

# Efficiency of Bus Priority Infrastructure\*

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## Abstract

We use bus GPS data across 500 routes to estimate the impact of priority infrastructure on buses' speed and ridership in Chile. Almost 100 million bus trips allow us to leverage within-route variation in the proportion of the route in which buses travel along bus lanes or Bus Rapid Transit (BRT) corridors. Corridors increase bus speeds by 20% at peak hours. Bus lanes, often seen as an equally effective but cheaper alternative to a BRT corridor, are, on average, ineffective. However, bus lanes achieve the same travel time savings as BRT corridors only when fully isolated from private vehicles, coupled with monitoring cameras and enforcement.

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# 1 Introduction

Bus Rapid Transit (BRT) is gaining popularity as a cost-effective way to improve commuting, especially in developing countries.<sup>1</sup> Compared to subways, BRT offers similar time savings at a 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 BRT corridors. As Borsje et al. (2023) discuss, while there are lower-cost alternatives, such as dedicated bus lanes and monitoring cameras, their impacts remain unclear.

In this paper, we offer new evidence of the impact of providing different types of bus priority infrastructure, including BRT corridors, on bus speeds and ridership. We rely on bus-level GPS data across 500 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 and (dedicated) bus lanes. BRT corridors are always fully isolated from other traffic; however, bus lanes are usually not. During our study period, Santiago implemented both traditional bus lanes (along unrestricted traffic) and bus lanes that were fully isolated from other traffic and implemented as bus-only streets. The main difference is that BRT corridors require substantial capital investment, and bus lanes in either form are regular lanes with pavement markings. The three types of infrastructure can be seen in Figure A.1.

Our econometric strategy is twofold. First, we exploit the infrastructure variation within routes over time using fixed effects by route and year. The fixed effects ensure that we compare bus speeds on the same route after the route experiences variation in the proportion that prioritizes buses. This strategy uses data about the share of each route traveling across bus lanes or corridors, which is published only once per year. We study, therefore, the impact of the average corridor and bus lane using the variation experienced by each route from year to year. To assess threats to our analysis, 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.

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<sup>1</sup>The Institute for Transportation and Development Policy (ITDP) defines BRT as a high-quality bus-based transit system that delivers fast, comfortable, and cost-effective services at metro-level capacities through the provision of dedicated lanes, among other features.

The main result is that providing priority with a BRT corridor, physically segregated from traffic, increases buses’ speed by 20% at peak hours and by 15% at off-peak hours. According to the BRT Standard developed by the ITDP, Santiago’s BRT corridors are on the lower quality spectrum. Nevertheless, they improve travel times substantially. Our analysis also reveals that bus lanes, often seen as equally effective but cheaper than a BRT corridor, are significantly less effective on average. Our main estimates indicate a positive yet small and statistically insignificant speed increase from bus lanes. This result aligns with the anecdotal evidence that low-quality BRT corridors are ineffective. As discussed above, Santiago implemented bus lanes along unrestricted traffic and fully isolated bus lanes, forming a bus-only street. Moreover, some bus lanes have monitoring cameras and enforcement, and others do not. The various types of bus lanes suggest that our estimate may mask heterogeneous effects.

We investigate possible heterogeneous effects with a matched difference-in-differences approach. In this part, instead of using the annual transit infrastructure dataset, we look at infrastructure events (e.g., implementation of bus lanes on a specific date). We estimate the impact of three projects, each affecting a subset of routes in our dataset of bus speeds. The first project is the construction of a 9 km BRT corridor (on *Vicuña Mackenna* avenue) in December 2017 that allows for comparing the impact of corridors across empirical strategies. The corridor affected 12 routes, increasing their average share in a corridor by 45 pp. The second project is the implementation in March 2017 of a new bus lane supported by monitoring cameras. 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. It increased the routes’ average share in bus lanes by approximately 5 pp. Private vehicles were not allowed to use the street except for residents. Finally, the third project is the installation of monitoring cameras in December 2016 on an already existing 6 km bus lane (“Macul – José Pedro Alessandri” avenue). These bus-only lanes are along two lanes for unrestricted traffic, are marked with painted pavement, and affect 12 routes.

The inauguration of the BRT corridor increased bus speeds, on average, by 6.7% and 5.4% at peak and off-peak hours, respectively. As the routes’ change in their share traveled in a corridor was 45 percentage points, results are consistent with those discussed above. The bus-only street with monitoring cameras of the second project increased bus speeds, on average, by 5.4% and 4.7% at peak and off-peak hours, respectively. In contrast, 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 results can be explained by the fact that most of the city’s bus lanes, particularly those that installed cameras in 2016, 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, among other reasons. On the contrary, for the 2017 implementation, the entire two-lane street was restricted to buses only. Contrasting this coefficient with the previous estimate, we can conclude that the 2017 bus lanes with monitoring cameras have a similar impact as the standard installation of BRT corridors observed in 2016-2019.

We also estimate the impact on ridership of providing priority infrastructure to buses using the same methodology as for speeds. We observe no statistical relationship between corridors and changes in the number of peak travelers. However, the inauguration of the BRT corridor increased ridership by 10% only at off-peak hours when capacity restrictions are less binding, and demand is more elastic. As for bus lanes, we only found positive effects for the bus-only street and during weekends that materialized after one year of inauguration.

Our results have policy implications relevant to the design and implementation of bus-priority infrastructure. 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.<sup>2</sup> Therefore, bus corridors can bring substantial welfare gains. We believe that this is a reasonable first-order approximation even though it ignores general equilibrium effects. On the other hand, the cost of implementing them 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](#) (April 4, 2024). This figure suggests that the investment could yield net benefits only 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 that is 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.

Our results also inform policymakers to prioritize place-based transportation policies.

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<sup>2</sup>We assume that 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 the peak and off-peak periods last four and six hours, respectively.

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 absent.

We contribute to the recent literature on the effectiveness of bus-priority infrastructure. Adler et al. (2021a,b) report positive effects of bus lanes when estimating the marginal external cost of road travel and the benefit from transit provision in Rome.<sup>3</sup> Adler et al. (2022) directly estimate the elasticity of bus travel time to traffic density for regular roads and bus lanes. 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 (2023) shows that implementing the BRT system in Bogotá brought substantial welfare gains. Balboni et al. (2020) finds a sizeable positive impact of Dar es Salaam’s bus rapid transport system and Kreindler et al. (2023) a positive impact on speeds of the expansion of the TransJakarta bus system in Jakarta. Moreover, our work complements the literature on policies to deal with traffic congestion. On the one hand, Parry and Small (2009) and Hall (2021) make a strong case for optimally pricing transit and car. 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.

Finally, we contribute to the literature that leverages high-frequency big data in urban transportation. Examples include Kreindler et al. (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.

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<sup>3</sup>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 (see, e.g., Durán-Hormazábal and Tirachini, 2016; Gibson et al., 2016; González et al., 2019).

## 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% of the country’s population and GDP (Banco Central, 2017). It has an extension of approximately 838 km<sup>2</sup> (INE, 2018), slightly larger than New York City, and is inhabited by more than 8 million people. In October 2019, several protests disrupted Santiago for months (González and Prem, 2023). To avoid possible confounding effects from the demonstrations, we used the data until September 2019.

### 2.1 Transantiago

The bus system in Santiago 2003 had a reputation for being low-quality and unsafe (Muñoz et al., 2009), and the Chilean government decided to intervene. It implemented a set of measures collectively known as *TranSantiago* inspired by Bogotá’s *TransMilenio*, the world’s first large-scale BRT system. The plan aimed to enhance the quality of the bus system to make public transport more attractive, thus increasing its usage. Unlike Bogotá’s Transmilenio, the system was designed as a feeder and trunk bus services network, with the Metro as the backbone. An integrated fare structure implemented through a smartcard payment system allows passengers to transfer between buses and the Metro without additional cost. Regarding infrastructure investments, the plan initially envisioned the construction of BRT corridors and improved bus stops. Still, these were postponed in favor of Metro line extensions and urban highway construction (Muñoz et al., 2009).

The system was launched in February 2007 without its essential elements. The reform included the implementation of 225 km of segregated bus corridors. Yet, there were only 13 km of bus corridors, 11 km of bus lanes, and 8 km of roads that could only be used by buses during peak hours (Gómez-Lobo, 2012). While the infrastructure increased significantly in the first years, it was still a minimal network share (Muñoz et al., 2014). In 2011, there were 62 kilometers of BRT corridors in place; in 2016, the first year of our study period, only 10 kilometers were added, and by the end of our study period, the total kilometers of BRT corridors were 83 (DTPM, 2022).

The reasons why BRT corridors have been delayed and sometimes indefinitely postponed are manifold. Residents and authorities oppose them because they perceive bus corridors as

a delay to their expectations of having a nearby Metro line (Muñoz et al., 2009). Another reason is that the system was planned without subsidization, yet after a while, it was evident that it needed subsidies. Since 2012, the annual subsidy has averaged nearly US\$ 1,000 million for operation, making additional funds for infrastructure challenging to obtain.

## 2.2 Current setting

The TranSantiago system is a comprehensive network managed by the Metropolitan Public Transport Directory (DTPM) with over 6,500 buses equipped with GPS devices. Buses operate daily in a network with 87 km of corridors and 300 km of bus lanes along an integrated Metro network consisting of 7 lines and 140 km of rails (DTPM, 2021). The fare scheme is based on trips, with a flat fare applied to trips of up to three stages. A small surcharge is used for metro network trips. The payment system is based on a contactless smart card called “bip!”.

The total number of trips made by public transport did not change significantly: it was 1,037 million in 2016, reached a peak of 1,100 million in 2018 and returned to 1,037 million in 2019 (DTPM, 2018, 2019). The monthly evolution of smartcard transactions is summarized in panel (a) of Figure A.3. On the other hand, buses’ speed has been a major concern; Figure A.2 shows that speeds decreased by around 25% from 2012 to 2019.

During our study period, buses do not run on a fixed schedule, but operators must fulfill a capacity requirement for each route and period. Every six months (excluding holidays), the authority and the operators agree on a plan that sets each route’s frequency. When speed decreases, the authorities often accept a frequency reduction to avoid investing more in rolling stock. In any case, firms and drivers have the incentives to complete the route as they are monitored by the GPS system, and as fast as possible, given that congestion is an issue.

The Origin-Destination Survey 2012 reports that the average bus trip was 8 km long and lasted 55 minutes. The figures for car trips reveal an average duration of 31 minutes with a similar length. Using data from the National Bureau of Statistics, Figure A.3 discloses that the motorization rate increased 4% in Santiago between 2016 and 2019.

### 3 Priority Infrastructure and Bus Speed

We leverage data on thousands of buses in more than 500 routes coupled with annual infrastructure measurements for each route. This information allows us to examine changes in bus speed within routes over time as a response to changes in bus priority infrastructure.

Replication code and data are available via González and Silva (2025).

#### 3.1 Data

We combine three administrative datasets. First, we employ official GPS data the Ministry of Transportation collected for the universe of public buses in Santiago for the 2016-2019 period. They provided us with information for each completed trip, i.e., for trips that started at their designated point of origin, passed through a midway control point and ended at their designated place to finish. We do not observe data for buses that suffer a breakdown or cannot complete the entire trip for another reason. Each planned route is two-way, so we define a trip as completing a one-way route (either inbound or outbound).

