The congestion relief benefit of public transit
Adler, Martin W.; Liberini, Federica; Russo, Antonio; van Ommeren, Jos N.

published in
Journal of Economic Geography
2021

DOI (link to publisher)
10.1093/jeg/lbaa037

document version
Publisher's PDF, also known as Version of record
document license
Article 25fa Dutch Copyright Act

Link to publication in VU Research Portal
citation for published version (APA)

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

• Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
• You may not further distribute the material or use it for any profit-making activity or commercial gain
• You may freely distribute the URL identifying the publication in the public portal?

Take down policy
If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

E-mail address:
vuresearchportal.ub@vu.nl

Download date: 24. Sep. 2023
The congestion relief benefit of public transit: evidence from Rome

Martin W. Adler*, Federica Liberini**, Antonio Russo***,† and Jos N. van Ommeren*

*Department of Spatial Economics, VU University Amsterdam and Tinbergen Institute, Gustav Mahlerplein 117, 1082 MS Amsterdam, Netherlands
**University of Bath, Claverton Down, Bath BA2 7AY, UK
***Loughborough University and CESifo, Epinal Way, Loughborough LE11 3TU, UK
†Correspondence to: email <a.russo@lboro.ac.uk>

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-percentage point reduction in public transit supply increases the travel time of motor-vehicles by about 1.6% 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.

Keywords: Congestion relief benefit, bus lanes, public transit, strikes
JEL classifications: H23, R41, H76

1. Introduction

Most cities throughout the world devote ample resources to subsidizing public transport.1 A key rationale 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 (Winston and Maheshri, 2007; Proost and Van Dender, 2008) and because of the small elasticity of car travel with respect to the price of public transport travel (Hensher, 1998).3

1 In the OECD, these subsidies range from 30% to 90% of operating costs (Kenworthy and Laube, 2001). U.S. public transit carries about 1% of passenger kilometers, but receive 25% of total transport 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 Proost, 2012; De Borger and Russo, 2018), 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, DC, Los Angeles and London. Börjesson et al. (2017) show the same for Stockholm, despite its adoption of road tolls.
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 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; 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. We 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 and thus 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, we estimate the congestion-relief benefit not only for motor-vehicle travelers but also for bus travelers. We are therefore able to evaluate the potential for public transport improvements to generate a ‘virtuous circle’, whereby road congestion falls, bus speed increases and public transport gets more attractive (Small, 2004).

Our data come from Rome, Italy, which provides an interesting setting for our study for several reasons. First, congestion is heavy compared with other cities of similar size, due to the high modal share of cars and motorbikes, combined with a limited supply of public transport infrastructure. Furthermore, Rome’s public transport system relies primarily on buses, which mostly share the roads with private traffic. This enables us to quantify the impact of road congestion on travel delays for bus travelers. In addition, 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-percentage point reduction in public transit supply increases the travel time of motor-vehicles (cars and motorbikes) by 1.6% in the morning peak, and about 3% on the most heavily congested roads. The reduction in bus speed caused by the higher congestion raises in-vehicle travel time of bus users by 1.3% 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-percentage point reduction in public transport supply produces about €75 million of losses from congestion per year, roughly 25% of which are due to extra bus travel time. These benefits are equal to at least 50% of the operator cost reduction from the downsizing.

---

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.
Lastly, we 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 high) is smaller than the socially optimal one.

Our findings contribute to a recent literature measuring the costs of congestion in the context of cities. Recent contributions include Couture et al. (2018), who estimate aggregate travel supply relationships for a large sample of U.S. cities and Yang et al. (2020), who estimate the marginal external cost of congestion in Beijing. We contribute to this literature by estimating the relation between the supply of public transport and road congestion, and by measuring the ensuing effect not only on motor vehicle but also on bus users.

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

2. Theoretical background

We aim to estimate the congestion-relief benefit of public transit. We will use estimates of the effect of road congestion on motor-vehicle travelers as well as bus users. To motivate our empirical approach, let us consider a road of fixed length (e.g., 1 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 is both decreasing in their respective generalized prices and increasing in the price of the other mode. The latter assumption captures the substitutability between the two travel modes.

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:

\[
T = \beta e^{\alpha D},
\]

where \( \alpha \) and \( \beta \) are the positive parameters.\(^6\)

Density on the road segment is the product of travel time and flow (or throughput) of motor-vehicles, \( F \) (measured in vehicles per minute). The latter is the quantity of motor vehicle travel on the road segment per unit of time. For our welfare analysis, it is useful to relate the flow of vehicles (quantity) to travel time (cost) characterizing a ‘supply curve’ of travel on the road segment. Using (1) and the fundamental relation \( D = F \times T \), one gets an 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

\(^6\) 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% of total traffic consists of buses. Hence, our empirical results remain essentially unchanged even if one bus creates the same congestion as 10 cars.
between $T$ and $F$ becomes negative, i.e., there is hypercongestion (Small and Verhoef, 2007). However, hypercongestion is observed very rarely in our data (less than 1.5% of all observed hours) and we thus ignore it throughout the analysis.

We assume the generalized price of bus travel is an increasing function of the monetary fare, $f$, and generalized travel time, $T^G_B$. The latter consists of in-vehicle travel time, $T^B$, and waiting time at stops, $T^W_B$. 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 (where we assume it is not affected by congestion).  

