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The Congestion Relief Benefit of Public Transit: Evidence from Rome

Abstract

We estimate the effect of public transport supply on travel times of motor-vehicle and bus users in Rome, Italy. We apply a quasi-experimental methodology exploiting hourly information on public transport service reductions during strikes. We find that a 10 percent reduction in public transit supply increases the travel time of motor-vehicles by about 1.6 percent in the morning peak. The effect on bus travel time is similar. The congestion-relief benefit of public transport is thus sizeable and bus travel time gains account for an important share of it. We also examine the welfare effects of providing bus lanes. All else given, a bus lane reduces bus travel time by at least 29 percent. We find that bus lanes are undersupplied in Rome, despite the potential costs due to reducing capacity available to cars.

JEL-Codes: H230, H420, R410.

Keywords: congestion relief benefit, bus lanes, public transit, strikes.

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1. Introduction

Most cities throughout the world devote ample resources to subsidizing public transport.[1] One of the main rationales for these subsidies is that the external costs of road congestion are typically not reflected in the price of car travel, implying that congestion is excessive.[2] An improved public transport service can relieve congestion and increase welfare (Small and Verhoef, 2007). However, the cost-effectiveness of public transport subsidies has been repeatedly questioned, because of the large resources they consume (Proost and Van Dender, 2008; Winston and Maheshri, 2007) and because of the small elasticity of car travel with respect to the price of public transport travel (Hensher, 1998).[3]

To evaluate the merits of public transport subsidies, one must quantify the effect of public transport service on road congestion. A thorough assessment of this effect should account not only for the travel delays of car users, but also of public transport users, because congestion reduces the speed of public transport vehicles (primarily buses). The first objective of this paper is to provide new evidence on the congestion-relief effect of public transport, considering the travel delays of private vehicles as well as buses.

Recent literature estimating the congestion-relief benefit uses a quasi-experimental approach, exploiting shocks in public transit supply due to labor strikes (Anderson, 2014, Adler and van Ommeren, 2016, and Bauernschuster et al., 2017). We take a similar approach but propose two key novelties. First, we take advantage of a large number of strikes that are highly heterogeneous in their effect on public transport supply. In addition, we also have information on *hourly* variation in the level of supply during these strikes. Consequently, we can estimate not only the average effect of public transport provision on travel delays, but also the marginal effect. Previous literature relies only on strikes that completely shut down the public transport system. Therefore, the literature cannot estimate marginal effects. Knowledge of these effects is relevant, however, because policy decisions typically focus on marginal supply changes (e.g. removing a certain number of buses from the fleet), rather than complete shutdowns. Second, as anticipated, we estimate the congestion-relief benefit for motor-vehicle travelers as well as

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[1] In the OECD, these subsidies range from 30 to 90% of operating costs (Kenworthy and Laube, 2001). US public transit carries about 1% of passenger kilometers, but receive 25% of transit funding (USDOT, 2018).

[2] Subsidies to public transport are not the only tool to curb the external costs associated to car travel. Other tools include road pricing and driving restrictions. However, the former is rarely adopted due to political constraints (De Borger and Russo, 2018; De Borger and Proost, 2012), whereas the latter have ambiguous effects on congestion and pollution (Davis, 2008. Gallego et al., 2013).

[3] Using numerical models, Nelson et al. (2007) and Parry and Small (2009) find that substantial subsidies are justified for Washington D.C., Los Angeles and London. Börjesson et al. (2017) show the same for Stockholm, despite its adoption of road tolls.

bus travelers. We thus aim to evaluate the potential for public transport improvements to generate a ‘virtuous circle’, whereby road congestion falls, bus speed increases and public transport gets even more attractive (Small, 2004).

Our data comes from Rome, Italy, which provides an interesting setting for our study for several reasons. First, congestion is heavy compared to other cities of similar size, due to the high modal share of cars and motorbikes, combined with a limited supply of public transport infrastructure.[4] Furthermore, Rome’s public transport system relies primarily on buses, which mostly share the roads with private traffic.[5] This enables us to quantify the impact of road congestion on travel delays for bus travelers. Furthermore, public transport strikes are frequent in Rome and vary in intensity. We exploit *hourly* information about strike-induced variation in public transit supply, which we use as exogenous shocks for identification purposes.

We find that a 10 percent reduction in public transit supply increases the travel time of motor-vehicles (cars and motorbikes) by 1.6 percent on average in the morning peak, and about 3 percent on the most heavily congested roads. On average, the reduction in bus speed caused by the higher congestion raises the in-vehicle travel time of bus users by 1.3 percent and waiting time at bus stops by about half as much. These findings suggest that the congestion-relief benefit is sizeable and bus travel time gains account for an important share of this benefit. The marginal effects are approximately constant over the full range of public transit supply levels. On aggregate, a 10 percent reduction in public transport supply produces about €75 million of losses from congestion per year, roughly 25 percent of which are due to extra bus travel time. These benefits are equal to at least 49 percent of the operator cost reduction from the downscaling.

We also use our estimates to study the welfare-optimal level of subsidies accounting for additional welfare effects, adapting the model of Parry and Small (2009). We find that the current level of subsidies in Rome (which, at about three quarters of operating costs, is already large) is smaller than the socially optimal one.

The importance of congestion for the quality of public transport services is testified by the adoption of dedicated bus lanes in many cities throughout the world. Bus traffic on these lanes is largely – but possibly not fully – separated from other vehicles.[6] Thus, the speed of

[4] Traffic congestion indexes rank Rome among the world’s most congested cities, similar to Mexico City, Jakarta and Bangkok, despite its smaller size The TomTom Traffic Index ranks Rome as the sixth most congested city during the morning peak.

[5] Until 2015, Rome had only two subway lines, recently augmented by a third short line. This number is low for a European city of comparable size (2.8 million inhabitants). Public authorities consider limited public resources and a high concentration of archeological sites as the main causes for the lack of infrastructure provision.

[6] In Rome dedicated lanes are shared with taxis, ambulances, police and other public service vehicles. Other cities (e.g. Zurich) adopt a starker separation of public transit vehicles.

buses increases, making them more attractive to users. Although implementing bus lanes is relatively cheap, the main drawback is that the road space available to cars is reduced, which potentially aggravates congestion and car travel delays.

Broadly speaking, there exist two types of dedicated bus lanes systems. The first is a Bus Rapid Transit (BRT) system, which is essentially a (cost-effective) alternative to rail-based mass transit. This type of system covers relatively large portions of a city's public transport network and is particularly popular in South American and Asian cities. There is a literature that evaluates the effects of BRT by means of theoretical models and simulation exercises (Kutzbach, 2009; Basso et al., 2011; Basso and Silva, 2014) and, more recently, with structural empirical analysis (Tsivanidis, 2018; Gaduh et al., 2018). The introduction of this type of dedicated lanes implies a structural, large-scale reorganization of a city's transportation system (as was recently the case, for instance, in Bogota' and Jakarta).

The second type of dedicated lanes are disconnected bus lanes supplied at severely congested parts on the bus route. The length of a bus lane may therefore be as short as a few hundred meters between two traffic lights. Most of the bus network takes place on non-dedicated lanes. The introduction of this type of bus lanes implies a rather marginal change in the city's transport system compared to the first one. The smaller-scale type of intervention is popular in European cities, e.g. London, Amsterdam, and Rome. Implementation costs are close to zero, but the social costs consist mainly of reducing the number of lanes available to other traffic. To our knowledge, there is essentially no evidence of the welfare effects of disconnected bus lanes on the cost of travel.

We focus on this second type of dedicated lanes. The second objective of our paper is to estimate the welfare benefits of disconnected bus lanes (i.e., the travel time benefits to bus travelers), as well as their cost (i.e., the increase in travel time costs to private motor vehicle users). Consistent with the idea that introduction of these bus lanes is a marginal change to the transportation system, we estimate their effects on a road-by-road basis. Specifically, we estimate the relationship between traffic density and travel time for private motor vehicles and buses for all roads in our sample. Based on these estimates, we provide counterfactual travel times and quantities for both modes for a set of two-lane roads that do not include a bus lane in the status quo, when hypothetically reallocating one lane to buses (given assumptions on travel demand).

We show that the provision of bus lanes reduces bus travel time by at least 29 percent. However, bus lanes tend to increase travel time for private motor-vehicles on most roads in equilibrium. We investigate the welfare implications in our counterfactual analysis, showing that the welfare gains from the bus lane depend, quite intuitively, on the elasticity of demand by motor-vehicle travelers on the given road. We single out roads for which the introduction of a bus lane would most likely increase welfare given a wide range of demand elasticities. On a few of these roads, it appears that, under plausible conditions, the bus lane would bring to lower travel time of bus as well as motor-vehicles in equilibrium. These findings suggest that dedicated lanes are undersupplied in Rome. Our results are consistent with previous theoretical literature (Basso et al., 2011; Basso and Silva, 2014) and have policy implications for large cities in emerging and less developed economies, where buses are the mainstay of the public transport system.

The paper proceeds as follows. Section 2 introduces the theory that underlies our identification strategy as well as welfare evaluations. Section 3 and 4 present the empirical approach and the data. Section 5 provides estimates of the effect of public transit supply on travel times of motor vehicle and bus travelers. Section 6 studies the effects of introducing dedicated bus lanes. Section 7 examines the welfare effects of public transport subsidies in Rome. Section 8 concludes.

2. Theoretical background

2.1 Setting

We aim to estimate the *congestion-relief benefit of public transit* and improve our understanding of the welfare effects of providing *dedicated bus lanes*. For both analyses, we will use estimates of the effect of road congestion on motor-vehicle travelers as well as bus users. To explain this in more detail, and to motivate our empirical approach, let us consider a road of fixed length (e.g., one km) with a given number of lanes. Individuals can travel either by private motor vehicles (cars, motorbikes) or public buses over this road. Demand for motor-vehicle and bus travel are both decreasing in their respective generalized prices. The demand for motor-vehicle travel increases in the generalized price of bus travel.

We assume that the generalized price of motor vehicle travel consists of travel time, T, which increases with road congestion. Following the transport engineering literature (Helbing, 2001), T is an increasing and convex function of motor vehicle density *per road lane*, D. In our application, we will measure T in minutes per kilometer, whereas we will measure D in vehicles per kilometer-lane. Because drivers choose their speed based on the distance to the car in front of them, greater density implies lower speed. Following Underwood (1961), we will estimate this relationship by assuming the following functional form:

(1) $$T = \beta e^{\alpha D},$$

where α and β are positive parameters.[7]

For our welfare analysis, it will be easier to relate travel time to the travel flow (or throughput) of motor-vehicles, F, i.e. the quantity of motor vehicle travel on the road segment per unit of time (measured in vehicles per minute). In Appendix E, we show that, using (1) one obtains the standard, upward-sloping relation between travel time, T, and flow, F, as long as the density is below a certain critical value. When density exceeds such value, the slope of the relation between T and F becomes negative, i.e. there is hypercongestion (Small and Verhoef, 2007). This condition is observed very rarely in our data (less than 1.5 percent of all observed hours). Therefore, we concentrate on the upward-sloping part of the travel time-flow relation. See Adler et al. (2019) for an analysis of travel costs that accounts for hypercongestion.

We assume the generalized price of bus travel is an increasing function of the monetary fare, f , and generalized travel time, T_B^G. The latter consists of in-vehicle travel time, T_B , and waiting time at stops, T_B^W. Bus travel time, T_B , consists in turn of two components: time *between* stops and time *at* stops. The latter depends on congestion, as well as on the number of boarding/alighting passengers at each stop, which we do not observe. Hence, we will ignore time at stops for now. However, we take it into account in the welfare analysis (although we assume it is not affected by congestion).[8]

Similar to private motor vehicles, buses drive slower in heavy traffic. We will estimate the congestion relief benefit on bus users through changes in in-vehicle bus travel time, T_B as well as waiting time, T_B^W. We assume that the relationship between bus travel time and traffic density has the same functional form as (1):

(2) $$T_B = \gamma e^{\sigma D},$$

where γ and σ are positive parameters, which may differ from α and β (see (1)).

Congestion also increases bus waiting time, T_B^W, because it decreases bus frequency, i.e. the average number of buses passing the road segment per unit of time. We do not observe T_B^W in our data, but we can estimate it. Let F_B be the frequency of buses, which is equal to the number of buses in operation, n_B, times their average speed, i.e. $1/T_B$. Assuming users arrive

[7] For simplicity, we only focus on density of motor vehicles. Buses typically have a stronger effect on travel time delays than cars. However, in Rome, less than 1 percent of total traffic consists of buses. Hence, our empirical results remain essentially unchanged even if one bus creates the same congestion as ten private cars.

[8] Congestion may affect time at stops, for example, because dense traffic makes it harder for buses to maneuver in and out of stops (e.g. if stops are on the side of road lanes). By ignoring this effect, we likely underestimate the overall impact of congestion on bus travel time.

at bus stops randomly, their expected waiting time is half the time interval between two successive buses (headway), i.e. the inverse of F_B.[9] Therefore:

$$T_B^W = \frac{0.5}{F_B} = \frac{0.5 \times T_B}{n_B}. \tag{3}$$

Given estimates of (2) and using (3), it is straightforward to derive the marginal effect of road congestion, through higher levels of *D*, on the bus waiting time T_B^W.

The relation (3) also provides a basic theoretical foundation to the congestion-relief benefit of public transport and to using strikes to measure this effect. It is convenient to write $n_B = n \times S$, where *n* is the scheduled number of buses at a given point in time and $S \in [0,1]$ is the share of the scheduled service which is actually available. In the absence of strikes, S equals one because there is no service disruption. If a public transit strike takes place, S drops below one and the bus supply, n_B, decreases. Thus, the reduction in supply due to the strike brings to an increase in waiting time (given the level of congestion) and in the generalized price of bus travel. Consequently, demand for motor-vehicle traffic increases and density, *D*, goes up in equilibrium. Therefore, in vehicle travel time by car, T, and by bus, T_B, increase as well, according to (1) and (2). The resulting effect on these last two variables is the negative of the congestion-relief benefit of public transport supply (Anderson, 2014).

2.2 Dedicated bus lanes

We are also interested in the welfare effects of introducing dedicated bus lanes. To evaluate the potential travel time gains for bus travelers, we focus on roads where traffic is currently mixed (i.e. buses travel on the same lanes as other vehicles) and derive the counterfactual bus travel time with a bus lane. We assume the average speed of buses on the bus lane equals the speed on a mixed traffic lane when there is no traffic, i.e. *D=0*. Given (2) and *D=0*, the counterfactual bus travel time on a bus lane is equal to $T_B^{DL} = \gamma$. Therefore, one can expect the generalized bus travel time, $T_B^{G,DL}$, to also drop.[10]

Given a road of fixed size, introducing a bus lane entails closing a lane for motor vehicles. We aim to know how this reduction in capacity affects the relation between traffic

[9] This assumption of random user arrivals is common in the literature (Jara-Diaz and Geschwender, 2009). It most likely applies in the context of Rome, where bus timetables are rather unreliable for several reasons (including heavy congestion). Note that we ignore possible bus bunching, which would increase the average waiting time to more than half the average headway.

[10] Previous studies have shown that bus travelers dislike waiting at stops, T_B^W, more than the time on the bus. Accordingly, in the welfare analysis later on, we will take this into account by assuming that $T_B^G = T_B + \phi T_B^W$ with ϕ = 2 (see, e.g. Basso and Silva, 2014).

density and motor vehicle travel time on this road. For concreteness, let us focus on a two-lane mixed traffic road (we shall focus on this kind of roads in the analysis below). Given two lanes in the status quo, introducing the bus lane reduces the space available for motor vehicles by half. To obtain the counterfactual relationship between travel time, T^{DL}, and density on the remaining lane, we refer to (1). This equation characterizes the motor vehicle travel time in the status quo when there are D vehicles per kilometer *per lane* and, under isotropic conditions, twice the number of vehicles per kilometer *in total*. We assume that, for any level of D, T^{DL} equals the travel time in the status quo given the same total number of vehicles, $2D$, placed on a single lane. Therefore, given the parameters α and β in expression (1), the relation between travel time and motor-vehicle density conditional on the introduction of the bus lane, is:[11]

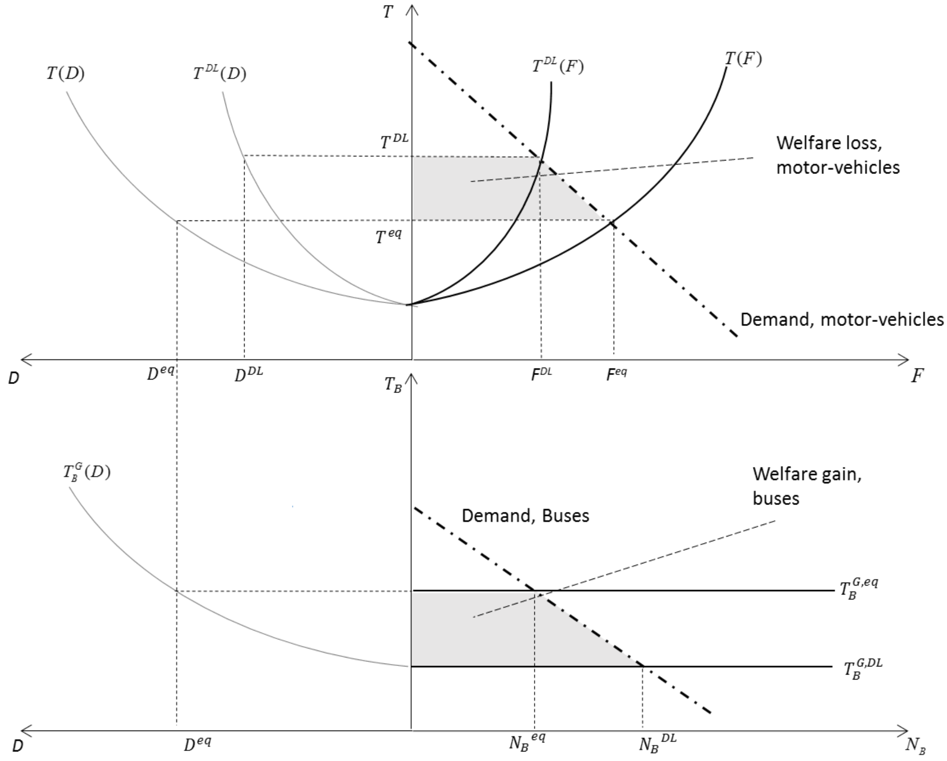
$$T^{DL} = \beta e^{2\alpha D}. \tag{4}$$

Intuitively, reducing the space available for motor vehicles implies a steeper relation between density and travel time. In Appendix E, we show that a reduction in the number of available lanes makes the travel time-flow relation steeper as well (to be precise, more than twice as steep).