For each of these trips, the dataset includes the route number and whether it is an inbound or outbound trip, the bus' license plate number, the distance covered (in kilometers), the average speed (in kilometers per hour), the date, type of day, and period of the trip. Buses, identified by the license plate, 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. The Ministry of Transportation categorizes days 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. The second dataset provides the amount of passengers transported by each bus.

The third administrative dataset consists of annual data provided by the Ministry of Transport on bus priority infrastructure utilization by route. In our study period, 11 km of corridors were built, and 19 km of bus lanes were implemented. This dataset provides us with the variation induced on the routes over time. In particular, we observe each route's total distance and the route's share corresponding to mixed traffic, bus lanes, and BRT corridors. Figure A.1 displays the difference between the types of bus priority infrastructure



that we study. Figure A.4 shows that almost 10% (5%) of the average route has bus lanes (corridors), increasing from 9% (4%) in 2016 to 11% (6%) in 2019. A total of 362 (390) routes did not experience changes in bus lanes (corridors) in 2016-2019.

Given that the bus priority infrastructure utilization by route is only available at the annual level, we reduce the dimensionality of the bus speed and ridership data to the level of a route, each observed annually in 2016-2019. 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 and the total ridership, 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 507 routes hosting trips during four years for a total of 2,028 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 off-peak hours and all hours during the weekend. Note that we only included routes that operated every year in the 2016-2019 period, which reduced the number of routes from 665 to 507.

Columns 1-3 in panel A of Table 1 present descriptive statistics for the 507 routes in the primary dataset. Buses travel at an average speed of 19 km/hour at peak periods. The average route is 15 km, but some are shorter than 8 km, and some are longer than 30 km. On average, a bus takes 1.8 hours per round trip during peak workday hours. Routes host more than 7,800 trips during peak hours in the 2016-2019 period, a little more than 1,900 per year, and transported over 300,000 passengers, which implies an average of approximately 40 passengers per bus trip. The remaining columns provide similar statistics for off-peak hours (columns 4-6) and all hours during the weekend (columns 7-9). As expected, bus speed increases in off-peak and weekend hours, which allows them to make more trips per route. Panel B presents descriptive statistics for priority infrastructure. On average, a route has 10% of bus lanes (2 km), doubling the availability of BRT corridors at 5%. 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. Crucially, there is significant variation in infrastructure within routes. Columns 4-9 show that the routes used during off-peak and weekends are essentially the same as those used during peak hours.

### 3.2 Econometric strategy

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

$$\log(\bar{Y}_{rt}) = \beta T_{rt} + \phi_r + \phi_t + \varepsilon_{rt} \quad (1)$$

where  $\bar{Y}_{rt}$  is the average bus speed or total number of travelers in route  $r$ , year  $t$ , during a specific hour (peak, off-peak, or weekend). 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  $\beta$  using within-route variation. Operationally, we can compare routes with themselves in nearby years by including route fixed effects  $\phi_r$ . For the estimation, we only include routes that operated annually in the 2016-2019 period, thus removing new and closed routes. 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  $\phi_t$ . We allow the error term  $\varepsilon_{rt}$  to be arbitrarily correlated within routes (i.e., we use route-level clustering).<sup>4</sup>

The coefficient of interest is  $\beta$  and measures the percentage increase in average bus speed or ridership 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, off-peak, and all weekend hours. We also estimate equation (1) separately for each infrastructure, but the results are virtually identical when including both transit infrastructure treatments on the right-hand side because of the relatively low correlation between both variables (see Table A.3 for the findings).

The causal interpretation of  $\beta$  requires the absence of unobserved variables correlated with bus lanes or corridors and average bus speed *within* routes. In other words, we must assume that bus lanes and corridors are not targeted to routes with a positive or negative trend in speed. This threat can be analyzed because we can 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  $t$ . Although we cannot entirely disregard a complex targeting of routes trending differently, the collection of findings and lack of correlation

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<sup>4</sup>The statistical inference is similar when clustering across routes that operate in nearby areas. For simplicity, we use robust standard errors clustered by route for the remaining analysis.

between changes in transit infrastructure and bus speeds in previous years suggests that targeting of routes is unlikely to explain our results (Tables A.1 and A.2).

### 3.3 Results

Column 1 in Table 2 presents estimates of equation (1) for bus speed on workday peak hours. Panel A shows that a 10 percentage points (pp) increase in corridors is associated with an increase of 2% in bus speed ( $p$ -value<0.01), approximately 0.4 km/hr faster. Although bus lanes are uncorrelated with bus speed, this relationship is notably noisier, and 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 off-peak hours (column 2) and absent during the weekend (column 3) when buses approach their maximum speed and traffic is notoriously lower.<sup>5</sup>

In contrast to bus speed, we observe little systematic and significant relationship between corridors and ridership (columns 4-6). We obtain a positive estimate only on workdays' off-peak hours, but it is significant only at the 10% level. As for bus lanes, increasing its share by ten percentage points induces an increase in ridership of between four and six percent only in off-peak hours on weekdays or weekends.

The staggered nature of the variation in our measures of transit infrastructure raises the question of whether our findings rely on forbidden comparisons (Roth et al., 2023). To deal with this identification threat, we make two changes. First, we discretize the continuous treatments into binary variables that take the value of one if the transit infrastructure exceeds 10% in a route-year. Second, we restrict our attention to valid comparisons using the method proposed by Borusyak et al. (2024).

Panel B of Table 2 presents the estimates obtained from implementing both changes.<sup>6</sup> It is reassuring to note that all findings related to bus speed remain consistent.<sup>7</sup> In contrast,

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<sup>5</sup>Table A.7 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.

<sup>6</sup>The results with alternative binary treatments are similar (see Tables A.4, A.5, and A.6).

<sup>7</sup>The coefficient for the binary treatment indicates the percentage variation in the speed of a route that transitions from having less than ten percent of its trip in corridors to more than that amount. Therefore, the magnitude would align with the result in Panel A if effects are linear and the average change of a treated route's corridor share is of 20 percentage points. The observed average for the treated routes is 15 percentage points, which is very similar.

the results for ridership are absent under this methodology: the point estimates are small and not statistically significant. These findings suggest that we cannot conclude that bus lanes have an impact on ridership. We will explore this issue further in the next section.

In addition, Panel A in Table A.9 shows that the 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 (“Unit”), and the proportion of the route that takes place on highways. Finally, the 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 Projects

This Section addresses the data limitation identified in Section 3—namely, the absence of variation in infrastructure within a single year—by employing event studies with well-defined treatment event dates. This approach enables the investigation of heterogeneous effects and strengthens internal validity. We use a matched difference-in-differences methodology to estimate the impact of three infrastructure projects, each affecting a subset of routes in our dataset of bus speeds.

We focus on specific infrastructure projects to analyze the variation in the average impact of bus lanes (see Table 2). One potential source of imprecise estimates in Table 2 is that bus lanes only improve speeds when priority is adequately enforced. Effective enforcement typically involves pairing bus lanes with monitoring cameras that detect unauthorized vehicles, enabling authorities to impose fines. The imprecision may result from a minor impact of many lanes lacking monitoring cameras, combined with a more significant effect from fewer well-enforced lanes or heterogeneity in bus lane designs.

The most common bus lane design is a single curbside lane adjacent to one or more unrestricted traffic lanes. This configuration often leads to congestion spillover, as private vehicles can temporarily use the bus lane to make right turns or stop. A less common but more restrictive design dedicates an entire one- or two-lane street exclusively to buses. In this design, except for residents, private vehicles are prohibited during working hours, ensuring better enforcement of bus priority.

## 4.1 Inauguration and installations

We study three projects that changed priority infrastructure significantly in a subset of routes in our data between 2016 and 2019. The first project is the construction of a 9 km corridor in a street that connects the city from north to south. The new corridor was inaugurated in December of 2017 and affected 12 routes in our data. On average, it changed the share of the route in corridors by 45 percentage points. The second project is the inauguration of bus lanes forming a bus-only street whose enforcement is supported by monitoring cameras. That project is part of the “Plan Centro” (Center Plan) policy implemented in March 2017 by the local government of Santiago. A 1.5km section of a street (“Santo Domingo”) was changed from being mostly an ordinary mixed-traffic street to being available only for buses (bus lanes) during workdays between 7.00 hrs and 21.00 hrs. and affected 11 routes in our data. The project changed the share of the routes in bus lanes by 5 percentage points. The third project is the installation of monitoring cameras on 12 routes that already had bus lanes. The central government designed and implemented the plan to install new cameras in December 2016 after reports that bus lanes were ineffective due to the lack of monitoring. After one month of piloting, 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 and covered 6.6 km.

## 4.2 Matched difference-in-differences

We study the average change in bus speed and ridership after the inauguration of bus lanes and installations of monitoring cameras by estimating the following econometric equation:

$$Y_{rt} = \sum_{t=-6} \beta_t D_{rt} + \phi_r + \theta_t + \varepsilon_{rt} \quad (2)$$

where  $Y_{rt}$  is the logarithm of the average speed (in km/hr) or the logarithm of the number of travelers of all buses operating in route  $r$  during month  $t$ . The sample period starts in January 2016 and ends in September 2019. Each indicator  $D_{rt}$  takes the value of 1 if route  $r$  is observed  $t$  months after the project of interest. We use the month before the project was completed  $t = -1$  as the omitted category. Our interest is in  $\beta_t$ , which, given the omitted category, measures the effect of the infrastructure project on bus speed  $t$  months after their completion. All specifications include fixed effects by route ( $\phi_r$ ) and month-year ( $\theta_t$ ). We

allow the mean-zero error term  $\varepsilon_{rt}$  to be arbitrarily correlated within routes over time using route-level clustering. We estimate equation (2) separately for peak hours during workdays, off-peak hours during workdays, and all hours during the weekend.

Equation (2) allows us to compare routes with infrastructure projects to a 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 500 bus routes and the observability of key route characteristics. We proceed in four steps. First, we focus on the cross-section of all routes one year before the infrastructure project was completed. 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 project 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), number of travelers, and the number of bus trips. Third, we predict the probability  $\hat{p}_r \equiv \hat{p}_r(I_r = 1|x_r) \in [0, 1]$  that each route  $r$  has an infrastructure project. Fourth, we select 20 control routes per each route that experiences an infrastructure project using (i) the Mahalanobis distance in  $\hat{p}_r$  as the matching criteria, and (ii) restricting attention to routes with common support in the propensity score distribution.<sup>8</sup> Overall, this procedure selects between 127 and 150 control routes for the routes with infrastructure projects.<sup>9</sup>

### 4.3 Results

Figure 1 presents our estimates for the change in bus speed and ridership after the inauguration of the bus corridor. Overall, panels (a) through (c) show that the corridor leads to a 7% increase in bus speed during peak hours, a 5% increase during off-peak hours, and a 1% increase during weekend hours. The change in bus speed takes place immediately after the inauguration of the corridor. In contrast, we observe no statistical relationship between the new corridor and changes in the number of peak travelers. Consistent with the findings reported in Table 2, there seems to be a positive effect of 10% on ridership during off-peak hours when capacity restrictions are less binding and demand is more elastic.<sup>10</sup>

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<sup>8</sup>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).