Similar to private motor vehicles, buses are slower in heavy traffic. We shall estimate the congestion relief benefit on bus users through changes in in-vehicle bus travel time, $T^B$, as well as waiting time at bus stops, $T^W_B$. We assume that the relationship between bus travel time and traffic density has the same functional form as (1)

$$T^B = \gamma e^{\sigma D}, \quad (2)$$

where $\gamma$ and $\sigma$ are the positive parameters (which may differ from $\alpha$ and $\beta$ in (1)). Congestion also increases bus waiting time, $T^W_B$, because it decreases bus frequency, i.e., the average number of buses passing the road segment per unit of time. We do not observe $T^W_B$ 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 at bus stops randomly, their expected waiting time is half the time interval between two successive buses (headway), i.e., the inverse of $F_B$. Therefore,

$$T^W_B = 0.5 \frac{0.5 \times T^B}{n_B}. \quad (3)$$

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

Relation (3) also provides a 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 1 and bus supply, $n_B$, decreases. Thus, the reduction in supply due to the strike induces 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 the latter variables is the negative of the congestion-relief benefit of public transport supply (Anderson, 2014).

---

7 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.

8 The assumption of random user arrivals is common in the literature (Jara-Díaz and Gschwender, 2009) and is reasonable for Rome, where bus timetables are rather unreliable for several reasons (including heavy congestion). We ignore possible bus bunching, which would increase expected waiting time.
3. Data

3.1. 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% 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% of which takes place during peak hours (PGTU, 2014). 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 15 km/h on weekdays.

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-kilometers as well as passenger-kilometers), see Table 1. Annual subsidies to public transport amount to €1.04 billion, i.e., approximately 72% of annual operating 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 2055 buses and 165 trams. It also operates three metro lines, and three train lines connecting Rome with the region of Lazio.

3.2. Motor-vehicle traffic data

Our data on motor vehicle traffic are provided by Rome’s Mobility Agency. We use information on hourly flow and travel time for 33 measurement points between 5 a.m. and midnight for 769 work days, during a period from the 2 January 2012 to the 22 May

---

9 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 13 km as reported by the Mobility Agency (PGTU, 2014).
Motor 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 12 one-lane (per direction) roads—all located in the city center and with a speed limit of 50 km/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.11

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.12 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.13 We provide descriptive information in Table 2. Note that we have more than 20,000 observations during strikes, i.e., more than 5% of the total.

<table>
<thead>
<tr>
<th></th>
<th>Car</th>
<th>Bus</th>
<th>Rail</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Peak</td>
<td>Off-peak</td>
<td>Peak</td>
</tr>
<tr>
<td>Annual veh-kms, millions</td>
<td>6116</td>
<td>8445</td>
<td>66.7</td>
</tr>
<tr>
<td>Annual passenger kms, millions</td>
<td>8623</td>
<td>12,837</td>
<td>3403</td>
</tr>
<tr>
<td>Vehicle occupancy (pass-km/veh-km)</td>
<td>1.4</td>
<td>1.51</td>
<td>51</td>
</tr>
<tr>
<td>Operating cost, €/veh-km</td>
<td>10</td>
<td>5</td>
<td>29</td>
</tr>
<tr>
<td>Fare, €cents/pass-km</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Subsidy, % of average operating cost</td>
<td>75</td>
<td>69</td>
<td>74</td>
</tr>
<tr>
<td>Generalized price, €cents/pass-km</td>
<td>34</td>
<td>40</td>
<td>25</td>
</tr>
</tbody>
</table>

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

2015.10 Motor 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 12 one-lane (per direction) roads—all located in the city center and with a speed limit of 50 km/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.11

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.12 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.13 We provide descriptive information in Table 2. Note that we have more than 20,000 observations during strikes, i.e., more than 5% of the total.

---

10 We do not observe strikes on weekends, so we focus on workdays (regulation restricts striking on weekends). We exclude nighttime hours because there is no public transit service between midnight and 5 a.m.

11 See Figure A5 in Appendix A 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 and 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 11 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.

12 The traffic data come 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).

13 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 2100 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% 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.
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 entire trip, for example, 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.14

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% of free-flow speed (defined by the 95th percentile of the speed distribution observed on that road). Using this definition, on average, roads are heavily congested about 1 hour per day, or 5% of the time. However, there is substantial variation between roads. We single out 10 ‘heavily congested roads’, which are heavily congested at least 1 h/day, with an average of about 3 h/day, whereas the other 23 roads are heavily congested less than 1 h/day.

### 3.3. 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 kilometer) and (ii) the total bus travel time—including time at stops (in minutes per kilometer).15 A total of 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 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.16

<table>
<thead>
<tr>
<th>Travel time [min/km]</th>
<th>Density [veh/km-lane]</th>
<th>Flow [veh/min-lane]</th>
<th>Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strike</td>
<td>1.36</td>
<td>14.6</td>
<td>11.1</td>
</tr>
<tr>
<td>No strike</td>
<td>1.32</td>
<td>13.4</td>
<td>10.5</td>
</tr>
<tr>
<td>Total</td>
<td>1.33</td>
<td>13.5</td>
<td>10.6</td>
</tr>
</tbody>
</table>

14 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.
15 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 are 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).
16 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 fifth percentile or above the 99th percentile for each bus line section. The results are robust to including these outliers.
Summary information in Table 3 shows that the average bus travel time is almost 2 min/km (speed of about 30 km/h) on dedicated lanes, whereas it is slightly above 3 min/km on mixed traffic roads (about 20 km/h). This difference is due to a higher driving speed on dedicated lanes (1.08 min/km versus 1.56 min/km in mixed traffic) and fewer stops (the average distance between stops is 0.47 km on mixed traffic roads, whereas it is 0.85 km on bus lanes).