Figure 1 summarizes the effects of introducing a bus lane on a two-lane road. The top panel refers to motor-vehicles. Starting from the status-quo equilibrium (superscript "eq."), assuming demand is negatively-sloped, we expect the counterfactual motor-vehicle travel time, T^{DL}, to increase, while motor-vehicle flow, F^{DL}, decreases. The bottom panel of Figure 1 refers to bus travel. Introducing a dedicated bus lane eliminates the effect of density on the generalized bus travel time, which drops from $T_B^{G,eq}$ to $T_B^{G,DL}$. The decrease in the generalized price of bus travel attracts additional users, which increase from N_B^{eq} to N_B^{DL}. The grey areas depict the welfare change produced by introducing the bus lane. Note that, consistently with our assumptions in the quantitative analysis, Figure 1 draws travel demand functions as linear. Note also that $T_B^{G,eq}$ and $T_B^{G,DL}$ are invariant with the number of bus users in the figure, because we assume that bus time at stops is given (neither travel time between stops nor waiting time depend directly on the number of users riding the bus). As argued in Section 6, with this assumption we likely underestimate the welfare gains from introducing dedicated bus lanes.

[11] This assumption is consistent with previous studies on the effects of road space allocation on travel time. See, e.g., Basso and Silva (2014, equation 7).

Figure 1: Effects of providing dedicated bus lanes



3. Empirical approach: the congestion relief benefit

3.1 The congestion relief benefit for motor vehicle travelers

We first focus on the congestion relief benefit of public transit for motor-vehicle travelers. To estimate this benefit, we shall exploit hourly information on public transport supply during labor strikes. Specifically, we have information on the ratio between the available public transit supply and the scheduled level of supply (see Section 4.4 for a more detailed description of this variable). We refer to this variable as the *available share of public transit*, denoting it by $S \in [0,1]$. Our identification strategy exploits variation in the intensity of public transit strikes as an exogenous shock to S. The variable drops below one when there are strikes which disrupt supply.[12]

In our baseline specification, the logarithm of motor-vehicle travel time on road *i* at hour *t*, $logT_{i,t}$, is estimated as a linear function of S_t, the share of public transit supply at *t*. Hence, we estimate the following relationship:

$$logT_{i,t} = \omega_i + \Psi^n S_t + \rho' X_t + \epsilon_{i,t}, \quad (5)$$

[12] If there is no strike, public transport largely follows a regular schedule, with practically constant supply between 8am and 5pm (see Figure A4 in Appendix) during weekdays. However, there is variation outside of these hours. Therefore, we shall control for hour of the day in the empirical analysis.

where X_t refers to control variables, $\epsilon_{i,t}$ is a random error and the coefficient Ψ^w captures the marginal effect of public transit on motor-vehicle travel time. We allow this effect to vary over the day by distinguishing between three periods, indexed by *n* (morning peak, afternoon peak, off-peak). Note that we include a road fixed effect ω_i.

If strikes are fully random, one can estimate Ψ^w consistently without the vector of controls, X_t. However, in Rome strikes are most likely not random (for instance, they tend to be more frequent on Fridays). Our vector of controls therefore includes time (hour-of-the-week and week-of-the-year fixed effects) and weather controls (rain and temperature). Given these controls, one can argue that variation in public transit supply due to strikes is random and use it as a quasi-experiment.[13] This argument is supported by our data: for example, conditional on time controls, strikes are uncorrelated to weather conditions.

We estimate (5) using a weighted regression with weights proportional to the (average hourly) flow of motor-vehicles per road, to make the estimated Ψ^w representative of the average motor-vehicle traveler in our sample. We cluster standard errors by hour.[14] We will also examine nonlinear models, where Ψ^w depends on the level of public transit supply S_t, to examine whether the marginal effect of public transit supply is constant. Furthermore, to facilitate interpretation of the effect of public transit supply on travel time, we also estimate the public transit supply effect on motor-vehicle travel flow, $F_{i,t}$.

3.2 The congestion relief benefit for bus travelers

We now consider the congestion-relief benefit for bus travelers. To estimate this effect, we follow the same approach explained in the previous section. That is, we estimate the effect of S on bus travel time, T_B. This approach is feasible because strikes in Rome are partial, so public transit is never completely shut down. Hence, we have information about travel times of buses that operate despite the strike. For identification purposes, we make the assumption that strikes do not have any effect on travel time of buses in operation, *except through changes in congestion*. This assumption is reasonable for bus travel time between stops, but unlikely to

[13] As we show in the sensitivity analysis, adding day fixed effects generates similar results. Using hour-of-the-weekday fixed effects rather than hour-of-the-day and day-of-the-week fixed effects also generates similar results. The week-of-the-year fixed effects in the above specification also control for the effect of a public transit fare increase in May 2012. The public transit fare increase allows us to estimate the effect of a public *fare* change on motor-vehicle travel time using a discontinuity regression approach. We use the latter as input for our welfare analysis.

[14] We obtain similar results without using weights. In the sensitivity analysis, we demonstrate that our results do not depend on the way we cluster standard errors, see Appendix A2.

hold for travel time at stops.[15] We therefore focus on the effect of public transit supply only on the former.

To estimate the effect of public transit supply on the travel time of bus travelers, $T_{Bi,t}$, we estimate the following reduced-form relationship:

$$logT_{Bi,t} = \mu_i + \Psi_B^n S_t + \rho' X_t + \eta_{i,t}, \quad (6)$$

where $\eta_{i,t}$ is a random error term. Note that we let again the main parameter of interest, Ψ_B^w, vary by period of the day. We also include road fixed effects, μ_i, and the same set of controls described above. We will also allow Ψ_B^n to differ between roads where buses travel in mixed traffic and on dedicated lanes.

One difficulty when estimating (6) is that, in contrast to motor-vehicle travel information, we observe bus information only for a short period (two months). Hence, we have a limited number of observations of bus travel time during strikes, resulting in rather imprecise estimates of Ψ_B^n. Thus, we also apply a two-step approach, combining the bus and motor-vehicle travel datasets. In the first step, using motor-vehicle travel data, we estimate the effect of public transit supply, S, on motor-vehicle density, D (rather than on bus travel time). Hence, similar to (6), we estimate the marginal effect of S_t on motor-vehicle density $D_{i,t}$:

$$D_{i,t} = \mu_i + \delta^n S_t + \rho' X_t + o_{i,t}, \quad (7)$$

where $o_{i,t}$ is a random error term. We again include road fixed effects and controls. The coefficient δ captures the marginal effect of public transit, varying by period of the day.

In the second step, combining bus travel and motor-vehicle travel data, we estimate the effect of traffic density, D, on log bus travel time, $logT_B$, as implied by (6).[16] To estimate this effect, denoted by σ, we estimate separate models for each road, using similar time controls as above (hour-of-the-day, day-of-the-week and week-of-the-year fixed effects). These controls aim to capture unobserved supply shocks that affect bus speed (e.g., roadworks). Furthermore, we include weather controls and bus stop fixed effects. We estimate:

$$logT_{Bi,t} = \pi_i + \sigma_i D_{i,t} + \vartheta_i{}' X_t + v_{i,t}, \quad (8)$$

where $v_{i,t}$ is the error term. Finally, we obtain the marginal effect of public transit supply, S, on log bus travel time, $logT_B$, through reductions in congestion, by taking the product of our

[15] For example, reduced service frequency implies higher occupancy and hence longer boarding times for buses in operation.

[16] Recall we consider only travel time between stops. We are not able to estimate the causal effect of congestion on time *at* stops because stopping time is an increasing function of the number of boarding and alighting passengers. We do not observe this number but suspect that it is correlated to traffic density.

estimates of δ^n and σ_i. The estimates we obtain are qualitatively similar to our estimates of Ψ_B^n, though with much smaller standard errors.

A challenge in the estimation of (8) is that $v_{i,t}$ may be correlated with $D_{i,t}$. Formally, the requirement that $E(D_{i,t}v_{i,t}|X_t) = 0$ might not hold. For example, on mixed traffic roads accidents may affect density and the speed of buses simultaneously. To deal with endogeneity, we use an instrumental variable approach exploiting variation in demand. Following the same logic as in Adler et al. (2019), we exploit regularities in travel demand over the hours of the week as a demand-shifting instrument. This approach makes sense, given that (8) is essentially a (technological) supply relationship. Specifically, we use *hour-of-the-week* dummies, z_t, as instruments (e.g. a dummy for Monday morning between 9 and 10 AM is one instrument). Our key assumption is that $E(z_t v_{i,t}|X_t) = 0$. Importantly, X_t includes three other types of time fixed effects – hour-of-the-day, day-of-the-week and week-of-the-year dummies – as controls. The variation we exploit is that demand is higher during a certain hour of the week, but we control for the hour of the day (i.e., we control for daily variation in sunlight, or any policy that applies only on certain hours of the day, e.g. traffic light changes), day of the week and week of the year (i.e., we control for roadworks that tend to occur only on certain days or that are specific to a certain period of the year). So, for example, we use the fact that demand is lower at 7am in on Mondays compared to 8am on the same day, and we control for the fact that at 7am there might be less light, which potentially influences the behavior of bus drivers for given levels of traffic density.

Our argument for why $E(z_t v_{i,t}|X_t) = 0$ must hold is that these *hour-of-the-week* dummies capture shifts in demand, conditional on other time fixed effects that control for any possible shifts in supply (e.g., for a given density, bus drivers may reduce speed in the evening because it gets darker).[17] Note that a hour-of-the-week dummy essentially measures the demand for a certain hour of the week averaged over the whole period. Hence the exclusion restriction is that, conditional on other time fixed effects, variation in *average* density over hour of the week, where we average over the full period of observation, is entirely due to changes in demand. Consequently, the instrument is valid given the nonrestrictive – and realistic in the context of Rome – assumption that that there are no supply shocks – including policies – that change bus speed systematically at a certain hour for a specific day of the week. Hence, this IV approach allows for policies that adapt road supply with a fixed pattern over the time of the day

[17] Note that the travel demand function is usually expressed as a relationship between travel time and flow. Because density is the product of travel time and flow, it means that a shift of the demand function results in a shift in the in the demand relationship between travel time and flow.

across different days of the week. For example, it allows for roadworks which only take place in the evening, or only on Fridays. Our controls also take care of environmental conditions that affect the speed of buses for given density at certain hours of the day, as well as weather conditions (rain and temperature).

3.3 The welfare effects of dedicated bus lanes

To measure the time gains for bus travelers due to bus lanes, we employ *road-specific* estimates of the effect of motor-vehicle density on bus travel time (i.e., σ_i and other parameters) from equation (8). Assuming zero traffic density on newly-introduced dedicated lanes (*D=0)*, we obtain the counterfactual bus travel time, $T_{Bi,t}^{DL}$. Combining this information with equation (3), provides the counterfactual waiting time of dedicated lanes (we assume here that the number of buses in operation, n_B, does not change when the bus lane is introduced).

We measure the cost of the introduction of a dedicated bus lane using a subsample of two-lanes mixed traffic roads (i.e. roads that do not include a bus lane), by calculating the expected increase in motor-vehicle travel time when closing one lane to motor-vehicles. To this end, we first estimate the effect of motor-vehicle density on motor-vehicle travel time based on (1). Specifically, after taking logs, and adding controls, we estimate:

$$logT_{i,t} = \mathcal{K}_i + \alpha_i D_{i,t} + \vartheta_i X_t + \varepsilon_{i,t}, \tag{9}$$

where $D_{i,t}$ is the density of vehicles per road lane. Our specification includes the same set of controls as for (8). Furthermore, because one can also expect similar endogeneity issues, as in (8), we rely on IV estimates using the same demand shifting instrument, z_t. Hence, we formally assume that $E(z_t \varepsilon_{i,t}|X_t) = 0$.[18] Given estimates of α_i and $\mathcal{K}_i$, we predict the counterfactual relationship between motor-vehicle travel time and density on road *i* when one lane is converted into a bus lane, $T_{i,t}^{DL}$, using equation (4).

Finally, we aim to characterize the counterfactual equilibria when converting one lane to a bus lane, as depicted in Figure 1, and compute the associated welfare changes. To do so, one needs to combine the estimated relations (1)-(4) with information about demand. We assume the following (inverse) linear demand for motor-vehicle travel:

$$T_{i,t} = \mu_{i,t} - \varphi F_{i,t}, \tag{10}$$

where $\mu_{i,t} > 0$, $\varphi > 0$. The fundamental assumption we make is that the slope of the demand for motor-vehicle travel, φ, is invariant across roads and hours whereas we let $\mu_{i,t}$ vary by road

[18] Note that given the fundamental identity $D \equiv FT$, (9) can be rewritten as $logF_{i,t} = \ln(D_{i,t}) - \mathcal{K}_i - \alpha_i D_{i,t} - \vartheta_i X_t - \varepsilon_{i,t}$. Therefore, in principle, α_i can also be obtained by estimating the effect of density on the logarithm of flow, where one controls for the logarithm of density with a coefficient constrained to one.

and hour. We proceed then by making assumptions about the demand parameter, φ. We consider several values, such that demand ranges from almost perfectly elastic to almost perfectly inelastic (see Section 6). We estimate $\mu_{i,t}$, which is possible given the earlier-made assumption that each hourly observation of motor-vehicle travel time and flow on a road describes an equilibrium. For bus travel demand, we follow a similar approach, assuming a linear demand for bus travel:

$$T_{Bi,t} = \mathrm{E}_{i,t} - \Gamma_{i,t} N_{Bi,t}, \tag{11}$$

where $N_{Bi,t}$ denotes the flow of buses and where $\mathrm{E}_{i,t} > 0$ and $\Gamma_{i,t} > 0$. We assume the value of Γ based on elasticities reported in the literature and estimate $\mathrm{E}_{i,t}$ then by road and hour accordingly.[19] Appendix D provides a detailed description of this procedure.

4. Data

4.1 Rome

Rome is Italy's capital and largest city, with a population of about 2.9 million inhabitants (4.3 million including the metropolitan area). The city belongs to the Lazio region, and includes more than 80% of the region's population. The city is densely populated and essentially monocentric around the ancient core. Rome's street network is largely based on the ancient Roman plan, connecting the center to the periphery with primarily radial roads that get narrower as one approaches the center. The city is heavily dependent on motorized travel: 50% of trips are by car and an additional 16% by motorbike/scooter.

Roughly, 28 percent of all annual trips take place by public transport, similarly to other large European cities such as Paris and Berlin. In Rome's metropolitan area there are about 1.65 billion motor vehicle trips per year, equivalent to about 21.5 billion passenger kilometers or 14.5 billion vehicle-kms, 42 percent of which takes place during peak hours (PGTU, 2014).[20] The rest of the trips take place by foot or bicycle. The city is one of the worst performing European cities in terms of air pollution and road congestion. The average instantaneous speed on inner-city roads can be as low as 15km/h on weekdays.

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[19] For simplicity, we ignore cross-price terms in the demand functions in this part of the analysis. Therefore, we most likely underestimate the effect of providing dedicated lanes on modal shift from cars to public transport. Previous literature (e.g., Parry and Small, 2009) suggests that cross-price elasticities between these modes are very small (in the order of 0.1). Allowing for positive cross price terms, calibrated using the elasticities available in the literature, does not change the results in a substantial way.

[20] According to the Mobility Agency, 376,024 motor-vehicle trips take place on average during peak hours. We assume 252 working days per year, 7 peak hours and 9 off-peak hours per working day, whereas each non-working day has 16 off peak hours. The number of trips during off-peak hours is assumed to be two thirds of the number in peak hours. We get then 1,685,599,000 trips per year. We assume an occupancy of 1.4 (1.51) passengers per vehicle in peak (off peak) hours). To obtain the quantity of passenger-kms, we multiply annual trips by the average trip length of 13km as reported by the Mobility Agency (PGTU, 2014).