<sup>9</sup>The average propensity score in the treatment group is 0.045 and 0.036 in the control group. Figure A.6 shows the probability that each one of the routes experiences an infrastructure project  $\hat{p}_r$ .

<sup>10</sup>According to Litman (2017), the elasticities for off-peak transit travel are typically 1.5-2 times higher than peak period elasticities.

Figure 2 shows that, similarly to the case of corridors, the inauguration of bus lanes forming a bus-only street with monitoring cameras also increased bus speeds. On average, bus speed increases by 5.4%, 4.7%, and 4.2% in peak, off-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% (Table A.7, column 1). Given that the projects 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 bus speed, these projects' lack of effect during weekend hours is expected.

The dynamic impact of the infrastructure projects 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. Bus speed slowly increases from month 7 to months 10-12 when it seems to reach a new 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.

The results on ridership in panels (d)-(f) of Figure 2 show a negative short-term effect of bus lanes on the number of travelers in peak and off-peak periods and a positive effect during weekends. In workdays, we find a pronounced negative effect in the first year, followed by a recovery that appears to take the ridership up to the pre-intervention levels. During weekends, the ridership increases substantially after one year, which coincides with the period when the speed increase is the largest.

Finally, Figure 3 shows 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 cameras. Importantly, these null results can confidently reject that average bus speed increases by more than 4%. The lack of an impact is similar during peak, off-peak hours, and weekend hours. Moreover, a decrease in ridership begins 15 months after the project. We attribute this decrease to the inauguration at the end of 2017 of a metro line that runs parallel to the bus lanes.

## 5 Discussion

We estimated the direct causal effect of different bus priority infrastructures on bus speed and ridership. We found that while bus lanes do not improve speeds, the performance of bus-only streets is as good as the average BRT corridor, with small effects on ridership. 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 2016 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.

We have presented evidence that suggests 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. These results underscore 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 and similar figures using Santiago data. Börjesson et al. (2017) conduct a similar analysis for Stockholm. 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.

## References

Adler, M. W., Liberini, F., Russo, A., and van Ommeren, J. N. (2021a). The congestion relief benefit of public transit: Evidence from Rome. *Journal of Economic Geography*, 21(3):397–431.



- Adler, M. W., Liberini, F., Russo, A., and van Ommeren, J. N. (2021b). Welfare losses of road congestion: Evidence from Rome. *Regional Science and Urban Economics*, 89:103692.
- Adler, M. W., Liberini, F., Russo, A., and van Ommeren, J. N. (2022). Dedicated bus lanes, bus speed and traffic congestion in Rome. *Transportation Research Part A: Policy and Practice*, 160:298–310.
- Balboni, C., Bryan, G., Morten, M., and Siddiqi, B. (2020). Transportation, gentrification, and urban mobility: The inequality effects of place-based policies. *Working Paper*.
- Banco Central (2017). GDP series. <https://si3.bcentral.cl/siete/secure/cuadros/arboles.aspx>.
- Basso, L. J., Feres, F., and Silva, H. E. (2019). The efficiency of bus rapid transit (BRT) systems: A dynamic congestion approach. *Transportation Research Part B: Methodological*, 127:47–71.
- Basso, L. J. and Silva, H. E. (2014). Efficiency and substitutability of transit subsidies and other urban transport policies. *American Economic Journal: Economic Policy*, 6(4):1–33.
- Börjesson, M., Fung, C. M., and Proost, S. (2017). Optimal prices and frequencies for buses in Stockholm. *Economics of Transportation*, 9:20–36.
- Borsje, R., Hiemstra-van Mastrigt, S., and Veeneman, W. (2023). Assessing passenger preferences for bus rapid transit characteristics: A discrete choice experiment among current and potential Dutch passengers. *Research in Transportation Economics*, 100:101307.
- Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting event-study designs: Robust and efficient estimation. *Review of Economic Studies*, in press.
- Chaves Maia, P. H. (2022). The commuting costs of high-intensity rains: Evidence from Rio de Janeiro. *Working Paper*.
- DTPM (2018). *Informe de Gestión 2017*. Directorio de Transporte Público Metropolitano.
- DTPM (2019). *Informe de Gestión 2019*. Directorio de Transporte Público Metropolitano.
- DTPM (2021). *Informe de Gestión 2021*. Directorio de Transporte Público Metropolitano.
- DTPM (2022). *Informe de Gestión 2022*. Directorio de Transporte Público Metropolitano.

- Durán-Hormazábal, E. and Tirachini, A. (2016). Estimation of travel time variability for cars, buses, metro and door-to-door public transport trips in Santiago, Chile. *Research in Transportation Economics*, 59:26–39.
- Frölich, M. (2004). Finite-sample properties of propensity-score matching and weighting estimators. *Review of Economics and Statistics*, 86(1):77–90.
- Gibson, J., Munizaga, M. A., Schneider, C., and Tirachini, A. (2016). Estimating the bus user time benefits of implementing a median busway: Methodology and case study. *Transportation Research Part A: Policy and Practice*, 84:72–82.
- Gómez-Lobo, A. (2012). The ups and downs of a public transport reform: The case of Transantiago. *Working Paper*.
- González, F. and Prem, M. (2023). The legacy of the Pinochet Regime in Chile. In Valencia, F., editor, *Roots of Underdevelopment: A New Economic and Political History of Latin America and the Caribbean*. Palgrave Macmillan.
- González, F. and Silva, H. E. (2025). Replication Code and Data for “Efficiency of Bus Priority Infrastructure”. *Journal of Urban Economics* [journal]. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], <https://doi.org/10.3886/E218041V1>.
- González, F., Valdivieso, V., De Grange, L., and Troncoso, R. (2019). Impact of the dedicated infrastructure on bus service quality: an empirical analysis. *Applied Economics*, 51(55):5961–5971.
- Gu, Y., Jiang, C., Zhang, J., and Zou, B. (2021). Subways and road congestion. *American Economic Journal: Applied Economics*, 13(2):83–115.
- Hall, J. D. (2021). Can tolling help everyone? Estimating the aggregate and distributional consequences of congestion pricing. *Journal of the European Economic Association*, 19(1):441–474.
- INE (2018). *Metodología para medir el Crecimiento Urbano de las Ciudades de Chile*. Departamento de Geografía, Instituto Nacional de Estadísticas. Comisión de Estudios Habitacionales y Urbanos, del Ministerio de Vivienda y Urbanismo.
- Khan, S. and Tamer, E. (2010). Irregular identification, support conditions, and inverse weight estimation. *Econometrica*, 78(6):2021–2042.

- Kim, J. and Ewing, R. (2024). Impact of “light” bus rapid transit (BRT-light) on traffic and emissions in a travel corridor. *Transport Policy*, 146:215–226.
- Kreindler, G., Gaduh, A., Graff, T., Hanna, R., and Olken, B. A. (2023). Optimal public transportation networks: Evidence from the world’s largest bus rapid transit system in Jakarta. *Working Paper*.
- Kutzbach, M. J. (2009). Motorization in developing countries: Causes, consequences, and effectiveness of policy options. *Journal of Urban Economics*, 65(2):154–166.
- Litman, T. (2017). *Transportation Elasticities: How Prices and Other Factors Affect Travel Behavior*. Technical Report, Victoria Transport Policy Institute, Victoria, BC, Canada. <http://www.vtpi.org/elasticities.pdf> (Accessed on March 20, 2017).
- Muñoz, J. C., Batarce, M., and Hidalgo, D. (2014). Transantiago, five years after its launch. *Research in Transportation Economics*, 48:184–193.
- Muñoz, J. C., de Dios Ortúzar, J., and Gschwender, A. (2009). Transantiago: the fall and rise of a radical public transport intervention. In *Travel Demand Management and Road User Pricing*, pages 151–171. Routledge.
- Our World in Data (2024). Data page: Registered vehicles per 1,000 people. Retrieved from <https://ourworldindata.org/grapher/registered-vehicles-per-1000-people> [online resource], Data adapted from World Health Organization, United Nations.
- Parry, I. W. and Small, K. A. (2009). Should urban transit subsidies be reduced? *The American Economic Review*, 99(3):700–724.
- Roth, J., Sant’Anna, P. H., Bilinski, A., and Poe, J. (2023). What’s trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*, 235(2):2218–2244.
- Tsivanidis, N. (2023). Evaluating the impact of urban transit infrastructure: Evidence from Bogotá’s Transmilenio. *Working Paper*.

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

	Work days								
	Peak hours			Off-peak hours			Weekend hours		
	Avg.	p50	St. dev	Avg.	p50	St. dev.	Avg.	p50	St. dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<b>Panel A: Buses and routes</b>									
Speed (km/hr)	19.22	18.21	4.23	20.87	20.01	4.03	23.88	22.94	4.37
Route distance (km)	15.18	13.51	7.83	15.30	13.72	7.42	15.57	13.80	7.92
Trips per route	7,931	7,082	3,212	11,499	10,656	4,505	10,429	9,941	3,673
Travelers (millions)	0.31	0.24	0.26	0.33	0.23	0.29	0.23	0.18	0.19
<b>Panel B: Infrastructure</b>									
Percentage of route with corridors	0.05	0.00	0.12	0.04	0.00	0.10	0.04	0.00	0.10
Percentage of route with bus lanes	0.10	0.03	0.15	0.10	0.04	0.15	0.10	0.04	0.14
Bus routes	507			442			420		
Observations	2,028			1,768			1,680		

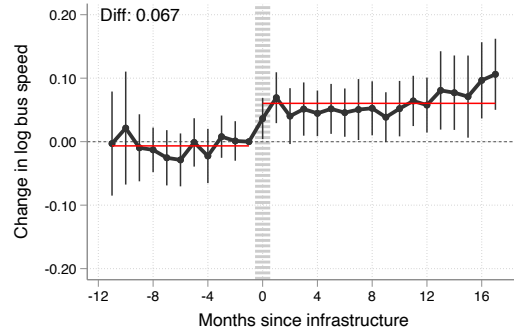
*Notes:* This table shows annual descriptive statistics (average, 50th percentile, and standard deviation) for bus routes in 4 years (2016-2019) during peak (columns 1-3) and off-peak (columns 4-6) hours in working days, and for all hours during the weekend (columns 7-9). Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. We restrict attention to routes observed every year between 2016 and 2019, i.e. the panel data is balanced.