Waiting time is substantially smaller when buses travel on dedicated lanes (4.34 versus 7.69 min), because bus frequency is two times higher than on mixed traffic roads (0.24 compared with 0.12 buses per minute). This difference is partly due to the higher speed of buses on dedicated lanes, and also to the fact that the public transport agency uses roads with dedicated lanes more intensively.

Finally, 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.

### 3.4. 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. A total of 27 of the observed strikes took place only in Rome (and sometimes its surroundings), whereas the other 16 were national strikes that may also have affected other transportation modes, for example, rail and aviation.17 We control for different types of strikes in the analysis.

All strikes in our data were announced to the public several days in advance. Seven were partially canceled (by one of the participating unions). We refer to the latter as semi-cancelled strikes in the sensitivity analysis (in Table B1 in Appendix B). An additional three announced strikes were fully canceled shortly before taking place.

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, May Day) and the city

---

17 Two of the strikes fall into a white-strike period (between the 7 and the 27 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).
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).\(^{18}\)

We improve upon earlier studies on public transit strikes (Anderson 2014; Adler and van Ommeren 2016; Bauernschuster et al., 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). Note that the variable refers to bus as well as rail service.

The role of the public transit agency is important here. 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, for example, due to budget cuts, so the reduction in public transit supply due to strikes is likely not systematically different from permanent ones.

During strike hours there are, on average, 839 buses/trams operating, in comparison with 1496 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 1. 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 2, 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.\(^{19}\)

We also use information on the non-strike scheduled service level, i.e., the usual number of vehicles operating per hour. The scheduled service Rome hardly varies between 8 a.m. and 5 p.m. on weekdays (Figures A4 and A6 in Appendix A report this information for bus service). These observations support the use of strikes as an exogenous way of identifying the effects of public transit supply.

In Figures 3 and 4, 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 Figure A10 in Appendix A. These figures indicate that travel time, density and flow increase during strikes.\(^{20}\) In these figures, we also show information on intensive strikes—whereby the available public transit share is below 0.5.

---

\(^{18}\) 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.

\(^{19}\) Figures A12 and A13 in Appendix A provide the same information as Figures 1 and 2, focusing only on the months of March 2014 and 2015, for which we have bus travel data.

\(^{20}\) 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
Travel time, density and flow appear systematically larger during intensive strikes. Figure 3 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.\textsuperscript{21} 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\% larger in the peak.

\textbf{Figure 1.} Public transit share for strikes.

\textbf{Figure 2.} Public transit share per strike hour.

Travel time, density and flow appear systematically larger during intensive strikes. Figure 3 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.\textsuperscript{21} 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\% larger in the peak.

\textsuperscript{21} In some instances, strikes may coincide with street demonstration by workers, which may involve the temporary closure of some roads in the center. None of the roads in our dataset was closed during strikes, but there may be some spillover effects affecting traffic conditions. While we cannot entirely rule out these effects, we note that demonstrations typically take place during large strikes involving not just public transport workers but other sectors. We control for this type of strikes in the analysis.
4. Empirical approach

4.1. 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 $S_{i,t}$. The variable drops below 1 when there are strikes which disrupt supply. In our baseline specification, the logarithm of motor-vehicle travel time on road $i$ at hour $t$, $\log T_{i,t}$, is estimated as a linear function of $S_{i,t}$, the share of public transit supply at $t$. Hence, we estimate the following relationship:

$$
\log T_{i,t} = \omega_i + \Psi^n S_{i,t} + \rho' X_t + \epsilon_{i,t},
$$

where $X_t$ refers to the control variables, $\epsilon_{i,t}$ is a random error and the coefficient $\Psi^n$ 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 and off-peak). Note that we include a road-fixed effect, $\omega_i$. The controls include temperature, rain, hour-of-the-week dummies, week-of-the-year dummies, type of strikes (specific to public transport or including other sectors) and road-fixed effects.

---

22 In principle, one could use the level of the public transport service (e.g., vehicle-km per hour). However, unlike the share variable, this information was made available to us only for the months of March 2014 and 2015 and only for buses. Hence, we focus on the share of transit available as our main explanatory variable.