Table 1 – Travel in Rome's metropolitan area

	Car		Bus		Rail	
	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Annual veh-kms, millions	6,116	8,445	66.7	67.7	10.24	7.2
Annual passenger kms, millions	8,623	12,837	3,403	2,304	1,639	628
Vehicle occupancy (pass-km/veh-km)	1.4	1.51	51	34	160	87
Operating cost, €/veh-km			10	5	29	17
Fare, €cents/pass-km			5	5	5	5
Subsidy, % of average operating cost			75	69	74	76
Generalized price, €cents/pass-km			34	40	25	27

Source: Own calculations based on information from Rome's General Traffic Plan (PGTU, 2014). The data refer to the year 2013.

The rate of motorization is high for a large European city, with 67 cars and 15 motorcycles per 100 inhabitants (about double the figures for Paris and London). There are about 1.6 cars per household. The high car ownership rate, combined with substantial public transit use, suggests that many regular transit users have access to a private vehicle, and are potentially able to switch mode in the event of a transit strike.

Public transit accounts for about 8 billion annual passenger kilometers a year in Rome, i.e. roughly 27% of total travel (ATAC SpA, 2013). The main share of public transit supply is through buses (about 70% in terms of vehicle-kms as well as passenger-kms), see Table 1. Annual subsidies to public transport amount to €1.04 billion, i.e. approximately 72% of annual operating of costs (€1.56 billion in 2013). The average operating cost per trip is about €0.90 (i.e., €0.08 per passenger kilometer) and the price of a single ticket is €1.50. We provide information on the tram and bus fleet in Table A1.

The provision of public transit services in Rome is assigned to a large provider, ATAC SpA (almost entirely owned by the city government), and several much smaller bus companies, operating under the banner of Roma TPL. ATAC covers approximately 90% of the transit market, operating about 360 bus and tramlines, with a fleet of 2,055 buses and 165 trams. It also operates three metro lines, and three train lines connecting Rome with the region of Lazio.

4.2 Motor-vehicle traffic data

Our data on motor vehicle traffic is provided by Rome's Mobility Agency. We use information on hourly flow and travel time for 33 measurement points between 5am and midnight for 769 work days, during a period from the 2nd of January 2012 to the 22nd of May 2015.[21] Motor

[21] We do not observe strikes on weekends, so we focus on work days (regulation restricts striking on weekends). We exclude nighttime hours because there is no public transit service between midnight and 5am.

vehicles include cars, commercial trucks and motorbikes, as measurement stations do not distinguish between types of vehicles.

The measurement locations, chosen by the Mobility Agency, include twelve one-lane (per direction) roads – all located in the city center and with a speed limit of 50km/h (1.2 min/km). The other 21 roads have two lanes. These include seven large arterial roads with a speed limit of 100 km/h (0.6 min/km), eight with speed limits between 60 and 100 km/h and six with a speed limit of 50 km/h.[22]

We measure flow as the number (count) of motor vehicles passing (a measurement point on) the given road per minute per lane. Travel time is measured in minutes per kilometer.[23] We calculate density based on the observed flow and travel time and measure it as the number of motor vehicles per kilometer of road lane. After excluding extreme outliers, we have in total 422,691 hourly observations for motor vehicle flow, density and travel time.[24] We provide descriptive information in Table 2. Note that we have more than 20,000 observations during strikes, i.e. more than five percent of the total.

Table 2 – Motor vehicle travel

	Travel time [min/km]	Density [veh/km-lane]	Flow [veh/min-lane]	Obs.
Strike	1.36	14.6	11.1	23,018
No strike	1.32	13.4	10.5	399,673
Total	1.33	13.5	10.6	422,691

On average, travel time of private motor vehicles is 1.33 min/km, which corresponds to an average (instantaneous) speed of 46 km/h. This speed is far above the average speed of an

[22] See Figure A5 in the Appendix for a map of the measurement locations. Rome has a restricted access zone called ZTL (Zona a Traffico Limitato). This zone is a small part of Rome's historic center, containing less than 1% of all trips in the city, where car inflow is restricted to permit holders (e.g. government officials, local residents). The city lifts restrictions on strike days. This is not problematic for our study because our measurement points are not within the zone. We also have information on eleven additional measurement locations. However, we ignore these, because they are either too close to traffic lights (and hence provide unreliable information) or present extreme variation with discrete breaks in the flows over the period observed, which is likely due to malfunctioning of loop detectors or closure of lanes.

[23] The traffic data comes from loop detectors. We observe the average speed of vehicles at an hourly level (we invert speed to obtain average hourly travel time). We also observe flow (i.e., the number of vehicles passing a detector) per hour and convert it in flow per minute assuming it is constant over the hour (i.e., we ignore within-hour variation).

[24] We drop a few observations when travel time either exceeds 5 min/km or is below 0.4 min/km, when flow is zero or exceeds 2,100 vehicles per hour. The results are robust to the inclusion of these outliers. Information from the measurement locations is sometimes missing (e.g., meters are malfunctioning). During some hours, we have information from only a couple of measurement locations. To avoid identification based on different time periods, we only include hours where at least 20 measurement locations are observed (we exclude 2.2 percent of total observations). Information on the whole month of August 2012 is missing, because the data collection agency moved to another office in this month. A few other days are missing for unknown reasons.

entire trip, e.g. because we exclude waiting time at traffic lights. In our data, flow per lane is above 11 vehicles per minute and density is about 13.5 motor vehicles per kilometer-lane. The distributions of travel time, flow and density are in Figures A7-A9 of Appendix A.[25]

These figures provide information for average traffic conditions, and thus mask substantial differences in congestion levels over time and between roads. We define a road as *heavily congested* during a certain hour when the speed on that road is less than 60 percent of free-flow speed (defined by the 95 percent percentile of the speed distribution observed on that road). Using this definition, on average, roads are heavily congested about one hour per day, or 5 percent of the time. However, there is substantial variation between roads. We single out 10 'heavily congested roads', which are heavily congested at least one hour per day, with an average of about three hours per day, whereas the other 23 roads are heavily congested less than one hour per day.

4.3 Bus travel data

To estimate the effect of road congestion on bus travel time, we focus on a subsample of 27 roads used by the city's bus network. Four of these roads include a dedicated bus lane. We calculate information for each bus line *section*, i.e., the segment between two successive stops. We have information about 58 bus line sections, located on the same road segments for which we observe motor-vehicle traffic data. Using bus microdata available for the months of March 2014 and 2015, we calculate *i)* the bus travel time between stops (in minutes per km), *ii)* time at stops (in minutes per stop), for each bus line section and *iii)* the total bus travel time – including time at stops (in minutes per km).[26] 44 bus line sections are located on mixed traffic roads (i.e., that do not include a dedicated bus lane). The remaining bus line sections are on roads with bus lanes. Note that for the latter roads we have information about motor-vehicle

[25] We weigh all descriptive statistics for travel time by the (time-invariant) average flow per road, as we are interested in the travel time *per motor-vehicle*.

[26] Bus travel time is derived from micro data on the time of arrival and departure at each stop of every bus running on the city's bus network. This data is provided by the Mobility Agency. For most road traffic measurement locations, we are able to precisely identify the bus line section that encompasses the location. For some locations, however, we do not have exact coordinates. In those cases, we use two or three successive bus line sections (per road direction), which surely encompass the measurement location. We consider at least two bus line sections per location (one for each traffic direction).

Table 3 – Bus travel

	Mixed Traffic	Dedicated Bus Lanes		Mixed Traffic	Dedicated Bus Lanes
Bus travel time between stops [min/km]	1.56	1.08	Bus users per section [pass-km/min]	5.16	9.96
Bus time at stops [min/stop]	0.69	0.78	Travel time motor veh. [min/km]	1.41	1.20
Bus travel time (incl. at stops) [min/km]	3.02	1.99	Density motor veh. [veh/lane-km]	14.8	13.5
Bus waiting time [min]	7.69	4.34	Number of roads	23	4
Line section length [km]	0.47	0.85	Number of bus lines	15	2
Bus flow per lane [veh/min]	0.08	0.24	Number of bus line sections	44	14
Bus flow per road [veh/min]	0.12	0.24			

Note: 71,645 observations for mixed traffic roads and 31,024 observations for dedicated bus lanes

traffic on the non-dedicated lanes. In total, we have 71,645 observations for mixed traffic roads and 31,024 observations for dedicated bus lanes.[27]

Summary information in Table 3 shows that the average bus travel time is almost 2 minutes per km (speeds of about 30 km/h) on dedicated lanes, where it is slightly above 3 minutes per km on mixed traffic roads (about 20 km/h). This difference is due to a higher driving speed on dedicated lanes (1.08 minutes per km versus 1.56 minutes per km in mixed traffic) and fewer stops on dedicated lanes (the average distance between stops is 0.47 km on mixed traffic roads, whereas it is 0.85 km on bus lanes). Note that buses tend to spend slightly more time at stops on dedicated lanes (the difference is 0.09 minutes per stop, so about six seconds) most likely because of higher passenger demand, which is about twice as high.[28]

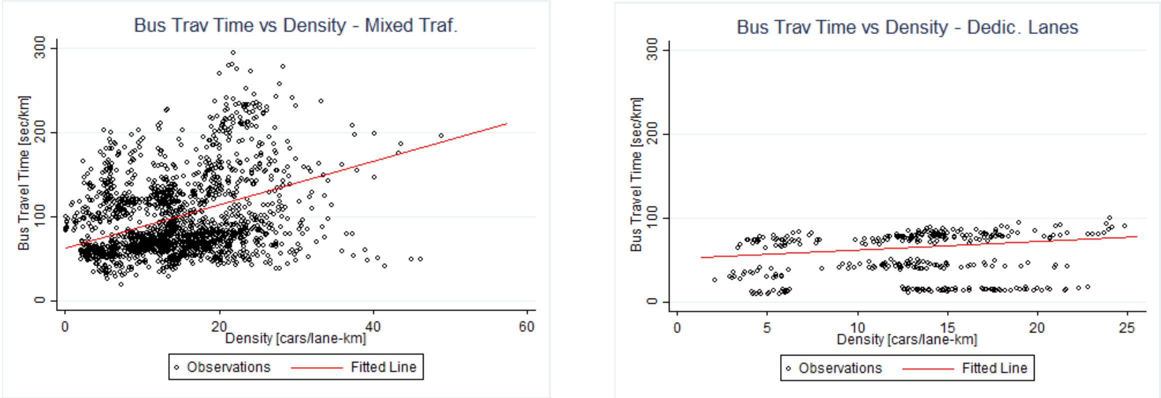
Bus travelers do not only care about the in-vehicle bus travel time, but also about the waiting time at stops. Waiting time is substantially smaller when buses travel on bus lanes (4.34 versus 7.69 minutes), because bus frequency is two times higher than on mixed traffic roads (0.24 compared to 0.12 buses per minute). This difference is partly due to the higher speed of buses on dedicated lanes, but the primary reason is that, as one would expect, the public transport agency tends to use roads with dedicated lanes more intensively. Accordingly, the total number of bus users is higher for bus sections on dedicated lanes.[29]

[27] We exclude six roads for which we have no traffic information over the months of March 2014 and 2015. We also exclude observations for which bus travel time is below the 5th percentile or above the 99th percentile for each bus line section. The results are robust to including these outliers.

[28] We do not observe the number of passengers at each stop, but we can provide a rough estimate of the boarding/exiting time. Assume an average bus occupancy of 42 pax/km (this is the average of the occupancy reported in Table 1), that a bus line consists of 20 stops and that each passenger travels 8 (resp. 5) stops on average. Hence, about 10.5 (17) passengers enter/exit the bus at each stop. Given an average stop time of 2.5 seconds per each entry/exit (as in Basso and Silva, 2014, Table 2), stop time due to boarding would be about 0.44 (0.70) minutes, which is consistent with our information about bus time at stops.

[29] For each line section, we calculate the total number of transit travelers, N_B as the product of F_B, the number of buses traveling on the section per unit of time (i.e. the flow of buses), and bus occupancy. We do not observe the

Figure 4 – Bus travel time and motor-vehicle density



Note: Bus travel time includes only time between stops.

Travel time also tends to be more variable on mixed traffic lanes: the average standard deviation (computed by line section and per each hour in our dataset) of travel time between stops is 0.54 min/km on these lanes, compared to 0.27 min/km on dedicated lanes. Variability in travel time at stops is slightly higher on dedicated lanes than on mixed traffic roads (the standard deviations are 0.25 and 0.20 min/stop respectively). Motor-vehicle traffic conditions are quite similar for both types of roads: roads with dedicated bus lanes have slightly lower motor-vehicle travel times and densities than mixed traffic roads.[30] Finally, note that one can expect the congestion-relief benefit for bus travelers to be substantial only if buses are strongly affected by road congestion. This seems to be the case for Rome. Figure 4 indicates that bus travel time (between stops) strongly increases with the density of motor-vehicles on mixed traffic roads. By contrast, for roads with dedicated lanes, bus travel times are hardly affected by density.

4.4 Transit strikes in Rome

Information on strikes is provided by the Italian strike regulator (Commissione di Garanzia per gli Scioperi). During the 769 working days we observe, there are 43 with a transit strike. Consequently, strikes are frequent in Rome. This is relevant for the interpretation of our study, because a higher strike frequency provides incentives for households to own cars, and thus switch to motor-vehicle travel during strikes. 27 of the observed strikes took place only in Rome

latter at the hourly-line section level. Therefore, we use aggregate data (see Table 1), indicating that average bus occupancy is 51 pass/km in peak hours and 34 pass/km in off-peak ones (PGTU, 2014).

[30] This suggests that dedicated bus lanes are not randomly assigned to roads.

(and sometimes its surroundings), whereas the other 16 were national strikes that may also have affected other transportation modes, e.g. rail and aviation.[31]

All strikes in our data were announced to the public several days in advance. Seven were partially cancelled (by one of the participating unions). We refer to the latter as semi-cancelled strikes in the sensitivity analysis (in Table A2 in Appendix). An additional three announced strikes were fully cancelled shortly before taking place.[32]

Italian law does not allow full transit service shutdowns during strikes, mandating a minimum service level during peak hours. Consequently, the strikes we observe are partial, in the sense that a positive share of service is always provided. Moreover, regulation forbids (with rare exceptions) strikes during bank holidays (e.g. Christmas, Labour Day) and the city experiences considerable fluctuations in the use of public transport during summer months, i.e. in August and September, when schools and small shops are closed and most locals take time off work for family holidays. Excluding these months, the distribution of strike activity is quite even over the year, with somewhat higher concentration in the spring period (see Figure A1 in Appendix). The law also does not allow strikes on weekends. Most strikes take place on Mondays and, in particular, Fridays (see Figure A2 in Appendix A).[33]

We improve upon earlier studies on public transit strikes (Anderson 2014, Bauernschuester et al. 2016, Adler and van Ommeren 2016), as we have information about hourly strike *intensity*. Specifically, Rome's Mobility Agency provided us with the share of scheduled service (based on the regular schedule during non-strike days) that took place during strike hours. This is the variable S that we described in Section 3.1. Thus, we are able to exploit *hourly* variation in the share of available public transit for identification purposes. We use information on this share at the city level: we do not observe service provision in different geographical areas. This is not problematic because the strike intensity of different public transit providers, who operate in different areas, is usually similar (see Figure A3 in the Appendix).[34]

[31] Two of the strikes fall into a white-strike period (between the 7th and the 27th of June 2014). White strikes refer to a labor action whereby bus service is reduced through strict adherence to the providers' service rules (e.g., bus maintenance periods, boarding regulation and ticket controls).

[32] We have also estimated models including cancelled strikes, which allows us to estimate the effect of cancelled strikes on motor-vehicle travel time. We do not find any effect. Given the assumption that announcing and cancelling of strikes has no effect on demand, it is possible to interpret the effect of cancelled strikes as a placebo test, which supports our identification strategy.

[33] Public transit fares are constant during our period of observation except for one major change in May 2012. We use this fare change to derive the price elasticity demand for public transit as well as the cross-price elasticity for car travel.