**Table 2:** Priority infrastructure, bus speed, and travelers

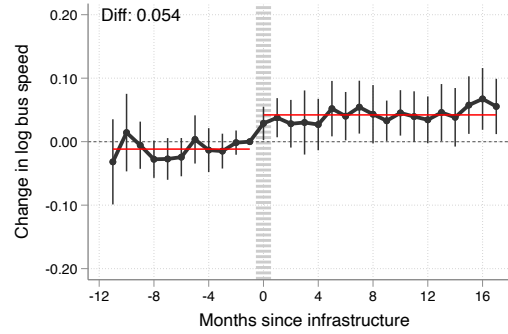
Dependent variable:	Log bus speed (km/hr)			Log million travelers		
	Work days			Work days		
	Peak hours	Off-peak hours	Weekend	Peak hours	Off-peak hours	Weekend
<b>Panel A</b>	(1)	(2)	(3)	(4)	(5)	(6)
<i>Percentage</i> route with bus corridors	0.197*** (0.042)	0.155*** (0.043)	-0.050 (0.039)	-0.177 (0.207)	0.246* (0.147)	-0.001 (0.101)
<i>Percentage</i> route with bus lanes	0.055 (0.081)	0.045 (0.084)	0.066 (0.074)	0.098 (0.207)	0.462* (0.253)	0.603** (0.268)
<b>Panel B</b>						
<i>Indicator</i> route with bus corridors	0.044*** (0.011)	0.033*** (0.010)	-0.002 (0.008)	-0.030 (0.065)	0.036 (0.030)	0.017 (0.016)
<i>Indicator</i> route with bus lanes	0.008 (0.008)	0.005 (0.008)	0.006 (0.008)	-0.008 (0.033)	-0.029 (0.030)	-0.006 (0.028)
Observations	2,028	1,768	1,680	2,028	1,768	1,680
Bus routes	507	442	420	507	442	420
Trips (in millions)	16.1	20.3	17.5	16.1	20.3	20.4
Avg. dependent variable (levels)	19.22	20.87	23.88	0.31	0.33	0.23
Route fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y

*Notes:* Panel A shows two-way fixed effects estimates between priority infrastructure (bus corridors, bus lanes) and (i) bus speed in columns 1-3, and (ii) travelers in columns 4-6. The unit of observation is a route in a given year between 2016 and 2019. Panel B presents estimates of the same relationship but using the method proposed by Borusyak et al. (2024). All regression specifications include route and year fixed effects. Panel A uses the percentage of the route with priority infrastructure as right-hand side variable while Panel B uses an indicator for routes with more than 10% of priority infrastructure. Each coefficient and standard error comes from a separate regression. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. Robust standard errors are clustered at the route level. Statistical significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

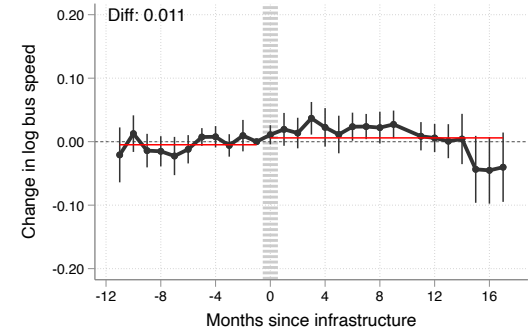
**Figure 1: Construction of corridor**



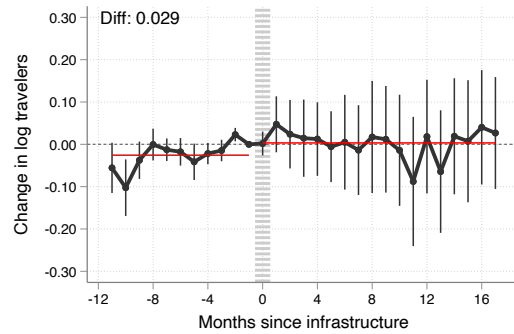
(a) Speed, workday peak hours



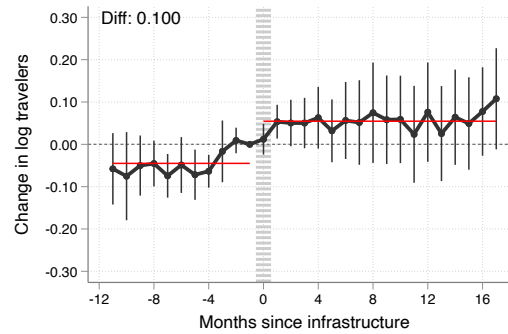
(b) Speed, workday off-peak hours



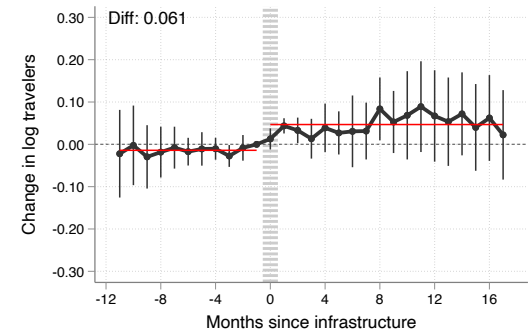
(c) Speed, weekend hours



(d) Travelers, workday peak hours



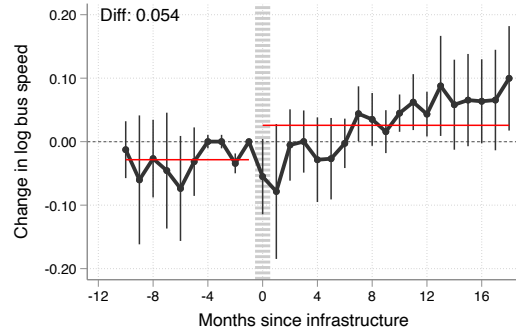
(e) Travelers, workday off-peak hours



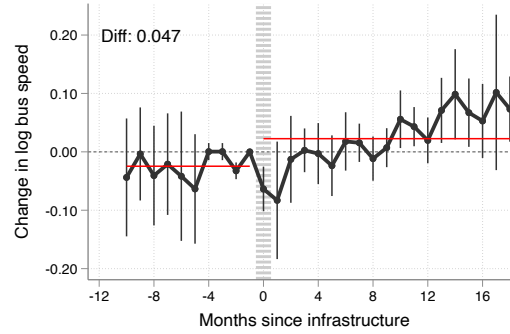
(f) Travelers, weekend hours

*Notes.* Each observation is a route in a month around the infrastructure project under study (December 2017). The project is the construction of a corridor that affects multiple routes. The number of treatment (control) routes is 12 (127). Control routes are chosen by a propensity score matching algorithm. All estimates include route and year fixed effects. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. Black dots represent point estimates, and vertical lines the 95% confidence interval. Horizontal red lines are averages of coefficients before and after the month the project was completed. “Diff” is the difference in averages before and after the project was completed. Robust standard errors are clustered at the route level.

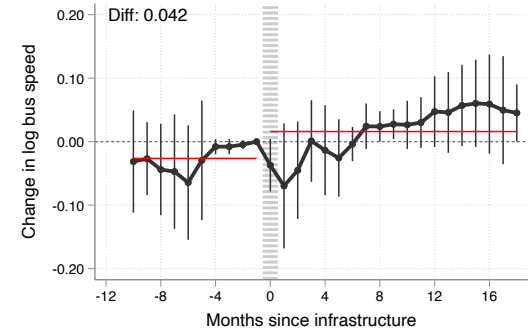
**Figure 2:** Bus lanes forming a bus-only street with monitoring cameras



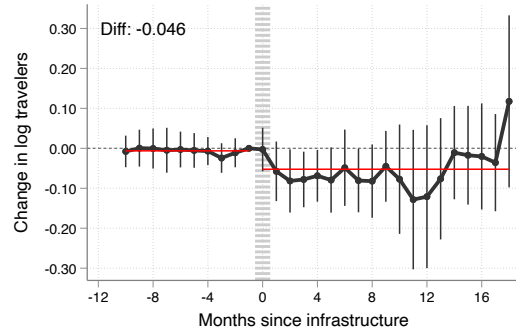
(a) Speed, workday peak hours



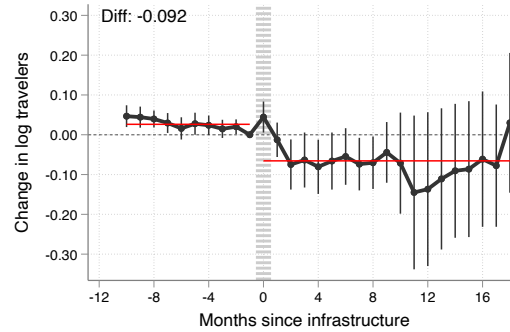
(b) Speed, workday off-peak hours



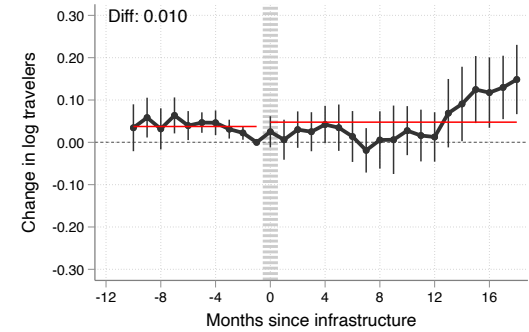
(c) Speed, weekend hours



(d) Travelers, workday peak hours



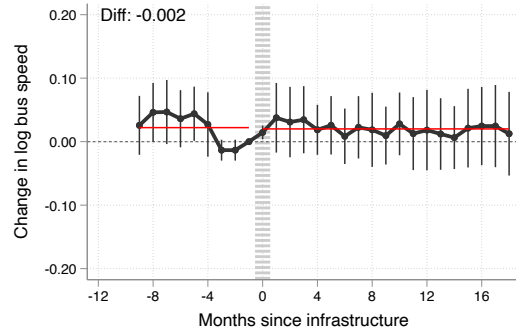
(e) Travelers, workday off-peak hours



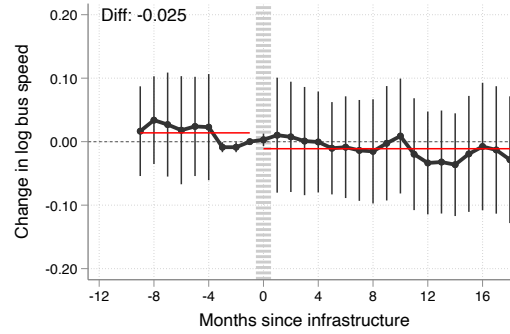
(f) Travelers, weekend hours

*Notes.* Each observation is a route in a month around the infrastructure project under study (March 2017). The project is the opening 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 (133). Control routes are chosen by a propensity score matching algorithm. All estimates include route and year fixed effects. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. Black dots represent point estimates, and vertical lines the 95% confidence interval. Horizontal red lines are averages of coefficients before and after the month the project was completed. “Diff” is the difference in averages before and after the project was completed. Robust standard errors are clustered at the route level.