23 According to the official timetables, public transport typically follows a regular schedule, with practically constant supply between 8 a.m. and 5 p.m. on weekdays when there are no strikes (see Figure A4 in Appendix A). However, there is variation outside of these hours. Therefore, we shall control for hour of the day in the analysis.
Recall that the public travel agency allocates available buses during strikes to the most important lines; hence, we can ignore endogeneity issues because strikers target specific bus routes. Consequently, if strikes happen randomly over time, one can estimate $\Psi^n$ consistently without the vector of controls, $X_t$. However, in Rome, it is unlikely that strikes are temporally random for a number of reasons. First, workers seem to have preferences when to strike. For example, strikes tend to be more frequent on Mondays and particularly Fridays, perhaps because public transit workers prefer to strike on a day close to the weekend for leisure reasons. Second, the law restricts the minimum presence of buses during strikes, which varies during the day. Our vector of controls therefore includes time (hour-of-the-week and week-of-the-year-fixed effects) and weather controls (rain and temperature). Third, strikes are spatially nonrandom because during strikes the public transit agency allocates available buses to the most important lines. Given these time controls, one can argue that variation in public transit supply due to strikes is random and can be used as a quasi-experiment. This argument is supported by our data: for example, conditional on time controls, strikes are uncorrelated to weather conditions. This conclusion is also supported in the sensitivity analyses. Adding day-fixed effects or using hour-of-the-weekday-fixed effects (rather than hour-of-the-day and day-of-the-week-fixed effects) generates similar results.\footnote{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. This 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.}

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

We estimate Equation (4) using a weighted regression with weights proportional to the (average hourly) flow of motor-vehicles per road, to make the estimated $\Psi^n$ representative of the average motor-vehicle traveler in our sample. We cluster standard errors by hour.\footnote{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 B1.}
We will also examine nonlinear models, where $\Psi^n$ 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, $F_{i,t}$.

### 4.2. 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 hold for travel time at stops. 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, $T_{B,i,t}$, we estimate the following reduced-form relationship:

$$\log T_{B,i,t} = \mu_i + \Psi^n B S_t + \rho' X_t + \eta_{i,t}, \quad (5)$$

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

One difficulty when estimating Equation (5) is that, in contrast to motor-vehicle travel information, we observe bus information only for a short period of time (2 months). Hence, we have a limited number of observations of bus travel time during strikes, resulting in rather imprecise estimates of $\Psi^n_B$. Thus, we also apply a two-step approach, combining the bus and motor-vehicle travel datasets. This approach is consistent, given the (reasonable) assumption that the effect of $S$ on bus travel time is entirely through a change in traffic density, $D$.

In the first step, using motor-vehicle travel data, we estimate the effect of public transit supply, $S$, on motor-vehicle density, $D$. Hence, similar to (5), we estimate the marginal effect of $S_t$ on motor-vehicle density $D_{i,t}$:

$$D_{i,t} = \mu_i + \delta^n S_t + \rho' X_t + \omega_{i,t}, \quad (6)$$

where $\omega_{i,t}$ is a random error term. We again include road-fixed effects and controls. The coefficient $\delta^n$ 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, $\log T_{B}$, as implied by Equation (6). To estimate this effect, denoted by $\sigma$, we use the same time controls as above.

---

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

27 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.
(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:

$$\log T_{Bi,t} = \pi_i + \sigma D_{i,t} + \theta'_i X_t + v_{i,t},$$

where $v_{i,t}$ is the error term. Finally, we obtain the marginal effect of public transit supply, $S$, on log bus travel time, $\log T_B$, through reductions in congestion, by taking the product of the estimates of $\delta^0$ and $\sigma$. We calculate the standard error of $\delta^0 \sigma$, using the standard formula for a standard error of the product of two independent random variables. We will see that the estimates of this two-step approach are comparable to the estimates of $\Psi^w_B$ when using Equation (5), though with much smaller standard errors. The intuition for this is that Equation (6) is estimated on a much larger sample (about five times larger), whereas $\sigma$ is estimated with very small standard errors, as the relationship between travel time and density is very tight.

A challenge in the estimation of Equation (7) 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. We exploit regularities in travel demand over the hours of the week as a demand-shifting instrument. This approach makes sense, given that (7) is essentially a (technological) supply relationship. Specifically, we use hour-of-the-week dummies, $z_i$, as instruments (e.g., a dummy for Monday morning between 9 and 10 a.m. is one instrument). Our key assumption is that $E(z_i v_{i,t}|X_t) = 0$. 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 7 a.m. in on Mondays compared with 8 a.m. on the same day, and we control for the fact that at 7 a.m. there might be less light, which potentially influences the behavior of bus drivers for given levels of traffic density.

Our argument for why $E(z_i v_{i,t}|X_t) = 0$ must hold is that the above 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).28 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 there are no supply shocks—including policies—that change bus speed systematically at a certain hour for a specific day of the week. Notice that this IV approach allows for policies that adapt road

28 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, a shift of the demand function results in a shift in the demand relationship between travel time and flow.
supply with a fixed pattern over the time of the day 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).

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 Equation (4). We distinguish between the effects in the morning peak, the afternoon peak and off-peak.

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 10-percentage point reduction in public transport supply increases travel time during morning peak hours by roughly 1.6%, about 0.024 min/km. The effect is substantially smaller during the evening peak, 0.67%, about 0.01 min/km. During off peak, the effect is smaller and equal to 0.39%, about 0.0065 min/km. 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.

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 several plausible explanations for the smaller size of our estimates. 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 10-percentage point reduction in supply is about 3%, 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

Note that we include only hours when public transit service is available (i.e., from 5 a.m. to midnight). In our data, during nighttime, 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).
one-lane roads during morning peaks is still substantial in magnitude (0.7%, 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).