[34] During strikes, the public transit agency allocates available buses to the most important lines (those serving the largest volume of passengers). It is plausible that the agency would behave similarly if it had to reduce service permanently, e.g. due to budget cuts, so the reduction in public transit supply due to strikes is likely not

During strike hours there are, on average, 839 buses/trams operating, in comparison to 1,496 buses/trams during non-strike hours. There is substantial variation in the hourly share of public transit available during strikes, as can be seen in Figure 5. This share varies between 0.05 and 0.83, the average being 0.56. Note that we observe relatively few strike (peak) hours with low intensity due to the regulatory scheme mentioned above. In Figure 6, we provide the range and three quantiles for the distribution of transit share that is available over the day. The median share is highest during the. morning peak (about 0.75) and the evening peak hour (about 0.65). During these hours, the variation in the share is also small. From 9 a.m. to 3 p.m., the share is not only substantially lower, but the range is also much wider.[35]

Figure 5 – Public transit share for strikes

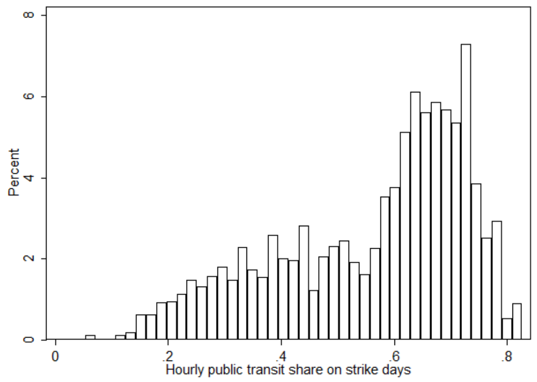
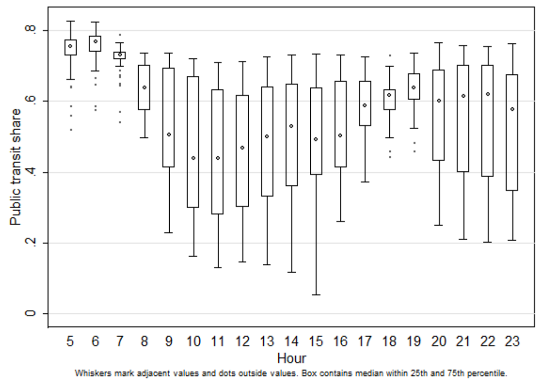


Figure 6 – Public transit share per strike hour



We also use information on the non-strike *scheduled* service level, i.e., the usual number of buses operating per hour. The number of scheduled buses in Rome hardly varies between 8am and 5pm except on strike days (Figures A4 and A6 in Appendix A). These observations support the use of strikes as an exogenous way of identifying the effects of public transit supply.

In Figures 7 and 8, we show levels of travel time and density by hour of the day distinguishing between strikes and no strikes. Similar information about travel flow is provided in Appendix A, Figure A10. These figures indicate that travel time, density and flow increase during strikes.[36] In these figures, we also show information on intensive strikes – whereby the

systematically different from permanent ones. We expect transit users to change to other, less convenient, bus lines during strikes, which one also expects given permanent reductions in supply.

[35] Figures A12 and A13 in Appendix provide the same information as Figures 4 and 5, focusing only on the months of March 2014 and 2015, for which we have bus travel data.

[36] The composition of motor-vehicle traffic may change during strikes. Anecdotal evidence, supported by the high level of car ownership, suggests that most public transit users do not have access to motorcycles (which are mainly used by young adults), but have access to one of the cars in their household. Hence, it is likely that the increase in motor-vehicle traffic is predominantly due to an increase in cars rather than motorcycles.

public transit available share is below 0.5. Travel time, density and flow appear systematically larger during intensive strikes. Figure 7 also shows that during peak hours the increase in travel time is substantially larger, suggesting that the marginal effect of public transit strikes is higher during these hours.[37] Not surprisingly, the figures also indicate that traffic flow, density and travel times are larger in peak than in off peak hours. Travel time, flow and density are respectively 13, 38 and 50 percent larger in the peak.[38]

Figure 7 – Motor veh. travel time

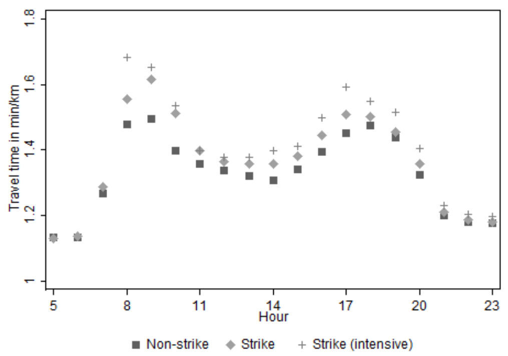
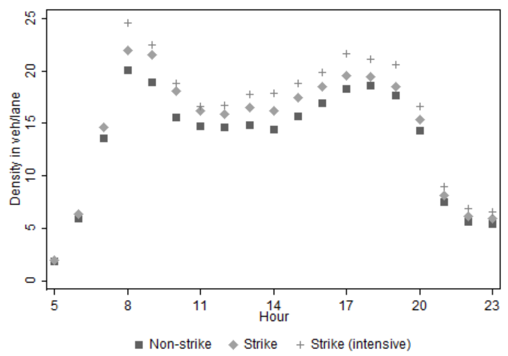


Figure 8 – Density



5. Results

5.1 The congestion relief benefit on motor-vehicle travelers

We start with the estimation of the congestion-relief benefit of public transit on motor-vehicle travel. We estimate the effect of public transit share on motor-vehicle travel time, using (5). We distinguish between the effects in the morning peak, the afternoon peak and off-peak.[39]

Table 4 reports the results of the effect of public transit on log travel time. We report the estimates for the entire sample of roads (column 1), as well as for heavily-congested roads (column 2), one-lane roads (column 3) and large arterial roads (column 4). We find for the entire sample that a ten percent reduction in public transport supply increases travel time during morning peak hours by roughly 1.6 percent, about 0.024 min/km. The effect is substantially smaller during the evening peak, 0.67 percent, about 0.01 min/km. During off peak, the effect

[37] Comparing Figures 7 and A10 shows that between 8am and 5pm variation in flow (or throughput) is much smaller than in travel time. This outcome is consistent with hypercongestion, a situation where congestion decreases a road's throughput (Small and Verhoef, 2007).

[38] One cannot statistically test whether strikes are fully random with respect to road conditions, but one can test whether strikes are correlated to another observed phenomenon. This does not turn out to be the case. For example, it appears that, conditional on time fixed effects, strikes are uncorrelated to weather conditions (results are available upon request).

[39] Note that we include only hours when public transit service is available (i.e., from 5am to midnight). In our data, during night time, travel times and flows are essentially identical on strike and non-strike days, which can be interpreted as a placebo test of strike exogeneity (see Anderson, 2014).

is smaller and equal to 0.39 percent, about 0.0065 min/km, in line with Figure 7. We will use these estimates later on in the welfare analysis of Section 5.3. There, we do not distinguish between morning and afternoon peak hours and we will use the average effect during the peak which is 0.017 min/km.

Table 4 –Log Travel Time

	All roads (33)	Heavily congested (10)	One-lane (12)	Arterial roads (7)
Public transit share (morning peak)	-0.160***	-0.293***	-0.071***	-0.261***
	(0.031)	(0.083)	(0.033)	(0.092)
Public transit share (afternoon peak)	-0.067***	-0.132***	-0.041**	-0.066**
	(0.013)	(0.032)	(0.012)	(0.022)
Public transit share (off-peak)	-0.039***	-0.077***	-0.028***	-0.042***
	(0.007)	(0.024)	(0.008)	(0.014)
Controls	Yes	Yes	Yes	Yes
Observations	422,691	117,790	158,427	81,981
R^2	0.5865	0.5291	0.8276	0.1656

Note: The dependent variable is log travel time. Standard errors (in parenthesis) robust and clustered by hour. The controls include temperature, rain, hour-of-the-week, week-of-the-year and road fixed effects. Significance levels: at 1%, ***, 5%, ** and 10%. *. The number in parenthesis in column titles indicates number of roads.

These results imply that the beneficial effect of public transit supply by reducing road congestion in Rome is far from negligible, particularly during the morning peak. Our estimates are substantially larger than the implied estimates used by Parry and Small (2009), but smaller than results reported by Bauernschuster et al. (2017) and Adler and Van Ommeren (2016) for inner cities. There are at least three explanations for this difference. First, contrary to previous studies, the effect we estimate relates to cars as well as motorbikes, which have a particularly large modal share in Rome. The effect of congestion on motorbikes is presumably less pronounced. A second explanation is that buses in Rome have low speed and high occupancy (due to the relatively low frequency of service), which makes public transit relatively unattractive to individuals. Transit supply shocks may therefore have a smaller effect on the probability of switching from cars to public transit than in other cities. Third, and most importantly, in Rome, strikes are always partial, so it is possible to switch to a less preferred public transit option that is unaffected by the strike. Hence, it is plausible that public transit travelers have somewhat more flexibility to adapt their travel schedule when strikes take place.

The effect of public transit share on travel time on heavily-congested roads is substantially larger than on the average road, particularly during the morning peak. The effect of a ten percent reduction in supply is about 3 percent, or 0.052 min/km (see column 2). The travel time reductions on arterial roads and one-lane roads (column 4), are systematically lower than on the heavily congested roads. Nevertheless, the effect of public transit in one-lane roads during morning peaks is still substantial in magnitude (0.7 percent, or 0.013 min/km, column

3). These results are consistent with the idea that the congestion relief benefit of public transit is much larger on congested roads than on other roads (Anderson, 2014; Tsivanidis, 2018).

Table 5– Log Flow

	All roads (33)	Heavily congested (10)	One-lane (12)	Arterial roads (7)
Public transit share (morning peak)	-0.082***	-0.022	-0.132***	-0.022
	(0.011)	(0.032)	(0.021)	(0.049)
Public transit share (afternoon peak)	-0.062***	-0.050***	-0.101***	-0.034**
	(0.007)	(0.015)	(0.017)	(0.014)
Public transit share (off-peak)	-0.083***	-0.075***	-0.118***	-0.052***
	(0.005)	(0.016)	(0.022)	(0.016)
Controls	Yes	Yes	Yes	Yes
Observations	422,691	117,790	158,427	81,981
R^2	0.8475	0.8245	0.6985	0.8340

Note: The dependent variable is logarithm of flow, expressed in veh/min-lane. Standard errors (in parenthesis) robust and clustered by hour. The controls include temperature, rain, hour-of-the-week, week-of-the-year and road fixed effects. Significance levels: 1%, ***, 5%, ** and 10%. *. The number in parenthesis in column titles indicates the number of roads.

The above results are supported by estimates of effect of public transit on vehicle flow, see Table 5.[40] The results imply that a ten percent shutdown in public transit supply increases traffic flow by about 0.6 to 0.8 percent. Notice that the effect tends to be smaller in heavily-congested roads (possibly because they operate close to capacity).

Another way to demonstrate the importance of public transit during peak hours is to estimate hour-of-the-day specific effects of public transit share on travel time as well as flow. As shown in Figures 9 and 10, the negative effect of public transit share on travel time is strong during (particularly morning) peak hours.

Figure 9 – Travel time

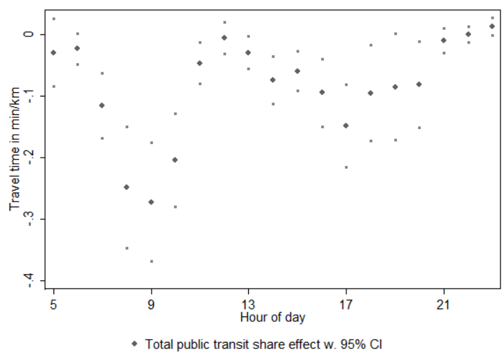
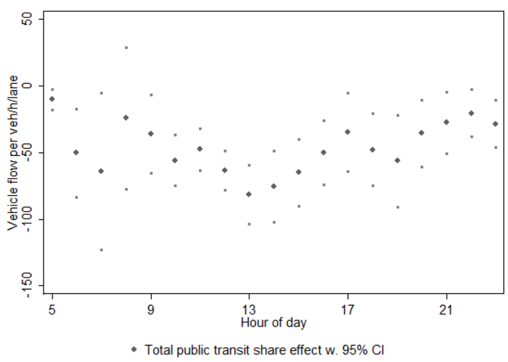


Figure 10 – *Flow*



The above estimates provide a measure of the *average* of the marginal congestion-relief benefits of public transit over the full range of public transit supply. Our study improves on

[40] In the analysis of vehicle flow, we estimate weighted regressions, with weights proportional to the number of lanes. In the analysis of travel time, we estimate weighted regressions with weights proportional to the hourly flow averaged over the whole period.

previous studies by investigating not a complete shutdown of public transit during strikes, but a partial shutdown (on average, 44 percent), which makes it more likely that our study captures *the marginal* congestion relief benefit. Furthermore, because we measure the intensity of strikes, our data also allow us to investigate whether the marginal benefit is constant at different supply levels. To investigate this, we have estimated travel time (and not log travel time) as a function of a polynomial of public transit supply. This analysis suggests that the marginal effect is somewhat larger for stronger reductions in public transit supply. However, statistical tests do not reject the hypothesis that the marginal effect is constant.[41] We present the results using a fifth-order polynomial of the public transit in Figures 11 and 12.

Figure 11 – Travel time

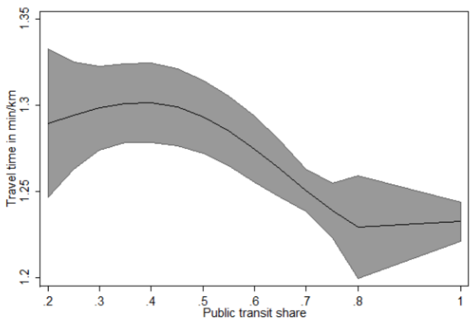
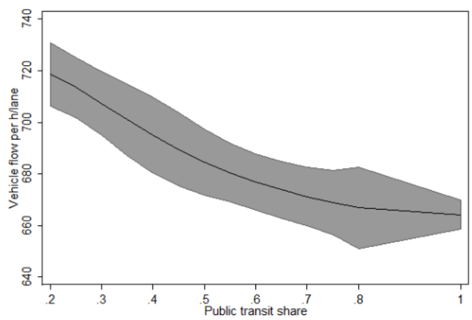


Figure 12 – Flow



In a sensitivity analysis (Appendix A2), to control for unobserved factors that vary between days, we also estimate models with day fixed effects. The results are rather robust. We perform other sensitivity analyses to take into account the type of strike (e.g. national), but our results remain robust. The way of clustering does not seem to affect our results either.

A possible criticism of above analyses is that we use exogenous variation in the public transit *share* (the ratio of the public transit level to the scheduled level of provision), rather than in the public transit level. This is problematic if we do not fully control for the (endogenous) scheduled provision through the inclusion of hour-of-the-day dummies. Furthermore, by using the public transit share, it is less clear how to calculate the congestion relief benefit of one bus. Recall however that the scheduled service level is essentially constant between 8 AM and 5 PM (see Figure A4 in Appendix). Hence, we have re-estimated the model for observations in that time interval (177,450 observations). The standard errors become somewhat higher, but the point estimates hardly change. For example, the estimated effect of a ten percent reduction

[41] We have few observations with public transit shares that are either between 0.75 and 1 or less than 0.3, so the power of this test is quite low.

public transit on motor vehicle travel time during peak hours is 0.017 (with a standard error of 0.0034), or 0.027 min/km, which is close to the original estimate.

5.2 The congestion-relief benefit on bus travelers

We now focus on the congestion relief benefit to bus travelers, which is estimated for 23 mixed traffic roads and 4 roads with dedicated lanes. See Table 6. The first two columns report the results for the one-step approach using (6). Public transit supply tends to reduce bus travel time T_B (between stops) on mixed traffic roads, but not on dedicated lanes. This effect is the strongest during the morning peak: a ten percent reduction in public transit supply increases bus travel time by about 0.75 percent, or 0.015 min/km (this is about half the effect we find for motor vehicles, see Table 4).

The standard errors in the estimates for the one-step approach are relatively large. We therefore focus on the results of the two-step approach, which are more precise. See the last two columns of Table 6.[42] These confirm that the effect of public transport is strongest during the morning peak: a ten percent supply reduction increases the travel time of buses by 1.27 percent on mixed traffic roads (i.e. about 0.025 min/km). This effect is somewhat smaller than the effect of public transit supply on motor-vehicle travel time in percentage terms (see Table 5), but practically identical in absolute terms. We find substantial effects of public transit supply on travel time of bus travelers also during the afternoon peak and off-peak. For example, during the off-peak, the effect is still about half of the effect during the morning peak. As one expects, the effect of public transit supply on bus travel time is absent when buses run on dedicated lanes, despite having very small standard errors.[43] This gives confidence in the estimation procedure.

Recall that these estimates refer to bus travel time between stops, but about half the travel time (per kilometer) on mixed traffic roads is idle time at stops (see Table 3). Therefore, assuming that traffic congestion does not increase bus stop time, these results imply that a ten percent reduction in public transit supply increases overall travel time of bus travelers during the morning peak by about 0.65 percent, if buses drive on mixed traffic roads.

Finally, we can use these results to derive estimates for the effect of public transit supply on bus *waiting time*, T_B^W, through lower road congestion. Equation (3) implies that waiting time

[42] See Appendix A4 for the separate results of each step in this approach. Overall, the estimates from the one-step and two-step procedure are statistically consistent with each other.

[43] In Appendix A3, we provide evidence that a unit increase in traffic density also increases the standard deviation of bus driving time, by about 2.5 percent (see Table A3). Hence, congestion also makes the bus system less reliable. The average standard deviation is 0.54 min/km in mixed traffic. Thus, on average an additional unit of density increases the standard deviation of travel time by 0.013 min/km.

is proportional to the ratio between bus travel time and the number of buses in operation. Hence, a reduction in supply has two effects on waiting time: a direct effect due to reducing the number of buses in operation (given the speed of buses) and an indirect one due to lower bus speed if congestion increases. Ignoring the direct effect for the moment (we shall consider it in the cost-benefit calculations below), our estimates suggest that a ten percent reduction in public transit supply increases waiting time by 0.65 percent during the morning peak *due to the increase in road congestion*. In absolute terms, a ten percent reduction in public transit supply increases waiting time through congestion by 0.032 minutes per trip in the morning peak. Assuming a trip length of 3 (resp. 10) kilometers, therefore, the effect on waiting time is equal to about 42 (resp. 13) percent of the overall effect on travel time of bus users. Therefore, a significant part of the congestion-relief benefit on bus users comes in the form of lower waiting time.