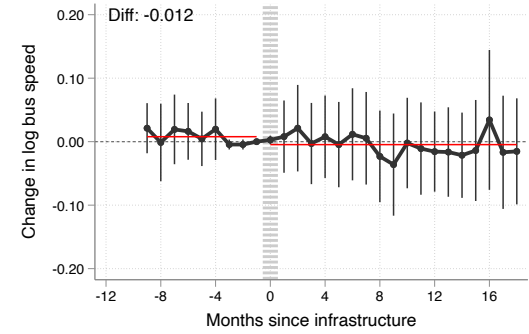
**Figure 3:** Monitoring cameras on top of already existing bus lanes



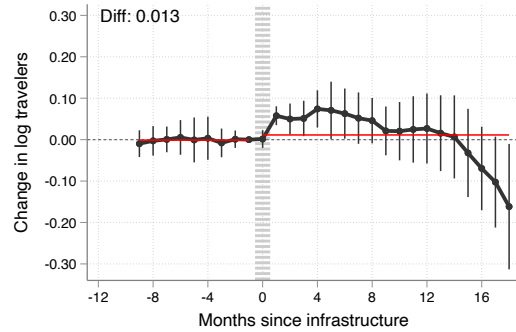
(a) Speed, workday peak hours



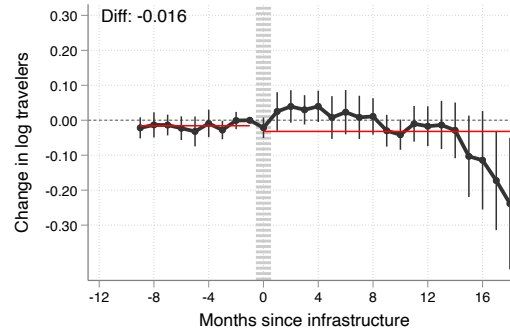
(b) Speed, workday off-peak hours



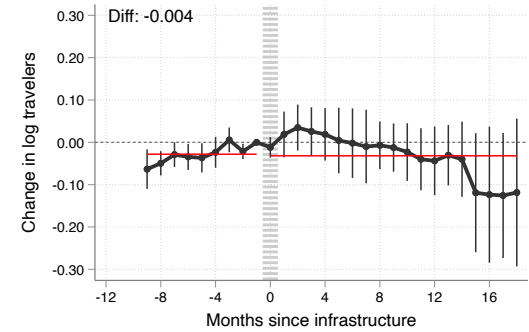
(c) Speed, weekend hours



(d) Travelers, workday peak hours



(e) Travelers, workday off-peak hours



(f) Travelers, weekend hours

*Notes.* Each observation is a route in a month around the infrastructure project under study (December 2016). The project is the installation of cameras (and fines) on top of already existing bus lanes. The number of treatment (control) routes is 12 (150). Control routes are chosen by a propensity score matching algorithm. All estimates include route and year fixed effects. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. Black dots represent point estimates, and vertical lines the 95% confidence interval. Horizontal red lines are averages of coefficients before and after the month the project was completed. “Diff” is the difference in averages before and after the project was completed. Robust standard errors are clustered at the route level.



# ONLINE APPENDIX

## Efficiency of Bus Priority Infrastructure

Hugo Silva and Felipe González

### List of Figures

A.1	Bus lanes and corridors . . . . .	ii
A.2	Speed evolution . . . . .	iii
A.3	Context in numbers . . . . .	iv
A.4	Bus lanes and corridors over time . . . . .	v
A.5	Estimated propensity score, construction of corridor . . . . .	vi
A.6	Estimated propensity score, Only Bus Lanes and Cameras . . . . .	vii
A.7	Estimated propensity score, cameras only . . . . .	viii

### List of Tables

A.1	Exogeneity test . . . . .	ix
A.2	Exogeneity test, longer time horizon . . . . .	x
A.3	Joint estimation of infrastructure effects . . . . .	xi
A.4	Main estimates with indicators for infrastructure . . . . .	xii
A.5	Alternative indicator, change of 5pp. in infrastructure . . . . .	xiii
A.6	Alternative indicator, change of 10pp. in infrastructure . . . . .	xiv
A.7	Non-linear effects of priority infrastructure, bus speed . . . . .	xv
A.8	Non-linear effects of priority infrastructure, travelers . . . . .	xvi
A.9	Robustness to model specifications . . . . .	xvii

**Figure A.1:** Bus lanes and corridors



(a) Bus lane alongside unrestricted traffic



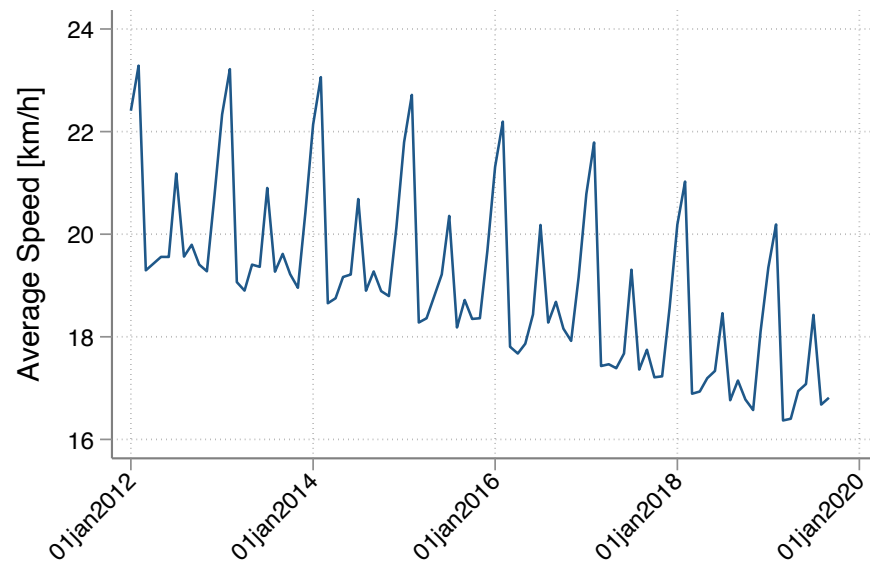
(b) Bus lanes forming a bus-only street



(c) BRT Corridor

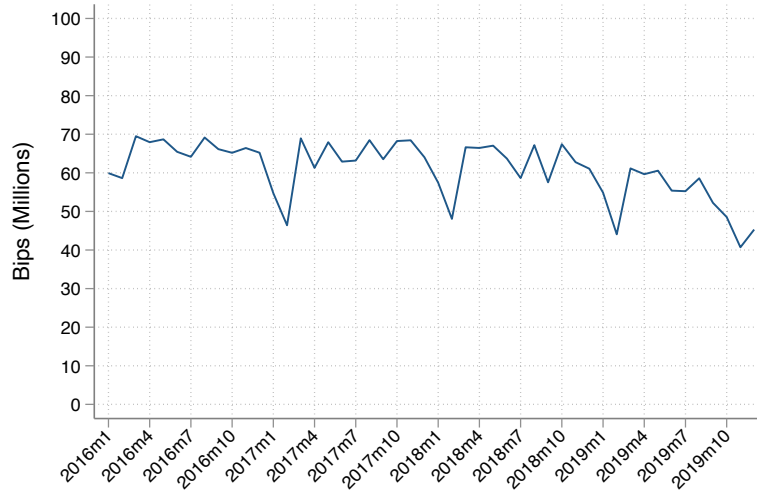
*Notes.* Examples of the priority infrastructure we study. All photos are from routes in our dataset. Panel (a) shows a typical bus lane alongside unrestricted traffic. This bus lane is in the data of yearly bus priority infrastructure that we use for the main analysis in Section 3. Panel (b) shows the bus lanes forming a bus-only street with monitoring cameras of the second project we study (Figure 2). Panel (c) shows the BRT corridor of the first project we study (Figure 1).

**Figure A.2: Speed evolution**

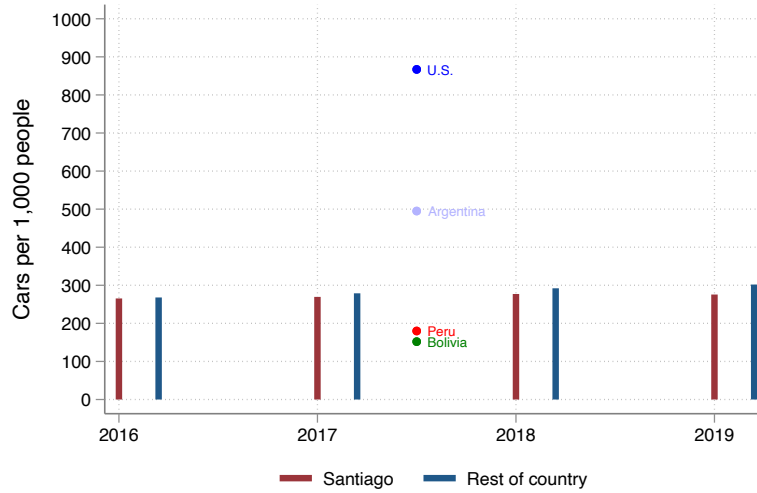


*Notes.* This figure shows the monthly average speed of all bus trips in peak periods in Santiago from January 2012 until September 2019. Speed increases significantly during the summer months (January and February).

**Figure A.3: Context in numbers**



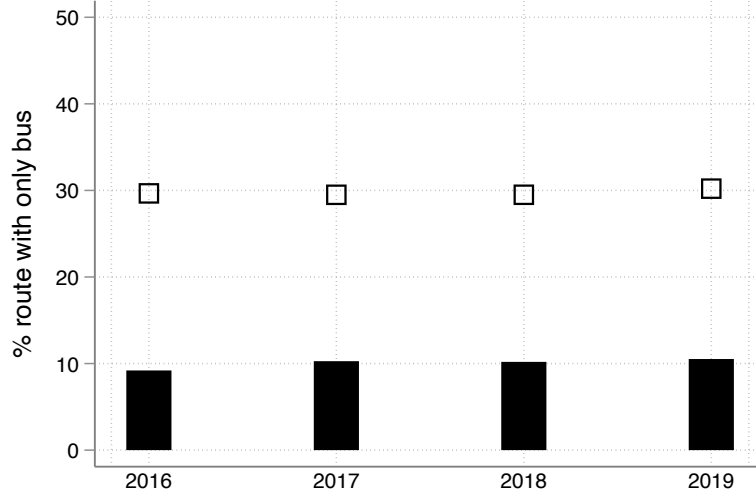
(a) Travelers, 2016-2019



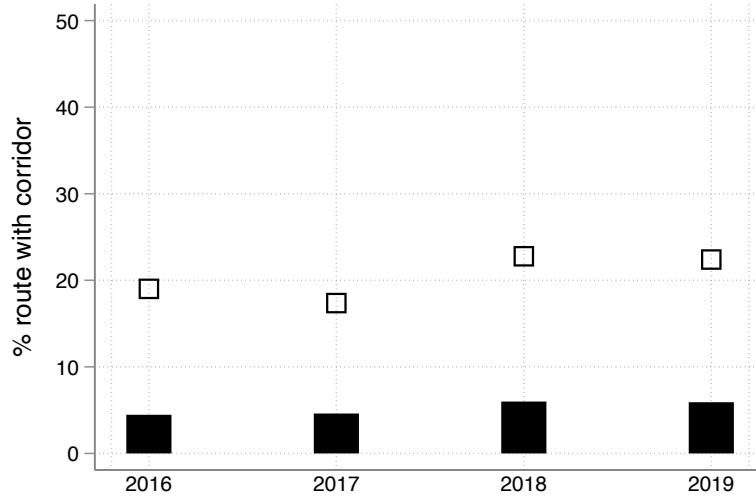
(b) Registered cars, 2016-2019

*Notes.* Panel (a) shows the number of users who paid to ride in a public bus in the city of Santiago. Ridership decreases significantly during the summer months (January and February). Panel (b) shows the number of registered cars per 1,000 people in Chile per year between 2016 and 2019. Annual data on registered cars and population are publicly available and published by the National Statistics Bureau. Red bars represent the number of cars per 1,000 people in the capital city of Santiago, defined as the province of Santiago and the municipality of Puente Alto. The population of the city of Santiago was 6.5 million in 2019. Blue bars represent the number of cars per 1,000 people in the rest of the country. For comparison, we also add the number of cars per 1,000 people circa 2017 in the three neighboring countries (Argentina, Bolivia, Peru) and the United States. Country-level car data are gathered and published by Our World in Data (2024).