The previous results are supported by estimates of effect of public transit on vehicle flow, see Table 5.30 The results imply that a 10% shutdown in public transit supply increases traffic flow by about 0.6–0.8%. 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 5 and 6, the negative effect of public transit share on travel time is strong during (particularly morning) peak hours.

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 previous studies by investigating not a complete shutdown of public transit during strikes, but a partial shutdown (on average, 44%), 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.31 We present the results using a fifth-order polynomial of the public transit share in Figures 7 and 8.

Table 4. Log travel time

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

Notes: 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, type of strikes and road-fixed effects. ***,**,*Significance levels at 1%, 5%, and 10%. The number in parenthesis in column titles indicates number of roads.

30 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.
31 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.
In a sensitivity analysis (Appendix B1), 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 we cluster standard errors 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. As mentioned above, we do not have sufficient information on the level of service actually provided during strikes. Using share of service 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 a.m. and 5 p.m. (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 larger, but the point estimates hardly change. For example, the estimated effect of a 10-percentage point reduction in 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 Equation (5). 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 10-percentage point reduction in public transit supply increases bus travel time by about 0.75%, 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. These confirm that the effect of public transport is strongest during the morning peak: a 10% supply reduction increases the travel time of buses by 1.27% 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, 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

---

32 See Appendix B2 for the separate results of each step in this approach. Overall, the estimates from the one-step and two-step procedures are similar, but a latter one has smaller standard errors.
buses run on dedicated lanes, despite having very small standard errors. This finding 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. Therefore, assuming that traffic congestion does not increase bus stop time, these results imply that a 10-percentage point reduction in public transit supply increases overall travel time of bus travelers during the morning peak by about 0.65%, 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, $T^W_B$, through lower road congestion. Equation (3) implies that waiting time 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 10-percentage point reduction in public transit supply increases waiting time by 0.65% during the morning peak due to the increase in road congestion. In absolute terms,
a 10-percentage point reduction in public transit supply increases waiting time through congestion by 0.032 min per trip in the morning peak. Assuming a trip length of 3 (respectively, 10) km, therefore, the effect on waiting time is equal to about 42% (respectively, 13%) of the overall effect on travel time of bus users. 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 a reduction in congestion. This finding lends support to the idea that public transport improvements produce a ‘virtuous circle’ (Small, 2004).

5.3. The aggregate congestion relief benefit of public transit

We now use our estimates to provide an approximate calculation of the overall congestion-relief benefit of public transit in Rome. Consider the effect of a marginal (10 percentage point) reduction in public transit provision (the overall provision is 201 million vehicle-kilometers per year). Recall that our previous results indicate that this effect is approximately constant with respect to the share of transit available (at least beyond 20% of service available, see Figure A11 in Appendix). Our estimates indicate that the short-run effect of this reduction of public transit service results in a 0.017 min/km increase in travel time in peak hours (averaging over mornings and afternoons), and 0.0065 min/km off-peak (as implied by Table 4). The forgone annual congestion relief benefit to motor-vehicle travelers is then about 3.8 million hours of travel time. Given a value of time of €15.59/h, this benefit is worth roughly €59.5 million. 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 4), the forgone annual congestion relief benefit for bus travelers is about 1.3 million hours of travel time. Given a value of time of €3.65/h, this benefit is worth roughly €4.7 million. 

Notes: 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 idle time at stops. The number in parenthesis in column titles indicates number of roads. The controls include temperature, rain, hour-of-the-week, week-of-the-year, type of strikes 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.
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 10% is at least 0.019 min per trip on mixed traffic lanes.34 Assuming an average trip length of 5 km and that half of these trips take place on mixed traffic roads, the additional loss is €2.8 million per year.35 The total loss due to extra congestion is thus €75 million annually, i.e., at least 50% of the operating cost savings for the transit agency. We report these results in the first column of Table 7.

Based on the above figures we can also provide an approximate estimate of the effect of a full shutdown of public transport services. We calculate a forgone annual congestion relief benefit to motor-vehicle travelers of about 38 million hours of travel, worth €595 million. This figure equals about 38% of public transport operating cost in Rome (1.56 billion euros in 2013). We emphasize however that this result is less trustworthy than the effect of marginal supply changes, because as Figure 11 suggests we have very little information about the effect of reductions in public transport supply once the share of available service gets below 0.3.

Another interesting exercise is to compute the marginal congestion relief benefit of an additional bus. In Rome, there are about 8623 million motor-vehicle passenger-kilometers in peak hours per year (see Table 1). Buses provide about 70% of vehicle-kilometers of transit service in Rome and there are 1800 buses circulating during the peak. Consequently, our finding that a 10-percentage point transit reduction in the peak increases travel time by 0.017 min/km implies that removing one bus from peak service for 1 h would increase aggregate motor-vehicle time by 5.3 h. Furthermore, given 3403 million annual bus passenger-kilometers in the peak, the aggregate increase of travel and waiting time on bus passengers would be 7.9 h. Assuming that the value of time for car users is €15.59 and €9.54/h 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 workday, the external benefit of a bus operating during the peak is about €1.106/day.

These results are based on short-run estimates, exploiting temporary service disruptions. Hence, they cannot be used to predict long-run effects of permanent changes in transit supply. Note, however, that car ownership is high in Rome. Furthermore, strikes are frequent and public transit supply is only partially reduced during strikes. During peak hours, in particular, the supply reduction is limited, suggesting that travelers are more likely to respond to strikes in a way is due to a permanent service reduction than in other cities (where car ownership is lower and infrequent strikes 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).