Overall, these results suggest that improving public transit supply reduces travel time of bus users substantially, through the reduction in congestion. This finding lends support to the idea that public transport improvements produce a 'virtuous circle' (Small, 2004).

Table 6 – Log bus travel time

	One-step approach		Two-step approach	
	Mixed traffic roads (23)	Dedicated Lanes (4)	Mixed traffic roads (23)	Dedicated Lanes (4)
Public transit share	-0.075**	-0.035	-0.127***	-0.018
(morning peak)	(0.034)	(0.050)	(0.028)	(0.031)
Public transit share	-0.019	-0.009	-0.079***	-0.008
(afternoon peak)	(0.034)	(0.056)	(0.014)	(0.012)
Public transit share	-0.049**	-0.031	-0.058***	-0.007
(off-peak)	(0.020)	(0.033)	(0.009)	(0.011)
Controls	Yes	Yes	Yes	Yes
Observations	71,645	31,024	71,645	31,024
R^2	0.467	0.666		

Note: The dependent variable is log bus travel time (min/km). Significance levels indicated at 1%, ***, 5%, ** and 10%. *. Standard errors in parenthesis. Bus travel time excludes time at stops. The number in parenthesis in column titles indicates number of roads. Controls include temperature, rain, hour-of-the-week, week-of-the-year and road fixed effects. Standard errors are robust and clustered by hour. For the two-step approach, we use two datasets. We provide here the number of observations for the second step.

5.3 The aggregate congestion relief benefit of public transit for Rome

We now use the above estimates to quantify the overall congestion-relief benefit of public transit in Rome. We will assume that the marginal effect of public transit supply on road traffic is constant, in line with earlier results (see Section 5.1). We have seen that the short-run effect of a full shutdown of public transit (consisting of 201 million vehicle-kms per year) results in a 0.17 min/km increase in travel time in peak hours (averaging over mornings and afternoons), and 0.065 min/km off-peak (as implied by Table 4). The forgone annual congestion relief benefit to motor-vehicle travelers is then about 38 million hours of travel time. Given a value of time of 15.59 €/h, this benefit is worth roughly €595 million.[44] This figure equals about 38% of public transport operating cost in Rome (1.56 billion euros in 2013). We summarize these findings in the first column of Table 7.

Table 7 – Congestion relief benefit of public transport, aggregate calculations

	Full shutdown	Marg. shutdown (10% of total veh-km)
Assumptions		
Annual veh-km, private motor vehicles	14.5 billion	
Annual veh-km, public transport	201 million	
Travel time increase cars (peak), min/veh-km	0.17	0.017
Travel time increase cars (off-peak), min/veh-km	0.06	0.006
Travel time increase buses (peak), min/veh-km		0.020
Travel time increase buses (off-peak), min/veh-km		0.011
Waiting time increase buses (average), min/trip		0.019
Value of time of car travelers, €/h	15.59	
Average op. cost public transport, €/veh-km	7.76	
Results		
Public transit congestion relief benefit, year	€595 million	€75 million
Operating cost saving, year	€1.56 billion	€152 million
Subsidy reduction	€1.03 billion	€152 million
Net congestion relief benefit (% of cost saving)	38%	50%

We can also consider the effect of a marginal (ten percent) reduction in public transit provision. This change induces €59.5 million in lost congestion relief benefits to motor-vehicle travelers. Furthermore, given an implied increase in bus travel time of about 0.020 min/km during the peak and 0.011 min/km outside peak (as implied by Table 6) and about 5.7 billion passenger kilometers by bus per year, there is also an annual loss of €12.7 million to bus travelers in travel time. In addition, there is an increase in waiting time. According to our estimates, the increase in bus waiting time caused by reduced bus speed when the supply of public transport decreases by ten percent is at least 0.019 minutes per trip on mixed traffic lanes.[45] Assuming an average trip length of 5km and that half of these trips take place on mixed traffic roads, the additional loss is €2.8 million per year.[46] The total loss due to extra congestion is thus €75 million annually, i.e. at least 50 percent of the operating cost savings for the transit agency. See the last column of Table 7.

[44] We multiply annual passenger-kms by private motor-vehicles (see Table 1) by the estimated travel time increases in peak and off-peak hours, and by the value of time.

[45] We compute this value using equation (3) and given the estimated increase in bus travel time (0.014 min/km). In this calculation, the number of buses in operation (denoted n_B in (3)), is obtained by multiplying the average flow of buses per road (0.12 veh/min) by the average travel time (3.02 min/km) on mixed traffic roads.

[46] Using equation (3), bus waiting time increases by an additional 0.42 minutes per trip on mixed traffic roads when the number of operating buses decreases by ten percent (keeping bus speed constant). This effect is not related to congestion per se, but it is notable because it is much bigger than the increase in waiting time due to reduced speed.

Another interesting exercise is to compute the marginal congestion relief benefit of an additional bus. In Rome, there are about 8,623 million motor-vehicle passenger-kilometers in peak hours per year (see Table 1). Buses provide about 70% of vehicle-kms of transit service in Rome and there are 1,800 buses circulating during the peak. Consequently, our finding that a full transit shutdown in the peak increases travel time by 0.17 minutes/km implies that removing one bus from peak service for one hour would increase aggregate motor-vehicle time by 5.3 hours. Furthermore, given 3,403 million annual bus passenger-kilometres in the peak, the aggregate increase of travel and waiting time on bus passengers would be 7.9 hours. Assuming that the value of time for car users is €15.59 per hour and €9.54 per hour for bus users, the marginal external benefit of a bus during one peak hour is about €158. Given that there are seven peak hours (including morning and afternoon) per work day, the external benefit of a bus operating during the peak is about €1.106 per day.

These results are based on short-run estimates, exploiting temporary service disruptions. Hence, one should apply some caution when using them to predict long-run effects of permanent changes in transit supply. In Rome, car ownership is high, strikes are frequent and public transit supply is often only partially reduced. During peak hours, in particular, the reduction is limited, suggesting that travelers may respond to strikes in a way that is more similar to a permanent service reduction than in other cities (where car ownership is lower, strikes are infrequent and cause a full shutdown of public transit services). Thus, our estimates are more likely to approximate long-run effects than previous literature using a similar methodology (e.g., Anderson, 2014).

It is plausible that the main difference between our estimates and long-term estimates is the possibility to cancel trips during strikes. Individuals who respond to strikes by canceling their trip likely have less leeway to do so in the long run and are more likely to switch to car use. If this conjecture is true, long-run effects of reductions in supply on road congestion are probably larger than indicated by our current estimates. Nevertheless, we do not capture the very long-run effects of transit supply changes, such as job, house and firm relocation, as well as the spatial structure of cities; overall, our estimates should therefore be interpreted as only indicative of the long-run effects of changes in transit service.

6. The effects of providing dedicated bus lanes

In this section, we evaluate the effects of separating buses from other traffic. The beneficial effect of providing a separate lane for buses is that bus speed increases. The information in Table 3 and 6 implies that providing a (fully-separate) dedicated bus lane on a road where traffic is currently mixed reduces bus travel time by 0.44 min/km on average, i.e. almost 15 percent of the average bus travel time.[47] Furthermore, expression (3) implies that, assuming the supply of buses does not change, the bus lane reduces waiting time by about 0.6 minutes.[48] These figures are supportive of findings of previous literature that relies on simulation models (e.g. Basso and Silva, 2014).

Obviously, the above results exclude the losses to motor-vehicles due to reduced road capacity and ignore changes in demand. To provide a more complete picture, we now focus on a subsample of ten two-lane mixed-traffic roads.[49] For these roads, we compare the status quo to the counterfactual equilibrium where one lane is reserved to buses, applying the methodology illustrated in Section 3.3 and Figure 1. We refer to Appendix D for details. We report the results (averaged for all hours and roads) in Table 8, given different values of the slope of the demand for motor-vehicle travel, φ. On these ten roads, the provision of dedicated bus lanes brings substantial benefits to bus travelers, as travel time decreases by about 18 percent and waiting time by about 12 percent. Given the higher bus speed, frequency increases by about 20 percent. Demand for public transport is quite sensitive to time improvements: following Parry and Small (2009, Appendix B), we assume an elasticity with respect to the generalized price of bus travel of -2.2. Thus, the provision of a bus lane causes a substantial increase in the number of bus users, by about 26 percent. The public transport modal share increases to about 40 percent, from an initial share of 29 percent. Note that these gains are calculated assuming no other changes in the supply of bus services as demand conditions change.[50] Recall also that we treat idle time at stops as given. Therefore, we most likely underestimate the welfare gains of bus lanes.

The net welfare effects of bus lanes depend on the elasticity of the demand for motor-vehicle travel. It seems reasonable to assume that demand *at the level of a road* is quite elastic (e.g., because there are alternative routes). We consider a range of values for the slope, denoted

[47] Table A5 in Appendix A shows that an extra vehicle (per km-lane) increases bus travel time by 1.95 percent (using our IV estimates). We multiply this value by the average density on mixed traffic lanes (14.8, see Table 4) to obtain the percent decrease in bus travel time by reducing the density towards zero. Furthermore, we use the fact that, on average, bus travel time between stops on mixed traffic roads is 1.56 min/km (see Table 4). See Table C2 in Appendix for disaggregate results by road.

[48] This has been calculated using the decrease in travel time (0.44 min/km) and assuming the average number of buses in operation on a mixed traffic road does not change. We obtain this number as the product of average travel time (3.02 min/km) and bus flow (0.12 veh/min), see Table 4.

[49] The set of roads we consider in this exercise are quite similar to the average road in our sample, although traffic tends to be slightly slower (travel time is 1.49 min/km versus 1.33 min/km for the full sample, see Table 3). Bus travel conditions are also quite similar to the average mixed-traffic road (see Table 4).

[50] Hence, we ignore several modifications that a welfare-maximizing public transit agency would probably adopt in response to the increase in user demand. For instance, the agency could increase the number of operating buses, with a further increase in frequency, exploiting economies of density (Mohring, 1972). Furthermore, the agency could adjust the size of buses and the average distance between stops (Basso and Silva, 2014). See Section 7 for an analysis that considers a public transport agency optimizing over some of these variables.

by φ in expression (10), ranging from $\varphi = 1$ to $\varphi = 0.1$ (corresponding to an implied elasticity of -0.12 to -2.53). When $\varphi = 1$, demand is highly inelastic and few motor-vehicle users are can avoid the road considered, despite the reduction in the available capacity. Hence, this reduction causes a severe increase in motorists' travel time, by about 150 percent. The result is a net loss of welfare equal to about 29 passenger-minutes per minute. By contrast, when demand is sufficiently elastic ($\varphi \leq 0.3$), i.e. the implied elasticity is less than -1, motorists can more easily avoid this road resulting in a relatively small increase in the equilibrium travel time. Therefore, the net welfare change from bus lanes is positive.

The averaged results mask significant differences between roads (see Appendix F). For one out of ten roads the travel time gains on buses are large, while the increase in motor-vehicle travel time is relatively small. Hence, the net welfare effect of dedicated lanes is positive even when demand is highly inelastic ($\varphi = 1$). By contrast, four other roads are so prone to congestion that reallocating space to buses results in travel delays for motor vehicles that are very large even when demand is quite elastic ($\varphi = 0.3$). Intuitively, not all roads are good candidates for introducing a dedicated lane. Nonetheless, it appears that the introduction of dedicated lanes would increase welfare in about 10 percent of roads in our sample, *without requiring any other changes to the transport system*.[51]

Table 8 – Effects of provision of bus dedicated lanes

	Status quo (mixed traffic)	Introducing a Bus Lane			
		$\varphi = 1$	$\varphi = 0.5$	$\varphi = 0.3$	$\varphi = 0.1$
Motor-vehicle flow [veh/min-lane]	9.20	6.96	6.50	6.37	6.04
Motor-vehicle travel time [min/km]	1.49	4.10	2.61	2.16	1.76
Bus flow [veh/min]	0.13	0.16	0.16	0.16	0.16
Bus travel time [min/km]	3.06	2.50	2.50	2.50	2.50
Bus travel time, between stops [min/km]	1.76	1.20	1.20	1.20	1.20
Waiting time [min]	7.21	6.35	6.35	6.35	6.35
Bus users [pass/min]	5.41	6.86	6.86	6.86	6.86
Motor-vehicle modal share [% pass-km]	71.16	59.53	57.88	57.38	54.49
Bus modal share [% pass-km]	28.84	40.47	42.12	42.62	45.51
Welfare gain [pass-min]	/	-29.39	-7.60	1.14	7.31

Note: To compute the modal shares, we assume an average occupancy of 1.45 passengers per motor-vehicle. Bus travel time includes travel time between stops and time at stops.

[51] As a consistency check, we have done a counterfactual analysis of removing bus dedicated lanes from roads that already include one. One difficulty is that we do not have information about the counterfactual bus travel time delay for each removed dedicated lane. We address that issue by using the average proportional bus travel time gains for the introduction of a dedicated lane on current mixed roads to calculate the counterfactual bus travel time delay. We find that removing current dedicated lanes reduces welfare, which gives confidence in our procedure.

Reducing the space available to motor-vehicles on a road may cause some motorists to switch to other roads, increasing travel times there as well (Wardrop, 1952). To check the robustness of our findings to the presence of alternative routes, we have also carried out the analysis under the alternative assumption that each road we consider is parallel to an identical road. We assume this two roads are perfect substitutes for motor vehicle users and that aggregate travel demand on this two-road network is perfectly inelastic. Although motor-vehicle travel time on the parallel road may increase (though not necessarily, see below), there are two countervailing effects that reduce welfare losses. First, some motor vehicle users who do not switch to public transport when the bus lane is introduced can use another road, instead of being priced out. Furthermore, introducing the bus lane on one of the two roads implies a smaller reduction in total capacity than when one considers each road in isolation.[52] Therefore, the increase in motor-vehicle travel time is smaller. In fact, on at least two of our ten roads, motor-vehicle travel time *decreases* after introducing the bus lane. The reason is that, given the reduction in demand for motor-vehicle kilometers (due to the improvement in bus travel time), traffic density per lane decreases on the remaining lanes.[53] Under this alternative assumption we find that introducing a bus lane increases welfare on at least three out of ten roads. We report these results in Appendix F (Tables F5 and F6).

Finally, another potential concern is that we ignore possible increases in bus idle time at stops due to higher passenger demand with dedicated lanes. We cannot address this concern directly because we do not observe bus travel demand nor the number of passengers boarding/exiting the bus at each stop. However, back-on-the-envelope calculations show that even if the transit agency does not change other supply conditions, this effect is unlikely to overturn our results.[54]

[52] For example, if the parallel road has one lane, there are three lanes available to motorists in total. Introducing the bus lane implies a reduction in capacity by one third. By contrast, if one considers a single two-lane road in isolation, the bus lane implies a reduction of capacity by one half.

[53] This outcome depends on the assumed size of the alternative road. If we assume the alternative road has a single lane, travel time decreases in two out of ten roads after the introduction of the dedicated lane. If we assume the alternative road has two lanes, travel time decreases on six out of ten roads.

[54] Table 9 indicates that, on average, bus occupancy is 42 passengers per km in the status quo, and increases by about 4 passengers per km with the dedicated lane. Assuming 20 stops per line and supposing (conservatively) that each extra passenger travels 4 stops on average, there are 2 additional entry/exits to/from the bus per each stop. Table 9 indicates that placing the bus on a dedicated lane brings to a reduction in travel time of 33.6 seconds per kilometer. Given there about 2 stops per kilometer on mixed traffic roads (see Table 4), this implies a reduction in travel time by 16.8 seconds per stop. Assuming each extra passenger entering/exiting generates a time loss of 2.5 seconds (Basso and Silva, 2014), the net decrease in travel time would still be equal to 11.8 seconds per stop, i.e. more than 70% of what we find. We also ignore the increase in crowding due to higher bus demand (De Palma et al., 2015). Table 9 reports that the implied frequency of bus increases by about 20 percent, while the number of bus users increases by 26 percent, hence slightly more. Therefore, one can expect a small increase in crowding.

7. The effect of public transit subsidies given adjustments in public transit supply

The results of the previous sections suggest that the congestion relief benefit of public transport is substantial. Although this finding provides some justification for the volume of public transit subsidies in Rome, it does not imply that their current level is optimal. Subsidies may have additional justifications (e.g., economies of scale, environmental externalities), but produce a price distortion. Furthermore, for a proper evaluation of public transit subsidies one has to consider possible adjustments in service by the transit agency, in response to changes in demand. To provide more insight on whether the current subsidy level is justified, we use the model of Parry and Small (2009). Note that, because we are only interested in the optimality of subsidies, we ignore the provision of dedicated lanes here.