**Figure A.4:** Bus lanes and corridors over time



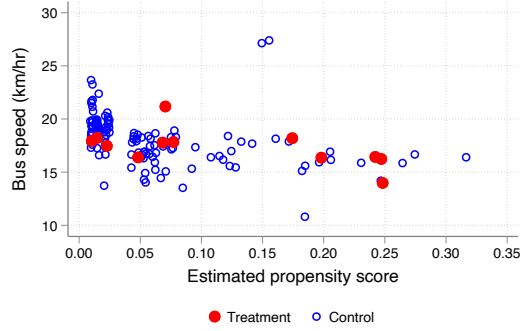
(a) Bus lanes



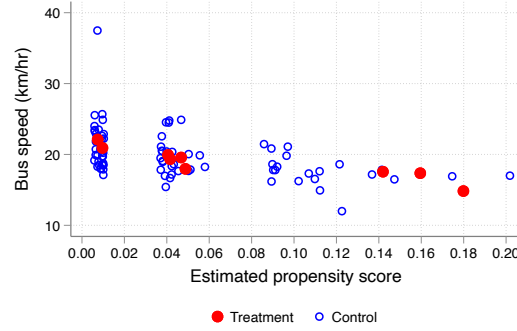
(b) Corridors

*Notes.* The figures in both panels describe the prevalence of priority infrastructure in the 507 routes in our main dataset. The  $y$ -axis represents the percentage of the route, and the  $x$ -axis represents the years in our dataset. Black bars (hollow squares) describe the percentage of priority infrastructure in the average (90th percentile) route. Panel (a) shows that bus lanes cover 10% of the average route, with a slight increase from 9% in 2016 to 11% in 2019. Panel (b) shows that bus corridors are less prevalent and covered only 4% of the average route in 2016, a number that increased to 6% in 2019. Hollow squares zoom into routes in the 90th percentile of the distribution of priority infrastructure and show that there are routes with one-third of their length with bus lanes and one-fifth with corridors.

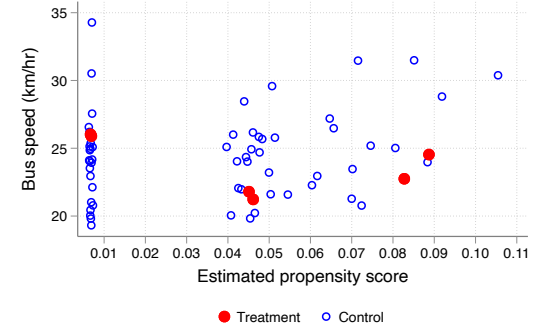
**Figure A.5:** Estimated propensity score, construction of corridor



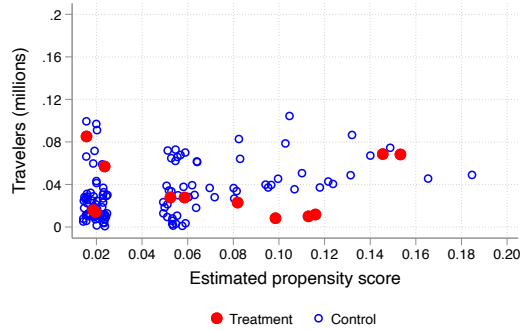
(a) Speed, peak hours



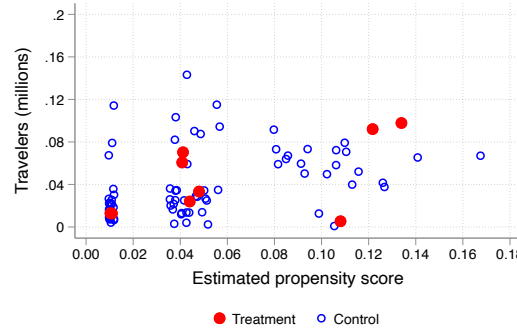
(b) Speed, off-peak hours



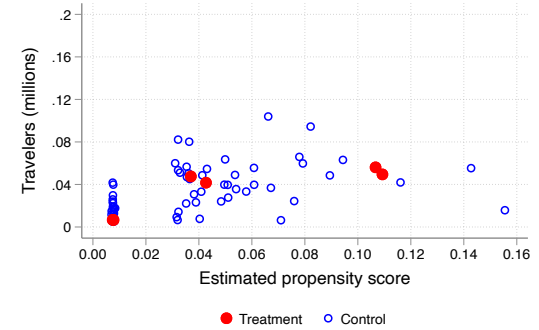
(c) Speed, weekend



(d) Travelers, peak hours



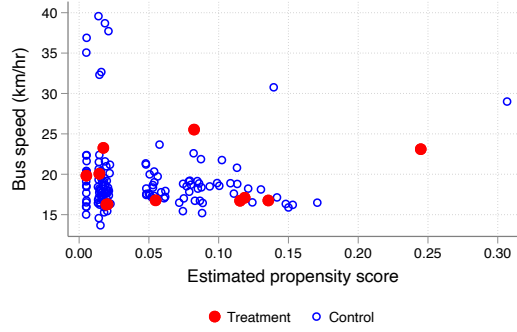
(e) Travelers, off-peak hours



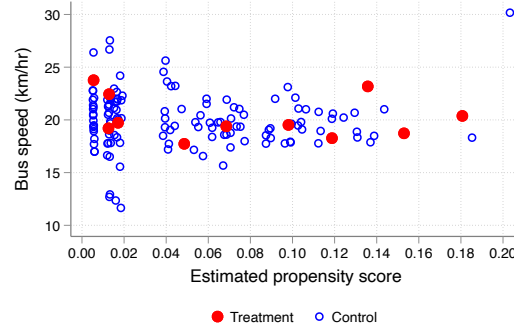
(f) Travelers, weekend

*Notes.* These figures present the predicted probability of experiencing the project under study based on observable characteristics (bus speed, number of travelers, route length, number of trips) 12 months before the project was completed. The  $y$ -axis shows the main predictor and the  $x$ -axis shows the predicted probability of the project, i.e., the propensity score. Each circle represents a route, with red circles representing the routes affected by the project and blue circles representing the chosen control routes that did not experience the project. The number of treatment/control routes is 18/255. We calculate all predicted probabilities with a cross-sectional probit model. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays.

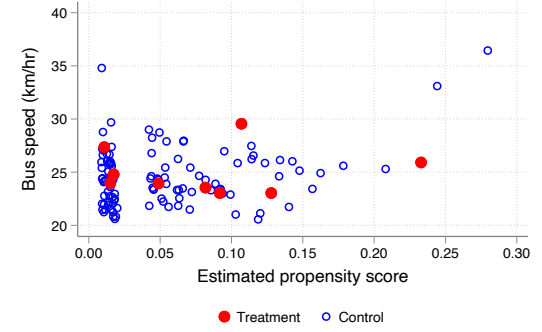
**Figure A.6:** Estimated propensity score, Only Bus Lanes and Cameras



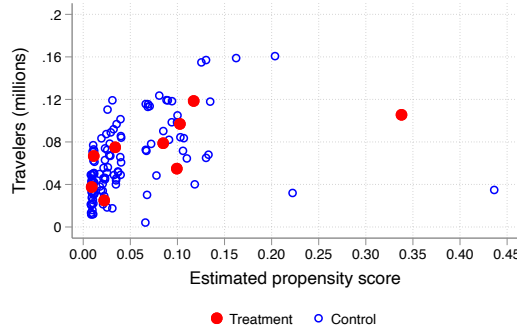
(a) Speed, peak hours



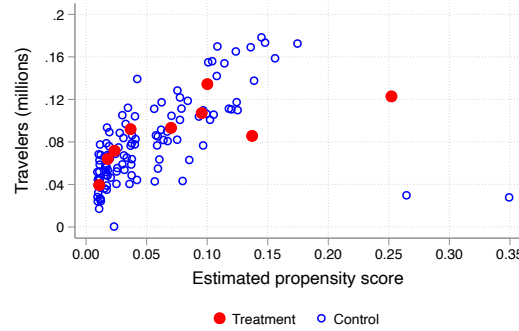
(b) Speed, off-peak hours



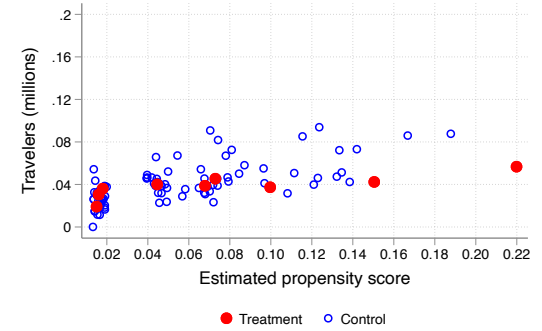
(c) Speed, weekend



(d) Travelers, peak hours



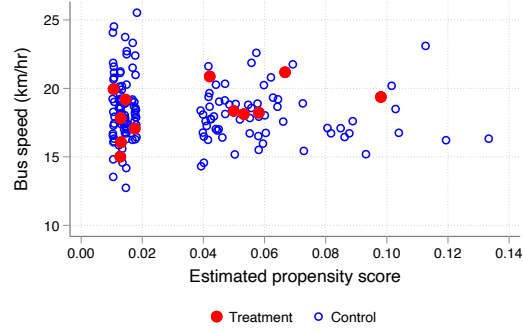
(e) Travelers, off-peak hours



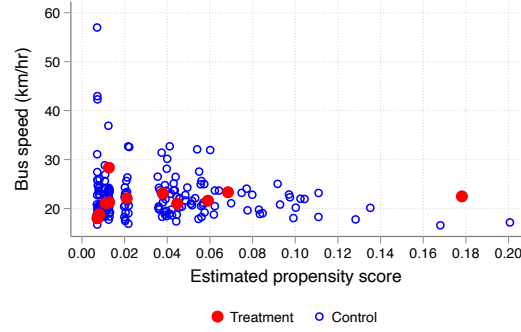
(f) Travelers, weekend

*Notes.* These figures present the predicted probability of experiencing the project under study based on observable characteristics (bus speed, number of travelers, route length, number of trips) 12 months before the project was completed. The  $y$ -axis shows the main predictor and the  $x$ -axis shows the predicted probability of the project, i.e., the propensity score. Each circle represents a route, with red circles representing the routes affected by the project and blue circles representing the chosen control routes that did not experience the project. The number of treatment/control routes is 11/108. We calculate all predicted probabilities with a cross-sectional probit model. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays.