34 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.

35 Using Equation (3), bus waiting time increases by an additional 0.42 min per trip on mixed traffic roads when the number of operating buses decreases by 10% (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.
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. Although we do not capture the very long-run effects of transit supply changes, such as job, house and firm relocation, as well as the changes in the spatial structure of cities, we believe that our congestion relief benefits estimates are useful for long-run policy for a number of reasons. First, the interval during which the short run benefits are enjoyed may be quite long. In addition, the economic mechanisms which reduce the congestion relief benefit in the long run by increasing travel times on the road (e.g., an increase in employment) tend to increase welfare overall.

6. 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 and 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 and rail) and two time periods (peak versus off-peak), while the

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

<table>
<thead>
<tr>
<th>Assumptions</th>
<th>Marg. shutdown (10% of total veh-km)</th>
<th>Full shutdown</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual veh-km, private motor vehicles</td>
<td>14.5 billion</td>
<td></td>
</tr>
<tr>
<td>Annual veh-km, public transport</td>
<td>201 million</td>
<td></td>
</tr>
<tr>
<td>Travel time increase cars (peak), min/veh-km</td>
<td>0.017</td>
<td>0.17</td>
</tr>
<tr>
<td>Travel time increase cars (off-peak), min/veh-km</td>
<td>0.006</td>
<td>0.06</td>
</tr>
<tr>
<td>Travel time increase buses (peak), min/veh-km</td>
<td>0.020</td>
<td></td>
</tr>
<tr>
<td>Travel time increase buses (off-peak), min/veh-km</td>
<td>0.011</td>
<td></td>
</tr>
<tr>
<td>Waiting time increase buses (average), min/trip</td>
<td>0.019</td>
<td>15.59</td>
</tr>
<tr>
<td>Value of time of car travelers, €/h</td>
<td></td>
<td>7.76</td>
</tr>
<tr>
<td>Average op. cost public transport, €/veh-km</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Results

| Public transit congestion relief benefit, year   | €75 million                          | €595 million |
| Operating cost saving, year                     | €152 million                         | €1.56 billion|
| Subsidy reduction                               | €152 million                         | €1.03 billion|
| Net congestion relief benefit (% of cost saving)| 50%                                  | 38%          |
(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 (reported in Appendix C).

We make slight adaptations to the model of Parry and Small as follows. First, instead of relying on the relations provided in their paper, we estimate motor-vehicle travel time as a function of density (Yang et al., 2020), based on the estimated relation (1). Specifically, we use the estimated parameter $a$ to calculate changes in travel time resulting from the change in subsidy level. Similarly, we use the estimated relation (2) to calculate changes in bus travel time (using the estimated value of $r$). We compute the marginal external costs of congestion on motor-vehicle and bus travelers given the estimated relations. Finally, we calibrate the fare elasticity of transit passenger-kilometers using our own estimates (exploiting one public fare increase) and data provided by the city of Rome. This elasticity is 0.22 (see Appendix B3), which is rather low in comparison to the elasticities assumed by Parry and Small. However, given that transit fares in Rome are much lower than in comparable European cities, a low elasticity seems reasonable.

Table 8 reports the results. The top panel reports the marginal external congestion cost per motor vehicle kilometer, which equals $0.29/\text{veh-km}$ in peak hours, and $0.13/\text{veh-km}$ during off peak (see the first row of Table 9). These costs are the sum of the external costs imposed on motor vehicle drivers ($0.21/\text{veh-km}$ in peak hours, $0.09/\text{veh-km}$ off-peak), as well as the external costs imposed on bus travelers ($0.08/\text{veh-km}$ in peak hours, $0.038/\text{veh-km}$ off-peak).

The bottom panel of Table 8 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-kilometer. 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-kilometer 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. In addition, we find that in the optimum—in

---

36 Parry and Small (2009) postulate a time-flow relation, whereby travel time is a power function of flow.
37 We observe one substantial public transit fare increase—by 50%—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% increases motor-vehicle travel times by 0.05 min/km implying that the elasticity of motor-vehicle travel time with respect to public transit fare is 0.078 (see Appendix B3 for details).
38 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 B3). 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.
39 The marginal congestion relief benefit is comparable to the average benefit obtained above (see Table 7), 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
the absence of road pricing—subsidies should cover at least 72% of operating costs (bottom row in Table 8).

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% 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% of the operational costs in Rome, appears to be justified.