In Parry and Small's model, travelers choose between three travel modes (private motor-vehicle, bus, rail) and two time periods (peak vs. off-peak), while the (welfare-maximizing) public transit agency chooses transit supply and fares subject to a budget constraint. We calibrate the parameters using our empirical estimates and data provided by the city of Rome (see Table G1 in Appendix for details).

Table 9 – Parry and Small model for Rome: optimal public transit subsidies

		Peak		Off peak	
Marginal external cost, motor vehicle travel. €/veh-km		0.29		0.13	
on other motor vehicles travelers		0.21		0.09	
on bus travelers		0.08		0.04	
		Rail		Bus	
		Peak	Off-Peak	Peak	Off-Peak
Current subsidy, share of op. cost		0.76	0.76	0.74	0.69
Marginal welfare effects	Weighted Avg.				
Marginal benefit per €cent/pax-km[a]	0.10	0.31	-0.07	0.11	0.21
marginal cost/price gap	-0.24	-0.38	-0.41	-0.34	-0.21
net scale economy	0.12	-0.02	0.21	0.04	0.31
Externality	0.15	0.53	0.14	0.31	0.02
other transit	0.08	0.19	0.11	0.10	0.09
Optimum subsidy, share of op. cost		>0.9	0.72	>0.8	>0.9

We make slight adaptations to the model of Parry and Small as follows. First, we assume that motor-vehicle travel time is a function of density, in line with (1).[55] In Table C1 in Appendix, we estimate that $\alpha = 0.019$. Similarly, we assume bus travel time is a function of density, see (2), using the value of σ estimated in Table A5, column 4. We compute the marginal external costs of congestion on motor-vehicle and bus travelers based on these parameters.

[55] Parry and Small (2009) postulate a time-flow relation, whereby travel time is a power function of flow.

Finally, we calibrate the fare elasticity of transit passenger-kms using our own estimates (exploiting one public fare increase) and data provided by the city of Rome.[56] This elasticity is 0.22 (see Appendix B for the derivation), which is rather low in comparison to the elasticities assumed by Parry and Small. However, given that transit fares in Rome are much smaller than in comparable European cities, a low elasticity seems reasonable.[57]

Table 10 reports the results. The top panel reports the marginal external congestion cost per motor vehicle kilometer, which equals €0.29/veh-km in peak hours, and €0.13/veh-km during off peak (see the first row of Table 9). These costs are the sum of the external costs imposed on motor vehicle drivers (€0.21/veh-km in peak hours, €0.09/veh-km off-peak), as well as the external costs imposed on bus travelers (€0.08/veh-km in peak hours, €0.038/veh-km off-peak).

The bottom panel of Table 9 reports the marginal change in social welfare resulting from a marginal increase in the public transit subsidy (assuming this increase results in a fare reduction), starting from the current level. The reported "marginal benefit" is the marginal welfare gain from a one-cent-per-km reduction in passenger fare, expressed in cents per initial passenger-km. We decompose this effect into four components: (i) a welfare loss due to the increased gap between marginal production costs of producing public transit and public transit prices, (ii) a welfare gain due to additional economies of scale, (iii) a welfare gain due to a reduction in externalities (congestion and motor-vehicle pollution reduction) and (iv) the welfare benefit of diverting passengers from other transit modes for which the marginal social cost per passenger-km exceeds the fare. The marginal social benefit of a fare reduction is positive for rail and bus services, except for off-peak rail. The average marginal social benefit is equal to 0.1. This finding suggests that, despite the already substantial level, increasing transit subsidies is welfare improving. On average, an additional cent of subsidy brings roughly 0.15 cents of externality-relief benefit, and 0.12 cents in scale economies.[58] In addition, we find that

[56] We observe one substantial public transit fare increase – by 50 percent –on May 2012. We have also estimated the effect of this price increase on motor-vehicle travel time using a discontinuity regression approach. Our results indicate that an increase in the public transit fare by 50 percent increases motor-vehicle travel times by 0.05 minutes per kilometer implying that the elasticity of motor-vehicle travel time with respect to public transit fare is 0.078 (see Appendix B for details).

[57] Our results do not change substantially when we use the elasticities assumed by Parry and Small (2009). Note also that our data suggest an elasticity of private motor vehicle flow to transit fares of 0.1 (see Appendix B). Given that the own price elasticity of transit is 0.22, this value is roughly consistent with a modal diversion ratio from cars to transit between 0.4 and 0.5, as assumed by Parry and Small.

[58] The marginal congestion relief benefit is comparable to the average benefit obtained above (see Table 10), though smaller. One reason is that the model of this section assumes that a higher subsidy translates into lower fares, which, given the low fare elasticity in Rome, attenuates them modal shift and, thus, the congestion relief benefit. By contrast, in Table 10 we consider the effect of a change in service (veh-kms). Furthermore, the methodology adopted in this section is more comprehensive. For example, it takes into account the effects on travel demand that come from both a change in prices and the adjustment in public transit supply.

in the optimum – in the absence of road pricing – subsidies should cover at least 72 percent of operating costs (bottom row in Table 10).

7. *Conclusion*

We estimate the effect of public transit supply on travel times of travelers for Rome, Italy, using a quasi-experimental methodology based on public transit strikes. We improve on previous approaches by exploiting hourly information on partial strikes with varying intensity. Another novelty is that we include information of travel time of bus travelers. We have shown these travelers benefit from reductions in road congestion, not only because buses travel faster but also because waiting time at bus stops are reduced through higher bus frequencies. We demonstrate that the marginal congestion relief benefit of public transit supply is substantial and equal to about half the operating cost of public transit. Interestingly, motor vehicle users and bus users appear to have roughly the same time gains due to reductions in congestion induced by improved public transport. We further show that the marginal congestion relief benefit of public transit provision does not vary with the level of public transit supply.

Urban economists typically advise road pricing to address road externalities, but this is often unfeasible. Our findings suggest that alternative policies still bring substantial welfare gains. Our findings suggest that the introduction of dedicated lanes for some roads should be a priority in Rome, as road congestion has a strong effect on travel time delays of bus (Basso and Silva, 2014; Börjesson et. al, 2017). Our results also support policies aiming at reducing road congestion through an increased supply of public transit. We find that public transit – which has a modal share of 28% in Rome – reduces travel time of motor vehicles by roughly 15 percent in the morning peak, on average. In light of the size of the congestion-relief effect, the current level of public transit subsidies, which is about 75 percent of the operational costs in Rome, appears to be justified.

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Appendix

Appendix A1: Figures and Tables

Figure A1 – Strikes by month

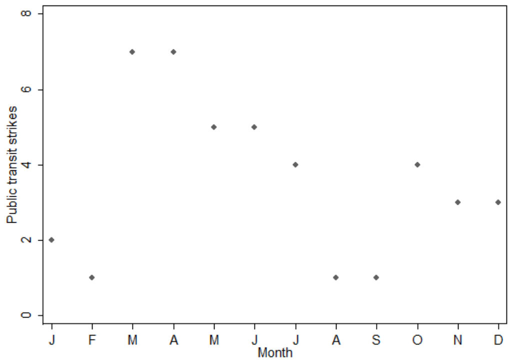

Figure A2 – Strikes by day

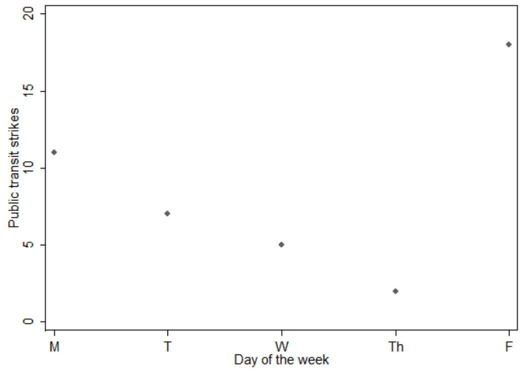

Figure A3 –Public transit share by company

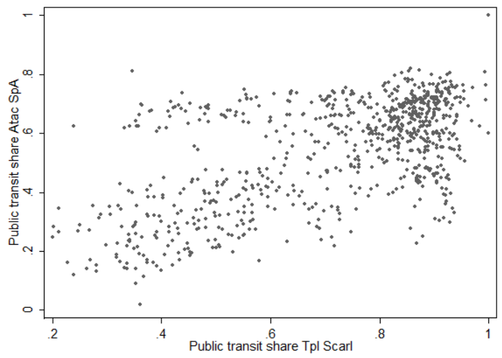

Figure A4 – Public transit on non-strike day

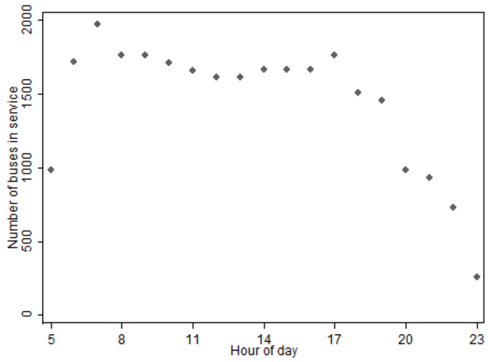

Figure A5 – Map of Rome and location of traffic measurement points

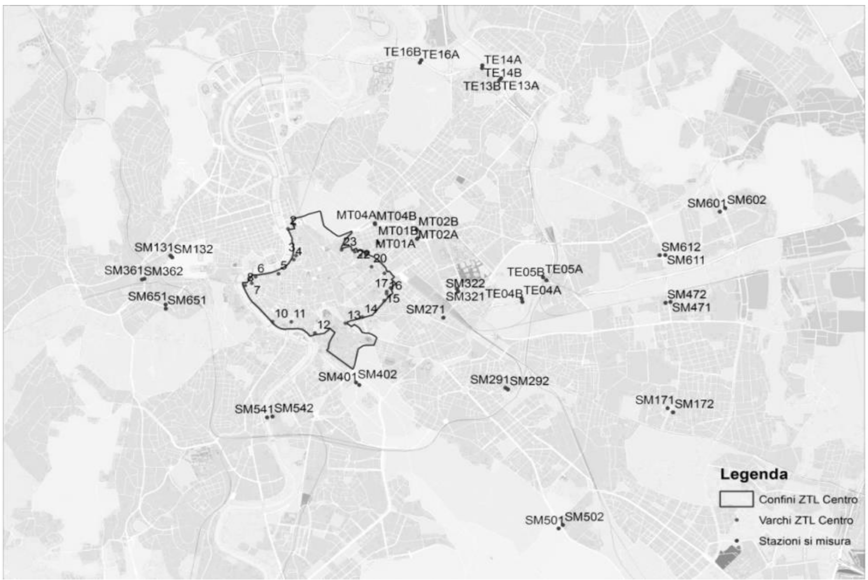

Figure A6 – Public transit service on strike days

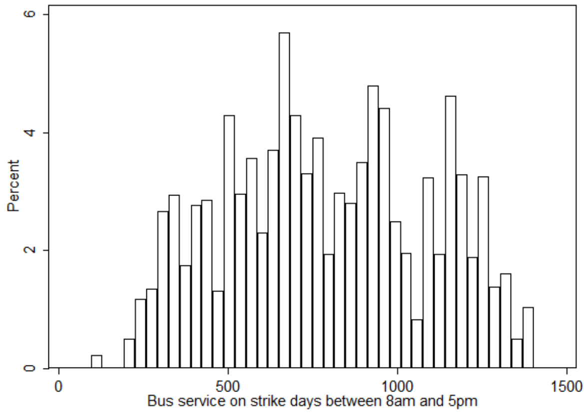

Figure A7 – Travel time histogram

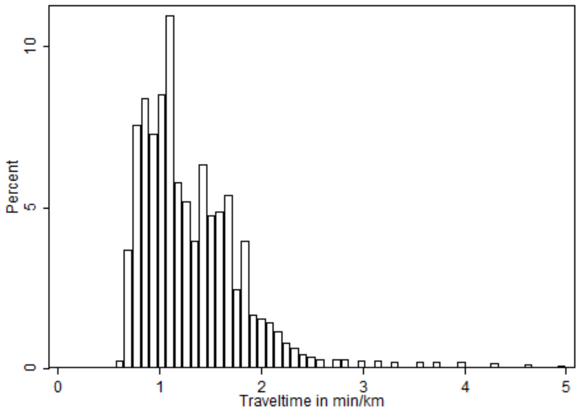

Figure A8 – Vehicle density histogram

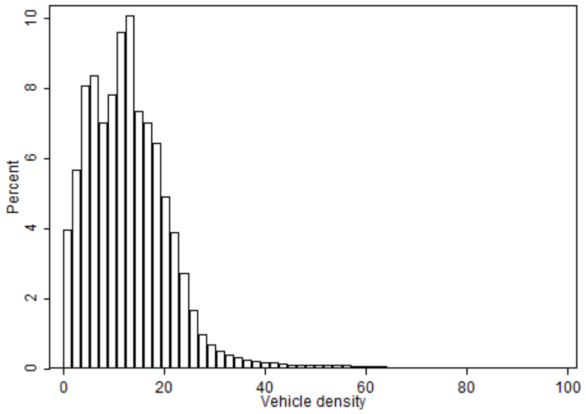

Figure A9 – Vehicle flow histogram

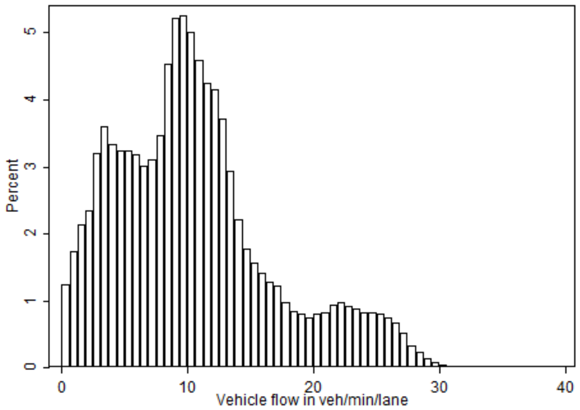

Figure A10 – Vehicle flow by hour of the day

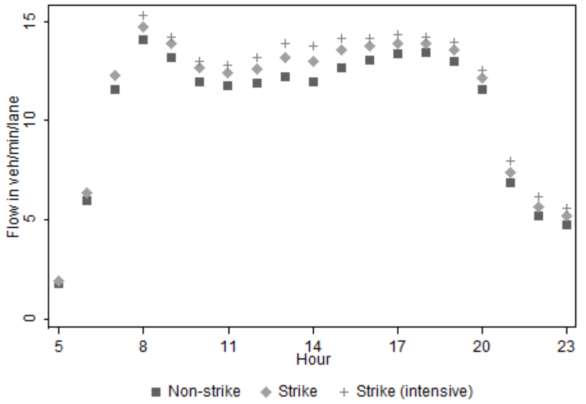

Figure A11 – Heavy congestion by hour

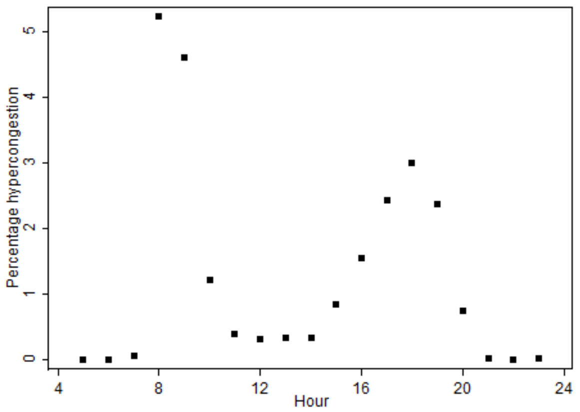

Figure A12 – Public transit share for strikes, subsample with bus travel information

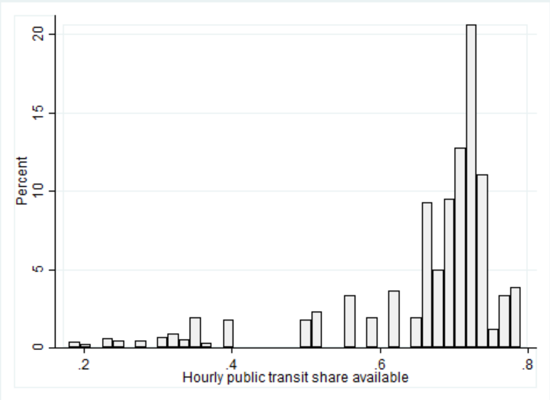

Figure A13 – Public transit share per strike hour, subsample with bus travel information

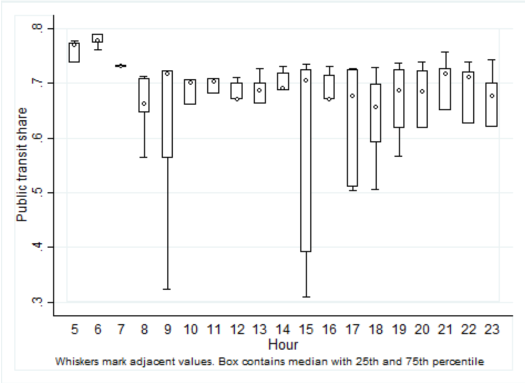

Table A1 – Public transit stock in Rome

Public transit company	Buses	Metro trains	Surface Trains	Employees
Atac SpA	2,055 (+165 trams)	102	66	11,696
Roma Tpl Scarl	450			839
Total	2,717	102	66	12,525

Note: Information for ATAC refers to the year 2015. For Roma TPL the data refers to the year 2011.