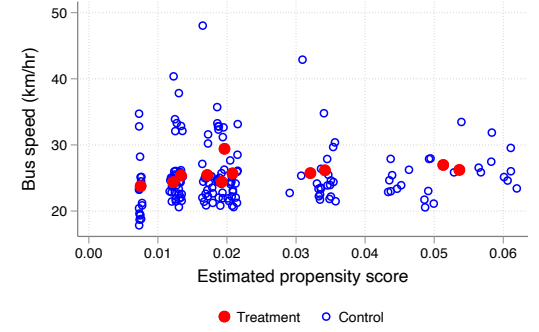
**Figure A.7:** Estimated propensity score, cameras only



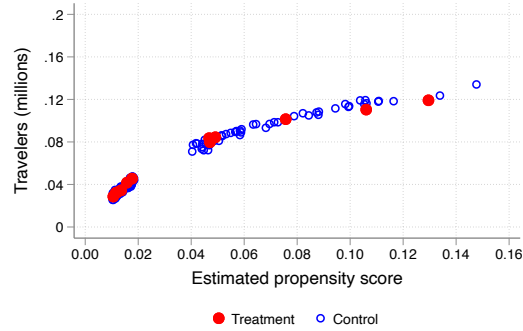
(a) Speed, peak hours



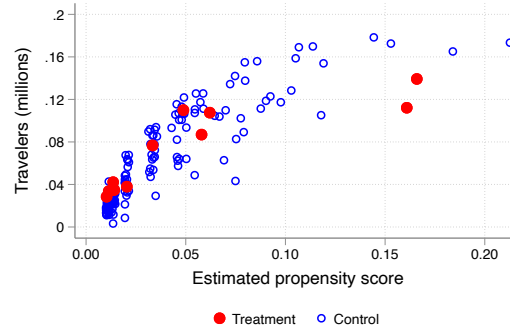
(b) Speed, off-peak hours



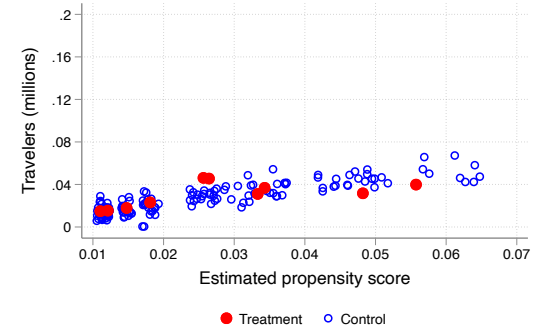
(c) Speed, weekend



(d) Travelers, peak hours



(e) Travelers, off-peak hours



(f) Travelers, weekend

*Notes.* These figures present the predicted probability of experiencing the project under study based on observable characteristics (bus speed, number of travelers, route length, number of trips) 12 months before the project was completed. The  $y$ -axis shows the main predictor and the  $x$ -axis shows the predicted probability of the project, i.e., the propensity score. Each circle represents a route, with red circles representing the routes affected by the project and blue circles representing the chosen control routes that did not experience the project. The number of treatment/control routes is 11/182. We calculate all predicted probabilities with a cross-sectional probit model. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays.



**Table A.1:** Exogeneity test

Dependent variable: Change in priority infrastructure next year			
	Work days		
	Peak hours	Off-peak hours	Weekend
<b>Panel A: Corridors</b>	(1)	(2)	(3)
Log bus speed	-0.033 (0.028)	-0.027 (0.023)	0.029 (0.020)
Log travelers	-0.008 (0.006)	-0.006 (0.005)	-0.006 (0.007)
<b>Panel B: Bus lanes</b>			
Log bus speed	-0.033 (0.022)	-0.030 (0.022)	-0.064** (0.026)
Log travelers	-0.004 (0.004)	0.007 (0.009)	0.001 (0.012)
Observations	1,521	1,326	1,260
Bus routes	507	442	420
Trips (in millions)	12.3	15.5	13.7
Avg. dep. variable panel A (%)	0.005	0.005	0.004
Avg. dep. variable panel B (%)	0.004	0.005	0.005
Route fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y

*Notes:* This table shows the relationship between changes in priority infrastructure (corridors in Panel A, bus lanes in Panel B) and (i) bus speed and (ii) travelers. The unit of observation is a route in a given year between 2016 and 2019. All regression specifications include route and year fixed effects. Each coefficient and standard error comes from a separate regression. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. Robust standard errors are clustered at the route level. Statistical significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table A.2:** Exogeneity test, longer time horizon

	Dependent variable: Change in priority infrastructure...					
	Two years ahead			Three years ahead		
	Work days		Weekend	Work days		Weekend
	Peak hours	Off-peak hours		Peak hours	Off-peak hours	
<b>Panel A: Corridors</b>	(1)	(2)	(3)	(4)	(5)	(6)
Log bus speed	-0.135* (0.072)	-0.075 (0.074)	-0.047 (0.033)	0.000 (0.001)	0.002 (0.002)	0.001 (0.001)
Log travelers	-0.007 (0.009)	0.026 (0.020)	0.052*** (0.018)	-0.001 (0.000)	-0.002 (0.001)	-0.002 (0.001)
<b>Panel B: Bus lanes</b>						
Log bus speed	-0.030 (0.022)	-0.071** (0.028)	-0.040** (0.019)	-0.006 (0.006)	0.003 (0.009)	0.004 (0.010)
Log travelers	0.001 (0.007)	0.002 (0.015)	-0.001 (0.008)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)
Observations	1,014	884	840	507	442	420
Bus routes	507	442	420	507	442	420
Trips (in millions)	8.2	10.2	8.8	4.3	4.9	4.1
Avg. dep. variable panel A (%)	0.007	0.006	0.005	0.000	0.000	0.000
Avg. dep. variable panel B (%)	0.001	0.001	0.001	0.003	0.003	0.003
Route fixed effects	Y	Y	Y	N	N	N
Year fixed effects	Y	Y	Y	N	N	N

*Notes:* This table shows the relationship between changes in priority infrastructure (corridors in Panel A, bus lanes in Panel B) and (i) bus speed and (ii) travelers. The unit of observation is a route in a given year between 2016 and 2019. Columns 1-3 examine the relationship separated by two years, while columns 4-6 repeat the exercise but three years apart. Regression specifications in columns 1-3 include route and year fixed effects. Each coefficient and standard error comes from a separate regression. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. Robust standard errors are clustered at the route level. Statistical significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table A.3:** Joint estimation of infrastructure effects

Dependent variable:	Log bus speed (km/hr)			Log million travelers		
	Work days			Work days		
	Peak hours	Off-peak hours	Weekend	Peak hours	Off-peak hours	Weekend
	(1)	(2)	(3)	(4)	(5)	(6)
Percentage route with bus corridors	0.198*** (0.042)	0.156*** (0.043)	-0.049 (0.040)	-0.175 (0.207)	0.253* (0.148)	0.013 (0.100)
Percentage route with bus lanes	0.060 (0.082)	0.048 (0.084)	0.065 (0.074)	0.094 (0.208)	0.467* (0.252)	0.604 (0.269)
Observations	2,028	1,768	1,680	2,028	1,768	1,680
Bus routes	507	442	420	507	442	420
Trips (in millions)	16.1	20.3	17.5	16.1	20.3	20.4
Avg. dependent variable (levels)	19.22	20.87	23.88	0.31	0.33	0.23
Route fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y

*Notes:* This table shows two-way fixed effects estimates between priority infrastructure (bus corridors, bus lanes) and (i) bus speed in columns 1-3, and (ii) travelers in columns 4-6. The unit of observation is a route in a given year between 2016 and 2019. All regression specifications include route and year fixed effects. Each column represents a separate regression. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. Robust standard errors are clustered at the route level. Statistical significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table A.4:** Main estimates with indicators for infrastructure

Dependent variable:	Log bus speed (km/hr)			Log million travelers		
	Work days			Work days		
	Peak hours	Off-peak hours	Weekend	Peak hours	Off-peak hours	Weekend
	(1)	(2)	(3)	(4)	(5)	(6)
Indicator route with bus corridors	0.040*** (0.010)	0.028*** (0.010)	-0.003 (0.007)	0.027 (0.030)	0.055** (0.024)	0.026 (0.017)
Indicator route with bus lanes	-0.000 (0.012)	0.004 (0.012)	0.007 (0.010)	0.025 (0.029)	0.048 (0.035)	0.054 (0.037)
Observations	2,028	1,768	1,680	2,028	1,768	1,680
Bus routes	507	442	420	507	442	420
Trips (in millions)	16.1	20.3	17.5	16.1	20.3	20.4
Avg. dependent variable (levels)	19.22	20.87	23.88	0.31	0.33	0.23
Route fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y

*Notes:* This table shows two-way fixed effects estimates between priority infrastructure (bus corridors, bus lanes) and (i) bus speed in columns 1-3, and (ii) travelers in columns 4-6. The unit of observation is a route in a given year between 2016 and 2019. All regression specifications include route and year fixed effects. All regressions use an indicator for routes with more than 10% of priority infrastructure. Each coefficient and standard error comes from a separate regression. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. Robust standard errors are clustered at the route level. Statistical significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table A.5:** Alternative indicator, change of 5pp. in infrastructure

Dependent variable:	Log bus speed (km/hr)			Log million travelers		
	Work days			Work days		
	Peak hours	Off-peak hours	Weekend	Peak hours	Off-peak hours	Weekend
<b>Panel A</b>	(1)	(2)	(3)	(4)	(5)	(6)
Indicator route with bus corridors	0.026*** (0.005)	0.021*** (0.005)	0.007 (0.005)	-0.022 (0.026)	-0.018 (0.021)	-0.021 (0.015)
Indicator route with bus lanes	-0.006 (0.004)	-0.003 (0.005)	-0.002 (0.005)	-0.026* (0.015)	0.007 (0.016)	-0.006 (0.013)
<b>Panel B</b>						
Indicator route with bus corridors	0.037*** (0.009)	0.029*** (0.009)	-0.002 (0.009)	-0.078 (0.069)	0.046* (0.027)	-0.007 (0.028)
Indicator route with bus lanes	0.004 (0.005)	0.000 (0.005)	0.002 (0.005)	-0.020 (0.025)	-0.002 (0.023)	0.013 (0.021)
Observations	2,028	1,768	1,680	2,028	1,768	1,680
Bus routes	507	442	420	507	442	420
Trips (in millions)	16.1	20.3	17.5	16.1	20.3	20.4
Avg. dependent variable (levels)	19.22	20.87	23.88	0.31	0.33	0.23
Route fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y

*Notes:* Panel A shows two-way fixed effects estimates between priority infrastructure (bus corridors, bus lanes) and (i) bus speed in columns 1-3, and (ii) travelers in columns 4-6. The unit of observation is a route in a given year between 2016 and 2019. Panel B presents estimates of the same relationship but using the method proposed by Borusyak et al. (2024). All regression specifications include route and year fixed effects. All regressions use indicators that take the value of one for routes with more than 5 percentage points (pp.) changes in priority infrastructure from one year to the following. Each coefficient and standard error comes from a separate regression. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. Robust standard errors are clustered at the route level. Statistical significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table A.6:** Alternative indicator, change of 10pp. in infrastructure