### Table 8. Parry and small model for Rome: optimal public transit subsidies

<table>
<thead>
<tr>
<th></th>
<th>Peak</th>
<th>Off-peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marginal external cost, motor vehicle travel. €/veh-km</td>
<td>0.29</td>
<td>0.13</td>
</tr>
<tr>
<td>on other motor vehicles travelers</td>
<td>0.21</td>
<td>0.09</td>
</tr>
<tr>
<td>on bus travelers</td>
<td>0.08</td>
<td>0.04</td>
</tr>
<tr>
<td>Current subsidy, share of op. cost</td>
<td>0.76</td>
<td>0.76</td>
</tr>
<tr>
<td>Marginal welfare effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marginal benefit per €/cent/pax-km[^a]</td>
<td>0.10</td>
<td>0.31</td>
</tr>
<tr>
<td>Marginal cost/price gap</td>
<td>−0.24</td>
<td>−0.38</td>
</tr>
<tr>
<td>Net scale economy</td>
<td>0.12</td>
<td>−0.02</td>
</tr>
<tr>
<td>Externality</td>
<td>0.15</td>
<td>0.53</td>
</tr>
<tr>
<td>Other transit</td>
<td>0.08</td>
<td>0.19</td>
</tr>
<tr>
<td>Optimum subsidy, share of op. cost</td>
<td>&gt;0.9</td>
<td>0.72</td>
</tr>
</tbody>
</table>

[^a]: Benefit. By contrast, 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.
Acknowledgements

The authors thank Rome’s Mobility Agency (Agenzia per la Mobilita) and the Italian regulator for public sector strikes (Commissione di Garanzia per gli Scioperi) for kindly providing data. They would like to thank the editor Frederic Robert-Nicoud, two anonymous referees, Alex Anas, Richard Arnott, Pierre-Philippe Combes, Gilles Duranton, Dan Jaqua, Ismir Mulalic, Luis Rizzi, Chris Severen, Ken Small and Erik Verhoeef for insightful comments. They are grateful to audiences at UC Irvine, University of Toronto, Newcastle University, London School of Economics, VU Amsterdam, Brno University of Technology, Vienna University of Economics and Business, Institut d’Economia de Barcelona, Universitat Autonoma de Barcelona, Danish Technical University, GATE Lyon, PUC Santiago, University of Tokyo, the UEA meeting in Minneapolis, the IIPF conference in Lake Tahoe, the International Trade and Urban Economics workshop in St Petersburg, the Verkehrso¨konomik und -politik Conference in Berlin and the meeting of the Italian Society for Transport Economics. All errors are their responsibility. Finally, they acknowledge financial contribution by the European Research Council—OPTION program.

References


Appendix

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.
Appendix B1: 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.\textsuperscript{40} Standard errors become only slightly larger. In column (3), we add additional interaction effects for national strikes and semi-canceled strikes as well as a white strike dummy.\textsuperscript{41} The estimated sizes of these interaction effects are very small. For example, during the white strike, travel time increases slightly by about 0.2\%, i.e., 0.032 min/km.

\begin{table}[h]
\centering
\begin{tabular}{lcccc}
\hline
Public transit company & Buses & Metro trains & Surface trains & Employees \\
\hline
Atac SpA & 2055 (+165 trams) & 102 & 66 & 11,696 \\
Roma Tpl Scarl & 450 &  &  & 839 \\
Total & 2717 & 102 & 66 & 12,525 \\
\hline
\end{tabular}
\caption{Public transit stock in Rome}
\label{tab:transit_stock}
\end{table}

\textit{Notes:} Information for ATAC refers to the year 2015. For Roma, TPL the data refers to the year 2011.

\textbf{Appendix B1: 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.\textsuperscript{40} Standard errors become only slightly larger. In column (3), we add additional interaction effects for national strikes and semi-canceled strikes as well as a white strike dummy.\textsuperscript{41} The estimated sizes of these interaction effects are very small. For example, during the white strike, travel time increases slightly by about 0.2\%, i.e., 0.032 min/km.

\textsuperscript{40} 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.

\textsuperscript{41} During the white strike, a period of 2 weeks where public transit service was reduced through alternative means of striking excludes two strike days that fell into this period.
Appendix B2: 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 (6)). As shown in Table B2, a full shutdown of public transport increases motor-vehicle density by about 3–7 vehicles per lane-km on mixed traffic roads, with a

Table B2. Motor-vehicle density

<table>
<thead>
<tr>
<th></th>
<th>Mixed traffic roads (23)</th>
<th>Dedicated lanes (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public transit share (morning peak)</td>
<td>−6.55***</td>
<td>−7.25*</td>
</tr>
<tr>
<td></td>
<td>(1.24)</td>
<td>(3.78)</td>
</tr>
<tr>
<td>Public transit share (afternoon peak)</td>
<td>−4.10***</td>
<td>−3.13***</td>
</tr>
<tr>
<td></td>
<td>(0.56)</td>
<td>(0.76)</td>
</tr>
<tr>
<td>Public transit share (off-peak)</td>
<td>−2.99***</td>
<td>−2.94***</td>
</tr>
<tr>
<td></td>
<td>(0.36)</td>
<td>(0.59)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>353,442</td>
<td>49,539</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.509</td>
<td>0.484</td>
</tr>
</tbody>
</table>

Notes: 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% levels. 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.
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.

As a second step, we estimate the effect of motor-vehicle density on bus travel time (using the same sample as for the estimates in Table 7). Table B3 reports the results. 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%. Given the use of IV, this effect is slightly higher and equal to 1.95%. The effect is much smaller and not statistically significant on dedicated lanes.

Appendix B3: Public transit fares and motor-vehicle demand

Rome’s public transit operator adjusted fare prices on 25 May 2012, most notably for single tickets from €1 to €1.5.\textsuperscript{42} 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 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. See Table B4.