Appendix A2: Sensitivity Analysis

We conduct a range of sensitivity analyses to verify the effect of public transit share on travel time. In column (1), we show results with day fixed effects. Our results are robust. In column (2), we cluster standard errors by road and week-of-year.[59] Standard errors become only slightly larger. In column (3), we add additional interaction effects for national strikes and semi-cancelled strikes as well as a white strike dummy.[60] The estimated sizes of these interaction effects are very small. For example, during the white strike, travel time increases slightly by about 0.2 percent, i.e. 0.032 min/km.

[59] Two-way clustering is possible because one dimension (measurement location) is much smaller than the other (i.e. week-of-year) and therefore we can make use of the asymptotic properties necessary for robust standard errors. As an alternative it seems useful to cluster standard errors both in terms of location and day, but this reduces the degrees of freedom below the value for which one can still estimate standard errors.

[60] During the white strike, a period of two weeks where public transit service was reduced through alternative means of striking excludes two strike days that fell into this period.

Table A2 – Log travel time: alternative specifications

	(1) Travel time	(2) Travel time	(3) Travel time
Morning peak: Public transit share	-0.158*** (0.030)	-0.162*** (0.032)	-0.152*** (0.029)
Afternoon peak: Public transit share	-0.066*** (0.013)	-0.068*** (0.014)	-0.054*** (0.016)
Off-peak: Public transit share	-0.036*** (0.006)	-0.035*** (0.007)	-0.028*** (0.008)
Public transit share × National strike			-0.018** (0.011)
Public transit share × Semi-cancelled strike			-0.012* (0.007)
White strike (dummy)			0.021** (0.009)
Day-fixed effects	Yes	No	No
Clusters of standard errors	Location	Week-of-year and location	Day
Observations	422,691	422,619	422,691
R^2	0.5865	0.0005	0.5865

Note: standard errors are robust and clustered. Significance level are indicated at 1%, ***, 5%, ** and 10%, * levels. Includes weather and time controls as in the main analysis.

Appendix A3: Variability of bus travel time and road congestion

We report here the results on the effect of traffic density on the *hourly* standard deviation of bus travel time for each road section to capture the variation in bus travel time *within* each hour. We estimate the same model as in (8) but the dependent variable is the logarithm of the standard deviation of bus travel time on line section i at hour t. We report OLS and IV estimates, where for the latter the instrument are hour-of-the-week dummies.

Table A3– Log standard deviation of bus travel time

	Mixed traffic OLS	Mixed traffic IV	Dedicated lanes OLS	Dedicated lanes IV
Density	0.0288***	0.0247**	0.0072	0.0060
	(0.0051)	(0.0103)	(0.0061)	(0.0136)
Controls	Yes	Yes	Yes	Yes
Observations	71,645	71,645	31,024	31,024
R-squared	0.391		0.678	

Robust standard errors in parentheses, clustered by bus line section. Instrument: hour-of-the-week. We control for weather conditions, hour-of-the-day, day-of-the-week, week-of-the-year, road and line section fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Appendix A4: Intermediate results for the two-step procedure to estimate the congestion-relief benefit on bus users.

As a first step, we estimate the marginal effect of public transit supply on motor-vehicle density (see equation (7)). As shown in Table A4, a shutdown of public transport increases motor-vehicle density by about 3 to 7 vehicles per lane-km on mixed traffic roads, with a similar effect on roads that include dedicated lanes. Because we can use our full dataset of motor vehicle traffic and strikes, the number of observations is large and standard errors are reasonably small.

Table A4 – Motor-vehicle density

	Mixed traffic roads (23)	Dedicated Lanes (4)
Public transit share (morning peak)	-6.55***	-7.25*
	(1.24)	(3.78)
Public transit share (afternoon peak)	-4.10***	-3.13***
	(0.56)	(0.76)
Public transit share (off-peak)	-2.99***	-2.94***
	(0.36)	(0.59)
Controls	Yes	Yes
Observations	353,442	49,539
R^2	0.509	0.484

Note: The dependent variable is motor-vehicle density. The controls include temperature, rain, hour-of-the-week, week-of-the-year and road fixed effects. Standard errors (in parenthesis) robust and clustered by road. Significance levels indicated at 1%, ***, 5%, ** and 10%. *. The number in parenthesis in column titles indicates the number of roads. The estimates refer to the 27 roads for which we observe bus travel information.

As a second step, we estimate the effect of motor-vehicle density on bus travel time for each road separately (using the same sample as used for Table 7). Table A5 reports the results, averaged over all roads (see Table C1 in Appendix C for road-by-road estimates). When using OLS, we find that on a mixed traffic road a unit increase in density (veh/lane-km) increases bus travel time by 1.6 percent. Given the use of IV, this effect is slightly higher and equal to 1.95 percent. It appears that the instrument is (very) strong for all roads, see Appendix C. The effect is much smaller and not statistically significant on dedicated lanes.

Table A5 – Log bus driving time

	Mixed traffic OLS	Mixed traffic IV	Dedicated lanes OLS	Dedicated lanes IV
Density	0.0160***	0.0195***	0.0023	0.0026
	(0.0009)	(0.0023)	(0.0019)	(0.0037)
Instrument		Hour-of-week		Hour-of-week
Controls	Yes	Yes	Yes	Yes
Number of roads	23	23	4	4
Number of obs.	71,645	71,645	31,024	31,024

Note: The dependent variable is the logarithm of bus travel time (min/km). The controls include temperature, rain, hour-of-day, day-of-week, week and bus line section fixed effects. Standard errors are in parenthesis. Significance levels indicated at 1%, ***, 5%, ** and 10%. *.

Appendix B: Public transit fares and motor-vehicle demand

Rome`s public transit operator adjusted fare prices on May 25th of 2012, most notably for single tickets from €1 to €1.5.[61] Fare prices are thought to affect demand for public transit and therefore its main alternative, private motor-vehicle use. Annual single ticket sales declined from 2011 to 2013 by 11% (ATAC 2011; 2013). This suggests that the price elasticity of public transit is -0.22, so public transit demand is rather inelastic, in line with previous findings (see, e.g., Parry and Small, 2009).

The fare increase allows us to estimate the effect of fares on travel time and flow using a discontinuity regression approach. We include observations for the year 2012, so we choose a half-year window on both sides of the boundary, and we use the same control variables as in Table 4, while including third-order polynomial time trends before and after the boundary rather than week fixed effects. For results, see Table B1.

We find that the fare hike increases flow by 30 vehicles per hour (about 5% of the mean, see Table 2). The cross-price elasticity of motorized vehicle travel with respect to transit prices is then about 0.10. More importantly the fare increase also increased travel time for motor vehicles by 0.048 min/km. The elasticity of motor vehicle travel time with respect to public transit fares is then about 0.078.

Table B1 – Travel time and flow as a function of public transit fare changes

	Travel time		Flow
	All roads	Heavily congested	All roads
Fare increase by 50%	0.048***	0.116***	30.8***
	(0.013)	(0.026)	(6.9)
Time trends before boundary	Yes	Yes	Yes
Time trends after boundary	Yes	Yes	Yes
Controls			
Public transit share	Yes	Yes	Yes
Road fixed effects	Yes	Yes	Yes
Hour-of-week fixed effects (120)	Yes	Yes	Yes
Weather	Yes	Yes	Yes
Observations	113,129	31,654	113,139
R^2	0.7338	0.7239	0.8934

Note: Time trends refers to 3rd order polynomials of time. Travel time regression is weighted by flow. Flow per lane regression is weighted by the number of lanes. Robust standard errors are clustered by hour. Significance levels indicated at 1%, ***, 5%, ** and 10%, *.

We have investigated the robustness of these results in several ways. In particular, we have estimated models controlling for linear trends while reducing the window size around the boundary. Given a six-months window (on both sides) but with linear controls, the results are

[61] At the same time the maximum allowed travel time on a single ticket was increased from 75 min to 100 min, so far some travelers the price increase was less steep. Fare prices increased for monthly and annual tickets in a similar way.

identical. Given a five months or four months window the estimates increase to 0.06 and 0.10. Given a three-month window, the estimate is again 0.04, and still highly statistically significant.

Appendix C: Disaggregate results by road

Table C1 – Motor vehicle and bus travel time effect of density, instrument hour of week

				Mixed Traffic Roads				
Road	Alpha OLS	Se OLS	Alpha IV	Se IV	Sigma OLS	Se OLS	Sigma IV	Se IV
1	0.0118	0.0001	0.0124	0.0008	0.0199	0.0030	0.0071	0.0096
2	0.0081	0.0001	0.0107	0.0005	0.0070	0.0015	0.0015	0.0038
3	0.0330	0.0001	0.0311	0.0009	0.0345	0.0010	0.0277	0.0035
4	0.0286	0.0001	0.0274	0.0006	0.0381	0.0010	0.0356	0.0029
8	0.0184	0.0001	0.0128	0.0007	0.0182	0.0011	0.0244	0.0031
9	0.0219	0.0001	0.0199	0.0008	0.0208	0.0020	0.0266	0.0057
10	0.0344	0.0001	0.0340	0.0005	0.0229	0.0022	0.0211	0.0042
11	0.0161	0.0002	0.0150	0.0007	0.0119	0.0040	0.0053	0.0098
12	0.0099	0.0001	0.0119	0.0010	0.0139	0.0027	0.0305	0.0072
13	0.0190	0.0002	0.0200	0.0006	0.0168	0.0042	0.0198	0.0074
14	0.0178	0.0005	0.0458	0.0029	0.1250	0.0094	0.1331	0.0213
15	0.0393	0.0003	0.0199	0.0026	0.0009	0.0054	-0.0021	0.0159
16	0.0191	0.0002	0.0180	0.0010	0.0112	0.0045	0.0035	0.0102
17	0.0161	0.0001	0.0143	0.0009	0.0027	0.0068	0.0169	0.0148
18	-0.0190	0.0006	0.0183	0.0059	0.0136	0.0089	0.0473	0.0268
19	0.0059	0.0001	0.0121	0.0014	0.0023	0.0018	0.0025	0.0053
21	0.0259	0.0001	0.0260	0.0005	0.0107	0.0011	0.0101	0.0032
22	0.0218	0.0001	0.0193	0.0010	0.0092	0.0045	0.0075	0.0116
23	0.0281	0.0002	0.0203	0.0014	-0.0132	0.0027	0.0125	0.0081
27	0.0291	0.0001	0.0279	0.0005	0.0004	0.0017	0.0003	0.0033
29	0.0295	0.0001	0.0279	0.0006	0.0092	0.0009	0.0114	0.0021
30	0.0340	0.0003	0.0211	0.0033	0.0191	0.0052	0.0293	0.0072
31	0.0271	0.0002	0.0114	0.0016	0.0132	0.0050	0.0273	0.0153
Average	0.0208	0.00004	0.0200	0.0004	0.0160	0.0009	0.0195	0.0023

				Roads with Dedicated Bus Lanes				
Road	Alpha OLS	Se OLS	Alpha IV	Se IV	Sigma OLS	Se OLS	Sigma IV	Se IV
5	0.0344	0.0002	0.0297	0.0011	0.0035	0.0024	0.0059	0.0048
6	0.0334	0.0005	0.0244	0.0040	0.0029	0.0032	-0.0063	0.0095
32	0.0053	0.0001	0.0054	0.0007	0.0045	0.0056	0.0068	0.0086
33	0.0114	0.0003	0.0022	0.0013	-0.0018	0.0036	0.0041	0.0060
Average	0.0211	0.0002	0.0157	0.001	0.0023	0.0019	0.0026	0.0037

Note: Road segment specific estimations for all roads. Dependent variable is log of bus travel time. For the IV estimation, we use hour-of-week dummies as instruments. Roads 7,20,24,25,26 and 28 are omitted because we do not have traffic data for the months of March 2014 and 2015, hence we cannot estimate the effect of traffic density on bus travel time.

Table C2 – Bus travel time gain with dedicated lanes

			Mixed Traffic Roads				
Road	Bus Flow	Bus Users	T_B	T_B^{DL}	T_B -T_B^{DL}	Passenger time gain	Lanes
1	10.11	6.87	2.07	1.73	0.34	2.36	1
2	12.05	8.28	2.38	2.12	0.26	2.13	1
3	8.45	5.72	0.63	0.45	0.18	1.03	2
4	8.52	5.79	1.43	0.83	0.60	3.48	2
8	2.90	2.01	1.79	1.13	0.66	1.32	1
9	3.02	2.09	1.41	0.84	0.57	1.19	1
10	2.79	1.93	1.64	1.17	0.47	0.91	2
11	2.44	1.69	1.74	1.67	0.07	0.12	2
12	3.48	2.35	2.78	1.52	1.26	2.96	2
13	6.08	4.18	1.20	0.89	0.31	1.30	1
14	4.76	3.25	2.71	1.36	1.35	4.39	1
15	17.14	11.64	1.10	1.03	0.07	0.79	2
16	7.93	5.38	1.07	0.92	0.15	0.82	1
17	7.65	5.23	1.31	0.85	0.46	2.42	1
18	3.79	2.68	0.92	0.54	0.38	1.01	1
19	4.08	2.88	0.45	0.29	0.16	0.45	1
21	17.42	12.02	1.31	1.10	0.20	2.44	2
22	7.80	5.31	1.29	1.05	0.24	1.27	2
23	16.29	11.10	1.38	1.09	0.29	3.24	2
27	7.56	5.11	1.41	1.11	0.30	1.53	2
29	4.99	3.46	1.79	1.40	0.38	1.33	2
30	5.29	3.67	1.58	0.99	0.59	2.16	2
31	9.03	6.10	2.53	1.87	0.66	4.02	2
Average	7.55	5.16	1.56	1.12	0.44	1.90	/

Note: Road-specific values, averaged over all observations. We consider only roads that do not already include a dedicated lane and for which we have bus travel information. Bus flow is the number of vehicles per hour. Bus users is the number of bus travellers per minute on the road segment. T_B is the observed bus travel time (min/km), considering only travel time between stops (ignoring time at stops). T_B^{DL} is the counterfactual travel time (between stops) with a fully dedicated lane (i.e. zero density). Passenger time gain is the reduction in travel time, times the number of bus users per minute.

Appendix D: Characterizing the counterfactual equilibria with dedicated bus lanes

We illustrate how we characterize the counterfactual equilibria in Table 9. We assume the demand for motor-vehicle travel is linear, with a time-invariant slope identical for all roads. See expression (10). We let the intercept μ vary by road (indexed by i) and hour (indexed by t). To determine this intercept, inverting (10) we get:

$$F_{i,t} = \frac{\mu_{i,t}}{\varphi} - \frac{T_{i,t}}{\varphi}, \tag{D1}$$

Given assumptions on φ and information on $T_{i,t}$ and $F_{i,t}$, one obtains $\mu_{i,t}$ by substitution.

Consider now the demand for bus travel. Inverting (11), we get:

$$N_{Bi,t} = \frac{E_{i,t}}{\Gamma_{i,t}} - \frac{T^G_{B,i,t}}{\Gamma_{i,t}}. \tag{D2}$$

To determine $\Gamma_{i,t}$, we assume the price elasticity of bus travel in Rome is -2.2. This is the value that Parry and Small (2009, Appendix B) implicitly assume for peak-hour travel in London. Using the above demand expression, this elasticity can be written as:

$$\varepsilon_B \equiv \frac{dN_B}{dT^G_B}\frac{T^G_{B,i,t}}{N_{Bi,t}} = -\frac{1}{\Gamma_{i,t}}\frac{T^G_{B,i,t}}{N_{Bi,t}}. \tag{D3}$$

Using this expression and information on $N_{Bi,t}$ and $T^G_{B,i,t}$, we can calculate $\Gamma_{i,t}$ for each road-hour combination:

$$\Gamma_{i,t} = \frac{T^G_{B,i,t}}{2.2 \times N_{Bi,t}}. \tag{D4}$$

By substitution of $N_{Bi,t}$, $T^G_{B,i,t}$ and $\Gamma_{i,t}$ in (D2), we also obtain the constant $E_{i,t}$.

Given the above demand functions, we can characterize the counterfactual equilibria with dedicated lanes for each road-hour pair. In the counterfactual equilibrium, the private supply cost of travel by motor-vehicle (conditional on the reduction in road space) must equal demand. Hence, $\mu_{i,t} - \varphi F_{i,t} = T^{DL}_{i,t}$ holds. We combine (10) above with the relation between density and travel time by motor-vehicles with reduced space, given in (4). The key parameters in this relation come from our IV estimates, reported in Table C1 for each road.

To obtain the counterfactual bus travel time between stops on dedicated lanes, we substitute $D_{i,t} = 0$ in (2), so this travel time equals γ. The counterfactual bus travel time, $T^{DL}_{Bi,t}$, is thus given by the sum of travel time between stops and time at stops, where the latter is assumed not to change with respect to the status-quo equilibrium. Finally, to obtain the bus waiting time, we replace $T^{DL}_{Bi,t}$ in expression (3) and assume the number of buses in operation,

n_B, is invariant with respect to the status quo. Given this information, we compute the bus travel demand using (D2).