Dependent variable:	Log bus speed (km/hr)			Log million travelers		
	Work days			Work days		
	Peak hours	Off-peak hours	Weekend	Peak hours	Off-peak hours	Weekend
<b>Panel A</b>	(1)	(2)	(3)	(4)	(5)	(6)
Indicator route with bus corridors	0.045*** (0.007)	0.034*** (0.006)	0.008 (0.006)	-0.031 (0.040)	-0.030 (0.037)	-0.024 (0.022)
Indicator route with bus lanes	-0.007 (0.007)	-0.007 (0.007)	-0.005 (0.006)	-0.001 (0.028)	0.037 (0.025)	0.006 (0.017)
<b>Panel B</b>						
Indicator route with bus corridors	0.063*** (0.011)	0.046*** (0.010)	-0.006 (0.009)	-0.050 (0.060)	0.040 (0.033)	0.018 (0.018)
Indicator route with bus lanes	0.014 (0.010)	0.007 (0.010)	0.008 (0.010)	-0.020 (0.036)	-0.036 (0.036)	-0.002 (0.038)
Observations	2,028	1,768	1,680	2,028	1,768	1,680
Bus routes	507	442	420	507	442	420
Trips (in millions)	16.1	20.3	17.5	16.1	20.3	20.4
Avg. dependent variable (levels)	19.22	20.87	23.88	0.31	0.33	0.23
Route fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y

*Notes:* Panel A shows two-way fixed effects estimates between priority infrastructure (bus corridors, bus lanes) and (i) bus speed in columns 1-3, and (ii) travelers in columns 4-6. The unit of observation is a route in a given year between 2016 and 2019. Panel B presents estimates of the same relationship but using the method proposed by Borusyak et al. (2024). All regression specifications include route and year fixed effects. All regressions use indicators that take the value of one for routes with more than 5 percentage points (pp.) changes in priority infrastructure from one year to the following. Each coefficient and standard error comes from a separate regression. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. Standard errors are clustered at the route level. Statistical significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table A.7:** Non-linear effects of priority infrastructure, bus speed

	Dependent variable: Log bus speed					
	Peak hours		Off-peak hours		Weekend	
	Corridor	Only bus	Corridor	Only bus	Corridor	Only bus
	(1)	(2)	(3)	(4)	(5)	(6)
Indicator for percentage $\in (0, 0.05]$	-0.006 (0.009)	0.009 (0.009)	-0.005 (0.014)	0.010 (0.009)	-0.001 (0.011)	0.007 (0.007)
Indicator for percentage $\in [0.05, 0.10)$	0.000 (0.010)	-0.008 (0.010)	0.001 (0.010)	-0.005 (0.011)	-0.012 (0.011)	-0.006 (0.009)
Indicator for percentage $\in [0.10, 0.15)$	0.028*** (0.010)	-0.001 (0.012)	0.021* (0.011)	0.010 (0.013)	-0.006 (0.009)	0.009 (0.011)
Indicator for percentage $\in [0.15, 0.20)$	0.044*** (0.015)	-0.008 (0.022)	0.034** (0.014)	0.001 (0.021)	-0.011 (0.011)	0.001 (0.017)
Indicator for percentage $\in [0.20, 0.25)$	0.047** (0.018)	0.017 (0.027)	0.032* (0.019)	0.010 (0.027)	-0.007 (0.013)	0.017 (0.023)
Indicator for percentage $\in [0.25, 0.30)$	0.061*** (0.020)	0.014 (0.019)	0.038** (0.019)	0.013 (0.017)	0.042* (0.023)	0.014 (0.014)
Indicator for percentage $\in [0.30, 0.35)$	0.078*** (0.026)	-0.007 (0.028)	0.070*** (0.023)	0.012 (0.023)	0.029 (0.020)	0.008 (0.021)
Indicator for percentage $\in [0.35, 0.40)$	0.070** (0.028)	0.073 (0.051)	0.033 (0.030)	0.069 (0.055)	0.011 (0.021)	0.050 (0.047)
Indicator for percentage $\in [0.40, 0.45)$	0.086** (0.035)	0.005 (0.036)	0.075* (0.043)	0.014 (0.053)	0.064* (0.037)	-0.007 (0.051)
Indicator for percentage $\geq 0.45$	0.118*** (0.023)	0.079** (0.036)	0.083*** (0.021)	0.122** (0.056)	0.011 (0.020)	0.077 (0.057)
Observations	2,028	2,028	1,768	1,768	1,680	1,680
Bus routes	507	507	442	442	420	420
Route fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y

*Notes:* Odd (even) columns in this table show the non-linear relationships between bus corridors (bus lanes) and bus speed. The unit of observation is a route in a given year between 2016 and 2019. All regression specifications include route and year fixed effects. The percentage of routes with priority infrastructure is discretized in indicators spanning 5 percentage points, from 0 to more than 45% of the route. Each column shows estimate from a different regression. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. All regressions are weighted by the number of trips in each route. Robust standard errors are clustered by bus route. Statistical significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table A.8:** Non-linear effects of priority infrastructure, travelers

	Dependent variable: Log travelers					
	Peak hours		Off-peak hours		Weekend	
	Corridor	Only bus	Corridor	Only bus	Corridor	Only bus
	(1)	(2)	(3)	(4)	(5)	(6)
Indicator for percentage $\in (0, 0.05]$	0.006 (0.017)	0.030 (0.038)	0.035** (0.015)	0.031 (0.039)	-0.031** (0.014)	0.086** (0.034)
Indicator for percentage $\in [0.05, 0.10)$	-0.006 (0.035)	0.048 (0.042)	0.068** (0.031)	0.103** (0.045)	-0.056* (0.032)	0.118*** (0.038)
Indicator for percentage $\in [0.10, 0.15)$	0.034 (0.031)	0.049 (0.044)	0.087** (0.034)	0.101** (0.045)	-0.023 (0.020)	0.134*** (0.041)
Indicator for percentage $\in [0.15, 0.20)$	0.037 (0.044)	0.076 (0.049)	0.085** (0.039)	0.111** (0.055)	0.026 (0.026)	0.149** (0.057)
Indicator for percentage $\in [0.20, 0.25)$	0.102** (0.051)	0.079 (0.054)	0.156*** (0.050)	0.130* (0.077)	0.043 (0.034)	0.195** (0.080)
Indicator for percentage $\in [0.25, 0.30)$	0.026 (0.072)	0.004 (0.059)	0.053 (0.065)	0.084 (0.063)	-0.042 (0.044)	0.127** (0.062)
Indicator for percentage $\in [0.30, 0.35)$	-0.108 (0.087)	0.071 (0.110)	0.026 (0.090)	0.084 (0.070)	0.023 (0.045)	0.283* (0.165)
Indicator for percentage $\in [0.35, 0.40)$	-0.042 (0.098)	-0.075 (0.087)	0.198** (0.096)	-0.021 (0.081)	0.067 (0.076)	0.125 (0.123)
Indicator for percentage $\in [0.40, 0.45)$	-0.101 (0.091)	-0.029 (0.106)	-0.032 (0.108)	0.167* (0.098)	0.001 (0.117)	0.351** (0.149)
Indicator for percentage $\geq 0.45$	-0.142 (0.115)	0.055 (0.108)	0.074 (0.088)	0.205** (0.088)	-0.036 (0.046)	0.421*** (0.143)
Observations	2,028	2,028	1,768	1,768	1,680	1,680
Bus routes	507	507	442	442	420	420
Route fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y

*Notes:* Odd (even) columns in this table show the non-linear relationships between bus corridors (bus lanes) and travelers. The unit of observation is a route in a given year between 2016 and 2019. All regression specifications include route and year fixed effects. The percentage of routes with priority infrastructure is discretized in indicators spanning 5 percentage points, from 0 to more than 45% of the route. Each column shows estimate from a different regression. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. All regressions are weighted by the number of trips in each route. Robust standard errors are clustered by bus route. Statistical significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .



**Table A.9:** Robustness to model specifications

	Peak hours		Off-peak hours		Weekend	
	CORR	OBL	CORR	OBL	CORR	OBL
<i>Baseline specification</i>	(1)	(2)	(3)	(4)	(5)	(6)
<i>Log bus speed (km/hr)</i>	0.209*** (0.043)	0.027 (0.078)	0.155*** (0.043)	0.045 (0.084)	-0.050 (0.040)	0.066 (0.074)
<i>Log travelers</i>	-0.199 (0.215)	0.100 (0.209)	0.246* (0.147)	0.462* (0.253)	-0.001 (0.101)	0.603** (0.268)
<b>Panel A: Bus speed</b>						
Adds controls: log route distance	0.196*** (0.041)	0.046 (0.083)	0.157*** (0.042)	0.033 (0.086)	-0.049 (0.039)	0.062 (0.074)
Adds controls: Unit effects	0.197*** (0.042)	0.055 (0.081)	0.155*** (0.043)	0.045 (0.084)	-0.050 (0.039)	0.066 (0.074)
Adds controls: Highways	0.198*** (0.042)	0.098 (0.060)	0.157*** (0.043)	0.066 (0.067)	-0.049 (0.039)	0.076 (0.065)
Dependent variable in levels (km/hr)	3.674*** (0.830)	1.022 (1.857)	3.292*** (0.934)	1.086 (2.039)	-0.842 (1.003)	1.772 (2.178)
Without weights by trips	0.252*** (0.034)	0.074 (0.072)	0.196*** (0.048)	0.056 (0.077)	-0.050 (0.048)	0.037 (0.076)
Weighted by kilometers traveled	0.161*** (0.049)	0.023 (0.094)	0.159*** (0.047)	0.034 (0.101)	-0.034 (0.045)	0.055 (0.092)
<b>Panel B: Travelers</b>						
Adds controls: log route distance	-0.190 (0.208)	-0.009 (0.167)	0.274* (0.147)	0.283 (0.194)	0.046 (0.116)	0.438** (0.211)
Adds controls: Unit effects	-0.177 (0.207)	0.098 (0.207)	0.246* (0.147)	0.462* (0.253)	-0.001 (0.101)	0.603** (0.268)
Adds controls: Highways	-0.178 (0.207)	0.072 (0.198)	0.241 (0.147)	0.422** (0.211)	-0.013 (0.100)	0.540** (0.213)
Dependent variable in levels (millions)	-0.027 (0.088)	-0.139 (0.118)	0.134 (0.089)	-0.012 (0.135)	0.049 (0.050)	0.085 (0.078)
Without weights by trips	-0.445 (0.436)	0.088 (0.199)	0.216 (0.169)	0.372 (0.243)	-0.065 (0.106)	0.607** (0.290)
Weighted by kilometers traveled	-0.022 (0.149)	0.171 (0.197)	0.219 (0.156)	0.486* (0.289)	0.015 (0.102)	0.616** (0.311)
Observations	2,208	2,208	1,768	1,768	1,680	1,680
Routes	507	507	442	442	420	420
Avg. dep. variable (panel A)	19.22	19.22	20.87	20.87	23.88	23.88
Avg. dep. variable (panel B)	0.31	0.31	0.33	0.33	0.23	0.23

*Notes:* This table shows the robustness of results in Table 2. Each coefficient and standard error comes from a separate regression. For reference, the upper panel (“Baseline specification”) presents the benchmark estimate. Panels A and presents robustness exercises for bus speed and travelers separately. Peak hours are from 6.30 to 8.29 hrs in the morning and from 17.30 to 20.29 hrs in the afternoon. Off-peak hours are from 9.30 to 12.29 hrs in the morning, from 14.00 to 17.29 hrs in the afternoon, and from 21.30 to 22.59 hrs at night. The remaining hours of the day correspond to “transition” or “night” hours. Work days include days from Monday to Friday that are not a holiday. Weekend hours include all hours on Saturdays, Sundays, and holidays. Robust standard errors are clustered by bus route. Statistical significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .