m. to 8:00 p.m. on workdays (Monday-Friday). Standard errors are clustered at the route level. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 1: bus lanes and corridors

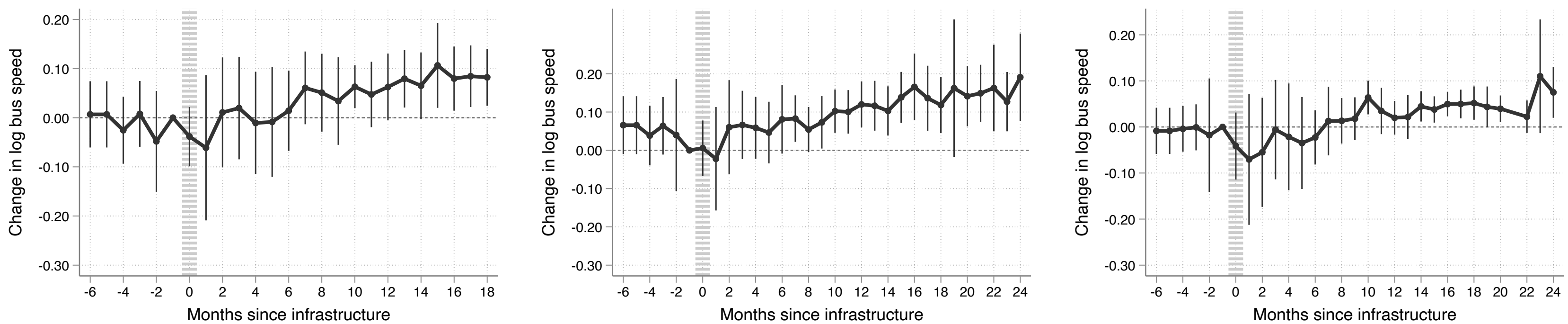
(a) Bus lane alongside unrestricted traffic.

(b) Bus lanes forming a bus-only street

(c) BRT Corridor

Notes. Examples of the priority infrastructure we study. All photos are from routes in our dataset.

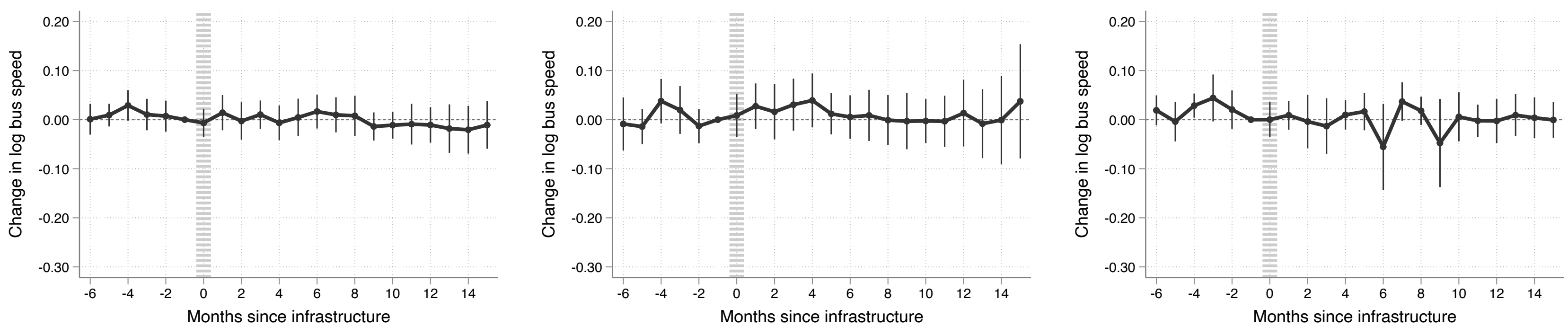
Figure 2: Bus lanes forming a bus-only street with monitoring cameras



(a) Workday peak hours (b) Workday non-peak hours (c) All hours during the weekend

Notes. Each observation is a route in a month around the infrastructure events under study (March 2017). The events are the openings of bus lanes, which form a bus-only street that includes cameras monitoring the usage of these lanes. The number of treatment (control) routes is 11 (81). Control routes are chosen by a propensity score matching algorithm. All estimates include route and year fixed effects. Peak hours go from 6:30 a.m. to 8:30 a.m. and 6:00 p.m. to 8:00 p.m. on workdays (Monday-Friday). Black dots represent point estimates, and vertical lines represent the 95 percent confidence interval. Standard errors are clustered at the route level.

Figure 3: Monitoring cameras on top of already existing bus lanes



(a) Workday peak hours

(b) Workday non-peak hours

(c) All hours during the weekend

Notes. Each observation is a route in a month around the infrastructure events under study (June 2018). The events are installations of cameras on top of already existing bus lanes to enforce the bus priority. The number of treatment (control) routes is 15 (121). Control routes are chosen by a propensity score matching algorithm. All estimates include route and year fixed effects. Peak hours go from 6:30 a.m. to 8:30 a.m. and 6:00 p.m. to 8:00 p.m. on workdays (Monday-Friday). Black dots represent point estimates and vertical lines the 95 percent confidence interval. Standard errors are clustered at the route level.

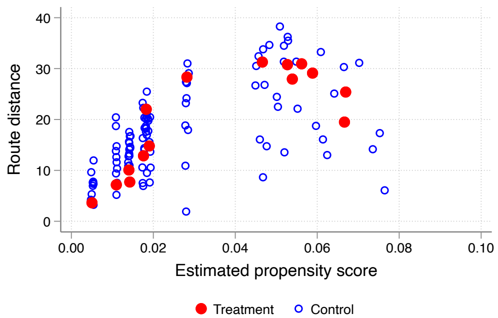
ONLINE APPENDIX

Hugo Silva and Felipe González

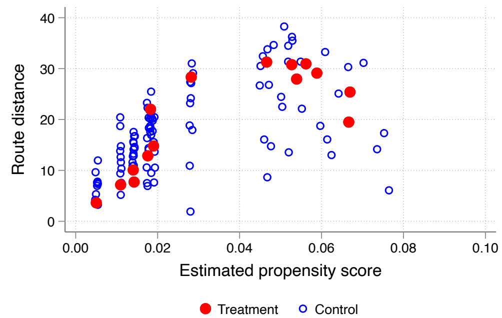
List of Figures

List of Tables

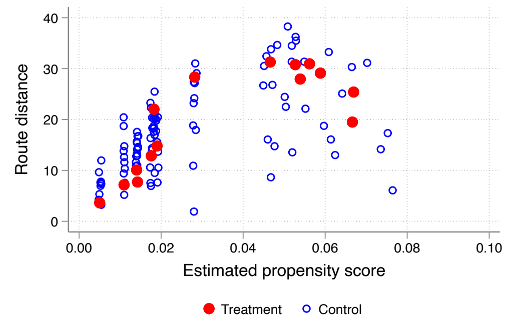
Figure A.1: Estimated propensity score



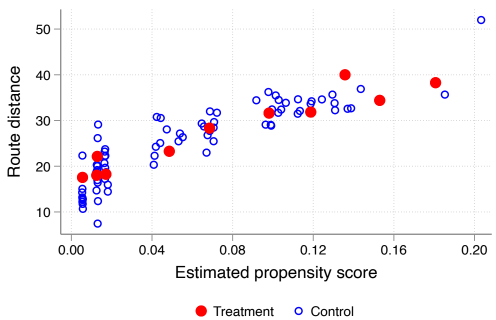
(a) Cameras Only, peak



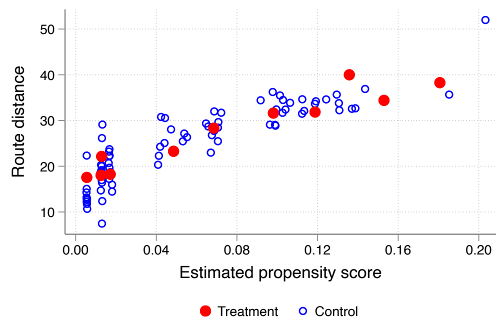
(b) Cameras Only, non-peak



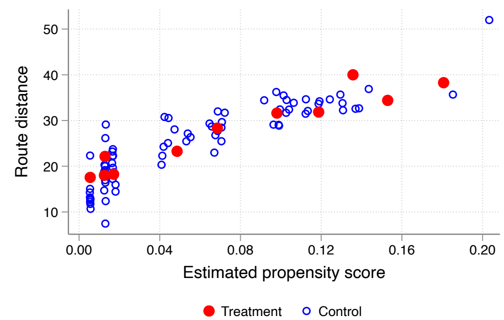
(c) Cameras Only, weekend



(d) OBL and Cameras, peak



(e) OBL and Cameras, non-peak



(f) OBL and Cameras, weekend

Notes. Estimated propensity score. The number of treatment/control routes is 15/121.

Table A.1: Exogeneity test

Dependent variable: Change in priority infrastructure next year			
	Work days		
	Peak hours	Non-peak hours	Weekend
Panel A: corridors	(1)	(2)	(3)
Log bus speed	-0.03	-0.02	0.03
	(0.03)	(0.02)	(0.02)
Panel B: bus lanes			
Log bus speed	-0.02	-0.02	-0.05*
	(0.02)	(0.02)	(0.02)
Observations	1,804	1,790	1,706
Bus routes	645	642	620
Trips (in millions)	14.7	18.7	16.1
Avg. dep. variable panel A (%)	0.006	0.005	0.005
Avg. dep. variable panel B (%)	0.005	0.005	0.005
Route fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y

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

Table A.2: Non-linear effects of priority infraestructure

	Dependent variable: Log bus speed					
	Peak hours		Non-peak hours		Weekend	
	Corridor	Only bus	Corridor	Only bus	Corridor	Only bus
	(1)	(2)				
Indicator for percentage $\in$ (0, 0.05]	-0.00	0.00	-0.00	-0.01	0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Indicator for percentage $\in$ [0.05, 0.10)	0.00	-0.01	0.01	-0.01	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Indicator for percentage $\in$ [0.10, 0.15)	0.03***	-0.01	0.02**	-0.00	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Indicator for percentage $\in$ [0.15, 0.20)	0.04***	-0.01	0.04***	-0.01	-0.00	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Indicator for percentage $\in$ [0.20, 0.25)	0.05***	0.01	0.05**	-0.00	0.01	0.01
	(0.02)	(0.03)	(0.02)	(0.03)	(0.01)	(0.02)
Indicator for percentage $\in$ [0.25, 0.30)	0.07***	-0.00	0.04**	0.00	0.03	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Indicator for percentage $\in$ [0.30, 0.35)	0.09***	-0.02	0.08***	-0.00	0.03*	-0.00
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Indicator for percentage $\in$ [0.35, 0.40)	0.09***	0.05	0.04	0.05	0.01	0.03
	(0.03)	(0.05)	(0.03)	(0.05)	(0.02)	(0.04)
Indicator for percentage $\in$ [0.40, 0.45)	0.08***	-0.01	0.07**	0.02	0.03	-0.01
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)
Indicator for percentage $\geq$ 0.45	0.12***	0.04	0.08***	0.07	0.01	0.03
	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)	(0.04)
Observations	2,421	2,421	2,400	2,400	2,285	2,285
Bus routes	665	665	662	662	641	641
Route fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	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.

Table A.3: Robustness to model specifications

	Dep. variable: Log bus speed (in kilometers per hour)					
	Peak hours		Non-peak hours		Weekend	
	Corr	OBL	Corr	OBL	Corr	OBL
Baseline specification	*0.20****	*0.03*	*0.15****	*0.03*	*-0.03*	*0.03*
	(0.04)	*(0.08)*	*(0.04)*	*(0.08)*	*(0.04)*	*(0.07)*
Panel A: Sample composition						
Excludes January	0.20***	0.02	0.14***	0.03	-0.04	0.04
	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.07)
Excludes February	0.21***	0.02	0.15***	0.03	-0.04	0.03
	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.07)
Excludes July	0.20***	0.03	0.14***	0.02	-0.03	0.02
	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.07)
Excludes December	0.21***	0.03	0.16***	0.03	-0.03	0.03
	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.07)
Excludes all	0.22***	0.02	0.15***	0.03	-0.04	0.02
	(0.05)	(0.08)	(0.04)	(0.09)	(0.04)	(0.07)
Panel B: Specification decisions						
Adds controls: log route distance	0.20***	0.02	0.15***	0.02	-0.03	0.03
	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.07)
Adds controls: Unit effects	0.20***	0.04	0.14***	0.04	-0.04	0.04
	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.07)
Adds controls: Highways	0.20***	0.07	0.15***	0.05	-0.03	0.04
	(0.04)	(0.06)	(0.04)	(0.07)	(0.04)	(0.06)
Dependent variable in levels (km/hr)	3.78***	0.60	3.08***	0.79	-0.45	0.99
	(0.80)	(1.76)	(0.91)	(1.95)	(0.96)	(2.05)
Without weights by trips	0.26***	-0.01	0.18**	-0.01	0.01	-0.12
	(0.03)	(0.11)	(0.09)	(0.10)	(0.22)	(0.08)
Weighted by kilometers traveled	0.16***	0.02	0.13***	0.04	-0.02	0.05
	(0.05)	(0.09)	(0.05)	(0.10)	(0.04)	(0.09)

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