We find road traffic density in the counterfactual by solving the following for $D_{i,t}$:

$$\text{(D5)} \qquad \mu_{i,t} - \varphi\,(D_{i,t}/\,\beta e^{2\alpha D_{i,t}}) \;= \beta e^{2\alpha D_{i,t}}\;,$$

Given the counterfactual density, we calculate the corresponding travel time and flow of motor vehicles. Finally, we calculate the welfare change on the motor-vehicle and bus market, respectively, computing the areas of the greyed areas in Figure 1.

Appendix E: Deriving the relation between travel time and flow of motor-vehicles

We now derive the relation between motor vehicle travel time and flow, i.e. the quantity of vehicles per unit of time on our (one-km) road segment (this relation is commonly referred to as the "road supply" relation). Let us denote this relation as $T(F)$. To derive it, we make use of (1) and a fundamental physical identity:

$$\text{(E1)} \qquad D \;\equiv FT.$$

Combining (1) and (E1), applying the Implicit Function Theorem, we obtain:

$$\text{(E2)} \qquad \frac{dT}{dF} = \frac{\frac{\partial T}{\partial D}T}{1-\frac{\partial T}{\partial D}F} = \frac{\alpha T^2}{1\;-\;\alpha \mathrm{D}}.$$

(E1) implies when D is zero, F is also zero (as T > 0). Now consider an increase in D. When $\alpha\mathrm{D} < 1$, a higher D raises T as well as F. A critical level $\overline{D} = \frac{1}{\alpha}$ is defined, where the denominator of (E2) equals zero and the derivative dT/dF approaches infinity. At densities above $\overline{D}$, $dT/dF < 0$ and $dF/dD < 0$ hold.

Here we show that closing of a lane makes the relationship between travel time and flow more than twice as steep:

$$\text{(E3)} \qquad \frac{dT^{DL}}{dF} = \frac{2\alpha {T^{DL}}^2}{1\;-\;2\alpha\mathrm{D}} > 2\,\frac{\alpha T^2}{1\;-\;\alpha\mathrm{D}} \;= 2\,\frac{dT}{dF},$$

where we have assumed the a positive relationship between travel time and flow which implies that $2\alpha\mathrm{D} < 1$.

Appendix F: Effect of dedicated lanes, disaggregate results

Table F1– Disaggregate results with $\varphi = 1$

$\varphi = 1$	Road										
	3	4	10	11	12	21	23	29	30	31	Average
Status quo											
Motor-vehicle flow [veh/min]	7.38	8.33	7.36	5.83	8.88	8.86	10.06	14.25	10.61	10.44	9.20
Motor-vehicle travel time [min/km]	1.61	1.31	1.81	1.28	2.41	1.58	1.38	1.34	1.19	0.99	1.49
Bus flow per lane [veh/min]	0.07	0.07	0.02	0.02	0.03	0.15	0.14	0.04	0.04	0.08	0.066
Bus travel time, total [min/km]	2.31	2.91	2.26	2.46	4.85	4.05	4.28	2.37	1.77	3.34	3.06
Bus travel time at stops [min/km]	1.64	1.48	0.61	0.71	1.13	2.75	2.96	0.57	0.29	0.81	1.30
Waiting time [min]	3.73	4.25	17.35	16.71	10.13	1.84	1.94	6.49	6.17	3.49	7.21
Bus users [pass/min]	5.73	5.85	1.95	1.70	2.38	12.17	11.03	3.49	3.71	6.05	5.41
Dedicated Lane											
Motor-vehicle flow [veh/min]	5.64	6.63	4.93	6.28	7.04	6.36	7.49	5.70	8.51	10.98	6.96
Motor-vehicle travel time [min/km]	3.50	3.34	4.86	1.50	4.42	4.23	4.14	10.01	3.76	1.22	4.10
Bus flow [veh/min]	0.29	0.27	0.06	0.06	0.14	0.56	0.55	0.18	0.21	0.34	0.16
Bus travel time, total [min/km]	2.03	2.31	1.79	2.39	2.64	3.84	4.05	1.98	1.28	2.69	2.50
Waiting time [min]	3.49	3.75	15.68	16.34	7.53	1.80	1.83	5.66	4.80	2.70	6.36
Bus users [pass/min]	6.77	7.97	2.90	1.83	4.15	13.24	12.40	4.73	5.85	8.72	6.86
Welfare gain [pass-min]	-17.5	-16.4	-21.0	-2.5	-7.3	-34.2	-42.5	-128.0	-27.9	3.76	-29.39

Table F2– Disaggregate results with $\varphi = 0.5$

$\varphi = 0.5$	Road										
	3	4	10	11	12	21	23	29	30	31	Average
Status quo											
Motor-vehicle flow [veh/min]	7.38	8.33	7.36	5.83	8.88	8.86	10.06	14.25	10.61	10.44	9.20
Motor-vehicle travel time [min/km]	1.61	1.31	1.81	1.28	2.41	1.58	1.38	1.34	1.19	0.99	1.49
Bus flow per lane [veh/min]	0.07	0.07	0.02	0.02	0.03	0.15	0.14	0.04	0.04	0.08	0.066
Bus travel time, total [min/km]	2.31	2.91	2.26	2.46	4.85	4.05	4.28	2.37	1.77	3.34	3.06
Bus travel time at stops [min/km]	1.64	1.48	0.61	0.71	1.13	2.75	2.96	0.57	0.29	0.81	1.30
Waiting time [min]	3.73	4.25	17.35	16.71	10.13	1.84	1.94	6.49	6.17	3.49	7.21
Bus users [pass/min]	5.73	5.85	1.95	1.70	2.38	12.17	11.03	3.49	3.71	6.05	5.41
Dedicated Lane											
Motor-vehicle flow [veh/min]	4.84	6.05	4.43	5.35	6.16	6.00	7.26	6.79	8.29	9.80	6.50
Motor-vehicle travel time [min/km]	2.70	2.18	3.11	1.48	3.36	2.77	2.51	4.73	2.07	1.16	2.61
Bus flow [veh/min]	0.29	0.27	0.06	0.06	0.14	0.56	0.55	0.18	0.21	0.34	0.16
Bus travel time, total [min/km]	2.05	2.31	1.78	2.39	2.63	3.84	4.04	1.97	1.28	2.69	2.50
Waiting time [min]	3.49	3.75	15.58	16.34	7.33	1.80	1.83	5.66	4.80	2.90	6.35
Bus users [pass/min]	6.77	7.97	2.90	1.83	4.15	13.24	12.40	4.73	5.85	8.72	6.86
Welfare gain [pass-min]	-8.13	-1.2	-2.98	-1.64	11.5	-13.3	-16.29	-51.3	-1.09	8.51	-7.6

Table F3– Disaggregate results with $\varphi = 0.3$

$\varphi = 0.3$	Road										
	3	4	10	11	12	21	23	29	30	31	Average
<u>Status quo</u>											
Motor-vehicle flow [veh/min]	7.38	8.33	7.36	5.83	8.88	8.86	10.06	14.25	10.61	10.44	9.20
Motor-vehicle travel time [min/km]	1.61	1.31	1.81	1.28	2.41	1.58	1.38	1.34	1.19	0.99	1.49
Bus flow per lane [veh/min]	0.07	0.07	0.02	0.02	0.03	0.15	0.14	0.04	0.04	0.08	0.066
Bus travel time, total [min/km]	2.31	2.91	2.26	2.46	4.85	4.05	4.28	2.37	1.77	3.34	3.06
Bus travel time at stops [min/km]	1.64	1.48	0.61	0.71	1.13	2.75	2.96	0.57	0.29	0.81	1.30
Waiting time [min]	3.73	4.25	17.35	16.71	10.13	1.84	1.94	6.49	6.17	3.49	7.21
Bus users [pass/min]	5.73	5.85	1.95	1.70	2.38	12.17	11.03	3.49	3.71	6.05	5.41
<u>Dedicated Lane</u>											
Motor-vehicle flow [veh/min]	4.63	5.83	4.35	5.01	5.93	5.91	7.19	7.54	7.99	9.30	6.37
Motor-vehicle travel time [min/km]	2.19	1.86	2.53	1.46	3.01	2.30	2.09	3.23	1.74	1.14	2.16
Bus flow [veh/min]	0.29	0.27	0.06	0.06	0.14	0.56	0.55	0.18	0.21	0.34	0.16
Bus travel time, total [min/km]	2.04	2.32	1.78	2.38	2.63	3.85	4.05	1.98	1.28	2.69	2.50
Waiting time [min]	3.49	3.75	15.58	16.34	7.33	1.80	1.83	5.66	4.80	2.90	6.35
Bus users [pass/min]	6.77	7.97	2.90	1.83	4.15	13.24	12.40	4.73	5.85	8.72	6.86
Welfare gain [pass-min]	-0.62	6.19	3.74	-1.01	18.18	-4.78	-7.14	-21.10	6.96	10.94	1.14

Table F4– Disaggregate results with $\varphi = 0.1$

$\varphi = 0.1$	Road										
	3	4	10	11	12	21	23	29	30	31	Average
<u>Status quo</u>											
Motor-vehicle flow [veh/min]	7.38	8.33	7.36	5.83	8.88	8.86	10.06	14.25	10.61	10.44	9.20
Motor-vehicle travel time [min/km]	1.61	1.31	1.81	1.28	2.41	1.58	1.38	1.34	1.19	0.99	1.49
Bus flow per lane [veh/min]	0.07	0.07	0.02	0.02	0.03	0.15	0.14	0.04	0.04	0.08	0.066
Bus travel time, total [min/km]	2.31	2.91	2.26	2.46	4.85	4.05	4.28	2.37	1.77	3.34	3.06
Bus travel time at stops [min/km]	1.64	1.48	0.61	0.71	1.13	2.75	2.96	0.57	0.29	0.81	1.30
Waiting time [min]	3.73	4.25	17.35	16.71	10.13	1.84	1.94	6.49	6.17	3.49	7.21
Bus users [pass/min]	5.73	5.85	1.95	1.70	2.38	12.17	11.03	3.49	3.71	6.05	5.41
<u>Dedicated Lane</u>											
Motor-vehicle flow [veh/min]	4.51	5.34	4.17	4.48	5.44	5.46	6.50	8.35	7.37	8.76	6.04
Motor-vehicle travel time [min/km]	1.95	1.55	2.09	1.39	2.70	1.85	1.66	1.86	1.46	1.11	1.76
Bus flow [veh/min]	0.29	0.27	0.06	0.06	0.14	0.56	0.55	0.18	0.21	0.34	0.16
Bus travel time, total [min/km]	2.10	2.31	1.79	2.39	2.65	3.85	4.05	1.98	1.28	2.69	2.51
Waiting time [min]	3.49	3.75	15.58	16.34	7.33	1.80	1.83	5.66	4.80	2.90	6.35
Bus users [pass/min]	6.77	7.97	2.90	1.83	4.15	13.24	12.40	4.73	5.85	8.72	6.86
Welfare gain [pass-min]	1.47	11.05	8.87	0.11	26.12	1.38	0.42	-0.77	12.11	12.39	7.31

Table F5– Disaggregate results with one-lane parallel road

One lane parallel road	Road									
	3	4	10	11	12	21	23	29	30	31	Average
Status quo											
Motor-vehicle flow [veh/min-lane]	7.11	8.45	7.35	5.87	8.77	8.91	10.04	14.21	10.40	10.73	9.19
Motor-vehicle travel time [min/km]	1.61	1.32	1.82	1.28	2.42	1.57	1.38	1.34	1.18	0.99	1.49
Bus flow per lane [veh/min]	0.07	0.07	0.02	0.02	0.03	0.15	0.14	0.04	0.04	0.08	0.07
Bus travel time, total [min/km]	2.25	2.94	2.26	2.45	4.91	4.04	4.27	2.36	1.75	3.36	3.06
Bus travel time at stops [min/km]	1.58	1.49	0.61	0.71	1.12	2.74	2.96	0.57	0.29	0.81	1.29
Waiting time [min]	3.75	4.13	17.27	16.88	10.17	1.86	1.92	6.55	6.35	3.45	7.23
Bus users [pass/min]	5.67	5.85	1.94	1.68	2.38	12.04	11.10	3.47	3.64	6.16	5.39
Dedicated Lane											
Motor-vehicle flow [veh/min]	10.49	11.69	10.70	8.52	12.38	12.87	14.74	20.69	14.97	14.92	13.20
Motor-vehicle travel time [min/km]	2.82	2.41	2.79	1.66	2.21	2.60	1.10	1.91	2.43	1.05	2.10
Bus flow [veh/min]	0.29	0.27	0.07	0.06	0.14	0.56	0.55	0.17	0.21	0.35	0.27
Bus travel time, total [min/km]	2.06	2.30	1.79	2.38	2.64	3.83	4.08	1.98	1.28	2.69	2.50
Waiting time [min]	3.47	3.74	15.25	16.29	7.16	1.78	1.81	5.73	4.80	2.86	6.29
Bus users [pass/min]	6.79	8.06	2.89	1.80	4.15	13.40	12.67	4.82	5.92	8.88	6.94
Welfare gain [pass-min]	-19.60	-8.00	-9.73	-8.25	22.48	-20.49	3.21	-17.97	-17.30	8.51	-6.71

Table F6– Disaggregate results with two-lane parallel road

Two-lane parallel road	Road									
	3	4	10	11	12	21	23	29	30	31	Average
Status quo											
Motor-vehicle flow [veh/min-lane]	7.11	8.45	7.35	5.87	8.77	8.91	10.04	14.21	10.40	10.73	9.19
Motor-vehicle travel time [min/km]	1.61	1.32	1.82	1.28	2.42	1.57	1.38	1.34	1.18	0.99	1.49
Bus flow per lane [veh/min]	0.07	0.07	0.02	0.02	0.03	0.15	0.14	0.04	0.04	0.08	0.07
Bus travel time, total [min/km]	2.25	2.94	2.26	2.45	4.91	4.04	4.27	2.36	1.75	3.36	3.06
Bus travel time at stops [min/km]	1.58	1.49	0.61	0.71	1.12	2.74	2.96	0.57	0.29	0.81	1.29
Waiting time [min]	3.75	4.13	17.27	16.88	10.17	1.86	1.92	6.55	6.35	3.45	7.23
Bus users [pass/min]	5.67	5.85	1.94	1.68	2.38	12.04	11.10	3.47	3.64	6.16	5.39
Dedicated Lane											
Motor-vehicle flow [veh/min]	9.24	10.76	9.57	7.80	11.26	11.58	13.09	18.66	13.38	13.67	11.90
Motor-vehicle travel time [min/km]	1.46	1.73	2.79	1.16	1.92	2.60	1.25	1.00	2.89	0.98	1.78
Bus flow [veh/min]	0.29	0.28	0.07	0.06	0.14	0.56	0.55	0.18	0.20	0.35	0.27
Bus travel time, total [min/km]	2.03	2.32	1.79	2.38	2.64	3.84	4.05	1.97	1.28	2.69	2.50
Waiting time [min]	3.44	3.61	15.24	16.55	7.02	1.78	1.83	5.68	4.92	2.84	6.29
Bus users [pass/min]	6.74	8.12	2.91	1.81	4.27	13.40	12.41	4.75	5.81	8.95	6.92
Welfare gain [pass-min]	3.87	5.73	-4.74	-0.37	34.15	-15.45	2.65	12.24	-21.21	12.25	2.91

Appendix G: Aggregate model for Rome adapting Parry and Small (2009)

Table G1– Aggregate model, parameters and results

	Rail Peak	Rail Off-Peak	Bus Peak	Bus Off-Peak
TRANSIT				
Annual passenger kms, millions	1 639	628	3 403	2 304
Vehicle occupancy (pass-km/veh-km)	160	87	51	34
Average operating cost, €/veh-km	29	17	10	5
Avg operating cost, €cents/pass-km	18	20	19	15
Marginal supply cost, €cents/pass-km	11	12	13	10
Fare. €cents/pass-km	5	5	5	5
Subsidy, % of average operating cost	74	76	75	69
Cost of in-vehicle travel time, €cents/pass-km	13	10	19	12
Wait cost, €cents/pass-km	2	6	4	11
Generalized price, €cents/pass-km	25	28	34	40
Marginal scale economy, €cents/pass-km	1	4	2	7
Marginal cost of occupancy, €cents/pass-km	2	0	1	0
Marginal external cost, €cents/pass-km	0.4	0.2	3.5	2.6
Marg. congestion cost. €cents/pass-km	0.0	0.0	2.2	1.3
Pollution. climate & acc cost. €cents/pass-km	0.0	0.0	0.1	0.2
Marginal dwell cost. €cents/pass-km	0.4	0.2	1.3	1.1
Elasticity of passenger demand wrt fare	-0.22	-0.22	-0.22	-0.22
Fraction of increased transit coming from				
auto--same period	0.50	0.40	0.50	0.40
same transit mode--other period	0.10	0.10	0.10	0.10
other transit mode--same period	0.30	0.30	0.30	0.30
increased overall travel demand	0.10	0.20	0.10	0.20
AUTO	Peak	Off-Peak		
Annual passenger-kms, millions	8 623	12 837		
Occupancy	1.41	1.52		
Marginal external cost, €cents/pass-km	21	7		
Marg. congestion cost. €cents/pass-km	23	8		
Poll. & acc. less fuel tax. €cents/pass-km	-2	-1		