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 B3. Log bus driving time

<table>
<thead>
<tr>
<th></th>
<th>Mixed traffic</th>
<th>Mixed traffic</th>
<th>Dedicated lanes</th>
<th>Dedicated lanes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density</td>
<td>OLS 0.0160***</td>
<td>IV 0.0195***</td>
<td>OLS 0.0023</td>
<td>IV 0.0026</td>
</tr>
<tr>
<td></td>
<td>(0.0009)</td>
<td>(0.0023)</td>
<td>(0.0019)</td>
<td>(0.0037)</td>
</tr>
<tr>
<td>Instrument</td>
<td></td>
<td>Hour-of-week</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of roads</td>
<td>23</td>
<td>23</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Number of observation</td>
<td>71,645</td>
<td>71,645</td>
<td>31,024</td>
<td>31,024</td>
</tr>
</tbody>
</table>

Notes: 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%.

\textsuperscript{42} At the same time, the maximum allowed travel time on a single ticket was increased from 75 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.
<table>
<thead>
<tr>
<th></th>
<th>Travel time</th>
<th></th>
<th>Flow</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All roads</td>
<td>Heavily congested</td>
<td>All roads</td>
</tr>
<tr>
<td>Fare increase by 50%</td>
<td>0.048***</td>
<td>0.116***</td>
<td>30.8***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.026)</td>
<td>(6.9)</td>
</tr>
<tr>
<td>Time trends before boundary</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time trends after boundary</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Public transit share</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Road-fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Hour-of-week fixed effects (120)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Weather</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>113,129</td>
<td>31,654</td>
<td>113,139</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.7338</td>
<td>0.7239</td>
<td>0.8934</td>
</tr>
</tbody>
</table>

Notes: Time trends refers to the third-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 6-months window (on both sides) but with linear controls, the results are identical. Given a 5 months or 4 months window the estimates increase to 0.06 and 0.10. Given a 3-month window, the estimate is again 0.04, and still highly statistically significant.
### Appendix C: Aggregate model for Rome adapting Parry and Small (2009)

Table C1. Aggregate model, parameters and results

<table>
<thead>
<tr>
<th></th>
<th>Rail peak</th>
<th>Off-peak</th>
<th>Bus peak</th>
<th>Off-peak</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TRANSIT</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual passenger kms, millions</td>
<td>1639</td>
<td>628</td>
<td>3403</td>
<td>2304</td>
</tr>
<tr>
<td>Vehicle occupancy (pass-km/veh-km)</td>
<td>160</td>
<td>87</td>
<td>51</td>
<td>34</td>
</tr>
<tr>
<td>Average operating cost, €/veh-km</td>
<td>29</td>
<td>17</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>Avg operating cost, €cents/pass-km</td>
<td>18</td>
<td>20</td>
<td>19</td>
<td>15</td>
</tr>
<tr>
<td>Marginal supply cost, €cents/pass-km</td>
<td>11</td>
<td>12</td>
<td>13</td>
<td>10</td>
</tr>
<tr>
<td>Fare, €cents/pass-km</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Subsidy, % of average operating cost</td>
<td>74</td>
<td>76</td>
<td>75</td>
<td>69</td>
</tr>
<tr>
<td>Cost of in-vehicle travel time, €cents/pass-km</td>
<td>13</td>
<td>10</td>
<td>19</td>
<td>12</td>
</tr>
<tr>
<td>Wait cost, €cents/pass-km</td>
<td>2</td>
<td>6</td>
<td>4</td>
<td>11</td>
</tr>
<tr>
<td>Generalized price, €cents/pass-km</td>
<td>25</td>
<td>28</td>
<td>34</td>
<td>40</td>
</tr>
<tr>
<td>Marginal scale economy, €cents/pass-km</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>7</td>
</tr>
<tr>
<td>Marginal cost of occupancy, €cents/pass-km</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Marginal external cost, €cents/pass-km</td>
<td>0.4</td>
<td>0.2</td>
<td>3.5</td>
<td>2.6</td>
</tr>
<tr>
<td>Marg. congestion cost. €cents/pass-km</td>
<td>0.0</td>
<td>0.0</td>
<td>2.2</td>
<td>1.3</td>
</tr>
<tr>
<td>Pollution, climate and acc cost. €cents/pass-km</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Elasticity of passenger demand wrt fare</td>
<td>−0.22</td>
<td>−0.22</td>
<td>−0.22</td>
<td>−0.22</td>
</tr>
<tr>
<td>Fraction of increased transit coming from</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Auto—same period</td>
<td>0.50</td>
<td>0.40</td>
<td>0.50</td>
<td>0.40</td>
</tr>
<tr>
<td>Same transit mode—other period</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td>Other transit mode—same period</td>
<td>0.30</td>
<td>0.30</td>
<td>0.30</td>
<td>0.30</td>
</tr>
<tr>
<td>Increased overall travel demand</td>
<td>0.10</td>
<td>0.20</td>
<td>0.10</td>
<td>0.20</td>
</tr>
<tr>
<td><strong>AUTO</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual passenger-kms, millions</td>
<td>8623</td>
<td>12,837</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Occupancy</td>
<td>1.41</td>
<td>1.52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marginal external cost, €cents/pass-km</td>
<td>21</td>
<td>7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marg. congestion cost. €cents/pass-km</td>
<td>23</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poll. and acc. less fuel tax. €cents/pass-km</td>
<td>−2</td>
<td>−1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>